eman ta zabal zazu

UPV EHU

Development of a Sensorized Tip for Physical Activity Classification and Fall Detection

Department of Automatic Control and Systems Engineering

Asier Brull Mesanza

Supervisors: Itziar Cabanes Axpe
Asier Zubizarreta Pico

eman ta zabal zazu

Universidad del País Vasco
Euskal Herriko Unibertsitatea

FACULTY
OF ENGINEERING
BILBAO
UNIVERSITY
OF THE BASQUE
COUNTRY

DEVELOPMENT OF A SENSORIZED TIP FOR PHYSICAL ACTIVITY CLASSIFICATION AND FALL DETECTION

ASIER BRULL MESANZA

PhD Thesis - 2022

Supervised by Itziar Cabanes Axpe and Asier Zubizarreta Pico

Department of Automatic Control and Systems Engineering

Contents/Aurkibidea

Acknowledgements/Eskerrak

Primero de todo, me gustaría agradecer a mis directores de tesis Itziar Cabanes y Asier Zubizarreta por los consejos aportados durante el desarrollo de la tesis y por todas las horas que han dedicado a orientar, mejorar y supervisar en el trabajo realizado.

I would also like to thank the supervisors that I had at Università di Bologna (UNIBO) during the research that I did while I was in Italy. Thank you Lorenzo for the welcome given to the research group in order to be able to develop the project we are carrying out. Thank you Luca for your warm welcome and for the help with the tests carried out, as well as the help in the development of the fall detector. Thank you Ilaria for your help in the development of the experiments as well as your advice on the fall detection methodology.

También me gustaría agradecer a los demás doctores que también me aconsejaron y me ayudaron a conseguir los objetivos de esta tesis, en especial agradezco a Aitziber, Eva, Ana y Jon. Bereziki eskerrak eman nahi dizkiot Aitziberi, tesia euskaraz idazten laguntzeagatik eta tesia garatzen laguntzeagatik. Me gustaría agradecer a mis compañeros de laboratorio los cuales me han ayudado a hacer más ameno el proceso de investigación, así como me han ayudado a avanzar cuando me han surgido dudas o problemas. Así como me gustaría agradecer a todos los compañeros que han aportado su participación en la tesis realizada. Un especial agradeciemiento a Patrick, Alejandro, Asier, Sergio, Janire, Aitor, Jonas, Clement, Tania, Iñigo y muchos otros más. Espero poder seguir disfrutando de vosotros y poder seguir compartiendo buenos momentos como hasta ahora.

También agradezco el tiempo de todos los voluntarios que participaron en los experimentos que hicimos. También agradezco a las instituciones que proporcionaron apoyo financiero para completar esta tesis: el Gobierno del País Vasco, la UPV/EHU y el Ministerio de Ciencia. Especialmente agradezco a la UPV/EHU por financiar económicamente mi tesis doctoral (PIF18/0067).

Por último, quiero dar las gracias a mi familia y a mis amigos, con los que no habría sido posible conseguir las fuerzas necesarias para seguir adelante. Eskerrik asko Ama, Ahinize, Dana, familia, a los Txoris y a todos los demás amigos que me animaron a cumplir un sueño y a seguir adelante con él en los momentos difíciles.

Abstract

The need for rehabilitation has increased over the years. The individualisation of rehabilitation plays an important role in improving the lives of people in need. Within this individualisation of rehabilitation, the use of physical activity data can be very useful to know the condition of the person. But the knowledge of constant physical activity is almost impossible for therapists.

The use of technology, with the purpose of helping to know the physical activity performed by people, is becoming more and more common. Through the sensorization of the person, very interesting data can be obtained to help in rehabilitation. In addition, thanks to this sensorization, it is possible to know other types of events, such as a fall, whose rapid action can avoid increasing the need for rehabilitation.

Typically this type of sensorization is done using wearable sensors, but several researchers have proposed the use of sensors integrated into assistive devices for walking for those who need them, as this solution is less invasive. While many of the devices can measure physical activity, they have the disadvantage that the sensing elements are fixed to the assistive devices for walking. This may prevent the user from being comfortable, as it is not the assistive device for walking that he/she normally uses. For this reason, the design of an interchangeable sensor tip between different assistive devices for walking is very important.

This paper presents an innovative prototype of a sensorized tip that can be interchanged between different assistive devices for walking. It is capable of classifying different physical activities as well as detecting falls. The developed tip is able to adapt to different assistive devices for walking on the market. In addition, this sensorized tip consists of a series of sensors that provide the information needed to classify physical activities and detect falls. These sensors are: a force sensor to measure axial forces; a 3-axis accelerometer, a 3-axis gyroscope and a 3-axis magnetometer to measure movement; and a barometer to measure height variations. In addition, the data from these sensors is sent via Bluetooth Low Energy, making the devices autonomy very high. Because people when using an assistive device for walking do not always use it in the most appropriate way and tend to twist the device, an algorithm is proposed to estimate what is the angle of advance. In this way the data of the Lateromedial

and Anteroposterior angles can be obtained in a simple way. This sensorized tip is validated by a series of tests to achieve good measurement errors.

In order to know the physical activity carried out by the assistive device for walking user, a classifier capable of classifying 5 different physical activities is created. The use of Machine Learning techniques is considered for this purpose. In order to use these techniques, it is proposed the segmentation of the data in windows by events to create a series of features for each window. Since the number of features is very high, a dimensionality reduction using Random Forest is proposed in order to use the most relevant ones. Once these most important features are known, it is proposed to use K-Nearest Neighbors (K-NN), Support Vector Machine (SVM) and Artificial Neural Network (ANN) to classify between walking, fast walking, going up stairs, going down stairs and standing still. The classifiers performed are compared with each other, achieving results between 92% and 97%, using only 7 features.

Moreover, a fall detector is proposed through the use of the sensorized tip. This fall detector, like the physical activity classifier, follows a methodology in which the data is first divided into windows and then a set of features is generated. This is followed by dimensionality reduction of the features and an SVM-based detector. This classifier is based on two modules, one of which detects when the assistive device for walking is fallen and the other one detects when the person with the assistive device for walking is fallen. Results higher than 0.96 F-Score are achieved. Finally, the results obtained by the sensorized tip-based detector are compared with the results obtained by wearable sensors.

Laburpena

Azken urteetan, errehabilitazio beharra areagotu da. Indibidualizazioak oso eginkizun garrantzitsua du errehabilitazio beharra duten pertsonen bizitza hobetzeko. Errehabilitazioaren indibidualizazio horren barruan, pertsonaren egoera ezagutzeko, jarduera fisikoari buruzko datuak erabiltzea oso baliagarria izan daiteke. Baina jarduera fisiko etengabea ezagutzea ia ezinezkoa da terapeutentzat.

Pertsonek egiten duten jarduera fisikoa ezagutzeko, gero eta ohikoagoa da, teknologiaren erabilera. Pertsonaren sentsorizazioaren bidez, errehabilitazioan laguntzeko oso datu interesgarriak lor daitezke . Gainera, sentsorizazio horri esker, erorketak bezalako beste gertaera mota batzuk ezagutzea lor daiteke, eta horien jarduera azkarrak errehabilitazio beharra areagotzea ekidin dezake.

Oro har, sentsorizazio mota hori sentsore eramangarrien bidez egiten bada ere, hainbat ikertzailek, laguntza teknikoko gailuetan sentsoreak integratzea proposatu dute, horrela hain inbaditzaileak ez diren soluzioak lortuz. Jarduera fisikoa detektatu dezaketen gailu asko badaude ere, sentsoreak ibiltzeko laguntza gailuetan finko egotearen eragozpena dute. Horrek erabiltzailea eroso egotea eragotz dezake, ez baita normalean erabiltzen duen ibiltzeko laguntza gailua. Hori dela eta, ibiltzeko laguntza gailu ezberdinen artean alda daitekeen Punta sentsorizatu baten diseinua oso garrantzitsua dela ondorioztatzen da.

Honen aurrean, lan honek, ibiltzeko laguntza gailu ezberdinen artean trukatzeko gai den Punta sentsorizatuaren prototipo berritzaile bat aurkezten du. Garatutako punta, merkatuko ibiltzeko laguntza gailuetara egokitzeko gai da. Gainera, sentsorizatutako punta honek, jarduera fisikoen sailkapena egiteko eta erorikoak detektatzeko informazioa ematen duten sentsoreak ditu. Hauek dira dituen sentsoreak: indar axialak neurtzeko indar-sentsore bat; mugemendua neurtzeko 3 ardatzeko azelerometro bat, 3 ardatzeko giroskopio bat eta 3 ardatzeko magnetometro bat; eta altuera aldaketak neurtzeko barometro bat. Gainera, gailuaren autonomia oso handia izan dadin, sentsore horien datuak Bluetooth Low Energy bidez bidaltzen dira. Horretaz gainera, jendeak ibiltzeko laguntza gailu bat erabiltzen duenean ez duenez beti modurik egokienean erabiltzen eta gailua okertzen duenez, aurrerapen angelua zein den kalkulatzeko algoritmo bat proposatzen da. Horrela, angelu lateromediala eta anteroposteriorra

lortuz. Punta sentsorizatu hori proba batzuen bidez balioztatu da, neurketa-errore onak lortuz.

Ibiltzeko laguntza gailuaren erabiltzaileak egindako jarduera fisikoa ezagutu ahal izateko, 5 jarduera fisiko sailkatzeko gai den sailkatzaile bat garatu da. Helburu hau lortzeko, Machine Learning teknikak erabili dira. Teknika horiek erabili ahal izateko, datuak gertaeren arabera leihoetan segmentatu eta leiho bakoitzeko hainbat ezaugarri sortu dira. Ezaugarrien kopurua oso handia denez, Random Forest erabiliz dimentsionaltasuna murriztu da, ezaugarri garrantzitsuenak aukeratuz. Ezaugarri garrantzitsu horiek ezagutu ondoren, K-Nearest Neighbors (K-NN), Support Vector Machine (SVM) eta Artificial Neural Network (ANN) erabili dira, ibiltzeko, azkar ibiltzeko, eskailerak igotzeko, eskailerak jaisteko eta geldirik egoteko jarduera fisikoak sailkatzeko. Garatutako sailkatzaile desberdinak elkarren artean alderatu dira, %92 eta %97 arteko emaitzak lortuz.

Gainera, Punta sentsorizatua, erorikoak detektatzeko erabili da. Erorikoen detektagailu horrek, jarduera fisikoen sailkatzaileak bezala, metodologia bati jarraitzen dio. Metodologia horretan, lehenik eta behin, datuak leihoetan zatitu eta zenbait ezaugarri sortzen dira. Ondoren, dimentsionaltasun murrizketan eta SVMn oinarritutako detektagailua garatzen da. Detektagailu hau, bi modulutan banatzen da; lehen moduluak ibiltzeko laguntza gailua erori dela detektatzen du, eta bigarrenak, ibiltzeko laguntza gailuaren erabiltzailea erori dela hautematen du. F-Score-ren 0.96tik gorako emaitzak lortzen dira bi moduluetan. Azkenik, Punta sentsorizatuan oinarritutako detektagailuak lortutako emaitzak sentsore eramangarrien bidez lortutako emaitzekin alderatzen dira.

Resumen

La necesidad de rehabilitación se ha visto incrementada con el paso de los años. La individualización de esta juega un papel muy importante para mejorar la vida de las personas que la requieren. Dentro de esta individualización de la rehabilitación, el uso de los datos de la actividad física puede ser muy útiles para conocer el estado de la persona. Pero el conocimiento de la actividad física constante es casi imposible para los terapeutas.

El uso de la tecnología, con el propósito de ayudar al conocimiento de la actividad física realizada por las personas, es cada vez más común. Mediante la sensorización de la persona se pueden conseguir datos muy interesantes para ayudar en la rehabilitación. Además, gracias a esta sensorización se puede conseguir conocer otro tipo de eventos, como una caída, cuya actuación rápida puede evitar incrementar la necesidad de rehabilitación.

Por lo general este tipo de sensorización se realiza mediante el uso de sensores vestibles, pero varios investigadores han propuesto el uso de sensores integrados en los dispositivos de ayuda técnica, para aquellas personas que los necesitan, siendo esta solución es menos invasiva. Si bien muchos de los dispositivos pueden medir la actividad física, estos tienen el inconveniente de que los elementos sensores se encuentran fijos en los dispositivos de ayuda a la marcha. Esto puede impedir que el usuario se encuentre cómodo, ya que no es el dispositivos de ayuda a la marcha que el usa habitualmente. Por ese motivo, el diseño de una contera sensorizada intercambiable entre los distintos dispositivos de ayuda a la marcha es muy importante.

Este trabajo presenta un prototipo innovador de contera sensorizada capaz de intercambiarse entre distintos dispositivos de ayuda a la marcha. Esta es capaz de clasificar diferentes actividades físicas, así como de detectar caídas. La contera desarrollada es capaz de adaptarse a los distintos dispositivos de ayuda a la marcha del mercado. Además, esta contera sensorizada consta de una serie de sensores que aportan la información para la realización de la clasificación de actividades físicas y detección de caídas. Estos sensores son: un sensor de fuerza para medir las fuerzas axiales; un acelerómetro de 3 ejes, un giroscopio de 3 ejes y un magnetómetro de 3 ejes para medir el movimiento; y un barómetro para medir las variaciones de altura.

Además, los datos de estos sensores se envían vía Bluetooth Low Energy, haciendo que la autonomía del dispositivo sea muy elevada. Debido a que la gente cuando usa un dispositivos de ayuda a la marcha no siempre lo usa de la manera más adecuada y suele torcer el dispositivo, se propone un algoritmo para estimar cual es ángulo de avance. De esta manera se pueden conseguir los datos de los ángulos Lateromedial y Anteroposterior de manera sencilla. Esta contera sensorizada se valida mediante una serie de pruebas consiguiendo unos errores de medición buenos.

Para poder conocer la actividad física realizada por el usuario del dispositivos de ayuda a la marcha, se realiza un clasificador capaz de clasificar 5 diferentes actividades físicas. Se propone del uso de técnicas de Machine Learning para este propósito. Para poder usar estas técnicas, se propone la segmentación de los datos en ventanas por eventos para crear una serie de características por cada ventana. Debido a que el número de características es muy elevado, se propone una reducción de dimensionalidad mediante el uso de Random Forest, para así poder usar las más relevantes. Una vez conocidas estas características más importantes, se propone el uso de K-Nearest Neighbors (K-NN), Support Vector Machine (SVM) y Artificial Neural Network (ANN) para clasificar entre andar, andar rápido, subir escaleras, bajar escaleras y estar quieto. Los clasificadores realizados se comparan entre si, consiguiendo resultados entre el 92% y el 97%.

Además, se propone un detector de caídas mediante el uso de la contera sensorizada. Este detector de caídas, al igual que el clasificador de actividades físicas, sigue una metodología en la cual primero se realiza una división de los datos en ventanas para después generar una serie de características. Luego se realiza una reducción de dimensionalidad y un detector basado en SVM. Este clasificador se hace en base a dos módulos, los cuales uno sirve para detectar cuando el dispositivos de ayuda a la marcha se ha caído y el otro detecta cuando se ha caído la persona con el dispositivos de ayuda a la marcha. Se consiguen resultados mayores del 0.96 de F-Score. Por último, se comparan los resultados obtenidos por el detector basado en la contera sensorizada con los resultados obtenidos por sensores vestibles.

Acronyms/Akronimoak

AA Adimen Artifiziala. 5, 22, 23, 71

ADW Assistive Device for Walking. i, iii, iv, 4–7, 9, 10, 13–15, 19, 25, 31, 35–39, 43, 45, 46, 48–50, 59–62, 64, 67, 68, 70–73

AI Artificial Intelligence. 5, 22, 23, 71

ANN Artificial Neural Network. iii–v, 21–25, 32, 33, 35, 36, 56–58, 71

BLE Bluetooth Low Energy. i, ii, 39, 40, 70

CFS Correlation based Feature Selection. 20

CNN Convolutional Neural Network. 18, 24, 32

DAQ Data Acquisition System. 15

DT Decision Trees. 20, 22, 24, 25, 33

EMG Electromyography. 9, 23

FL Fuzzic Logic. 23, 33

GPS Global Positioning System. 13, 31

I2C Inter-Integrated Circuit. 15, 39, 40

ILG Ibiltzeko Laguntza Gailua. ii, iv, v, 3–7, 9, 10, 12–17, 19, 25, 31, 35–39, 42, 45, 46, 48–50, 59–62, 64, 67, 68, 70–73

IMU Inertial Measurement Unit. iii, iv, 8, 9, 13, 14, 30, 39, 40

JF Jarduera Fisikoa. ii, iv, v, 2–6, 8, 9, 16, 21–25, 35, 37–39, 49, 51, 53, 56, 58–62, 70, 71, 73, 74

K-NN K-Nearest Neighbors. iv, v, 21–25, 32, 33, 35, 56–58, 71

KMCA K-Means Clustering. 20

LR Logistic Regression. 24, 25, 33

ML Machine Learning. iv, v, 1, 2, 5, 6, 21, 22, 25, 32, 33, 35, 36, 49, 50, 55–58, 60, 62, 71, 72

MLP Multilayer Perceptron. 18, 23, 24, 32, 33, 56

MOE Munduko Osasun Erakundea. 2, 4

NB Naive Bayes. 22, 24, 25, 33

PA Physical Activity. i, iv, 1–6, 8, 9, 16, 22, 23, 25, 35, 37–39, 49–51, 58–62, 70–74

PCA Principal Component Analysis. 20, 21

RF Random Forest. i, ii, iv, v, 20, 21, 24, 25, 33, 53, 55–58, 63–68, 71

RMS Root Mean Square. 43, 48

RNN Recurrent Neural Network. 18, 24, 32, 33

SD Secure Digital. 15

SNN Spiking Neural Network. 24, 25

SPI Serial Peripheral Interface. 15

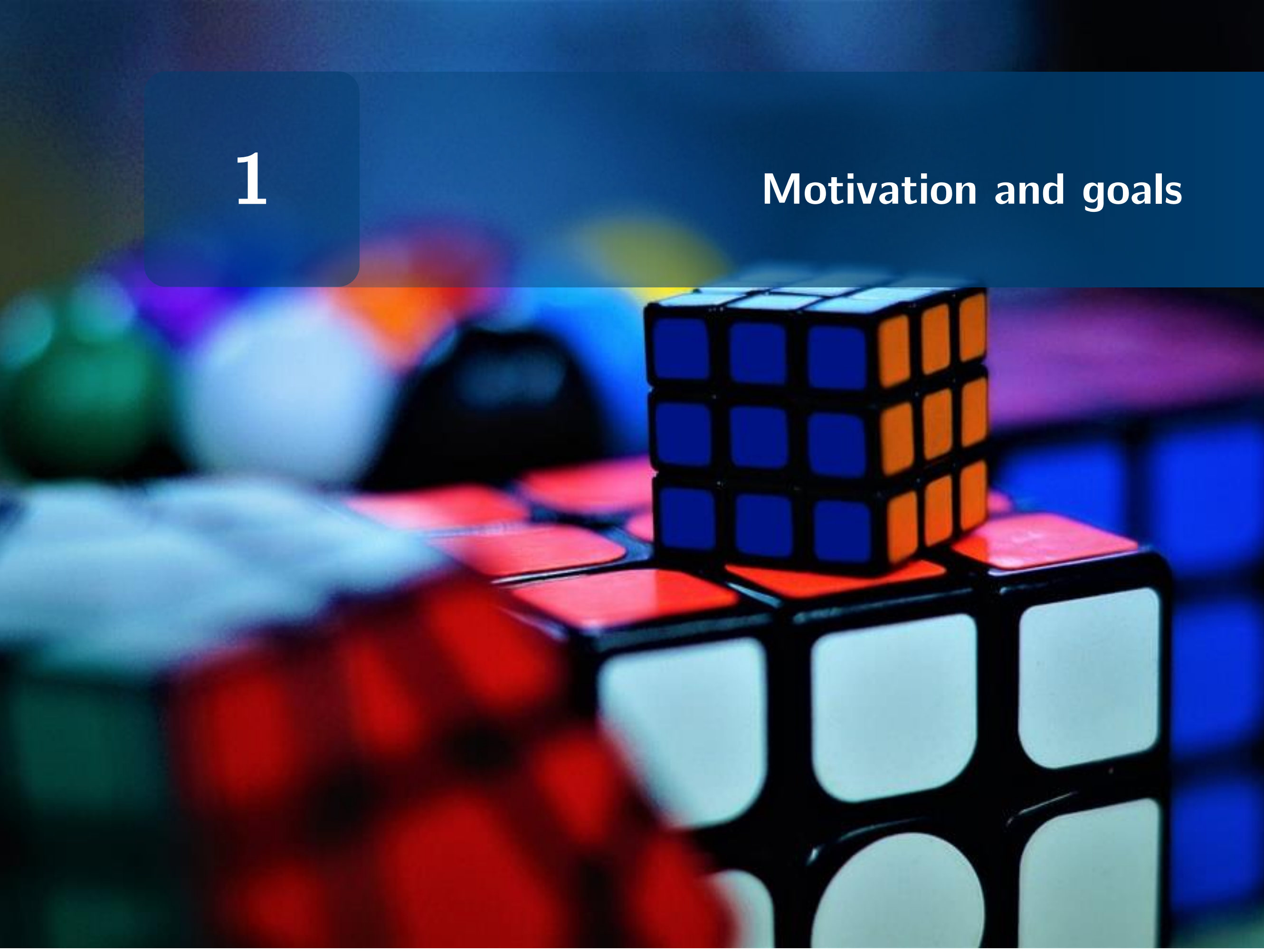
SVM Support Vector Machine. i, ii, iv, v, 20, 22–25, 32, 33, 35, 36, 56–58, 60, 63, 65–68, 71, 72

UPV/EHU Euskal Herriko Unibertsitatea/Universidad del País Vasco. 1, 40, 69

USB Universal Serial Bus. 38

WHO World Health Organisation. 2, 4

WIFI Wireless Fidelity. 15



1 Motivation and goals

This doctoral thesis has been carried out by **Asier Brull Mesanza** in the *PhD program in Control Engineering, Automation and Robotics* of the *Euskal Herriko Unibertsitatea/Universidad del País Vasco* (*UPV/EHU*), and has been supervised by **Dr. Itziar Cabanes Axpe** and **Dr. Asier Zubizarreta Pico**.

The research presented in the doctoral thesis has been carried out in the *Virtual Sensorization (ViSens) Research Group* of the *Department of Automatic Control and Systems Engineering* of the *Bilbao School of Engineering* of the *Euskal Herriko Unibertsitatea/Universidad del País Vasco* (*UPV/EHU*). This doctoral thesis was supported by the *Euskal Herriko Unibertsitatea/Universidad del País Vasco* (*UPV/EHU*) under grant **PIF18/067**.

The doctoral thesis is presented as a compendium of papers index in JCR of Science Citation Index, being these **Sensorized Tip for Monitoring People with Multiple Sclerosis that Require Assistive Devices for Walking** (Appendix 1 [28]), **A Machine Learning Approach to Perform Physical Activity Classification Using**

a Sensorized Crutch Tip (Appendix 2 [126]) and **Machine Learning based Fall Detector with a Sensorized Tip** (Appendix 3 [125]).

1.1 Motivation

According to the World Health Organisation (WHO), rehabilitation plays a very important role in the recovery of people after suffering an injury or illness [140, 78, 59]. Worldwide, around 2.4 billion people suffer from a health problem that benefits from rehabilitation [1]. Among the diseases that contribute most to the necessity for rehabilitation are musculoskeletal disorders, with next to 1.7 billion people around the world suffering from them [41]. The need for physical rehabilitation has increased, given that in the last 37 years, the number of years of life with a disability has grown by 66.2% [86]. This increase in the time a person suffers from a dissability means longer rehabilitation treatments are needed to ensure a more independent life. Moreover, this requirement for rehabilitation grows with the ageing of the population [78], as more and more people experience a deterioration in functioning that leads to the requirement for appropriate rehabilitation. In addition, older people tend to fall more easily, increasing the likelihood of suffering an injury that requires rehabilitation [48].

One of the most important factors to be able to live a life with quality and autonomy is to have good mobility in the lower limbs. It is very important, a correct rehabilitation for the recovery of this mobility. Furthermore, neurological diseases or trauma injuries can cause a loss of mobility in the lower limbs, limiting the personal life of those who suffer from them. Because of the impact that this type of condition can have, trying to achieve a partial or complete recovery of the functions of this important part of the body is one of the main objectives when designing a rehabilitation strategy for each patient [63, 48, 82]. Among those neurological diseases that affect mobility and require proper rehabilitation is Multiple Sclerosis, which affects 2.3 million people, creating a great social and economic impact for those who suffer from it [60].

Some of the main factors for rehabilitation interventions to be as efficient as possible is that they must be adapted to the individual patient condition throughout the rehabilitation process [101]. Individualisation of rehabilitation is very important, and carrying out rehabilitation in the home environment can help to adapt to each person's needs and time, improving the effectiveness of rehabilitation [96, 184]. This process of rehabilitation adapted to the patient's particular condition can help in a faster improvement, as the exercises performed are more specific to the patient's condition. This individualisation of therapy depends on the patient's particular condition, which is related to the patient's ability to perform daily activities [43]. For example, a more active patient who is able to walk a couple of kilometres every day will present different necessities than one who does not perform such activity. Therefore, an objective quantification of patients' Physical Activity (PA) performed during the day can be a valuable tool for efficient therapy planning. Patient adaptation also includes the selection of the assistive device that best suits the patient's needs according to their functionality. If the patient has lost the ability to walk independently, the use of wheelchairs or scooters is the best option, while crutches or canes are often used when gait function is partly maintained. Therefore, the therapist is required to assess the patient's condition periodically to monitor the evolution of the patient's state, in order to be able to adapt the requirements to the patient's stage of rehabilitation.

In order to be able to individualise the patient's condition at all times, a constant clinical assessment is required, which can help to understand the person's condition. This assessment is usually carried out using data collected through testing in clinical settings, which are usually highly controlled. These clinical settings often do not take into account the variabilities that may occur on a day-to-day basis, so that the assessment may not best reflect the realities of the situation. For this reason, the monitoring of the types of PA performed by the patient throughout the day is becoming increasingly important in the functional assessment of patients, when Physical Activity is defined as "any bodily movement produced by skeletal muscles that results in energy expenditure" [31]. This monitoring of PA can help to give an assessment of the level of autonomy of the person, and can provide a clinical evaluation of the person's level of autonomy [90]. In addition, important information can be obtained about the way of moving or the force exerted, which can help to know what is the general state of the person. It has recognised health benefits, as well as contributing to the prevention of non-communicable diseases [176, 22]. Through the information collected from PA monitoring, it is possible to interpret the results of periodic tests and thus give individualised recommendations and feedback on how much and how to perform these activities to help the person's recovery process [19]. This cannot happen if only clinical assessment is performed, which can only take a snapshot of the patient's condition [11, 151].

One of the great challenges in the continuous monitoring of PA is that it cannot be done by the therapist, as it would be unfeasible for the therapist to follow the patient constantly. Traditionally, this individualization has been done through surveys, and most traditional instruments fail to assess PA throughout daily life [84]. Moreover, in many middle-income settings, there are fewer than 10 professionals per million inhabitants with the skills to carry out rehabilitation [1], which makes it difficult to realise this individualisation. For this reason, thanks to today's advances in the field of sensor technology, this monitoring has begun to be done by incorporating sensors into a person's daily life [174, 55]. Through this possible sensorisation of the person's life, it is possible to monitor gait, knowledge of which is an important factor in the design of individual rehabilitation. Also it is possible to know the functional state of the user at all times, helping considerably in the individualisation of rehabilitation. The use of these sensors can provide more quantitative data, providing data on movement, force, etc. This quantitative information gives the rehabilitation staff the possibility to better understand the patient's condition at all times, making it possible to adapt to the circumstances.

The monitoring of Physical Activity is done through the use of many types of sensors, which provide a range of data that can be used to assist in the understanding of the activities being performed. The use of different sensors, by fusing them, for the detection of PA, provides the ability to obtain different significant variables, which can give a more detailed description of the activity that is being carried out.

Within the casuistry of gait monitoring, there is a subset of solutions focused on the monitoring of patients requiring Assistive Device for Walking (ADW), such as canes or crutches. Thanks to the ability to embed sensors in different elements, this interest in the development of smart assistive devices has increased significantly, given their potential for the quantification of the patient's condition. Those who require an ADW are often constantly on the move with it, which makes it easier to obtain information on the day's progress. In this area, some studies [25] have proposed the sensorisation of canes or crutches.

The use of ADWs as wearable sensors to identify physical activities and thus aid rehabilitation has not been studied extensively. Being the use of these elements interesting for these tasks, since the use of sensorized ADW has advantages over the inclusion of wearable sensors in the body or the use of sensors such as cameras. Firstly, these sensors will not have parasitic noise, because they will be placed in rigid areas. Secondly, the sensors do not have to be put on and taken off and can remain fixed on the assistive system, which helps to ensure that the positioning of the sensors is always appropriate. Finally, sensors and acquisition systems do not cause discomfort during movement, as can those that are attached to the body.

Sensorisation of the individual for gait monitoring can be used for two purposes. First, it can be used to monitor the Physical Activity performed, and in this way can help in the individualised rehabilitation of people. Secondly, this monitoring can be used as a system for fall detection to prevent falls and thus prevent possible injuries that may require further rehabilitation.

As mentioned above, as people get older, the number of falls people suffer is increasing. A fall in a person of adult age or with a physical problem can cause a great impact on the person who suffers it [143, 73]. Rapid action in the event of a fall is essential, particularly for people living alone, as the longer it takes to react to the event, the higher the morbidity or mortality rate [74, 192]. This may increase the need for rehabilitation, increasing the necessity for health care personnel to carry out rehabilitation.

Studies, including those of the WHO [199, 164], show that more than 28% of the population over 64 years of age suffers at least one fall per year, and this group is also among the most sensitive to the consequences of a fall. A fall can cause physical injuries in 6% of people [179, 172], of which 14% can be serious injuries [175]. On the other hand, a fall also has consequences on the functioning of the elderly people [172], in such a way that 15% reduce their social activity outside the home.

For all these reasons, both the prevention of falls and their early detection and action are very important. However, it is often impossible for the person who has fallen to take quick action when a fall occurs. Often the fall can lead to a loss of consciousness or disorientation, making this impossible. In addition, many people are alone when they fall, so there is no one who can help them instantly. In addition, it has been shown that the use of ADWs can reduce the number of falls in people who use ADWs for mobility [116].However, even though the use of ADWs can prevent users from falling as much, these people still have movement difficulties and are still more prone to falls than other people [158].

For this reasons, it is necessary to look for solutions that can detect a fall, and act accordingly. With this in mind, sensors embedded in everyday life are increasingly being used in conjunction with Artificial Intelligence (AI)-based methodologies to detect if a fall has occurred, so that early warning can be given and action can be taken quickly. Through the application of technology in fall detection, it is possible to detect falls and provide early warning, thus avoiding possible consequences leading to rehabilitation.

The detection of falls in people who use an ADW in their daily life to move around is not a well studied field. However, it is an important area in which to act, as people who require an ADW are usually more likely to require rehabilitation in the event of a fall.

Taking into account the ability of sensor systems to assist in the quantification of Physical Activity, and thus help in the individualisation of rehabilitation. In addition, it should be noted that early detection of falls, and thus early action, can help to avoid further rehabilitation. In addition to taking into account the advantages of using Assistive Device for Walking as a sensor element with respect to other types of sensor elements. For all these reasons, this doctoral thesis proposes the development of a sensor tip capable of adapting to the different ADWs, with which it will be possible to know the PA of the users by means of Machine Learning (ML), as well as being able to detect when a fall occurs, to be able to give early warning and act accordingly.

In summary, individualisation of rehabilitation is an important factor in improving the rehabilitation process of patients. This individualisation can be achieved by monitoring people's Physical Activity, allowing physiotherapists to evaluate the patient's evolution in order to create a specific rehabilitation routine, with the use of sensors being the best alternative to achieve this. The sensors used for this task are usually wearable sensors which tend to have disadvantages, however, the use of sensors in Assistive Device for Walkings can eliminate many of the problems presented by wearable sensors. This monitoring can provide insight into a person's daily activity, as well as detect possible falls and warn people accordingly, thus helping to improve people's lives.

1.2 Objectives

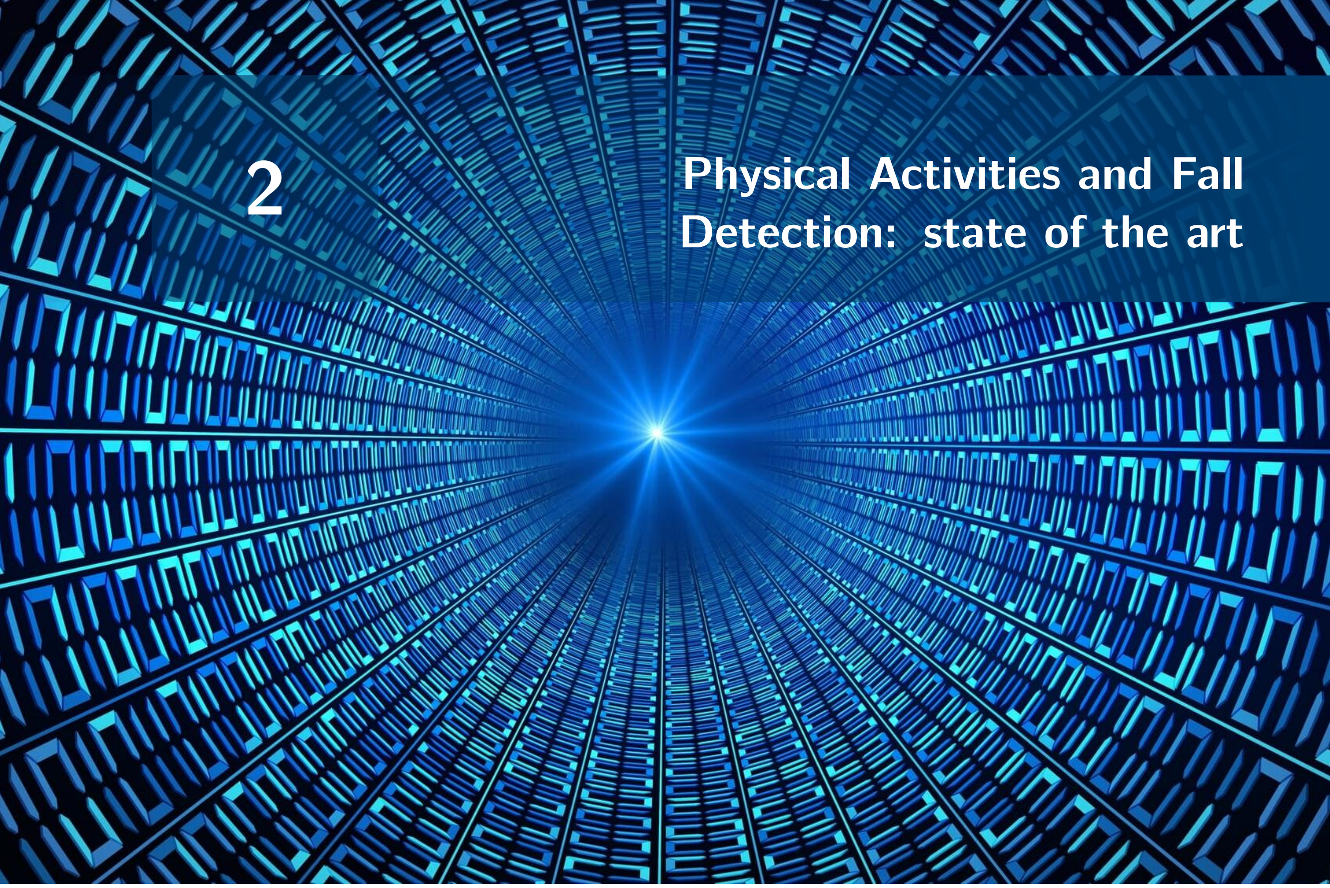
As mentioned above, in order to improve the process of individualisation of rehabilitation, the monitoring of the Physical Activity performed during the day by people is presented as an alternative capable of improving the recovery process of people. However, to achieve the monitoring of Physical Activity, a set of comfortable and non-invasive sensors that detect the activity carried out during the day is required. Therefore, the main objective of this thesis is to **design an intelligent sensor system capable of quantifying Physical Activity and detecting falls**.

This general objective is divided into the following sub-objectives:

- **Design a Sensorized Tip capable of adapting to the different Assistive Device for Walking (ADW) available.** As mentioned above, the use of a set of sensors capable of providing data from the individual is essential for monitoring Physical Activity. Therefore, after analysing the methods that have been proposed to carry out this task, it is necessary to design a sensor system incorporated into the tip of the ADW, which can detect the movements made without being cumbersome because it has to be incorporated into the body. Furthermore, this Sensorized Tip is interchangeable so that it can be changed by different ADWs without any complexities.
- **Design a Physical Activity (PA) classifier based on the sensors embedded in the ADW tip.** Once the system capable of capturing the data has been designed, in order to be able to monitor Physical Activity properly, a classifier capable of detecting these activities must be designed. In other words, the design of a PA classifier capable of differentiating between the different basic physical activities performed when using the ADW is required. In order to achieve this goal, we will explore Machine Learning-based classification, which has been successfully used in other Physical Activity classification systems.
- **Design a fall detector based on the sensors built into the ADW tip.** If the individualisation of rehabilitation is important for the improvement of people's lives, avoiding having to undergo rehabilitation due to a late reaction to a fall is just as important. Therefore, taking advantage of the use of sensors in the ADW to detect falls can help to achieve this.

1.3 Structure

The rest of the work is organised as follows: Chapter 2 presents an analysis of the different technologies and devices proposed for physical activity classification and fall detection; Chapter 3 presents a summary of the articles presented by article compendium (Appendix 1 [28], Appendix 2 [126] and Appendix 3 [125]), in which a Sensorized Tip is designed and developed, a Physical Activity classifier and a fall detector are generated, both based on the data provided by the Sensorized Tip and using Machine Learning techniques; finally, Chapter 4 present the most important conclusions and the lines for future work.



2 Physical Activities and Fall Detection: state of the art

As the main objective is to develop a Sensorized Tip that is able to classify the physical activities of ADW users, it is essential to know the sensor systems used and their characteristics, as well as the techniques used to classify physical activities and detect falls.

For this reason, Chapter 2.1 presents an introduction to the sensing elements used in ADWs. Then, in Chapter 2.2, the systems and methodologies used to perform the classification of physical activities are analysed. Chapter 2.3 is dedicated to the analysis of the types of systems used for fall detection and the methodologies used for this purpose. Finally, Chapter 2.4 summarises the main ideas of the State of the Art and draws the most important conclusions.

2.1 Methodologies for the detection of physical activities

The sensors used for the detection of people's physical activity are very varied [55]. It can be found systems that detect this activity using vision-based systems. Others take advantage of the capabilities of inertial motion-based sensors to do this work.

In terms of data capture and tracking, different technological solutions have been proposed [155]. Through the use of these technologies, it is possible to know the movement of the person, the force exerted or other parameters that help in the identification of different daily activities.

Traditionally, in the recognition of physical activities, various vision-based systems have been found [178, 5, 147]. Among the vision-based devices, several authors have proposed the use of camera-based devices in rooms. Among these are those using Kinect cameras [81], which recognise a person's gait. Others are able to recognise activities of daily living through room sensorisation [64]. Although these types of systems have achieved good results when classifying different physical activities, they can produce problems with the violation of privacy in some cases [21]. Furthermore, they are generally not systems that are conducive to detecting PA in uncontrolled outdoor or indoor environments, as they can generate a large number of interferences due to variations in the environment. In addition, they tend to be more expensive than other systems that can be used for the same task.

Today, among the different technologies used, the most popular are those based on wearable devices, which must be attached to specific locations on the patient's lower limb and usually capture motion data using Inertial Measurement Unit (IMU) [194, 70]. These devices capture motion data using IMU, such as [191, 72, 12, 16, 166, 127, 76, 190, 9, 187, 91, 110, 66, 118, 186, 139, 149, 188, 58] (see Figure 2.1). This type of device captures acceleration and/or velocity, providing enough information to get the physical activity being performed at all times.

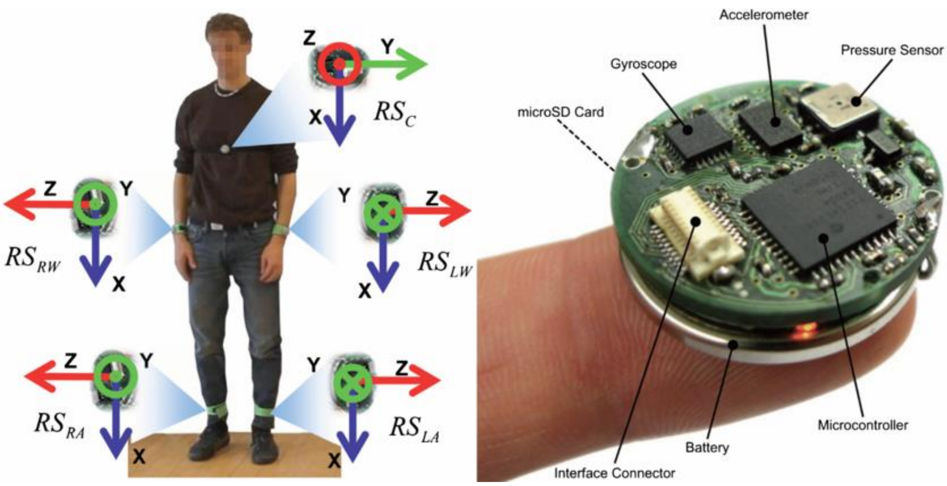


Figure 2.1: IMU device (right) and positioning on the body (left) [127].

But not all wearable devices are based on IMUs, but within these we can also find those that capture data for physical activity through biomedical signals such as Electromyography (EMG) [133, 178]. This type of signal detects small changes in the electrical activity of the muscles, and it can be known what movement a particular muscle has made, which can help in the knowledge of the activity being performed.

Such solutions require correct positioning and restraint of the limbs, and can lead to patient rejection. To reduce the impact of monitoring devices, the use of integrated sensors from smartwatches and mobile phones has been proposed [4, 117, 106, 85, 120, 95]. The latter devices do not have a specific location on the body, but on the other hand, this flexibility of positioning and the variability introduced by parasitic movements are issues to be taken into account when processing the data.

The use of elements that read the force applied are becoming more and more common when it comes to detecting Physical Activity. Among them are those based on sensor mats [150], capable of detecting different types of gaits. Others use sensor resistors for the same purpose [200]. On the one hand, these elements provide the ability to measure the force applied at each instant, making it possible to know the distribution of the weight load. On the other hand, these elements are often carpets that are difficult to move and have limited operating space.

Among the different authors using such devices to detect physical activity, there are several commercial devices on the market, such as XSens [170], BioStampRC [173], Tracmor [76]), FlexiForce [130], BioCapture [178].

In conclusion, although all the devices mentioned above are capable of providing a solution for PA classification, not all of them are suitable for all-day activity detection. Some of these devices such as camera-based devices cannot detect activity throughout the day and are not suitable for use in uncontrolled external enviroments. Others, such as wearable sensors, have the disadvantage that they require correct positioning to be able to measure data properly, and depending on the area in which they have to be placed, they can be cumbersome. For these same reasons, the use of Sensorized walking aids for detecting Physical Activity can be one of the best solutions, since people who require them will use them practically all day long, and they are not bothersome and do not require constant fitting.

2.1.1 Sensor elements of sensorized Assistive Device for Walking (ADW)

The Assistive Device for Walking (ADW) are devices that provide additional support of the human body to the ground during walking. Their purpose is to enable movement and mobility, as well as standing upright. These devices can be classified into different types: walkers, multi-podal canes, crutches or canes.

In recent years, the number of publications related to sensorized Assistive Device for Walking has grown significantly (see Table 2.1). Most of them follow the same operating scheme (see Figure 2.2), in which sensors are incorporated into the ADW and sent data to a computer or mobile device via a capture system.

Most of the works that focus on this area propose the use of systems capable of measuring the force that is applied to the assistive device, as well as the movement that is performed [163, 47, 100, 180, 77, 122, 121, 165, 33, 49, 61, 123, 159, 168] (see Figure 2.3). More specifically, there are works that include sensors capable of measuring the force applied to the handle [124, 99, 132, 185, 123] or sensors that detect the proximity of objects [185, 14].

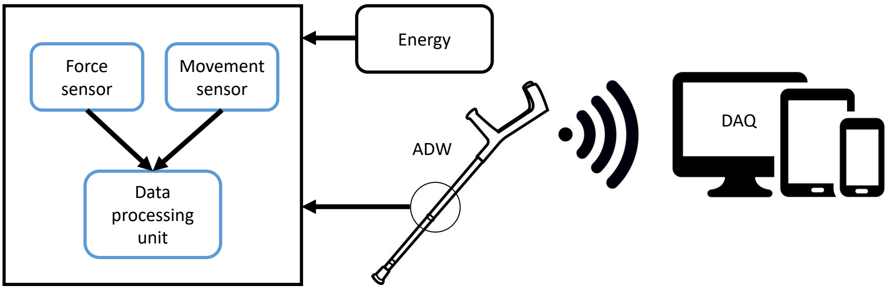
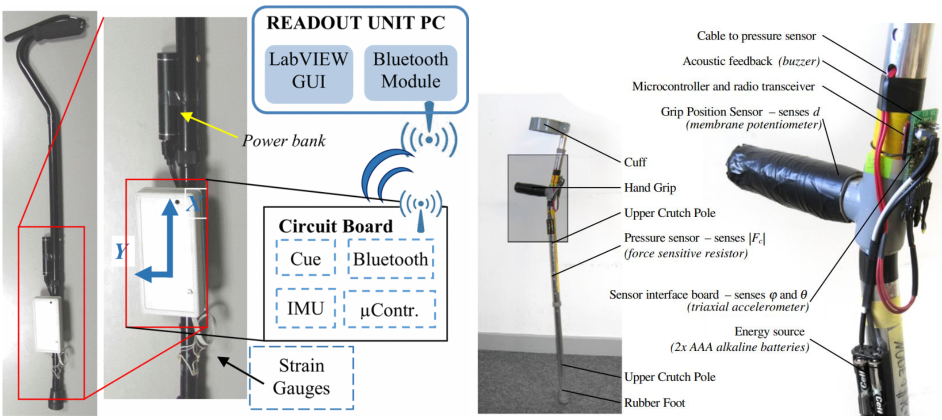


Figure 2.2: Schematic of the sensorized ADWs.



(a) F. Mekki et al

(b) G. Merrett et al

Figure 2.3: Sensorized ADW [122, 124].

Table 2.1: Main aspects of studies about instrumented ADW designed. A = Accelerometer, G = Gyroscope, M = Magnetometer, F = Force).

Study	Sensors	Sensors Location
[13]	2x FSR	FSR in the tip and electronics in a box in the stem.
[14]	Ultrasonic, Water sensor, LDR, GPS	On the cane stem.

Continuation of Table 2.1		
Study	**Sensors**	**Sensors Location**
[33]	F cell	F in the tip and electronics inside the crutch.
[36]	2x strain gauges, F cell, 3-axis A, G, M	F in the tip and electronics attached to the stem.
[47]	F cell, 2-axis G, 3-axis A, M	F in the tip and electronics and G, A, M in a box in the stem.
[49]	3x 3-axis A, G, M	Stem attachments
[62]	Millimetre wave radar	Stem attachments
[61]	5x 3-axis A, G, M	Stem attachments
[65]	9x F cells, 3-axis G	Inside the stem, and the F in the tip.
[68, 69]	4x strain gauges, 3-axis A, G, M	Inside the handle
[77]	3x FSR, 3-axis A, G, M	FSR in the tip and electronics and theA, G, M in a box in the stem.
[99]	2x F, 3-axis A, G	One F in the tip, the other in the handle,and A, G and electronics under the handle in a box.
[100, 163]	3x strain gauges, 3-axis A	Stem attachments
[121]	3-axis A, FSR	Electronics under the handle (glued) and the F in the handle.
[122]	4x strain gagues, 3-axis A, G, M	F in the tip and electronics and A, G, M in a box in the stem.
[123]	F cell, 3-axis A	F in the handle and electronics and A in a box in the stem.
[124]	FSR, Rectilinear membrane potentiometer, 3-axis A	F in the handle and electronics and A attached in the stem.
[132]	Strain gagues, 3-axis A, G, M	F in the handle and electronics and A, G, M in a box in the stem.
[159]	F	Inside the stem.
[165]	4x F, 2-axis A	F in the tip and electronics and A in a box in the stem.
[168]	F	Stem attachments.
[180]	G, 2x FSR	F in the tip and electronics and G in a box in the stem.
[185]	F cell, 8x FSR (in hand grip) 2x 3-axis A, 3-axis G, M, Ultra sonic	F in the tip and handle and all other sensors and electronics in the stem.
[196]	GPS, Light sensor, Pulse sensor	Encapsulated in a box in the stem.

2.1.1.1 Force measurement

The measurement of the axial force applied to the assistive device is relatively straightforward, so most work includes this measurement. In the literature, two approaches are traditionally used: the use of integrated force sensors, and the use of strain gauges (as shown in Table 2.1).

Integrated force sensors [33, 47, 185, 36, 65] are commercial devices that allow the axial (or triaxial) measurement of loads applied on the sensor. In general, they can be based on the detection of the pressure change of the internal filling fluid, or on load cells. Although their accuracy is usually high, their cost is also high, and a proper signal matching stage is usually required. Due to the cylindrical shape of these elements, they are more feasible to adapt to technical support systems.

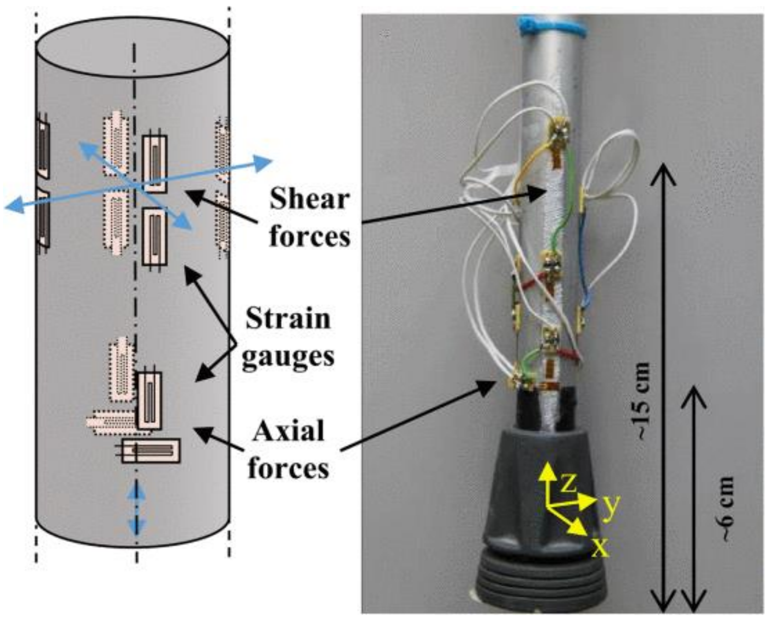


Figure 2.4: Technical support systems with strain gauges on the shank [100].

In the case of strain gauges, [124, 180, 100, 77, 163, 122, 121, 165, 13, 159, 168], the cost of which is lower than that of force sensors, as is their accuracy. In order to improve the measurement, several gauges are often incorporated into the device, thus requiring a more complex system. In addition, these elements usually require a more elaborate capture system than the previous ones, since a circuit capable of reading the change in the resistance value is needed, as well as an amplifier system in case the signal provided is much lower than the desired one. Strain gauges work thanks to the piezoresistive effect, with which the deformation of a conductive element can be measured thanks to its resistive value. On the other hand, these elements are very malleable, which makes them very interesting for measuring forces without modifying the structure of the technical aid. In the literature, they have been used to measure the deformations of verticality of crutch or canes [100] (see Figure 2.4), as well as to measure the force applied to the handle of the assistive device [124]. This malleability can also be an obstacle to stable positioning, as they can move or deform more easily.

2.1.1.2 Measurement of movement

In addition to force, a large number of authors incorporate sensors to measure the movement of the sensorized assistive technology device.

Most of the authors who measure motion do so using Inertial Measurement Unit (IMU) [77, 47, 185, 122, 132, 68, 69, 61, 99, 49, 61]. These types of sensors are used in fields such as aviation, automotive or navigation for positioning. Most IMUs are able to measure linear accelerations and angular velocities in the 3 spatial axes, through the arrangement of accelerometers and gyroscopes in each of the 3 axes. Thanks to the possibility of knowing the velocity and acceleration at each instant of the sensor, these elements are suitable for estimating the movement of the assistive device. Although the advantage of an IMU is the possibility of having all the data available to be able to fuse them, there are works that have opted for the use of only accelerometric sensors [100, 163, 124, 121, 165, 123] or gyroscopic sensors [180, 65]. However, these elements have the disadvantage that they often have drifts that need to be corrected during use. On the other hand, in order to know the displacements made when walking with the ADW, other authors opt for the use of Global Positioning System (GPS) measurement [195, 14, 2].

Note that the use of IMUs (or accelerometers or gyroscopes) does not directly provide the orientation of the Assistive Device for Walking, and different estimation techniques have to be applied to get the absolute orientation of the system. One of the simplest methods is based on the direct integration of the rotational speed provided by the gyroscope, periodically correcting the accumulated error [180]. The previous solution generates a significant drift over time, so other authors have proposed using a quasi-static approach, in which the orientation is determined from the projection of the gravity vector on each axis [100, 124, 163, 185]. The latter approach neglects the relevant dynamic accelerations and impacts. Solutions based on Kalman filters can also be found [47, 88, 113]. These filters are able to combine information from various sensors to obtain an estimate of the absolute orientation based on an internal model of the system. In these cases this type of filter typically works by combining the output provided by gyroscopes and accelerometers plus a magnetometer together with a set of covariances. In this way, the estimation of the Euler angles at which the technical aid system is oriented can be achieved. Finally, there is a last set of solutions based on the use of complementary filters, whose main advantage over the Kalman filter is their low computational cost. An example of this filter is the CAHRS [51].

In conclusion, most sensorized aids consist of at least one force sensor and/or at least one inertial sensor. In this way, these sensors can be used to determine both the movement of a person and the force applied to the walking aid. In the case of force sensors, strain gauges and load cells are used in a similar way. While strain gauges are lighter and cheaper, they usually require more precise positioning and a somewhat more complex acquisition system. Force sensors, on the other hand, while heavier, are usually more robust and easier to attach to assistive devices. Analyzing the motion sensors used by the different authors, the vast majority opt for the use of IMUs. This is due to the possibility of having different sensors in the same space.

2.1.2 Sensors position

The positioning of the sensors along the technical support system varies depending on the author consulted as summarized in Table 2.1. Many of the authors place the electronics in a box built into the Assistive Device for Walking [47, 77, 100, 122, 165, 132, 49, 13, 61], this box is usually attached to the stem of the crutch and can be awkward in certain circumstances (see Figure 2.5). Other authors have opted to introduce the electronics inside the stem, taking advantage of the fact that it is usually hollow. In the case of the sensors responsible for force measurement, many of these are added to the stem [47, 100, 124, 163], in the tip [77, 122, 165, 99, 13] or in a structure built to contain them [185, 36]. The big problem with this type of device is that the positioning of the sensors becomes difficult to interchange between different assistive technology systems, making the sensorization of the system customized for a single cane or crutch.

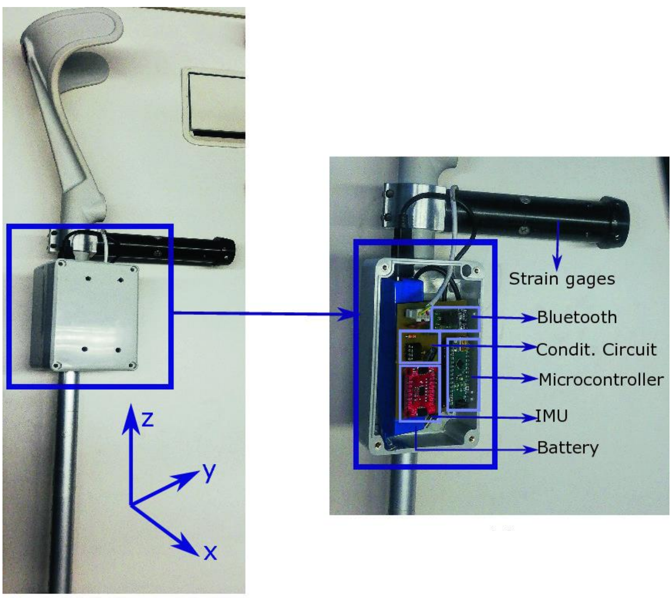


Figure 2.5: Technical support systems in a self-made enclosure [132].

In short, the location of the sensors is important in the realisation of a sensorized ADW. There is no clear consensus among the different authors on the location of the sensors, which means that they can be found in different places depending on the designer. Many of the sensors that are placed in assistive technology systems are positioned in places from which they cannot be removed later, or which require extra effort to do so. This means, as mentioned above, that the sensors are tied to one and the same Assistive Device for Walking, making it impossible for the user to switch from one device to another easily, as this requires prior preparation of the device with the sensors.

2.1.3 Data acquisition and communication systems

All of the above-mentioned sensors usually provide the sensing information in different ways. They range from sensors that send the value from an analogue value, to those that send the value via a communication method, such as Inter-Integrated Circuit (I2C) or Serial Peripheral Interface (SPI). Because of this, a device is usually required to capture this data and give it a form, either to store it or to send it to another device. These elements are usually an embedded Data Acquisition System (DAQ), which is usually of in-house design [36, 165, 185, 100, 163]. Although there are Arduino-based approaches among the different authors [122]. This type of element has the advantage of the low cost of the processors, as well as the ability to have multiple libraries to facilitate the programming of the data acquisition system. Finally, DAQs based on rapid prototyping devices can be found [122]. These can be systems from companies such as National Instrument or other companies, which tend to have a high cost, but their reliability and capabilities are often superior to those of other types of devices.

These acquisition systems usually communicate with other systems for the storage of the corresponding data, although most of the ways in which the data is sent is wireless, devices can be found that send data via cable [180, 165]. Among the methods used for wireless data transfer, two main methods are found, Bluetooth [47, 100, 163, 185, 122, 132, 99], which is the most widely used method, and Wireless Fidelity (WIFI) [124, 36, 77]. On the other hand, there are also devices that store information on removable memory such as Secure Digital (SD) cards [68, 69].

In short, the vast majority of authors undoubtedly choose to design their own data acquisition system. This very design of the DAQs greatly facilitates the possibility of incorporating the systems in the technical aid device, making it possible to adapt it to the desired measurements.

The method used for sending data is Bluetooth in most cases. The use of this communication system can be justified because of its small electronic footprint and the fact that it does not require a large antenna to operate. In addition, Bluetooth is capable of sending information over a decent distance wirelessly, and thus not having to be constantly close to the receiving device and being able to move a few metres away from it. However, one of the major drawbacks of this technology is often the interference it presents.

2.2 Methodologies for the classification of physical activities

In order to properly monitor Physical Activity (PA), it is not only necessary to have a sensor device or a group of sensor devices that captures the data, but it is also necessary to work on the data obtained in order to be able to monitor the Physical Activity. This required work is usually based on a classifier capable of differentiating the different PA that are proposed. Similarly, processing of the data obtained from the sensors is required in order to be able to use them as elements to create the classifiers.

Normally, a methodology is used for the classification of Physical Activity [11, 151] (see Figure 2.6). This methodology starts with the adequacy of the data by dividing them into windows and generating on them some features, with which it will work. Once the features to be worked with have been generated, a selection of the most important ones is usually made. Finally, the classifier of physical activities is created (see Table 2.2).

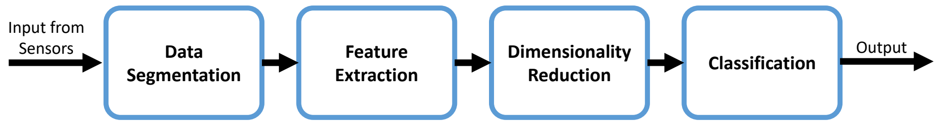


Figure 2.6: Scheme of steps followed for the detection of physical activities.

2.2.1 Segmentation and processing of physical activity monitoring data

In order to achieve the classification of the PA, once the desired data has been captured, a series of treatments must be carried out, as a general rule, in order to be able to use the data. Normally, the captured data are usually vectors, whose data are separated by a time space. In order to be able to manage these data better, they are usually divided into smaller segments of information, which are then used to obtain features.

2.2.1.1 Segmentation of monitoring data

When implementing technological solutions in health diagnostic applications, the processing of data extracted from sensors is fundamental. The purpose of data processing can be diverse: either a specific features can be obtained (maximum speed, maximum force, range, distance,...) [145, 30] or the data can be associated with a standardised clinical scale [98]. In general, the aim of all features is classification, this being an area of particular interest in diagnosis: classifying the patient's status.

In order to address this classification, in the literature, a first stage using windowing techniques is common. In these techniques, the signal obtained from the sensors is divided into much smaller time segments that help to identify the actions performed by the user of the motion capture system. This processing allows the information to be segmented in such a way that it is easier to use for classification.

The creation of these windows can be defined during data collection, in case of real time data processing, or it can be done after the complete data capture. Depending on the window creation needs, one method or another will be used to obtain the windows.

Mainly three different types of windows are used in the data classification, each with a different window creation method.

The first method of obtaining the window is called *sliding window*. In this type of window the captured signal is divided into windows that have a fixed size and the space between these windows does not exist. Depending on the necessities of the classification, the size of the window is different, and it can be of a larger or smaller time [83, 15, 11, 151, 188, 127, 166]. These types of sliding windows do not require signal processing, making them ideal for use in real time. This type of divisions can be used when the frequency of the signal is very constant; in case the signals to be divided do not have a constant frequency, the windows can be divided in such a way that finally the section to be studied can be left out of one of the windows.

The second method consists of *event windows*. Event windows require preprocessing to locate a specific event. The event defines the start of the window, which does not have a defined size. The end of the window can be defined in two different ways, by using a following repetition of the same event with which the event starts, marking this event both the end of the current window and the beginning of the next one, or by using another type of event independent of the start event. The event that marks the start of the window can be obtained from the detection, with a new sensor, of the impact against the ground for example [15, 190, 202], or other different methods. The use of such windows helps to always keep a set of data encapsulated inside the windows. This technique is the most widely used when segmenting in windows, thanks to its capacity to adapt to the different situations that can be created when capturing data. In the case of gait data capture, if the person changes the pace of walking, the windows can still contain one step each.

The third window technique used is that defined by *activities*. The windows are defined according to points where the different activities are separated [138]. This type of technique is the least used for the creation of windows.

In summary, the segmentation of sensor-derived data is a factor to be taken into account when working with sensors. The use of windows for this purpose is a suitable alternative, with event-driven windows being the most appropriate if one wants to work in real time. The segmentation of the data helps to realise a reduction of the dimensionality of the data, furthermore, the realisation of windows can have a relevant meaning, for example, to realise a separation into windows for each gait cycle.

2.2.1.2 Generation of features

Once the raw data is provided by the monitoring device and segmented into windows, this data must be processed to better classify the activity.

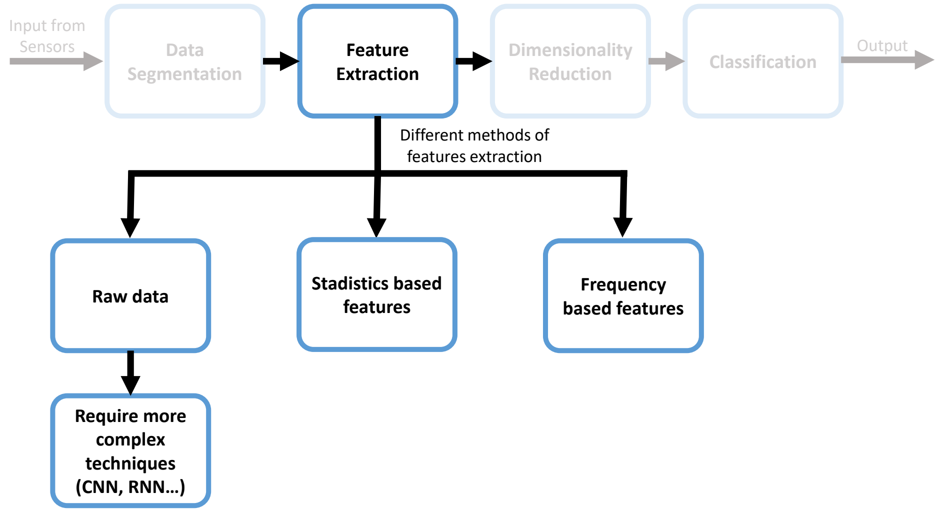


Figure 2.7: Different methods used for the extraction of the features.

Some works have designed classification approaches that use the raw data. These are a minority, as opposed to those who perform classification by pre-processing which is used to extract the features that aid classification (see Figure 2.7).

Generally, to achieve a classification consisting of raw data at the input, more complex activity recognition algorithms with a higher computational cost are required, such as Convolutional Neural Network (CNN) [72], Recurrent Neural Network (RNN) [44] or traditional Multilayer Perceptron (MLP) neural networks with a large number of hidden layers [190]. For this reason, the use of this type of raw data is not commonly used, tending to make classifications in which the data is pre-processed.

While, as mentioned in the previous paragraph, there are works that use raw data, but there are also many papers that perform feature extraction in order to reduce dimensionality [11, 151, 152, 70], using the data divided into windows. Among these feature extraction can be found those obtained from statistical calculations or by using frequency calculations.

As mentioned above, these features can be obtained from statistical calculations. Among the statistical processing, the most common ones that can be found are the root mean squares of the data in each segmented window, the maximum values found in the windows, the standard deviation or the peak-to-peak value [9, 70, 188, 83, 149, 58]. On the other hand, there are somewhat more complex statistical data that are often used alongside the simpler ones [151, 76, 127, 120, 166], such as kurtosis, interquartile range or percentiles. By using this type of data, it is possible to have an informative value of how the data behaves in each divided section, so it is possible to have a clearer study of the different actions to be analysed.

Another way in which data can be adapted for further use for classification is by using frequency-based data [200, 111, 193, 83, 127], such as the average oscillation cycle of each window. Also, there are those that use in-phase analysis [16] or generate a series of heuristic features [54]. These types of features are not as common as statistical data, due to the greater complexity of their interpretation.

In the literature, for the cases of gait data analysis, different features have also been defined to characterise gait, such as the number of steps required for a given distance or the average speed or time between steps [171]. This type of data can give an insight into how fast a person moves. By knowing the time between steps, it is possible to know how fast a person is walking, and thus to know in more detail how that person is moving.

Focusing on those Assistive Device for Walking that measure axial force, these usually generate features based on the maximum load [159, 168] or average load [168] with respect to the patient's weight. This data is usually done with respect to the patient, because not all people can carry the same load, those with a higher weight will carry more than those with a lower weight.

In summary, while there is a wide variety in the selection of features to be used for activity classification, as a general rule the most common and easiest to implement are those based on statistics. These can give a simple and suitable interpretation of the source data for the application.

2.2.1.3 Selection of the most relevant features

With the features selected and calculated for each window, a selection of the most relevant ones must be made in order to work with them [11, 151]. This is because when carrying out a classification, it is not the most appropriate thing to introduce all the features that can be obtained as input. Therefore, it is necessary to carry out a phase in which this type of selection work on the most important features is carried out (see Figure 2.8).

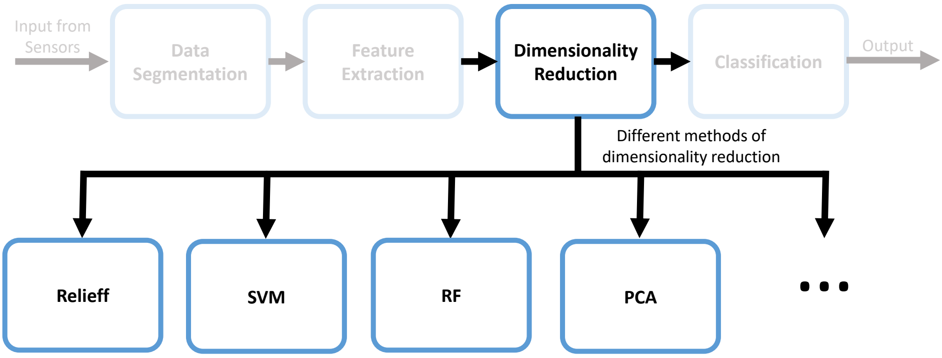


Figure 2.8: Different methods used for the selection of the most relevant features.

Sometimes the selection of those features that are the most suitable for use as input elements for the subsequent classification can be carried out visually. This visual way consists of observing how the data in the database is distributed. However, this use is not very widespread because it is very difficult to find relationships between the different variables that can help classification, and in the case of many variables, the time required to carry out this analysis is very high.

For this reason, other alternatives can be found to achieve this goal. The variety of alternatives and solutions proposed in the different papers is very large, and solutions based on many methodologies can be found [39]. One of these alternatives is the use of Relieff based feature selection [12, 127, 93, 38]. Relieff assigns weights to each characteristic by estimating relevance in terms of how well it can differentiate data points from classes that are the same and different. In both cases, a weight is obtained for each feature, which the higher the value means that the feature has more relevance.

Other alternative proposed is the use of Support Vector Machine (SVM)-based systems [105, 188], the K-Means Clustering (KMCA) [83], Correlation based Feature Selection (CFS) [120, 39] or Forward-Barckward Sequential Search [149]. All of them achieve a considerable reduction in the dimensionality of the features.

Another of these alternatives is the use of algorithms such as Random Forest (RF) [177, 39]. RF refers to any method of constructing a classifier or regression from the generation of different Decision Trees, the output of which is the most frequently predicted class. As just indicated, the Random Forest is a combination of Decision Trees, so that each tree is made up of a vector of samples and random features. A decision tree is a graphical and analytical way of representing all the events that can arise from a decision made at a certain point in time. These Decision Trees help to make the best decision from a range of possible decisions.

Different methods can be found that can be encompassed within RF. Among these methods is Decision Forest [89], which works by combining several Decision Trees. This can generate a system that is able to classify or regress more accurately. Using this technique, it is possible to generalise to a greater extent while maintaining the accuracy of the training data.

Another technique for designing classifiers or predictors that can be included in the RF is Bagging [79, 23]. This technique consists of different DT that provide their results, and by averaging all of them, the global result is obtained.

A technique very similar to Bagging is AdaBost's [154] technique. This differs from Bagging in that it is not performed by randomly picking examples from the training set based on a uniform probability distribution, but by using a set of weights for each sample from the training set. The larger the weight, the more influence the sample has on learning the next classifier. The classification error will also depend on these weights.

All these techniques have, according to studies [52], problems when it comes to error generalisation. For this reason, new techniques have been proposed that are capable of alleviating this problem, such as Random Forest-RI [24]. This method is based on the previously mentioned Bagging method, but it has a modification, which consists in the fact that when constructing each tree, apart from the randomisation of the replacement samples, there is also a randomisation without replacement of the characteristics. This Random Forest-RI method can have two purposes: to create a random tree to classify samples different from the training samples or to measure the relative importance between the features of a database.

However, not only feature reduction methodologies have been used, but also feature transformation methods have been proposed [11]. In this type of technique, the dimensionality is reduced by a smaller number of features, defined from those contained. An example of this type of techniques is the Principal Component Analysis [198, 112, 66, 64, 110, 150]. This method chooses a new coordinate system for the data set, simplifying the dimensionality of the system. The new variables that are created are obtained from the variances of the data.

As mentioned above, this technique makes it possible to know the influence of the correlation between the different features and thus to know in a better way what weight each feature has in the ranking.

In conclusion, there is no general consensus on the choice of methodology used to identify the most relevant features, so as not to work with the hundreds of features that can be obtained, thus reducing the dimensionality of the problem and allowing for better classification. All of them achieve the stated objective in a good way.

2.2.2 Classification of physical activity monitoring data

After the correct segmentation of the data and the generation and selection of the most appropriate features, the classification of the data is usually done by using classification techniques [11, 151] (see Figure 2.9).

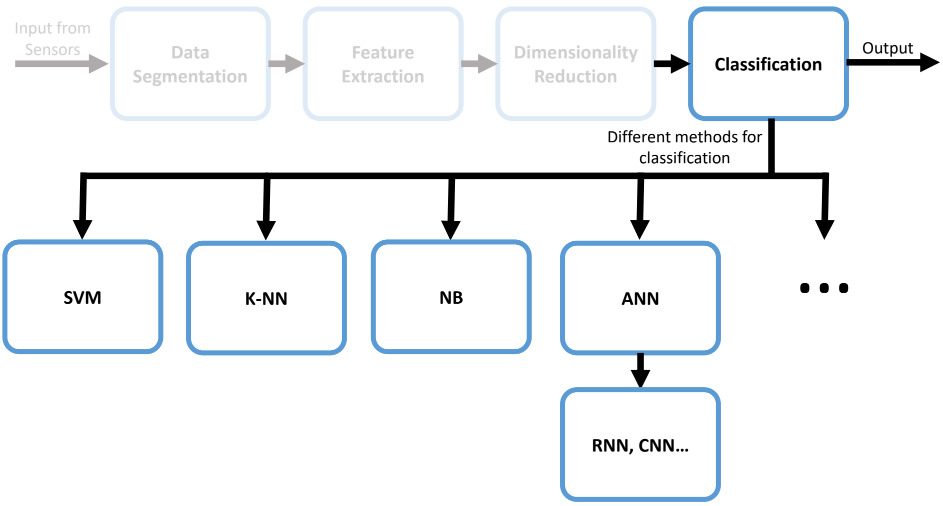


Figure 2.9: Different methods used for the classification.

The use of Machine Learning (ML) techniques is becoming more and more widespread in the medical and rehabilitation area [42]. All kinds of techniques can be found that handle a large number of different application. These systems are used to detect outlier clusters in homogeneous data, to classify the severity of pneumonia according to 4 inflammatory markers, to predict the efficacy of certain drugs or to predict a patient's risk of heart attack. Different ML techniques are used for all kinds of tasks, from Artificial Neural Network to K-Nearest Neighbors.

On the other hand, these techniques have also been used to classify PA [11, 151] and can be applied to aid rehabilitation. In the area of Physical Activity (PA), the classification systems used provide information on whether stair climbing or descending actions are being performed, whether the person is walking or stationary, whether they are walking on a slope or not, etc. This type of classification of activities of daily living can help to understand a person's behaviour. Through the knowledge of this behaviour, a quantitative help can be given to the rehabilitation professional in order to make a diagnosis or to individualise the rehabilitation.

In the implementation of classifiers, different solutions are found in the literature [161, 11, 151], varying from the use of statistical techniques to the use of intelligent techniques. In most cases the sensors for the classification system are placed on the lower extremities of the body.

Statistical methods have been widely used in various areas of engineering to implement classifiers. Among the statistical methods are threshold-based methods (thresholding). This technique uses a predetermined threshold, or several thresholds, to indicate whether one activity or another is being performed. This type of classification has been used in the literature [139, 46] with good results in the detection of falls.

Another statistical method used are hierarchical methods. They implement a hierarchical classification scheme, where the structure consists of binary decisions that lead to another node where another binary decision has to be made. Through a series of consecutive nodes, the decision that corresponds to the case at hand can be reached. In the area of gait characterisation this method is mostly used for the classification of different activities [58], such as running or going up and/or down stairs. One system to ranking by hierarchical methods is one that uses Decision Trees. This type of structure uses rigorous algorithms that automate the decision making process and creates a set of rules [58, 120, 166, 111], making the decision at the nodes more complex. As in the hierarchical cases, the decision tree method performs well in the case of classification of different activities of daily walking, such as walking or climbing slopes. The results obtained using this type of system are not the best, reaching an accuracy of 70% [166].

Naive Bayes (NB)-based systems can also be found that classify physical and chemical activities [150, 120, 15, 193]. This is a probabilistic classifier, which is based on Bayes theorem. Good results are achieved in the works analysed, as in the case of [150] with a specificity of 94%.

The other major group of classification alternatives is based on Artificial Intelligence techniques. K-Nearest Neighbors (K-NN) is one of the techniques that can be found within AI [127, 120, 150, 186, 166, 15, 38, 93, 108, 111, 149]. This method performs classification by constructing a multidimensional feature space. Using a set of training data, the feature space is created, which will be used to classify the data among the different cases marked in the training phase. In this case, the results obtained are very varied to classify PA, taking into account that these results depend on the data used, the results are 73% [186], 80% [166] or near 90% [127].

Another AI technique that can be found is Support Vector Machine (SVM) [66, 150, 107, 157, 64, 76, 17, 118, 188, 198, 105, 12, 38, 39]. It is a supervised learning algorithm and can be introduced into the category of linear classifiers. Given a set of training points, or data, in which each of them belongs to one of several possible categories, a model is built that is able to predict whether a new point belongs to one group or another. This method represents the sample points in space by separating the classes into two spaces as wide as possible by means of a separation hyperplane. When new data are introduced, depending on which plane they correspond to, they are classified in one class or another. Learning in this method consists of selecting a separation hyperplane that is equidistant from the closest examples of each class in order to achieve a maximum margin on each side of the hyperplane. As in the case of the K-NN results, the SVM results vary widely to classify the PA, taking into account that these results depend on the data used, data close to 80% [107, 118] or better results close to 98% [157] can be found.

Another of the AI methods found that are used for the classification of the type of physical activity a person is performing, is that based on Fuzzic Logic (FL) [162]. This method mimics how a person makes decisions by using imprecise or ambiguous input information. This technique allows working with information that contains a high degree of imprecision, such as information derived from the movement of the lower limbs.

Finally, within the intelligent techniques are Artificial Neural Network (ANN) [80, 151, 76, 117, 81, 178, 17, 190, 72, 9, 187, 91, 110, 200, 150, 169, 133, 95, 148, 44, 188, 58, 157, 39, 149, 62], which are currently the most widely used technique, as they provide better results in this problem. These techniques have great potential for diagnosis in the areas of health [8], and have grown considerably in recent years [146]. This method tries to simulate the way the nervous system of animals works. It consists of a series of interconnected weighted neurons (see Figure 2.10), which produce an output value according to the input provided and according to the experience obtained from previous training. For example, by using Artificial Neural Network and data obtained from an EMG sensor it is possible to identify the stance phases of a foot (stance and swing phase) [133].

There is a wide variety of ANN, among these the one most commonly used in simple physical activity classification systems are the Multilayer FeedFordward or Multilayer Perceptron (MLP) Artificial Neural Network [133, 108, 178, 95, 148, 188, 58, 157]. These types of ANN fall into the group of supervised training networks. MLP networks consist of a set of inputs and outputs that are interconnected with each other at the nodes in the hidden layers. Thus, the output value is achieved according to the transfer function within the layers and the weighting assigned to the nodes. Such structures typically have good results above 90% [108] or 97% [178].

These types of classifications can be used for classification of activities of daily living. For example, there are authors who have used this type of classification systems

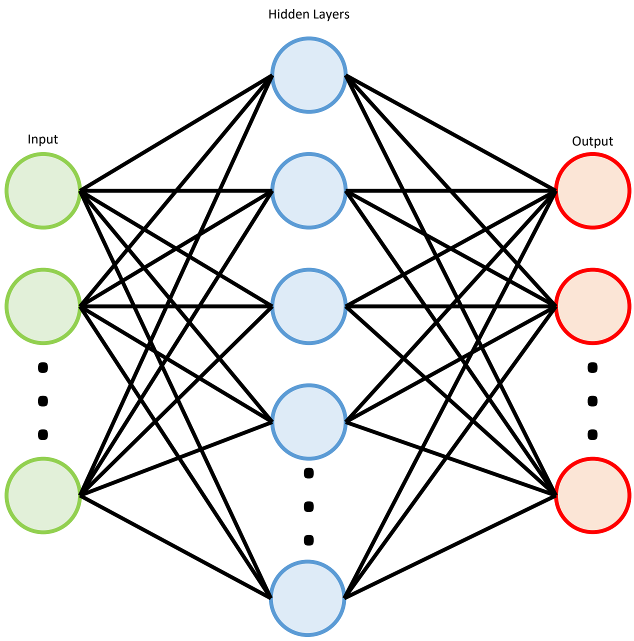


Figure 2.10: Structure of an ANN.

to recognise complex activities [117] such as eating, working, shopping, etc. These complex activities are those that have high-level semantics. For the realisation of this type of classification it uses a complex structure of several neural networks. Among these neural networks, the outputs of which feed into the next one, are Convolutional Neural Network (CNN) [72, 61] and Recurrent Neural Network (RNN) [44]. These are used because they classify complex activities; such these systems are not typically used for the classification of simpler activities of daily living, such as walking or climbing stairs.

In order for the neural network to "learn" in a supervised manner, a correct training algorithm is necessary. Among the algorithms used for the training of Artificial Neural Network, the Back-Propagation [91, 190, 9, 187, 150, 148, 58, 157] stands out. Similarly, to facilitate learning, modifications such as prior initialisation of the weight of the network are applied [9].

The number of hidden layers and the number of neurons in each layer varies according to the needs and the application, although in most cases the hidden layers are usually only one. The neurons in the input and output layers vary depending on the amount of data to be analysed and the desired results. Inner layers with a small number of neurons can be used [9], as well as hidden layers with a large number of neurons [72, 190].

Other types of neural networks that have been used for classification are probabilistic ANNs, which use example patterns stored in memory, offering higher speed, or Spiking Neural Network (SNN) [183], which are designed to accept binary inputs and are able to process information in a way that is more similar to biological neural networks. In this type of network, the inputs are pulses that are distributed over time and usually constitute a series of pulses.

The results obtained with ANNs are generally very good for classification of the PA, taking into account that these vary according to the data used. Values above 90% are generally obtained for example in [76, 81, 178].

Some studies make a comparison between different techniques. For example, in the case of [150], the results of ANN, SVM, K-NN and Naive Bayes are compared. In this case, the best results obtained are those provided by the SVM and the ANN, 90.6% and 92% respectively, with greater sensitivity and specificity than in the other cases. Another comparative study carried out between the results obtained from SVM, K-NN and DT [166]. Here, too, the best SVM results are achieved, with a success rate of 89%. Another compares the results of K-NN, RF, Logistic Regression (LR), Naive Bayes, ANN and SVM [157], obtaining very good results with ANN and SVM, being higher than 95%. Other works compare ANN, SVM and RF, with close results for all cases [39]: 88% for ANN, 87.5% for SVM and 86.9% for RF.

After analysing the state of the art of classification systems, it can be concluded that currently the Artificial Neural Network method is mainly used. Despite being the most widely used system, other Machine Learning systems are also used for classification such as a SVM. As far as Physical Activity classification of people is concerned, the vast majority of the studies focus on the classification of normal Physical Activity and do not work with ADW such as crutches or canes. On the other hand, almost all of the works analysed use wearable sensors, which can be invasive, an issue that is to be solved by introducing sensors in everyday items, such as crutches, to characterise patients.

Therefore, in the area of rehabilitation and quantification of the patient's condition, the results of the work carried out demonstrate the potential of these techniques as classifiers.

Table 2.2: Main aspects of studies about instrumented physical activities classification. (A = Accelerometer, G = Gyroscope, M = Magnetometer, F = Force).

Study	**Sensors**	**Dimensionality Reduction Method**	**Classification Method**
[6]	3-axis A, GPS		RF
[9]	4x A		ANN
[12]	A, G	CFS, FCBF, Relieff	SVM
[15]	5x 3-axis A		Decision Tree, NB, K-NN, Decision Table
[16]	3-axis A, G, M		LDA, PV, PV+CS

Continuation of Table 2.2			
Study	**Sensors**	**Dimensionality Reduction Method**	**Classification Method**
[17]	Video system		SVM, ANN
[32]	3-axis A	Mean decrease impurity test, Greedy selection	RF, Threshold
[38]	3-axis A	Relieff	K-NN, SVM
[39]	A	Relieff, RF, One-R, SFS, CFS and others	ANN, SVM, RF
[44]	3-axis A, G, M		RNN
[45]	3-axis A, G		RLE test
[46]	2x A		Threshold
[58]	3-axisA, GPS		Decision Tress, ANN, Hybrid model
[61]	Instrumented Cane		CNN
[64]	A, M, Camera and others	PCA	SVM
[66]	A, G	PCA	SVM
[71]	3-axis A, G		RF
[72]	5x 3-axis G, A		CNN
[76]	3-axis A		Decision Trees, ANN, SVM, Majority voting
[81]	Kinect Sensor		ANN
[83]	3-axis A		K-means
[54]	3-axis A		Threshold
[91]	3-axis A		ANN
[93]	B, 3-axis A, G	Relieff, Rand Features	K-NN
[94]	3-axis A		Decision Trees
[95]	Smartphone A		ANN
[103]	A		RF, Gradient Boosting
[108]	Vision sensors		K-NN
[110]	A, G	PCA	ANN
[109]	A		Threshold
[111]	3-axis A, Microphone, Light sesnsor		K-NN, Decision Tree
[112]	3-axis A	PCA	Bayesian

Continuation of Table 2.2			
Study	**Sensors**	**Dimensionality Reduction Method**	**Classification Method**
[118]	3x 3-axis G, A		SVM
[120]	eWatch (A)	Correlation based, CFS	Decision Trees, K-NN, NB, Bayes Net
[117]	Multimodal sensors	CNN	ANN
[127]	5x ReSense wereable (P, A, G)	Relieff	K-NN
[133]	EMG		ANN
[138]	1-axis A		Direct spatial correlation of discrete dyadic wavelet coefficients
[139]	A, B		Threshold
[148]	Smartphone (A, G, M)		
[149]	2-axis A, G, F, Light sensor, Heart Rate sensor,3-axis A	Forward backward search	K-NN, ANN
[150]	F carpet	PCA	ANN, SVM, K-NN, NB
[157]	3-axis A		SVM
[159]	Instrumented cane		Stadistical Methods
[162]	2-axis A		Fuzzy Logic
[166]	3-axis A		Decision tree, K-NN, Ensemble method
[169]	Vision Captures, F		ANN
[178]	EMG, Video cameras		ANN
[188]	A	SVM	ANN, SVM
[187]	3-axis A		ANN
[186]	A	LDA	K-NN
[190]	A, Foot switch		ANN
[193]	A, G, ECG		NB
[200]	F		RBF networks
[202]	3-axis A		Threshold

2.3 Methodologies for the falls detection

In order to prevent a possible rehabilitation effects due to the effects of a delayed response to a fall, the use of sensors that monitor daily life to detect and warn when a fall occurs is becoming more common (see Table 2.3). In this way, getting an early warning about the suffering of the fall can help a quick reaction, which in many cases can be essential.

2.3.1 Sensing elements for fall detection

The detection of falls can be done by using various sensing devices, in order to generate an alarm signal and act accordingly.

Among the sensing systems proposed in the literature, there are 3 major groups of devices, differentiated according to the nature of the signals they capture [144, 129, 154]: 1) vision systems; 2) environmental sensing systems; and 3) wearable sensor-based systems.

Within the first category of fall detection sensors are those that perform detection through the use of vision systems. The use of these elements as fall detectors is quite widespread and a large number of different devices that perform this task can be found [18, 50, 108, 115, 137, 156, 67, 167, 75]. These devices are usually conventional cameras that can be found on the market, which sometimes implement night (or dark) capture modes and whose data are further processed [50, 115] (see Figure 2.11). Vision-based systems have a good success rate in detecting falls, with this value ranging from 91% [156] to 96% [50]. Additionally, they can provide an image of the fallen person to the person receiving the warning, allowing them to know the state of the person who has fallen beforehand. However, these systems have some drawbacks, including the limited capture range available (usually limited to a specific room), which limits their applicability. To overcome this, the range of the system can be extended by increasing the number of sensor elements, but this would increase the price and complexity of the system. In addition, having vision-based systems in the home constantly active may cause privacy issues or mistrust towards them [108, 21].

Figure 2.11: Vision-based fall detection system [50].

In the second group we find systems that rely on the variation of environmental signals for fall detection [129]. These systems are based on the measurement of different signals: radio signals [87, 189, 160], sound signals [34, 201, 56] or ground vibrations [7].

The first group, associated with the one based on radio signals, are those based on changes in the frequency of the reflected radio signal when there is a change in velocity [87], achieving more than 97% success rate in detecting falls. Another common approach is to use radio signals to triangulate the position of the body (see Figure 2.12) [189]. As in the case of the use of these sensors detecting changes in frequency, good results are achieved when detecting falls, with a value of 94%. Although these approaches are capable of detecting falls adequately, in the case of position detection, a fall can be confused with another type of action that consists of a change of position, which can generate many false positives, and this situation can also occur in the case of those that detect changes in speed.

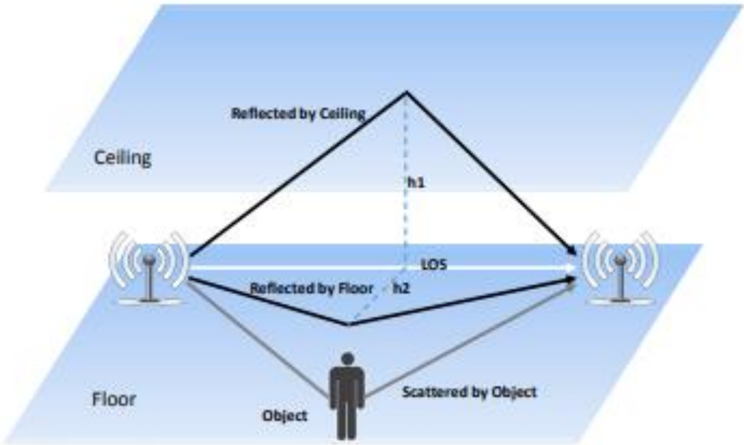


Figure 2.12: Radio-based positioning system [189].

In the second group, sound-based systems focus mainly on differentiating the sound of a fall from other activities of daily life [34, 201]. The use of such sensors provides a good success rate of up to 98% [34]. Although the implementation of these systems is relatively simple and requires a number of microphones, they are influenced by ambient and external noise, which can alter the accuracy of fall detection. Additionally, as with vision systems, they can raise privacy concerns.

Finally, vibration-based systems [7] rely on identifying vibration patterns on the ground, differentiating falls from other activities. In this case, the detection of 100% of falls in a controlled situation is achieved successfully. This system does not have the privacy problems of the previous solution, but its effectiveness will be limited by the effect of external noise and vibrations.

The solutions in this group, although lower in cost than vision-based solutions, are also limited to specific spaces, as they are based on environmental sensing.

In order to solve the problem of the two previous solutions, the third large group of solutions is wearable sensors, which are those that can be worn by the person. Thanks to their small size, they can be placed on almost any part of the body. The vast majority of the proposals for devices in this group are based on inertial sensors, especially accelerometers [197, 35, 37, 53, 57, 181, 182, 114, 97, 142, 10, 67, 131]. Similarly, some works propose the use of IMUs which combine with other sensors such as gyroscopes or magnetometers to obtain a greater amount of information to analyse [153, 136, 141, 44] (see Figure 2.13).

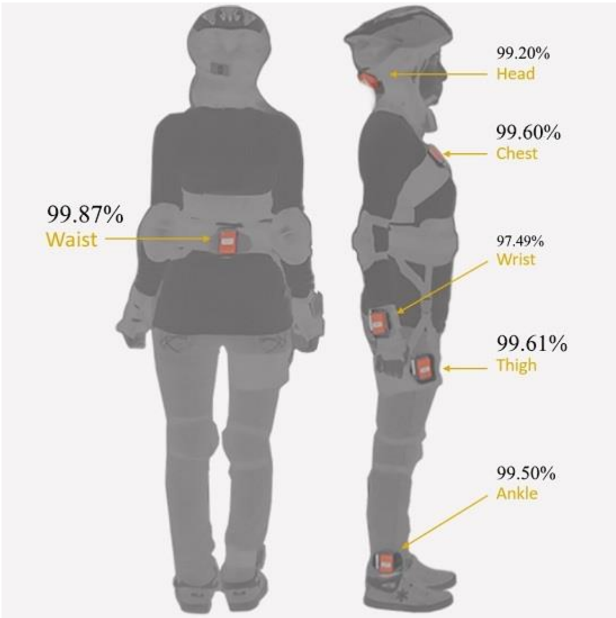


Figure 2.13: System based on wearable systems, position and success rate [141].

Although most solutions are based on the above devices, some authors have proposed other solutions, such as the use of barometers [20] or the use of sensors integrated in smartphones and smartwatches, including the accelerometer and gyroscope [3, 92, 119, 104, 128], or even the microphone [34].

One of the most relevant characteristics of wearable sensors is that they have to be worn by the person, thus increasing their capture capacity. However, this also opens up a field of research in terms of their optimal placement. Note that the placement of this element is important, as the signals received will vary depending on this relative position.

Although there is no clear consensus among the different authors, most of them opt for placing the sensors on the waist [35, 53, 114, 182, 20, 54]. However, there are also authors who propose its use on the wrist [197, 181, 67], foot [57] and back [136]. Recent studies have addressed the problem of defining optimal sensor placement by evaluating the positions associated with the ankles, chest and waist [37], and adding to these the head, wrists and thigh [141]. Both studies conclude that the best sensor position for fall detection is at the waist, although optimal results are also achieved with the sensor element placed on the chest [37, 10].

In those solutions that propose the use of smartphones as sensor elements [44], some authors have also studied [3] the ideal position for carrying them when performing fall detection, in this case analysing the positioning of the smartphone on the belt or in the pocket, obtaining similar results in both cases.

In conclusion, wearable sensors have a major advantage in terms of their capture range, as they are not limited to a specific area. However, there are some drawbacks. They mostly require a correct positioning, in order to eliminate parasitic noises that may be generated. Furthermore, depending on the position in which it is placed, this element can disturb the user, especially if he or she is elderly. In the case of the use of smartwatches and smartphones, on the other hand, the filtering of the parasitic movements of the devices in the pocket or wrist is an area of research that is still open.

On the other hand, sensors are gradually being incorporated into walking aids to detect falls [195, 65, 99]. Among these are those that incorporate sensors in instrumented walking sticks [99, 195, 40], or crutches [65]. In these types of elements, more than one sensor is often used to perform fall detection. Typical combinations include the use of inertial sensors with force sensors [99, 65], or an approach in which inertial sensors are incorporated with GPS and a heart sensor [195]. Among these advantages is that the sensorisation of these elements for fall detection would not require constant correct positioning, as it would be located in the Assistive Device for Walking system from the start, meaning that the user of the ADW system would not have to worry about correct positioning, but rather an expert person would be in charge of this.

In conclusion, although all the devices mentioned above are capable of detecting falls in an optimal way, each one has a series of advantages and disadvantages that make them more or less suitable depending on the context and the user. In the case of those based on vision systems or those based on the processing of environmental signals, they have the major problem that once they leave the work area of these elements (controled room) they cease to have any effect, which requires the installation of a large number of them to cover large areas. Moreover, their applicability is limited to indoors, since it is not feasible to use these devices outdoors. In addition, systems based on the detection of variations in environmental signals have the major drawback that they can easily suffer from external disturbances such as noise.

In this sense, wearable sensors can solve the problem associated with the capture range, at the cost of a greater invasiveness of the user, and can even disturb the person using them. This is especially critical for people who require crutches or canes to move around. Given that these devices are essential for use, the inclusion of sensorisation in them to detect falls or perform other monitoring activities combines the advantages of low invasiveness and high capture range. In this sense, this is still an open area, with a great potential for research in which little work has been done.

2.3.2 Data processing for fall detection

The detection of falls is carried out by appropriately interpreting the data provided by the sensors integrated in the aforementioned devices. In this sense, there are two approaches. The first consists of using raw data [197, 181], which is traditionally based on introducing it into Neural Networks. This approach has a higher computational cost, and provides sub-optimal and uninterpretable solutions.

The second approach consists of defining a series of features or characteristics of the signal, which allow us to compact the information of the time series into a metric and reduce the dimensionality of the problem [57, 135, 141, 182, 119, 142, 102]. Most of these features are obtained by applying statistics to time windows (mean, variance, kurtosis, autocorrelation...).

Once data extraction and feature definition have been applied, the literature traditionally deals with the design of a classifier to determine whether or not there is a fall based on the data provided by the features. To design this classifier, Machine Learning techniques have traditionally been applied [134]. Within these techniques, a wide variety of techniques can be found with which to define these classifiers [154].

One of the most widely used techniques for fall detection is Artificial Neural Network [5, 136, 181, 182, 197, 141, 18, 34, 53, 114, 135, 137, 119, 87]. ANN can be of various types. Among the classical solutions for neural networks is the MLP topology [136, 135, 53, 181, 182, 141]. This technique is mainly focused on the classification of falls based on the features extracted from the sensor signals, given that by introducing them in the input layer of the MLP network, it is possible to obtain an assessment of the existence of a fall. Although the effectiveness of the implementation of neural networks depends on the training process, related work [182] has shown that the use of MLPs makes it possible to obtain results with success rates of 98% for the case of fall detection, using a triaxial accelerometer placed on the waist of the user of 11 users who simulated 11 different falls.

There are certain authors who opt for the use of more complex techniques to perform the detection of the falls [87, 197, 119, 114, 137, 67, 160]. Among these can be found the RNN [114, 119], where accelerometers are used to detect falls in conjunction with this technology. This type of system consists of a large amount of data in the database for training. These networks, unlike those analysed above, are based on the feedback of the output data of the neurons during a certain period of time, thus achieving the classification. Another of the complex technique used are CNN [137, 67, 160], networks based on this type of technique are normally used for image recognition. This type of networks consider images as inputs, and certain elements of the images are assigned a weight. The different hidden layers of which this type of network is composed are capable of recognising different elements of the image. Each layer specialising in a type of recognition, in this way the complete set of hidden layers is capable of recognising more complex shapes. This type of complex networks requires a large amount of time and consumption of computational resources, due to the feedback itself. The results obtained for this type of system is close to 100%, or in some cases 100% [197], which is achieved using a wearable sensor (triaxial accelerometer) placed on the wrist, or 94% [137] using images as input.

In addition to neural networks, Machine Learning techniques include other techniques aimed at classification, such as SVM [136, 37, 57, 119, 141, 201, 97, 20, 142, 128, 56]. These techniques construct vectors that limit the region in which the different classes to be classified are found. To obtain these vectors, a series of training sessions are required in which a series of points belonging to different classes are provided. As in the case of systems based on MLP networks, they are mainly focused on working with the features of processed signals, and obtain a very good success rate in the results provided, with values of more than 98% [57].

K-NN techniques are also classic techniques in the field of Machine Learning traditionally used for classification [50, 108, 142]. This is a supervised classification method, which queries to which class the K nearest elements belong, thus assigning the class according to the highest number of elements of a class among the K nearest elements. This technique has a similar application to that of the SVM, achieving hit rates of 96% [50] in the detection of falls.

Finally, other lesser-used technologies can be found for fall detection. Among them we find the use of Thresholds [7, 35, 153, 195, 104], which detect falls when one or several of the parameters exceed a threshold; Naive Bayes systems [119, 3, 141, 142], this type of algorithm performs the classification by making each of the features independent of the others; Fuzzic Logic [53], this has an approach to variable processing that allows multiple values to be processed through the same variable; Decision Trees [3, 99], Random Forest [189, 142], rule-based systems [92], Logistic Regression [18, 142] or LSM [34, 141].

In general, there is no consensus on the suitability of one technique over another. In this sense, some authors have proposed comparisons to evaluate the effectiveness of the different techniques. In [3] the authors compare K-NN, Decision Trees and Naive Bayes, showing that the best result is given by DT, although the results obtained by Naive Bayes are similar. In [119] they compare SVM, Naive Bayes and RNN, obtaining the best results in the latter (with 100%) compared to 93.45% for SVM. In [141] various technologies, sine positioning, and classifiers such as K-NN, SVM, least squares, Bayesian decision making, Dynamic Time Distortion and ANN are compared. The best result of the comparison is the use of K-NN by placing the sensors at the waist, although it is true that in all cases the accuracy exceeds 90%.

In conclusion, although there is a great variety in the techniques used for fall detection, there is a tendency to use systems based on ANN or SVM. In general, all the technologies used for the detection of falls have a success rate of over 90% in the works analysed. Although there are techniques such as RNN that achieve results of 100% success, these techniques usually require a higher computational cost and a greater number of samples, making the development of these detectors more expensive.

These technologies are commonly used in other fields, which makes them more widely known. In addition, these technologies are easy to implement, and do not require excessively large databases.

Table 2.3: Main aspects of studies about fall detection. (A = Accelerometer, G = Gyroscope, M = Magnetometer, F = Force).

Study	Sensors	Sensors Position	Detection Method
[4]	Smartphone A	Pocket, Belt	Decision Trees, K-NN, NB
[5]	Video		ANN
[10]	A, G	Chest	Threshold
[18]	Video		SVM, ANN, Logistic Regresion
[34]	Smartphone audio	Pocket	K-NN, SVM, LSM, ANN
[35]	A	Waist	Threshold
[37]	3-axis A	Pocket, Chest, Waist	SVM
[44]	Smartphone IMU	Pocket	RNN
[50]	Video		K-NN
[53]	A	Waist	Fuzzy logic, ANN
[57]	A	Foot	SVM
[61]	IMU	Instrumented Cane	Threshold, Event
[65]	F, 3-axis G	Instrumented Crutch	Threshold
[87]	Radar		Deep Learning
[92]	Smartwatch	Wrist	Threshold
[99]	F, 3-axis A, G	Instrumented Crutch	Threshold
[108]	Video		K-NN
[114]	A	Waist	RNN
[115]	Video		Optical flow change
[119]	Smartwatch A	Wrist	SVM, NB, Deep Learning
[136]	3-axis A 2x G	Back, Belt	ANN, SVM
[137]	Video		CNN
[141]	6x 3-axis A, G, M	Head, Chest, Waist, Wrist, Ankle, Thigh	K-NN, SVM, LSM, BDM, ANN, DTW
[142]	Inertial sensors	Lower back	SVM, NB, Logistic Regresion, K-NN, RF
[153]	A, G		ANN, Threshold
[181]	3-axis A	Wrist	ANN
[182]	3-axis A	Waist	ANN
[189]	Radio signal		SVM, RF
[196]	GPSG, G, Heart sensor	Instrumented Cane	Angle identification
[197]	3-axis A	Wrist	ANN

2.4 Conclusions

As discussed in this chapter, the use of certain sensors to classify Physical Activity and to detect falls can be very successful. However, although progress in this research area is evident, there are still a number of aspects for improvement.

As noted in Chapter 2.1, the use of certain types of sensors can have many drawbacks. Both wearable and vision-based sensors have privacy issues or nuisance generation from the sensors. Although wearable sensors obtain good results when used for their intended purpose, the difficulty required for correct placement can lead to errors in the measurement, as they can be placed in the wrong way. In addition, they can generate parasitic noise, due to positioning on clothing or the body. For this reason, the approach of placing the sensors in other locations, such as ADWs, may solve some of the disadvantages. Among the devices that choose to use the ADW as a sensor system, there is a wide variety of different sensors used. The vast majority use sensors that provide information on the movement performed, through the use of inertial sensors, or report the force performed, through the use of force sensors.

Although wide variety of sensorized assistive technologies can be found, but most of them are dependent on the ADW itself, i.e. they require the user to use the same customized ADW every time. This can be a problem, as the Assistive Device for Walking that works for one person does not have to be the same as the one that works for a different person. In addition, many of the sensors in Assistive Device for Walking make them impractical to use. The use of sensor systems capable of adapting to different ADWs is an unexploited area. The design of sensor systems capable adaptable to different ADWs is an interesting area of study, as it gives the opportunity to adapt the sensors to the ADW that is most comfortable for the user. For this reason, in this doctoral thesis, a **Sensorized Tip capable of adapting and interchanging between the different ADWs** is designed.

As explained in the Chapter 2.2, the processing of the data obtained and the methodology used for classification is very important. The methodology followed for the classification of physical activities is normally divided into a data adapting phase, a features generation phase, a features reduction phase, and finally a classification phase. Although most of the works analysed follow this structure, the methods used for this purpose vary widely. In the case of data fitting, methodologies based on window splitting are usually presented, with the type of window varying depending on the needs of each case. If the process of generating features is analysed, although the vast majority use features based on statistical calculations, it is also possible to find works that use other types of features. As far as feature dimensionality reduction is concerned, there is a wide variety of strategies used, almost all of them with a good result. Analysing the methodologies used for classification, we can also find a lot of variety, but in this case there is a tendency to use Machine Learning based technologies, such as SVM, K-NN or ANN. For all these reasons, this doctoral thesis proposes the development of **an intelligent Physical Activity classifier based on Machine Learning** using the data obtained by the Sensorized Tip attached to the ADW.

As seen in Chapter 2.3, it should be noted that the vast majority of the elements used for fall detection are wearable sensors. Although these types of sensors are the most practical, as they can detect falls in different environments, they have the great disadvantage that they can become cumbersome or must always be correctly positioned. One of the most practical and suitable solutions is to add sensors capable of detecting falls in the ADW, although nowadays are not very many ADW devices capable of detecting falls. For this reason, this doctoral thesis proposes the design of a **fall detector** using the sensors available in the Sensorized Tip, in order to avoid the need for rehabilitation due to the consequences of a late reaction to a fall. Within the methodologies used for fall detection, as a general rule, the most commonly are based on Machine Learning systems, mainly ANN and SVMs.

In the following sections it will be shown the developments made in the thesis, analysed in this chapter, providing new solutions to the problems detected.

3 Sensorized Tip for Physical Activities Classification and Fall Detection

This chapter presents a summary of the work carried for development the Intelligent Sensorized Tip for monitoring/quantifying Physical Activity, including fall detection. As this doctoral thesis is presented as a compendium of papers, what is summarised in this section can be found in more detail in the papers presented in Appendix 1 [28], Appendix 2 [126] and Appendix 3 [125].

3.1 Sensorized Tip for ADW

This section summarises the interchangeable Sensorized Tip designed for Physical Activity (PA) monitoring. The detailed explanation of this section can be found in the paper in Appendix 1 [28], which is published in the open access journal called *Sensors*.

After analysing in Chapter 2.1 the sensors used in different Assistive Device for Walking (ADW)s and the way they are incorporated for monitoring physical activities, it was decided to develop a Sensorized Tip. The aim of the development of this Sensorized Tip is to be able to measure the Physical Activity of people wearing an ADW. Through the use of a sensorized Tip that can be adapted to different ADWs, the aim is to eliminate some of the disadvantages of the other types of sensors currently used for monitoring PA.

3.1.1 Sensorized Tip prototype

The system of which this Sensorized Tip is composed is made up of two main elements (see Figure 3.1): the Sensorized Tip, which contains the sensors and the electronics to process and send the data obtained from the sensors; and an external standard $5V$ USB battery, which will power all the electronics of the Sensorized Tip. Unlike other Sensorized ADWs mentioned in Chapter 2.1, this Sensorized Tip is designed to be attached to any ADW (crutch, cane...) to monitor PA by means of a simple attachment system.

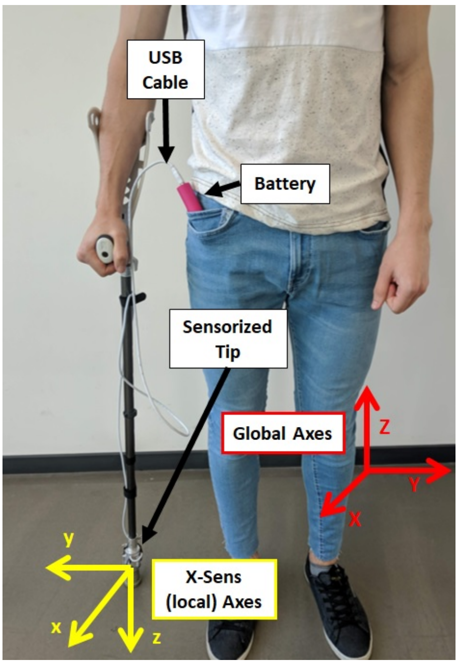
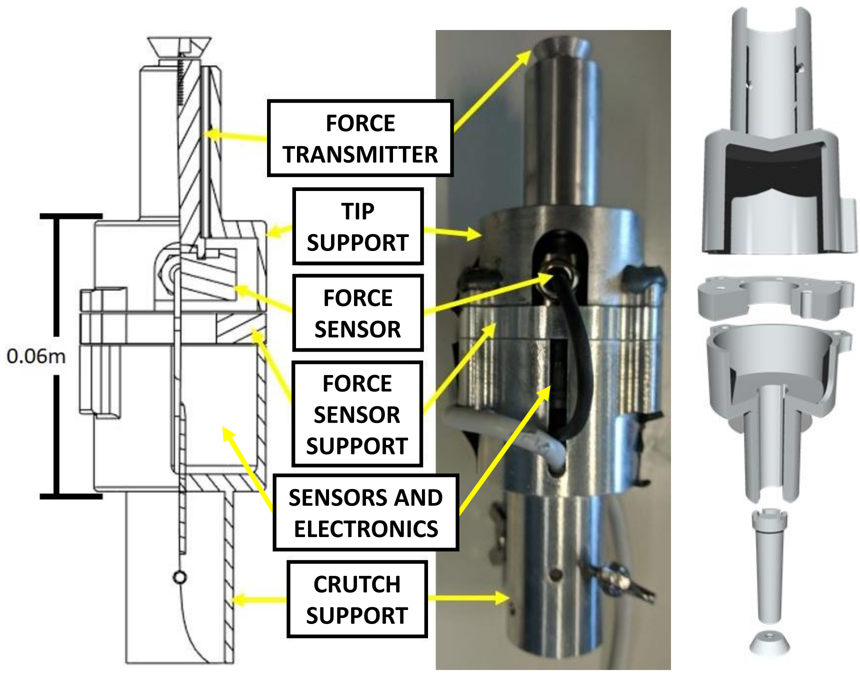


Figure 3.1: System elements and reference axes.

The structure of the Sensorized Tip is a proprietary design (patent pending), which can integrate the sensors it contains, as well as the data processor and sending system. This structure is designed in aluminium, and in such a way that the weight is the lowest. The weight of Sensorized Tip is $180g$ together with the sensors, without taking into account the external battery. In addition, its longitudinal size ($0.06m$) has been selected to minimise the need to adjust the height of the crutch, as $0.06m$

is equivalent to three discrete positions in the longitudinal adjustability of a standard crutch. The structure of the Sensorized Tip consists of 5 parts (see Figure 3.2): crutch support, which holds the Sensorized Tip to the ADW stem and contains most of the sensors and the processor; force sensor support, which holds the force sensor; force transmitter, which transmits the axial force to the force sensor; Tip support, which contains the force sensor and the ruggedised Tip, which attaches to this part.



(a) (b)

Figure 3.2: Sensorized Tip mechanical structure.

The Sensorized Tip consists of a series of sensors that measure various PA variables. As mentioned in Chapter 2.1, the most important variables defined in Sensorized ADWs are those based on movement and those based on the force applied to the ADW. Taking into account the elements used in the different works, in this case an Inertial Measurement Unit (IMU) MTi-1 from X-Sens will be implemented. It integrates a 3-axis accelerometer, a 3-axis gyroscope and a 3-axis magnetometer. This IMU, in addition to the data from the indicated sensors, also provides the value of the absolute Roll-Pitch-Yaw angles, calculated from the data of the sensors. A C9C sensor from HBM is used to read the longitudinal force. In order to adapt the output signal of this force sensor, a signal amplification circuit is incorporated at the output of this sensor. Finally, it consists of a BMP280 barometric sensor developed by Bosh.

All these sensors communicate with a data processing unit that processes the data and sends it via Bluetooth to an external data acquisition system. This data processing unit is a BLE Nano v2 based on an nRF52 processor IC. The IMU and the barometer send data to the BLE Nano via I2C communication, while the force sensor uses one of the analogue inputs provided by the BLE Nano. This BLE Nano processor acquires the data and sends it via Bluetooth Low Energy (BLE). Thanks to the low power consumption of BLE, the Sensorized Tip does not consume a large amount of battery power. More exactly, it has a power consumption of 0.225W at 5V.

Table 3.1: BLE package data

First Package	**20 Bytes**	**Second Package**	**20 Bytes**
	Number of Bits		*Number of Bits*
Iteration	**4**	Iteration	**4**
Force	**16**	Accelerometer	**45**
Altitude	**32**	Y axis	20
Euler Angles	**78**	Z axis	25
Roll	26	Gyroscope	**60**
Pitch	26	X axis	20
Yaw	26	Y axis	20
Accelerometer	**30**	Z axis	20
X axis	25	Magnetometer	**48**
Y axis	5	X axis	16
		Y axis	16
		Z axis	16

The data acquired by the BLE Nano from the sensors is sent via Bluetooth to a device, on which the data will be stored. The data to be sent shall be encapsulated in two packets and sent with a frequency of 50Hz. A total of 40 bytes are sent in each sampling period, the data being as shown in Table 3.1.

3.1.2 Characterization of the measurement errors

In order to know the accuracy of the Sensorized Tip, the error of the sensors used in the Sensorized Tip is characterised in this section.

In order to validate the Euler angles provided by the X-Sens sensor, a VICON 3D Motion capture System installed at the UPV/EHU is used to compare the results obtained by the Sensorized Tip. This system consists of 8 cameras covering an area of 4x4m (see Figure 3.3a). In order to be able to capture with this camera system, 6 reflective markers are incorporated into the crutch used with the Sensorized Tip (see Figure 3.3b).

A series of tests are designed to validate the Euler angles. Five trajectories were considered (see Figure 3.3a): three 4m straight walking tests, with different crutch

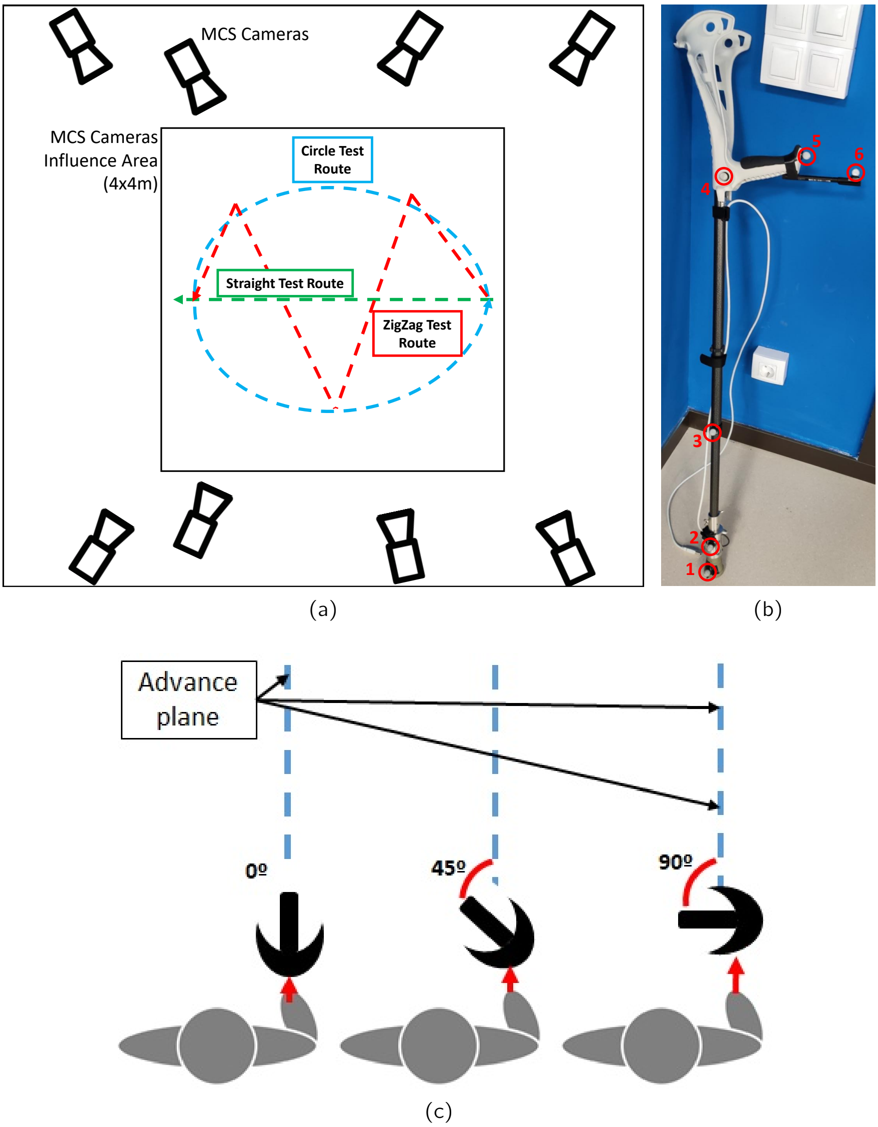


Figure 3.3: (a) 3D Motion Capture Laboratory Schematic with camera placements, capture area and defined test trajectories. (b) Reflective marker distribution on the tested crutch (the markers are identified with numbers). (c) Position of the crutch handle with respect to the advance plane, in the different validation tests of Euler angles provided by the X-Sens.

handle orientations (more or less 0°, 45° and 90° rotation) (see Figure 3.3c), a zig-zag trajectory (0° rotation) and a circular trajectory (0° rotation).

Once the tests have been carried out, the results show that the Sensorized Tip has an error of less than 1.5° for the Roll and Pitch angles (see Table 3.2). It is higher in the case of the Yaw angle, with an inferior value of 4.3° (see Table 3.2). These values are similar to those proposed in the literature and acceptable for the required application.

Table 3.2: X-Sens Euler angles estimation error.

Test	**Handle Orientation**	**RMS Error** Roll (°)	Pitch (°)	Yaw (°)
Walk straight 4 meters	0°	0.5439	1.0971	2.3457
Walk straight 4 meters	45°	0.8482	0.7325	2.1725
Walk straight 4 meters	90°	0.5429	1.0984	2.3404
Zigzag	0°	0.6736	0.8693	4.3096
Circle	0°	0.935	1.5278	4.3099
Mean		0.7267	1.0777	3.4688

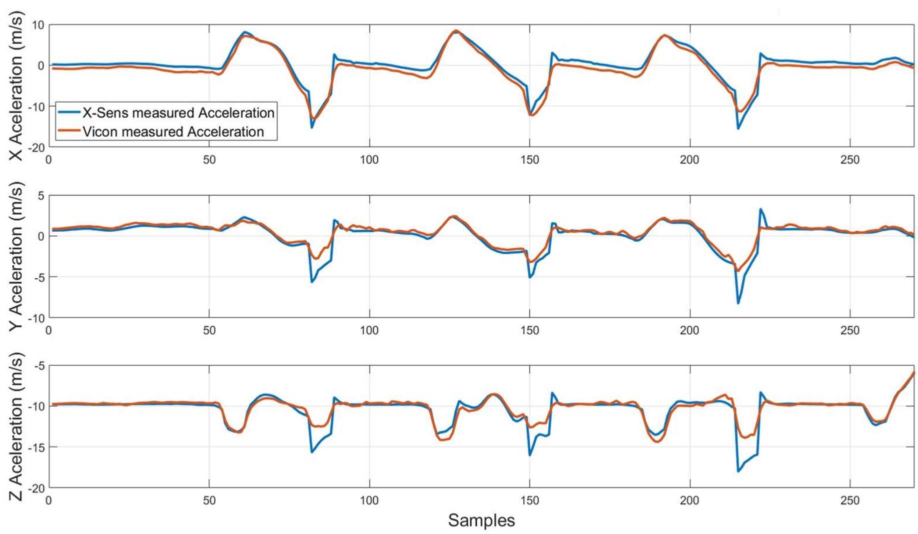


Figure 3.4: Comparison of acceleration measured by X-Sens and Vicon.

Using the same VICON system, the accuracy of the accelerometric sensor in the X-Sens is validated. The $4m$ walk test (0° rotation) is used to do this. The results of error obtained are less than $1.4m/s^2$ in all 3 axes. As can be seen in Figure 3.4, the curve obtained by the VICON and by the X-Sens sensor are very similar, except when an impact is suffered on the ground, where there is a greater acceleration due to this effect.

To conclude with the X-Sens sensors, the 3-axis gyroscope is validated. For this purpose, the Sensorized Tip is rotated with a servomotor, which is rotated at 3 different speeds: $100°/s$, $200°/s$ and $300°/s$. The error increases as the rotational speed of the engine grows, with a higher error in the case of $300°/s$ rotation. However, it has been checked that the angular velocity of movement of the ADW of a healthy person is less than $180°/s$ in the x and y axes and $220°/s$ in the z axis. This guarantees that the error will be less than $1°/s$ in this speed range.

To validate the C9C force sensor used, it is compared with the data obtained by a Bertec 4060-15 force plate. First, the curve function is calculated by adding weight to the Tip in kg increments, the resultant curve is

$$y = -230.71x^2 + 797.3736x - 285.6619 \tag{3.1}$$

Once this function has been achieved, different axial forces are tested and compared with the results of the force platform. The resulting curves can be seen in Figure 3.5. Although the error is not very high, it is acceptable for the task (RMS error of $21.1N$).

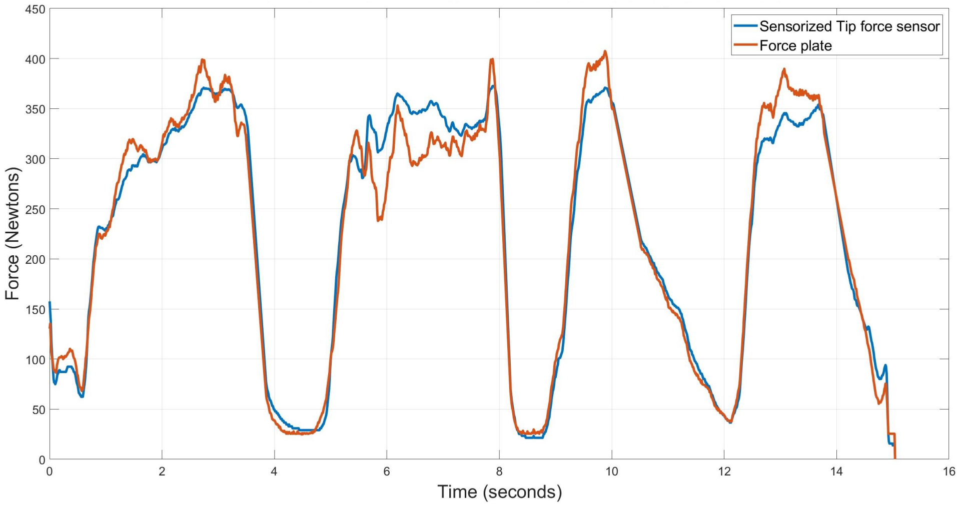
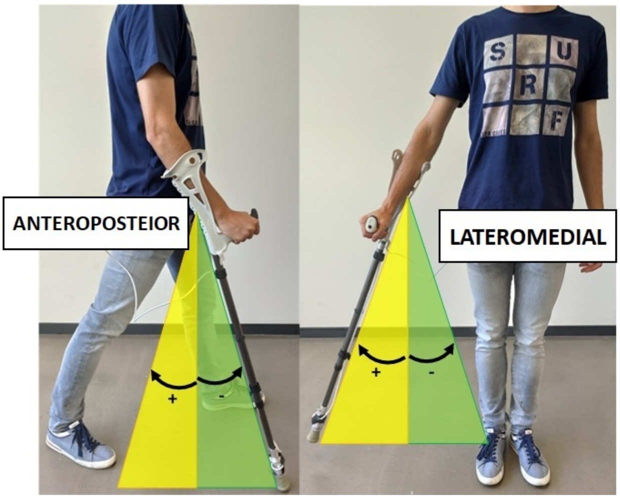


Figure 3.5: Force sensor after calibrate curve and data obtained from the scale.

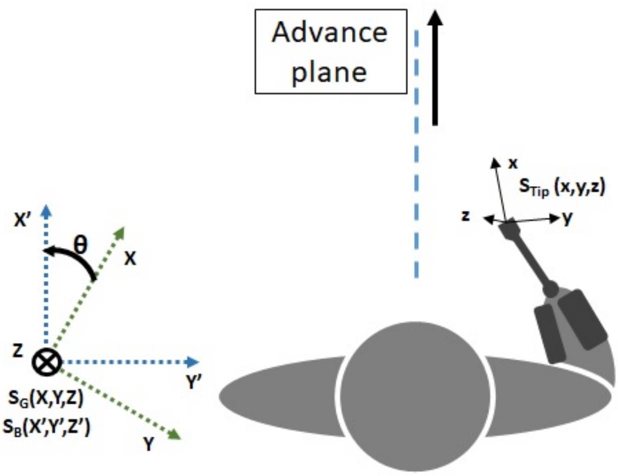
Finally, the accuracy of the BMP280 barometer is tested. To do this, a simple test was carried out, using a set of stairs as a reference. It was divided into four flights, with 12 stairs per flight and a total of $2.04m$ between flights. Considering the flat areas associated with each flight of stairs in the time evolution, the RMS error is $0.2716m$, while the mean error is $-0.0466m$. Note that this is in accordance with the manufacturer's data, which gives a relative accuracy of $0.12hPa$.

3.1.3 Estimation of the Orientation of the Device

In the particular case of the device used, the integrated Mti-1 sensor provides, by means of a proprietary algorithm based on a Kalman Filter, the Euler orientation angles relating the local reference frame of the Sensorized Tip $S_{tip}(x, y, z)$ to a global reference frame $S_G(X, Y, Z)$.



(a)



(b)

Figure 3.6: (a) Anteroposterior and Lateromedial angles. (b) Global, Body and Sensorized Tip reference frames.

However, for the specific application of the Sensorized Tip, the relative motion of the Assistive Device for Walking with respect to the patient's body is required. That is, the lateromedial and anteroposterior angles, as seen in Figure 3.6a.

In order to get the calculation of these angles, two steps are followed. First, the body's reference system and the advance plane is obtained from the data provided by the sensor. Secondly, the lateromedial and anteroposterior angles are calculated.

To obtain the body reference frame, these is considered to be aligned with the Z axis of the global reference frame that creates the MTi-1. But its X' axis always points in the direction of the body motion, which defines the advance plane $X'Z'$. Therefore, the global and body reference frames are related by the rotation of θ with respect to the global Z axis (see Figure 3.6b). Therefore, to achieve this reference frame, the direction of motion in the plane (XY) of the global reference frame has to be defined. For this it has to be taken into account that the global reference frame of the Mti-1 only secures the Z axis, and people using ADW can grip the handle of the with multiple angles.

In this way, in order to know the forward plane, first of all the phases of the steps (stance phase and swing phase) are defined by using the force sensor. Knowing these phases, in the stance phase process, the Euler angles are stored and the 3D orientation of the ADW is represented (see Figure 3.7). For each set of captured Euler angles, a rotation matrix can be defined, which relates the local reference frame of the sensing Tip and the global reference frame of the Mti-1. As the local Z axis of the Sensorized Tip is aligned with the axis of the Sensorized Tip, it is possible to define the representation of the unit vector ${}^{G}\mathbf{u}_z$ associated with the local Z axis in the global reference frame by extracting the third column of $\mathbf{R}_{rpy}$.

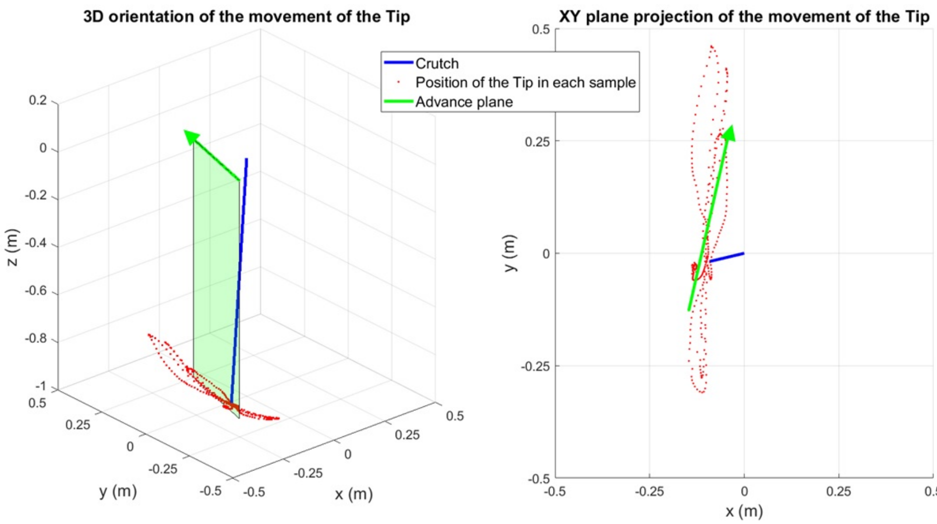


Figure 3.7: 3D Orientation of the Sensorized Tip and (XY) plane projection.

As with the sensors of the Sensorized Tip, the proposed algorithm is validated to check its validity. In this case, different trajectories are performed in which the rotation of the handle is varied. These tests are carried out in the VICON environment in order to compare the results obtained. The error achieved is less than 5° for all cases except when walking in circles, where the error is close to 8° (see Figure 3.8). This error is due to the feature of the circular motion, in which the steps are not made in a straight line and consequently there is no fixed forward plane during the steps. Even so, as can be seen in Figure 3.8, the calculated forward planes approximate the realised circular trajectory to a polygon fairly close to the realised trajectory.

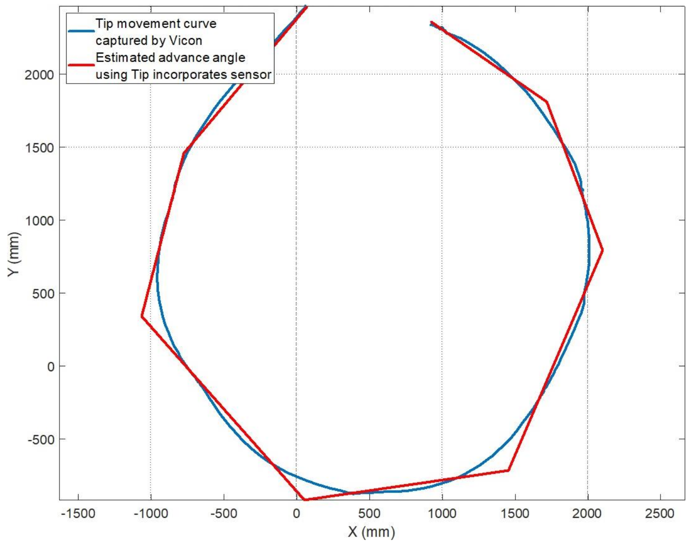


Figure 3.8: Advance plane estimation in the circular test (Worst Case Scenario) with respect to the real trajectory.

Finally, the anteroposterior and lateromedial angles are calculated. For this, the projection of the z axis of the reference axes of the Sensorized Tip with respect to the reference axes of the body is used.

3.1.4 New version of the Sensorized Tip

In order to improve the accuracy of the force sensor, and to be able to transfer the longitudinal force realised in the ADW more realistically, an improved version of the Sensorized Tip is produced (see Figure 3.10). This version only undergoes changes in the mechanical structure of the Sensorized Tip.

One of the changes that has been made is to modify the attachment system of the Sensorized Tip to the ADW. This system moves from a bolt-based system to a clamp-based system. This improvement makes it easier to hold the Sensorized Tip, as well as making it more robust.

The other change is in the transmission of force to the force sensor. Friction between the individual elements of the Tip is avoided, so that a better precision is not achieved. As can be seen in Figure 3.10, the curve of the force sensor is practically

Figure 3.9: New Sensorized Tip.

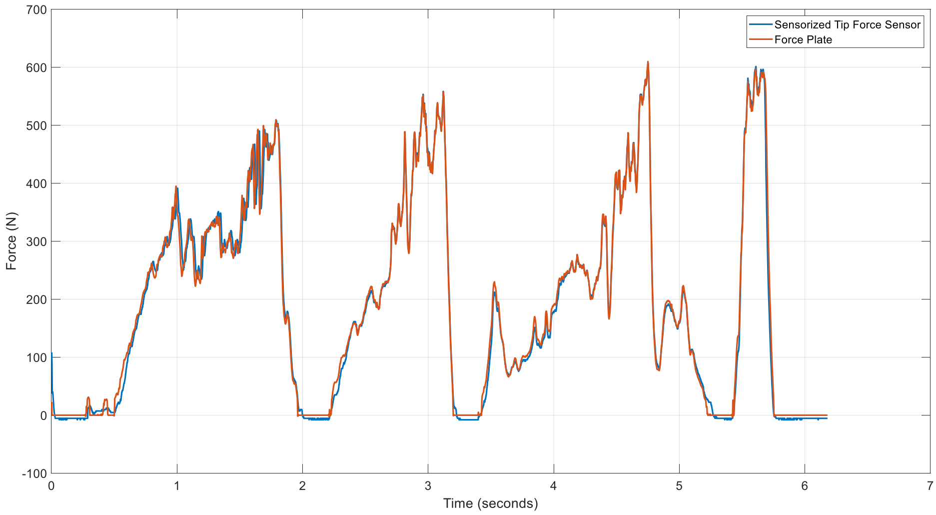


Figure 3.10: New Sensorized Tip Force sensor after calibrate curve and data obtained from the scale.

the same as that obtained by the pressure plate. Compared to the results obtained from Figure 3.5, the difference in accuracy is considerable (RMS error of 11.4 N).

3.1.5 Conclusions

This section presents a Sensorized Tip that can be attached to any ADW. This Sensorized Tip has the ability to monitor the activity of people using the ADW. The proposed element contains a number of sensors that provide information on the force and movement of the element. This device is designed to be used via Bluetooth and to add as little weight as possible to the ADW.

The error of the Sensorized Tip is characterised by means of a series of tests. In addition, an algorithm is used to estimate the lead angle and, together with this, to calculate the lateromedial and anteroposterior angles. The results obtained show that the errors obtained are small, validating the use of the Sensorized Tip for monitoring the activity of people using ADW.

In addition, a new version of the device has been designed, which improves the results obtained.

3.2 Physical Activity classificator

This section summarises the Physical Activity classifier developed using the data acquired by the sensors of the Sensorized Tip. The detailed explanation of this section can be found in the paper in Appendix 2 [126], which is published in the open access journal called *IEEE Access*.

Following the development of the Sensorized Tip capable of monitoring Physical Activity, a methodology capable of classifying the different physical activities performed is required. As mentioned in Chapter 2.2, the vast majority of the proposed PA classifications follow the same methodology. Once the data has been collected with the sensors, this methodology divides the data into smaller segments, then features are generated, after these, a reduction of the features created is carried out and finally the classifier is performed. For each of the cases in Chapter 2.2, different methods have been proposed.

3.2.1 Data capture test

In order to realise a Physical Activity classifier based on the Sensorized Tip, the generation of a database is required. For the generation of this database, it has to be selected which activities can be classified. In this way, a series of experiments containing these activities are designed. Thus, it was decided to classify 5 different physical activities:

- Walking 30m in a straight line at the normal speed.
- Walking 30m in a straight line at a speed higher than normal (approximately 30% faster).
- Standing still for approximately 10 seconds.
- Going up an 11-step flight of stairs.
- Going down an 11-step flight of stairs.

Eleven different people are used to carry out the tests (4 women and 7 men, ranging between 24–48 years), and each of them repeats each of the tests three times.

3.2.2 Data Segmentation

Once the desired data has been captured through the tests, the data is segmented. To do this segmentation, analysing the alternatives seen in Chapter 2.2, it is decided to create windows by events, these windows will contain the phases of use of the ADW (stance phase and swing phase) (see Figure 3.11). The force sensor integrated in the Sensorized Tip is used to achieve this division. The beginning of the window is defined by the beginning of the stance phase, while the end of the window is defined by the end of the swing phase. The total number of windows obtained in the above test is summarised in Table 3.3.

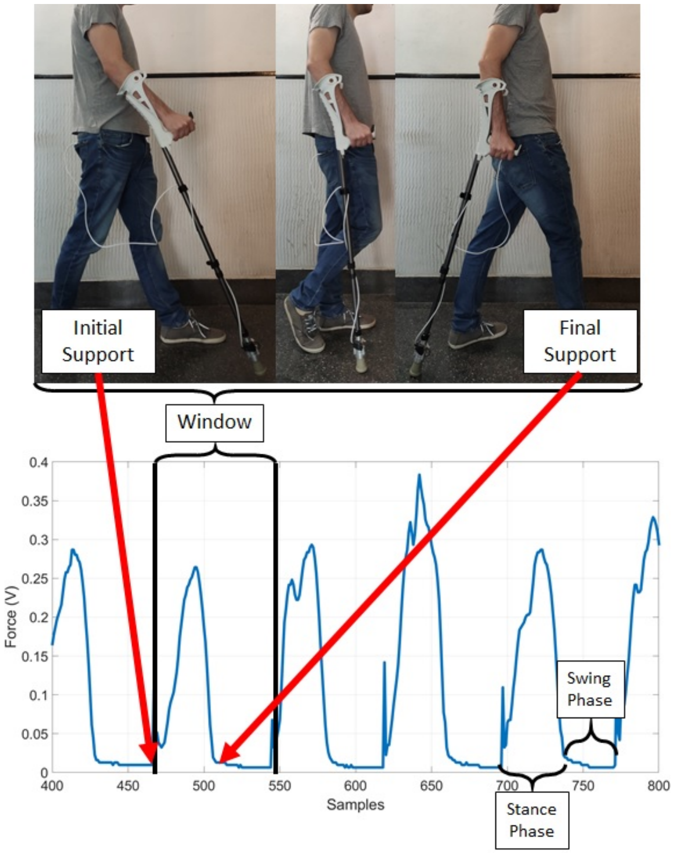


Figure 3.11: Cycle of use of an ADW and its phases. Data Segmentation in windows by using the data acquired from the force sensor.

In order to achieve the PA classifier, the data is divided into two different sets, one for the training of the ML based systems and one for the testing of the results. This division is made using approximately 70% of the data for training and the rest for testing (see Table 3.3).

3.2.3 Machine Learning-based PA classifier design methodology

Once the data has been divided into windows, we proceed to work with the database to adapt it and finally create the PA classifier. Following the methodology mentioned in Chapter 2.2 (see Figure 3.12), once the data has been divided, a set of potential features has to be generated. Once these features have been obtained, the dimensionality of the features must be reduced, selecting those that are the most important

Table 3.3: Number of Windows per Physical Activity (PA). Test and Training Sets

Type of PA	Number of Windows	Training Set	Test Set
Walk Normal	724	254	123
Walk Fast	528	264	118
Go Up Stairs	360	251	109
Go Down Stairs	357	251	106
Standing Still	329	218	111
Total		1238	567

for the selected task. Finally, the classifier is generated to differentiate between the different physical activities.

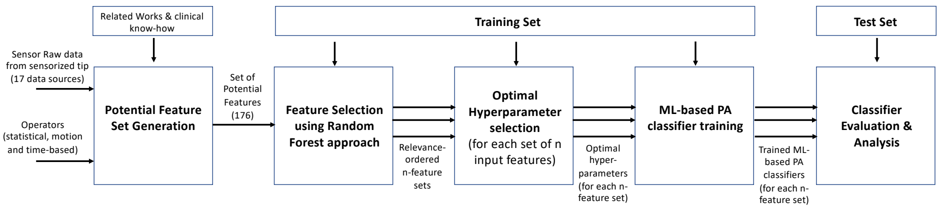


Figure 3.12: Methodology followed for the creation of the Physical Activity classifier.

3.2.3.1 Potential set feature generation

The first step in the development of the PA classifier is to generate a series of features that simplify each of the windows. As discussed in Chapter 2.2, in most of the work carried out, features based on statistical calculations are used. In this doctoral thesis we propose to use a series of features based on statistical operations, as well as a series of features based on motion and time. These features are applied to all the windows obtained, being applied to the windows resulting from the 17 data obtained from the sensors. This gives a total of 176 features per window (see Table 3.4).

3.2.3.2 Feature selection

While the set of 176 features in each window can be used to develop the PA classifier, the use of all features for this development may not be very effective. The introduction of all the features for the classifier realisation, apart from increasing the computational cost of the classifier, can have an impact on the classification efficiency. For this reason, a dimensionality reduction system is proposed.

As mentioned in Chapter 2.2, the methodologies used in order to reduce dimensionality are very varied. One of the ways in which dimensionality reduction can be achieved is through visual analysis of the selected features. For a simpler activity classifier (classifying 3 PA), [26] presents a dimensionality reduction done in this way. In

Table 3.4: Features generated from the data provided by the sensorized Tip (R = Roll, P = Pitch, Y = Yaw, A = Anteroposterior, L = Lateromedial).

Operators \ Data Source	Accelerometer (X, Y, Z)	Gyroscope (X, Y, Z)	Magnetometer (X, Y, Z)	Angle (R, P, Y)	Angles (A, L)	Barometer (With Filter)	Barometer (Without Filter)	Force Sensor
Mean	X	X	X	X	X	X	X	X
Standard Deviation	X	X	X	X	X	X	X	X
Variance	X	X	X	X	X	X	X	X
Kurtosis	X	X	X	X	X	X	X	X
Corr. Coef. XY	X	X	X					
Corr. Coef. XZ	X	X	X					
Corr. Coef. YZ	X	X	X					
Corr. Coef. RP				X				
Corr. Coef. RY				X				
Corr. Coef. PY				X				
Corr. Coef. AL					X			
25th Percentile	X	X	X	X	X	X	X	X
50th Percentile	X	X	X	X	X	X	X	X
75th Percentile	X	X	X	X	X	X	X	X
Area	X	X	X	X	X	X	X	X
Interquartile Range	X	X	X	X	X	X	X	X
Stance Start Value					X			
Value at Max. Force					X			
Stance End Value					X			
Amplitude					X			
Cycle time								X
Stance Ph. %								X
Feature Number	30	30	30	30	27	9	9	11

this case, this differentiation of the 3 cases is made by analysing the histogrammatic distribution of the features. In this way, those features (6) in which the greatest difference in the histogram distribution has been observed are used (see Figure 3.13).

In the paper presented in [29], the same classifier of physical activities is proposed, but in this case, apart from using the features selected in [26], three more are incorporated (cycle time, percentage of the stance phase in each cycle and the average acceleration in the z-axis accelerometer).

Although it is possible to visually reduce the dimensionality of the features, the features chosen are not necessarily the most appropriate. Moreover, it is not possible to visually see the possible correlations between the features. For this reason, the use of Random Forest (RF) is proposed in this case to achieve this goal (this methodology is carried out in Appendix 2 [126] and [27]). For that purpose, only the samples contained into the *Training Set* defined have been used. The proposed RF has been implemented considering the following set of hyperparameters, experimentally selected:

- The number of trees in the forest has been tuned to 5000.
- A sample with replacement strategy has been selected.
- A node size of 1 was defined.
- The number of variables randomly chosen at each split ($mtry$) has been tuned to $\sqrt{M}$, where M is the total number variables.
- The predictor used has been the *interaction-curvature* to avoid the disturbances caused by correlated features.

Table 3.5 shows the results of the first 30 features considered to be the most important. It should be borne in mind that the RF provides the weight that each feature has for the assigned task, so that the higher the value obtained, the greater the importance of that feature in the activity classification. Analysing the results obtained, the one that is most important according to the Random Forest is the Area Under the Curve of the Yaw Angle.

3.2.3.3 Classifier generation

Once the features have been ordered according to their relevance for the classification of physical activities, the corresponding classifier is designed. The aim of the classifier is to differentiate between different physical activities. In the case of [26] and [29] a classifier is designed to differentiate between 4 physical activities (walking, climbing stairs, descending stairs and standing still). However, in order to increase the number of physical activities to be classified, the paper presented as a compendium (Appendix 2 [126]) proposes a classifier that detects 5 different physical activities: normal walking, fast walking, going up stairs, going down stairs and standing still.

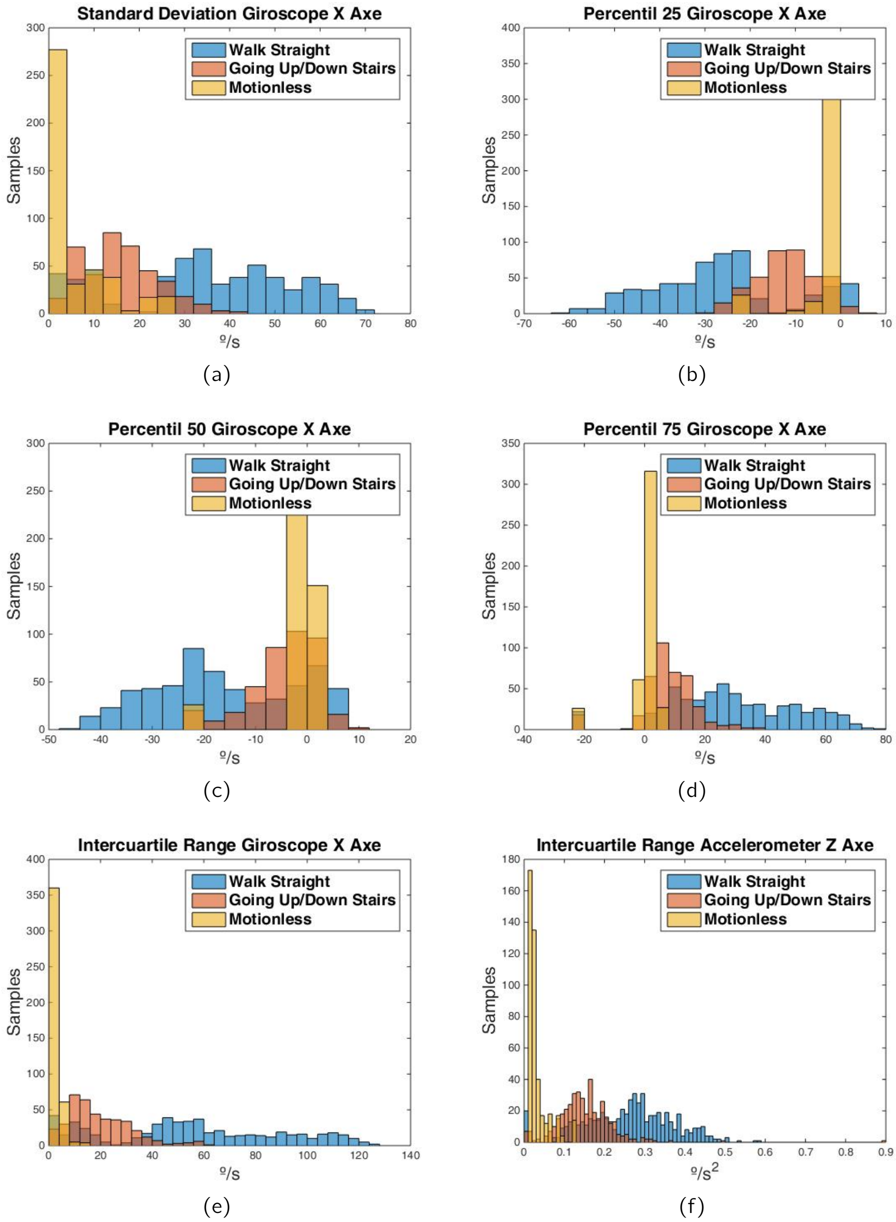


Figure 3.13: Histogram of the most relevant indicators obtained from visual analysis.

Table 3.5: Feature significance and their relative weight according to Random Forest procedure. (Magne = Magnetometer, Accel = Accelerometer, AUtC = Area Under the Curve, 25P = 25th Percentile, 50P = 50th Percentile, 75P = 75th Percentile, IR = Intercuartile Range, SD = Standard Deviation, Corr. Coef. = Correlation Coefficient, Antero = Anteromedial Angle, Latero = Lateromedial Angle, WoF = Without Filter, WF = With Filter, n = Position).

n	Feature	Weight	n	Feature	Weight
1	AUtC Yaw	2.276	*16*	Antero SD	1.213
2	Cycle Time	2.242	*17*	Antero Variance	1.178
3	Accel SD X	2.216	*18*	Accel 25P Z	1.159
4	Accel Variance X	2.002	*19*	Gyro IR Y	1.131
5	Magne 75P X	1.992	*20*	SD Pitch	1.126
6	Gyro 25P Y	1.978	*21*	Accel SD Z	1.103
7	Antero IR	1.766	*22*	Variance Pitch	1.087
8	Magne Mean X	1.698	*23*	Accel Variance Z	1.078
9	Accel Mean Z	1.671	*24*	Gyro 75P X	1.063
10	IR Pitch	1.635	*25*	Accel IR Y	1.060
11	Magne AUtC X	1.582	*26*	Accel AUtC Z	1.022
12	Accel IR Z	1.527	*27*	Accel 50P X	1.021
13	Accel 25P Y	1.507	*28*	Accel Mean X	1.003
14	Magne 50P X	1.503	*29*	Gyro 50P Y	0.966
15	Magne 25P X	1.402	*30*	Accel 75P X	0.942

In the case of the classifier created from [26] and [29], it will have 4 different outputs. However, in the case of the paper in Appendix 2 [126], due to the increase in physical activities to be classified, in this case the classifier will have 5 outputs, each one associated with each of the activities mentioned.

The number of entries in the three different studies varies. In the case of [26], only 6 features are used as entries (those selected visually). In the case of [29], 3 more features are added to the 6 features selected above. Finally, in the case of the Appendix 2 [126] classifier (the one corresponding to the compendium of papers), the number of inputs corresponding to the classifiers will be varied to find the optimal number of features to be used for the design task. In this way, as many classifiers will be made as the number of features, varying the number of entries to be had. The first classifier to be designed using a single input, being the most relevant feature according to the RF (Area Under the Curve angle Yaw). The second classifier will consist of two entries, these being the 2 features with the highest weight according to the RF. The third classifier will consist of the 3 most important features as input, and so on until reaching the *n* features proposed above.

In order to carry out the classification in this doctoral thesis, methodologies based on Machine Learning (ML) have been proposed. In this case, analysing the methodologies analysed in Chapter 2.2, we decided to focus on the use of the most common ones, K-Nearest Neighbors (K-NN), Support Vector Machine (SVM) and Artificial Neural Network (ANN). In the case of [26] and [29], ANN-based classifiers are implemented. In the specific case of [29], a two-step classifier is implemented (see Figure 3.14), in which rules are used to differentiate between going up and down stairs, standing still and walking, while an ANN classifier is used to differentiate between going up and down stairs.

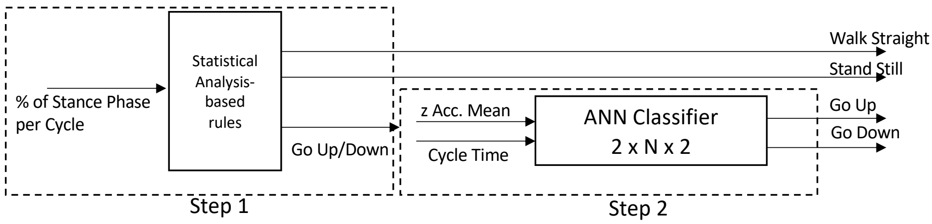


Figure 3.14: Two Step 4 physical activities ANN-based Classifier.

On the other hand, the optimal subset of hyperparameters for each ML-based classifier must be found. For this purpose, a K-fold cross-validation approach with $K = 5$ is proposed. This approach allows for efficient evaluation of different ML-based models. In the case of SVM and K-NN, the Matlab Toolbox Static and Machine Learning is used to select the most optimal hyperparameters for each classifier. In the case of ANN, we choose to use a Multilayer Perceptron (MLP) network with a single hidden layer. As mentioned before, the number of output neurons is 5, while the number of input neurons will be n. However, for the selection of the neurons of the hidden layers, training will be performed having in the hidden layer from 1 to 10 neurons, the one that gives the best results will be the chosen one.

3.2.4 Comparative Analysis

This section provides a comparative analysis of the results obtained from the application of the methodology proposed in the previous section.

The results obtained with the methodologies followed in [26] and [29], classifiers capable of differentiating between the 4 physical activities proposed are obtained. In the case of [26], the success rate results are close to 90% for classifying the 4 activities, with only an 80% success rate for classifying the activities of going up and down stairs. However, thanks to the two-step classifier proposed in [29], results of 97% are achieved.

However, in order to improve the results, the methodology followed in Appendix 2 [126] is proposed. As mentioned before, 3 different ML approaches (SVM, K-NN and ANN) are used to perform the classifier, the results of the 3 approaches are compared to analyse which is the best result obtained. In addition, as mentioned before, training is carried out by increasing the number of entries (according to the order provided by the RF), in this way it is possible to analyse which is the most appropriate number of features to use in each approach.

The results can be seen in Figure 3.15, where the overall success rate for each of the classifiers is plotted. As can be seen, if the 7 most relevant features are used, a success rate of over 90% is achieved in all three cases (92.8% for the K-NN, 97% for the SVM and 96.8% for the ANN). The best success rate is achieved with 66 features in the case of K-NN (98.4%), 87 features in the case of SVM (99.1%) and 174 features in the case of ANN (99.6%).

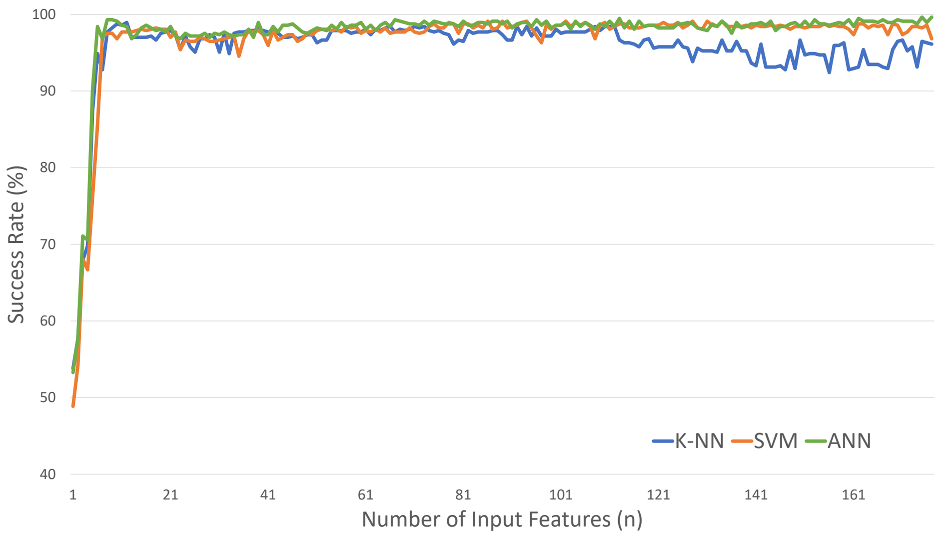


Figure 3.15: Success rate of the classifiers based on K-NN, SVM and ANN, with respect to the number of the *n* most relevant features ordered according to the RF.

As can be seen in Figure 3.15, in the case of SVM and ANN the increase in the success rate from the introduction of 7 features is very small. From this it can be deduced that a correct selection of features has been made. In this particular case, it can be said that with the use of the 7 most relevant features, results with a success rate of more than 95% can be achieved with a low computational cost.

On the other hand, as mentioned before, in order to know the appropriate number of neurons for the ANN, classifiers have been made with neurons in the hidden layer from 1 to 10. Analysing the results, it can be seen that the most appropriate value of neurons in the hidden layer is 9.

In order to check the correct selection of importance of features, the above procedure is repeated, but in this case incrementing the features from the least important to the most important. That is, a set of 176 features is analysed again: first using as input the least important feature, then introducing the two least important features, and so on. The results can be analysed in Figure 3.16, which shows how the success rate increases as more important features are incorporated according to the Random Forest.

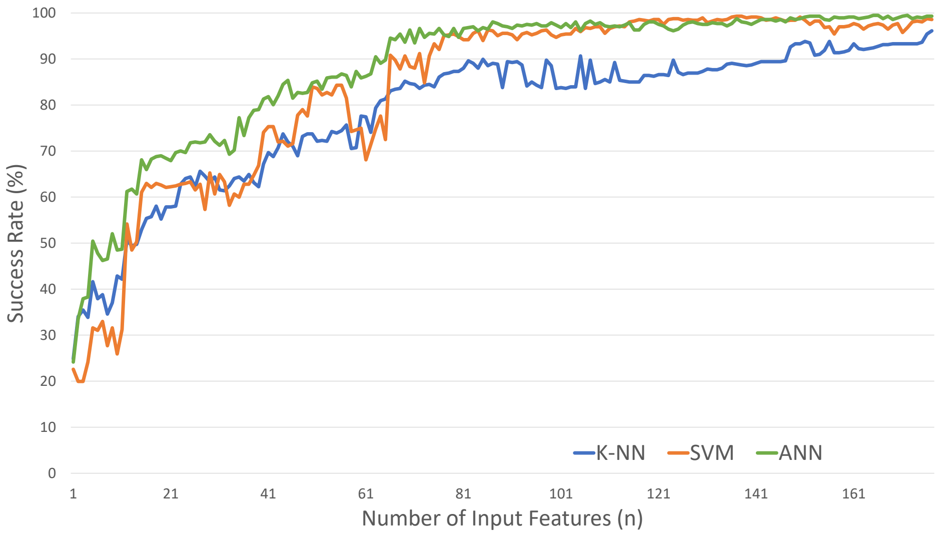


Figure 3.16: Success rate of the K-NN, SVM and ANN based classifiers, with respect to the number of the *n* less relevant features ordered according to the RF approach.

3.2.5 Conclusions

This section presents a classifier capable of classifying between different Physical Activity (PA) by using the Sensorized Tip. In order to realise this classifier, a Machine Learning based approach is proposed. Prior to performing the classification, an approach is proposed in which the data obtained from the tests are divided and transformed into a set of features. With the features obtained, a Random Forest based dimensionality reduction approach is proposed.

The approach is validated by implementing three different ML based PA qualifiers: SVM, K-NN and ANN. Results of between 92% and 97% are obtained using the 7 most important features (according to RF).

3.3 Fall Detector

This section summarises the developed fall detector based on the designed Sensorized Tip. The detailed explanation of this section can be found in Appendix 3 [125], published in the open access journal *IEEE Access*.

In order to make an early detection of the falls that are suffered, and thus to be able to act in consequence avoiding possible consequences of a late response, a fall detector is designed. As mentioned in Chapter 2.3, the use of sensors and the position of these sensors for fall detection is very varied, thanks to having a Sensorized Tip, a fall detector is developed using these sensors available. On the other hand, after analysing the methodologies used in Chapter 2.3 for the detection of falls, it can be seen that these are very varied. In this case, a similar methodology followed in the designed PA classifier is proposed to design a fall detector based on the Sensorized Tip.

The approach proposed in this doctoral thesis is to develop a fall detector based on two modules (see Figure 3.17). The first module is responsible for detecting the fall of the ADW, while the second module uses the fall data to evaluate whether the user has fallen with the ADW, or whether the ADW has fallen without the user. This second module is designed to avoid false positives due to accidental ADW falls.

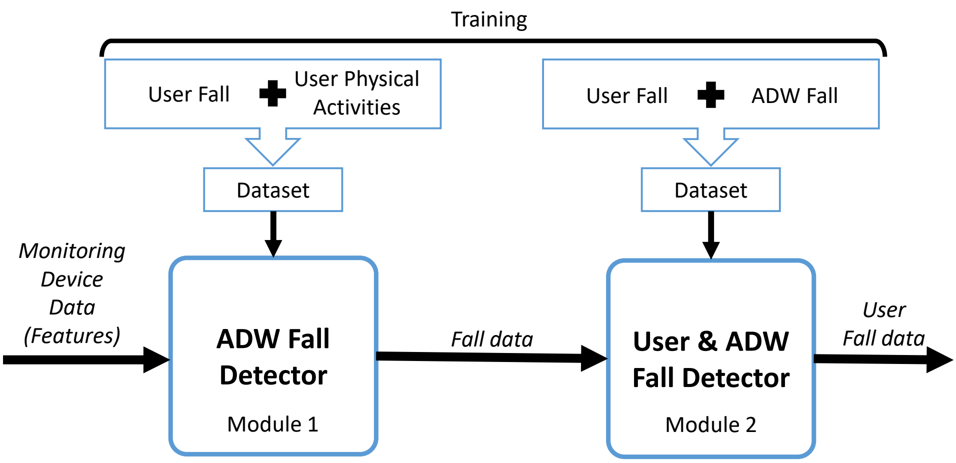


Figure 3.17: Two-module methodology followed for falls detection.

Different data datasets are used for each of the modules developed. The dataset of the first module is composed of user falls with the ADW and a set of different physical activities using the ADW. The second module combines data from the user's falls with the ADW (used in the first module), together with falls from the ADW without the user.

As in the Physical Activity classifier, a methodology is followed after capturing the desired data. First, a set of features is generated to characterise the falls. Second, the dimensionality of the features is reduced. Finally, the fall detector is created based on Machine Learning, more specifically SVM. In order to evaluate the proposed approach, results will be compared with datasets.

Wearable sensors are used to compare the results obtained from the designed fall detector with the Sensorized Tip. The sensors used for this purpose are 4 GENEActiv accelerometers located on the wrist, waist, back and pocket. These are used in the simulation of people's falls and in different physical activities. With the data obtained from the GENEActiv, a fall detector will be made, which will be used to compare the results of the GENEActiv and the GENEActiv.

3.3.1 Experimental Protocol and Dataset Generation

In order to realise the fall detector, the appropriate database must be created. To obtain these data, a series of experiments are carried out on 12 healthy people (4 women and 8 men, ranging between 25–40 years, 3 left-handed and the rest right-handed). These experiments have been carried out with the approval of the Ethics Committee 149960 of the University of Bologna. A mattress was used for the falls in order to avoid damage.

As mentioned above, 3 different datasets are generated. The first one of user falls using the ADW (User Fall dataset), the second one of a set of physical activities performed using the ADW (User Physical Activity dataset) and the third one of ADW falls without the user (ADW fall dataset).

In the case of the User Fall dataset database, simulations of people's falls are carried out using the ADW. After analysing the falls of the videos in the Databrary database, 16 different scenarios are considered:

1. While standing still, try to take a step and trip over the ADW and fall.
2. Fall forward.
3. Fall backwards simulating a faint.
4. Fall backwards.
5. Rotate 90º to the right and fall to the right.
6. Fall right.
7. Rotate 90º to the left and fall to the left.
8. Fall left.
9. Walk towards the mattress, trip over the ADW and fall forward.
10. Walk towards the mattress, simulate a trip over an object and fall forward.
11. Walk towards the mattress, simulate a trip over an object and fall left.

12. Walk towards the mattress, simulate a trip over an object and fall right.

13. Walk towards the mattress, simulate a trip over an object and fall backwards.

14. Loss of balance, try to regain it by walking a few meters forward and fall forward.

15. Loss of balance, try to regain it by walking a few meters backwards and fall backwards.

16. Walk and slide to end up falling backwards.

In the case of User Physical Activity dataset, 7 different physical activities are simulated:

1. Walk at a normal pace: a circuit has been defined in which the volunteer has to walk straight in several directions and make turns.

2. Walk fast: the same circuit performed previously is repeated, but in this case walking approximately 30% faster.

3. Standing still: stay still in place for 30 seconds.

4. Going up and down stairs: going up and down stairs repeatedly.

5. Get up and sit in a chair: get up and sit down from a chair using the crutch, this will be repeated for 30 seconds.

6. Stopping to pick up an object from the floor and standing up, this will repeated for 30 seconds.

7. Short loss of balance (near fall) with regaining of balance, repeated 4 times.

Finally, a series of tests are carried out in which the ADW is dropped without a user:

1. Crutch placed in different static positions on the floor or while leaning on a site.

2. Dropping the crutch while standing still, or while walking. 80 crutch falls will be performed (40 per each).

In total 192 falls are achieved with the user using the ADW, 9 minutes of physical activities using the ADW per volunteer, 5 minutes of static positions of the ADW and 80 falls of the ADW with the user.

3.3.2 Methodology

Once the datasets are generated, the two module algorithms proposed in Figure 3.17 are designed. As mentioned above, the first module (ADW Fall Detector) is designed to detect falls and the second module (User & ADW Fall Detector) determines whether the ADW has fallen with the user. The output of the first module determines whether the second module is used. Similarly, as mentioned above, the two modules use different input data. The methodology followed for the design of both modules is similar, this methodology follows the structure set out in Figure 3.18.

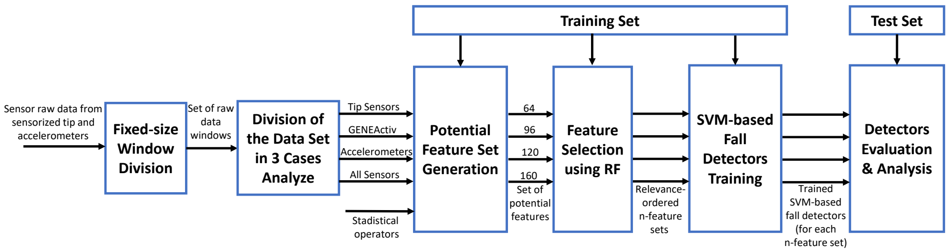


Figure 3.18: Methodology followed for the design of the Fall Detector modules based on Machine Learning.

3.3.2.1 ADW Fall Detector Design

This module is responsible for detecting when the ADW suffers a fall. The User Fall dataset and the User Physical Activity dataset are used in this module.

Table 3.6: Distribution of the dataset and adjustment of the number of data.

			Windows		
			Train	**Test**	**Total**
Participants			8	4	12
Fall Detector Set	*Non Adjusted*	Falls	2770	1216	3986
		Not Falls	5805	2600	8405
	Adjusted	Falls	759	382	1141
		Not Falls	866	433	1299
User Fall Detector Set		User Falls	128	64	192
		ADW Falls	50	30	80

First, the data is divided into sliding windows. The size of the windows is 100 samples (2s), furthermore the start of the windows are separated by 20 samples (0.4s). A sample size of 100 has been chosen because this is the average period of time when a person falls down, analysing the whole set of experiments performed. Once this segmentation has been carried out, it is necessary to indicate which of the windows obtained correspond to falls. Therefore, those windows that contain 50% or more of the fall period will be considered as falls, those that do not have 50% will be eliminated. The data obtained is divided into a training data set and a test data set, with the data from 8 volunteers being used for training and the other 4 for testing. The data will be balanced in order to perform the detector in the most appropriate way (see Table 3.6).

Second, after segmenting the data into windows, a series of features are selected that will characterise each window. In this case, a features based on statistical operators have been selected:

- Mean (MEAN).
- Standard Deviation (STD).
- Variance (VAR).
- Kurtosis (KUR).
- Intercuartile Range (IR).
- Area Under the Signal (AUS).
- Maximum value of the window (MAX).
- Minimum value of the window (MIN).

These statistics are applied to each window of the previously mentioned dataset. Each of the windows consists of the following sensor data: Sensorized Tip's force sensor, Sensorized Tip's gyroscope (x, y, z), Sensorized Tip's accelerometer (x, y, z) and Sensorized Tip's inclination angle (α). A total of 64 features are achieved per window in the case of the Sensorized Tip.

Thirdly, after the selection of the potential features to be used, the dimensionality reduction is carried out. This dimensionality reduction consists of giving a weight to each of the features in the assigned task. As mentioned in Chapter 2.3, there are many methodologies in the literature that do this. In this paper, a comparison is made between the Relief and RF approaches in order to choose the one that provides the best order. The order of importance and the weights of the 15 most important features can be seen in Table 3.7, where a difference can be seen between the order of importance and the weights of the 15 most important features.

Finally, the generation of the fall detector is performed. In this case, the number of inputs will be varied in order to determine the optimum number of inputs for this task. In this way, first a detector is made with only one input, this being the most important feature, then another detector is generated with two inputs, these being the two most important ones, and so on until all the features are introduced. The fall detector will be performed with an SVM approach, the hyperparameters will be optimised using K-Fold cross validation with a K=10.

Table 3.7: Weight of the features provided by the RF and Relief. (α = ADW inclination angle, accel = accelerometer, gyro = gyroscope)

Random Forest			Relieff		
n	*Feature*	*Weight*	*n*	*Feature*	*Weight*
1	α MAX	3.587	*1*	Tip force AUS	0.086
2	Tip gyro MIN Z axis	2.803	*2*	Tip gyro KUR X axis	0.057
3	Tip gyro KUR X axis	2.788	*3*	α MAX	0.048
4	α MEAN	2.631	*4*	Tip accel AUS Y axis	0.038
5	Tip gyro MIN X axis	2.545	*5*	Tip accel AUS X axis	0.028
6	α STD	2.485	*6*	Tip accel MEAN X axis	0.026
7	Tip gyro KUR Y axis	2.395	*7*	Tip accel KUR Z axis	0.016
8	α VAR	2.380	*8*	α STD	0.015
9	α AUS	2.348	*9*	Tip force MIN	0.014
10	Tip accel MEAN Z axis	2.342	*10*	α MEAN	0.013
11	Tip gyro MIN Y axis	2.168	*11*	α AUS	0.013
12	Tip accel AUS Z axis	2.165	*12*	Tip gyro KUR Y axis	0.010
13	Tip accel MAX Z axis	2.095	*13*	Tip gyro MAX Y axis	0.010
14	Tip accel KUR Z axis	1.947	*14*	α KUR	0.008
15	Tip force MEAN	1.915	*15*	Tip gyro MEAN Y axis	0.006

3.3.2.2 User & ADW Fall Detector Design

This module is responsible for detecting when the ADW is fall with or without the user. The methodology used is similar to the methodology of the first module. In this module the division into windows is done in a different way. Thanks to the previous module, when the ADW has suffered a fall, only the area considered as a window is used as a window. This results in 192 falls of the ADW with user and 80 falls of the ADW without user (see Table 3.6).

The set of features chosen is the same as in the first module, as is the dimensionality reduction method. Finally, as in the other module, SVM with K-Fold cross validation is used to create the detector.

3.3.3 Results and Comparative Analysis

This section analyses the results obtained after following the methodology explained above. In addition, the results obtained from the Sensorized Tip detector are compared with those obtained by other sensor arrays. Four approaches are proposed for comparison (see Table 3.8): 1) The proposed approach based on the Sensorized Tip Data ; 2) The use of the GENEActive wearable sensor data; 3) The use of all possible accelerometers (Sensorized Tip internal accelerometer and four GENEActiv accelerometers); and 4) The use of all data sensors. In order to compare the four approaches, the methodology followed in all four approaches is the same.

Table 3.8: Analyzed Cases considering sensor input. (Accel = Accelerometer, Gyro = Gyroscope, α = Angle of Inclination)

Device	**Sensors**	**Different analysis forms**			
		Sensorized Tip	**GENEActiv Sensors**	**Accel. Sensors**	**All Sensors**
Sensorized Tip	α	X			X
	3 axis Gyro.	X			X
	Force Sensor	X			X
	3 axis Accel.	X		X	X
4x GENEActiv Accel.	3 axis Accel.		X	X	X

3.3.3.1 ADW Fall Detector module evaluation

Based on the order observed in Table 3.7, the process of generating the detector is carried out to compare which is the one that gives the best result, and based on the selection of the method that gives the best results, this method is used for all cases. In this case, although the results are very similar with the two approaches, slightly better results are achieved with the features selected by the Random Forest, so this will be the approach used for this case.

Once the dimensionality reduction method is selected, it is applied to the 4 cases to be compared. In the case of using only the sensors of the Sensorized Tip, the most important feature is the maximum inclination angle. If the results provided by the GENEActiv sensors are seen, it can be seen that the most important feature is the maximum angle of inclination, the 3 most important features are derived from the sensor located at the back of the user (in particular its X axis, vertical), which is the one which suffers the most variation when the user falls. If all the available accelerometers are taken into account (the GENEActiv and the accelerometer in the Sensorized Tip), the most relevant features are those of the accelerometer in the Tip and the GENEActiv sensor on the back. When all sensors are used, it is again found that the most important feature is the one related to the maximum angle of inclination.

Once the importance of the features is known, the SVM-based detector is generated. As mentioned above, these will be trained by increasing the number of input features, according to the order provided by the RF.

Table 3.9: Results of the different cases to be analyzed of the SVM-based Fall Detectors (No. In = Number of inputs for each classifier, P = Precision, Sp = Specificity, Se = Sensitivity, F = F-score).

	Sensorized Tip				**GENEActive**			
No. In	*P*	*SP*	*Se*	*F*	*P*	*SP*	*Se*	*F*
1	0.982	0.984	1.000	0.991	0.941	0.945	0.984	0.962
2	0.986	0.988	1.000	0.993	0.956	0.960	1.000	0.978
3	0.980	0.982	1.000	0.990	0.957	0.960	1.000	0.978
4	0.982	0.984	1.000	0.991	0.957	0.961	1.000	0.978
5	0.983	0.985	1.000	0.991	0.953	0.957	0.999	0.976
6	0.983	0.984	1.000	0.991	0.969	0.972	1.000	0.984
7	0.987	0.988	1.000	0.993	0.978	0.980	1.000	0.989
8	0.982	0.983	1.000	0.991	0.971	0.973	1.000	0.985
9	0.982	0.984	1.000	0.991	0.970	0.973	0.999	0.985
10	0.982	0.984	1.000	0.991	0.974	0.977	0.997	0.986
	Accelerometers				**All Sensors**			
No. In	*P*	*SP*	*Se*	*F*	*P*	*SP*	*Se*	*F*
1	0.979	0.982	0.979	0.979	0.970	0.972	1.000	0.985
2	0.979	0.982	0.981	0.980	0.986	0.988	1.000	0.993
3	0.982	0.984	0.989	0.985	0.986	0.988	1.000	0.993
4	0.984	0.985	1.000	0.992	0.982	0.984	1.000	0.991
5	0.980	0.982	1.000	0.990	1.000	1.000	1.000	1.000
6	0.990	0.991	1.000	0.995	1.000	1.000	1.000	1.000
7	0.997	0.998	1.000	0.999	1.000	1.000	1.000	1.000
8	0.981	0.983	1.000	0.991	1.000	1.000	1.000	1.000
9	0.984	0.986	1.000	0.992	0.992	0.993	1.000	0.996
10	0.982	0.983	1.000	0.991	0.989	0.991	1.000	0.995

Analysing these results, it can be seen that by using the Sensorized Tip only, an F-Score greater than 0.99 is achieved in all cases (see Table 3.9). Furthermore, it can be seen that the number of features in this case is not relevant, as good results can be achieved even using only one feature. Still, the best results are achieved by using 2 features.

The other two cases, in which the complete sensors of the Sensorized Tip are not involved, have somewhat worse results, but are still good. In the case of the use of GENEActiv, the best result is an F-Score of 0.989 using the 7 most important features (see Table 3.9). On the other hand, using all the accelerometers, an F-Score of 0.999 is achieved with 7 features as well (see Table 3.9). On the other hand, if the results of all the sensors are analysed, the best results are achieved, with an F-Score of 1 with 5 features (see Table 3.9). Despite the fact that the best results are achieved with the sensors of the Sensorized Tip and with the lowest number of features, it can be said that with the 4 cases analysed, a very high F-Score result can be achieved, with a value above 0.98 of F-Score in the worst case scenario.

3.3.3.2 User & ADW Fall Detector evaluation

The User & ADW Fall Detector is only used if the previous detector detects a fall. As mentioned above, the dataset used in this detector is different from the previous one, so dimensionality reduction is performed again. RF is used as before, with the 5 most important features in this case being those associated with the Tip force sensor. This importance comes from the fact that when a person falls with the ADW, tries not to fall by trying to lean on it, which is not the case when the ADW falls without the user.

Once the order of importance of the features has been obtained, the same methodology used before is applied to calculate the SVM. The results are summarised in Table 3.10. F-Score values of over 0.89 can be observed, which is a good value. If analysed in detail, the best result is obtained using the 6 most relevant features.

Table 3.10: Results of the ADW Fall Detector with and without user (No. In = Number of inputs for each classifier, P = Precision, Sp = Specificity, Se = Sensitivity, F = F-score).

No. In	*P*	*Sp*	*Se*	*F*
1	0.876	0.717	0.936	0.905
2	0.880	0.733	0.917	0.898
3	0.888	0.757	0.906	0.897
4	0.880	0.737	0.906	0.893
5	0.940	0.867	0.984	0.962
6	0.943	0.873	0.984	0.963
7	0.940	0.867	0.984	0.962
8	0.930	0.843	0.969	0.949
9	0.926	0.833	0.967	0.946
10	0.943	0.873	0.981	0.962

3.3.4 Conclusions

This section presents a fall detector using a Sensorized Tip that can be attached to different ADW. In order to detect falls, a methodology based on two modules has been implemented. The first module is in charge of detecting ADW falls. In the event that the ADW detects a fall, the second module is in charge of detecting when the ADW has fallen with a user. The modules consist of an SVM-based algorithm for the detection of ADW falls and user falls. In addition, the use of RF-based dimensionality reduction is considered in prior.

The results obtained from the fall detector show a high accuracy, with a 0.993 and 0.963 F-Scores for the ADW and User & ADW, respectively. A comparison has been made using wearable sensors (see Table 3.9), obtaining better results with a lower number of input features, 0.993 of F-Score with 2 features for the case of the Sensorized Tip and 0.989 of F-Score with 7 features for the case of the wearable GENEActive sensors.

4 Conclusions

This section presents the conclusions of the work carried out during the development of this doctoral thesis, analysing what has been done and the technological contributions made. It also details the publications derive from the work developed (in high-impact peer-reviewed JCR journals and Springer books from international conferences), allowing to fulfill the requirements to present this thesis as a compendium of publications, as defined in the PhD legislation of the Euskal Herriko Unibertsitatea/Universidad del País Vasco (UPV/EHU). Finally, this section indicates the future work generated in the field in which it has been carried out, showing the possible future lines of research open in the field in which this doctoral thesis has initiated.

In recent decades, in view of the need to improve the quality of life of people requiring rehabilitation, the individualisation of rehabilitation has been increasing. Thanks to advances in the field of sensorization, and especially in human sensorization, sensor systems capable of assisting in this rehabilitation task have begun to be proposed. However, these types of sensors often cause discomfort to the people who use them, and for this reason, work has begun to be proposed in which this sensorization is carried out through the ADW. But the sensor devices incorporated in the ADWs are difficult to fit and are only suitable for the ADW for which they are made, which is an important aspect to be improved. In addition, in order to achieve this individualisation of rehabilitation, it is very important to know what Physical Activity a person performs. For this reason, integrating sensors to recognize physical activities in the daily life of people have begun to been carried out. On the other hand, by taking advantage of the sensorization of people, many works propose the detection of falls, in order to prevent a person from requiring further rehabilitation as a result of a fall. In view of this situation, this doctoral thesis aims to contribute to the area of ADW sensorization.

In order to achieve this challenge, the thesis has been structured in three main contributions.

The first contribution is focused on the design and validation of the **Sensorized Tip capable of adapting to the different ADWs** on the market. In it, after analysing the most important variables to be measured in order to know the Physical Activity, a series of suitable sensors have been selected to measure these variables. Subsequently, a suitable Tip structure has been designed to be able to incorporate the sensors and also to be incorporated into the various ADWs. After this, the data acquisition system was programmed to collect the data from the sensors via Bluetooth Low Energy (BLE). In this way, a Sensorized Tip capable of adapting to different ADWs was achieved, and it is also able to measure the force applied to the ADW, the height at which it is located and the movements of the ADW. Finally, the sensors used were validated on a VICON camera system, obtaining very satisfactory results.

> *A Sensorized Tip has been developed, which has the capacity to be adapted to the different Assistive Device for Walking (ADW)s available on the market (crutches, canes...). For the development of this Sensorized Tip, the next methodology has been followed. First of all, the most important variables to be measured in order to carry out the measurement have been analysed. This analysis helps to identify the best sensors configuration, which consists in a force sensor that measures axial force, a 3-axis accelerometer, a 3-axis gyroscope and a 3-axis magnetometer that measure the movement of the Sensorized Tip and a barometer that helps measure changes in altitude. Secondly, the optimized structural design of the Tip is carried out, as well as the programming of the electronics that will collect and store the data. The device has been designed to be as light as possible, as well as to be as interchangeable between different ADWs. In order to have a high autonomy, the communication between the acquisition system and the processor that collects the data from the sensors has been carried out via Bluetooth Low Energy (BLE). Thirdly, a series of algo-*

rithms have been developed in order to estimate the forward plane of the person using the ADW and to obtain the anteroposterior and lateromedial angles. Finally, different experimental tests are carried out, with the aim of validating the developed Sensorized Tip.

Therefore, it is concluded that the **Sensorized Tip developed** *using the proposed methodology is* **suitable for use in monitoring Physical Activity and detecting falls**.

The second contribution deals with the development of a classifier of 5 different Physical Activities by using Artificial Intelligence techniques integrated in the designed Sensorized Tip. In order to achieve this Physical Activity classifier, a series of tests have been designed to simulate these activities when using an ADW. With the data obtained, a process of data adequacy and statistics features extraction is carried out. Subsequently, with the data obtained, a dimensionality reduction of the features is performed out based on Random Forest. Finally, 3 different classifiers are implemented, based on K-NN, SVM and ANN.

The development of the classifier has followed the next methodology. The first step is the selection of the activities to be classified, which are walk, walk faster, going up stairs, going down stairs and standing still. A series of experiments to simulate these activities have been performed, in which is used an ADW while the innovative Sensorized Tip is incorporated. The second step consists in dividing the data obtained from the tests into windows that represent the cycles, and for each window a series of features are obtained that will be used to create the classifier. The third step is to perform a dimensionality reduction from the features obtained using Random Forest, in order to select the most important features to be able to realize the Physical Activity classification. The last step is the development of the classifier based on ML. In this case, 3 different methodologies have been implemented to perform the classification: K-NN, SVM and ANN. The results obtained between the 3 classification methodologies used are compared. It is shown that the dimensionality reduction obtained by RF is adequate. Furthermore, using the 7 most important features, according to the RF, a success rate of more than 96% is achieved in the case of SVM and ANN.

Therefore, it is concluded that a **Physical Activity classifier has been designed based on the designed Sensorized Tip, using Machine Learning, capable of differentiating between the 5 defined different activities**.

Finally, the third contribution of the doctoral thesis focuses on the design of an intelligent **fall detector** based on the designed Sensorized Tip. This fall detector is based on SVM, and **detects when the user falls with the sensorized ADW falls with the ADW or when the ADW falls without anyone**. Experimental series of tests have been carried out, from which data have been obtained and adapted. From these data, a series of features have been obtained and their dimensionality has been reduced. Finally, the innovative fall detector has been implemented in two modules based on Machine Learning.

The new fall detector has followed the next methodology. First, experiments have been designed to simulate a series of falls and physical activities while using the developed Sensorized Tip incorporated into a Assistive Device for Walking. Secondly, the design of the architecture based on Machine Learning, consisting on a two-serial-module detector. The first one detects when the ADW has fallen and in case of a fall. The second module detects whether the ADW has fallen with or without the user, i.e., detects false positives. Both modules consist of an SVM-based detector, for the design of which the same methodology followed in the Physical Activity classifier has been used. Finally, a comparison of the results obtained with a fall detector based on wearable sensors has been carried out. Results above 0.99 F-Score have been achieved for the first module. On the other hand, results of 0.96 F-Score were achieved.

Therefore, it can be concluded that a **fall detector has been designed** *based on the developed Sensorized Tip,* **capable of detecting when the ADW has fallen with or without the user**.

4.1 Contributions: publications

The contributions described in this doctoral thesis have given rise to a set of results that have been published in journals with an impact index and presented at international conferences of recognised prestige in the field of research. The work carried out has given rise to the following publications.

Papers in JCR Journals (used as a compendium of papers):

- Asier Brull, Asier Zubizarreta, Itziar Cabanes, and Ana Rodriguez-Larrad. Sensorized Tip for Monitoring People with Multiple Sclerosis that Require Assistive Devices for Walking. *Sensors*, 20(15):4329, aug 2020.

  doi: https://doi.org/10.3390/s20154329 JCR2020: 3.576 (Q1)

  Appendix 1

- Asier Brull Mesanza, Sergio Lucas, Asier Zubizarreta, Itziar Cabanes, Eva Portillo, and Ana Rodriguez-Larrad. A Machine Learning Approach to Perform Physical Activity Classification Using a Sensorized Crutch Tip.*IEEE Access*,8:210023–210034, 2020.

  doi: https://doi.org/10.1109/ACCESS.2020.3039885 JCR2020: 3.367 (Q2)

  Appendix 2

- Asier Brull Mesanza, Ilaria D'Ascanio, Asier Zubizarreta, Luca Palmerini, Lorenzo Chiari, and Itziar Cabanes. Machine Learning based Fall Detector with a Sensorized Tip. *IEEE Access*, pages 1–1, dec 2021.

  doi: https://doi.org/10.1109/ACCESS.2021.3132656 JCR2020: 3.367 (Q2)

Appendix 3

Papers published in Springer Books proceedings from International Conferences:

- Asier Brull, Aitor Gorrotxategi, Asier Zubizarreta, Itziar Cabanes, and Ana Rodriguez-Larrad. Classification of Daily Activities Using an Intelligent Tip for Crutches. *Advances in Intelligent Systems and Computing*, 1093 AISC:405–416, nov 2019.

  doi: https://doi.org/10.1007/978-3-030-36150-1_33

- Asier Brull, Asier Zubizarreta, Itziar Cabanes, Jon Torres-Unda, and Ana Rodriguez-Larrad. A Smart Crutch Tip for Monitoring the Activities of Daily Living Based on a Novel Neural-Network Intelligent Classifier. pages 113–122. *Springer*, Cham, sep 2021.

  doi: 10.1007/978-3-030-57802-2_11

- Asier Brull, Sergio Lucas, A. Zubizarreta, Eva Portillo, and Itziar Cabanes. A Random Forest Based Methodology for the Development of an Intelligent Classifier of Physical Activities. *Biosystems and Biorobotics*, 28:85–89, oct2020.

  doi: https://doi.org/10.1007/978-3-030-70316-5_14

4.2 Future Works

The work carried out throughout this doctoral thesis has made it possible to detect a series of lines of interest for future research work:

- In this doctoral thesis a Sensorized Tip, suitable for Physical Activity monitoring and fall detection, has been presented. However, both the mechanical structure and the electronics can be modified to embed the battery in the tip, in order to make it more comfortable to use. In addition, self-developed sensors could be used instead of the commercial sensors that have been integrated, thus reducing the dimensions of the system.

- In order to implement this innovative Sensorized Tip in more complex ADWs, such as a walker, it would be desirable to develop the communication system to synchronize gait monitoring using two Sensorized Tips.

- In the doctoral thesis a PA classifier has been presented that is able to differentiate between 5 different activities. However, many more physical activities can be found throughout daily life. In this situation, it would be appropriate to be able to increase the physical activities that the classifier is able to differentiate. In order to be able to do this, it would be necessary to carry out an analysis of what these new physical activities to classify are, as well as designing some experiments and regenerating the classifier.

- The implementation of the Sensorized Tip in clinical rehabilitation environments would be appropriate. In this way, it would be possible to obtain feedback from professionals on the quantified daily activity information provided by the developed system.

- In order to improve the developed fall detector, a larger set of physical activities and falls could be simulated in order to collect as many cases as possible where falls can be detected. In order to do this, a set of experiments would have to be re-designed in which the new cases to be studied would be collected, in addition to generating again the detector.

- In order to improve the classifier and the fall detector, these could be implemented in real time in the data acquisition system. Additionally, to be able to store the data in the cloud. In this way to be able to report the Physical Activity performed at the moment and to be able to inform in case of a fall to the healthcare staff. Leading to a digitalisation of the health care.

eman ta zabal zazu

UPV EHU

Jarduera Fisikoa Sailkatu eta Erorikoak Detektatzeko Punta Sentsorizaty baten Garapena

Sistemen Ingeniaritza
eta Automatika Salia

Asier Brull Mesanza

Zuzendariak: Itziar Cabanes Axpe
Asier Zubizarreta Pico

Universidad del País Vasco
Euskal Herriko Unibertsitatea

eman ta zabal zazu

BILBOKO INGENIARITZA ESKOLA
ESCUELA DE INGENIERÍA DE BILBAO

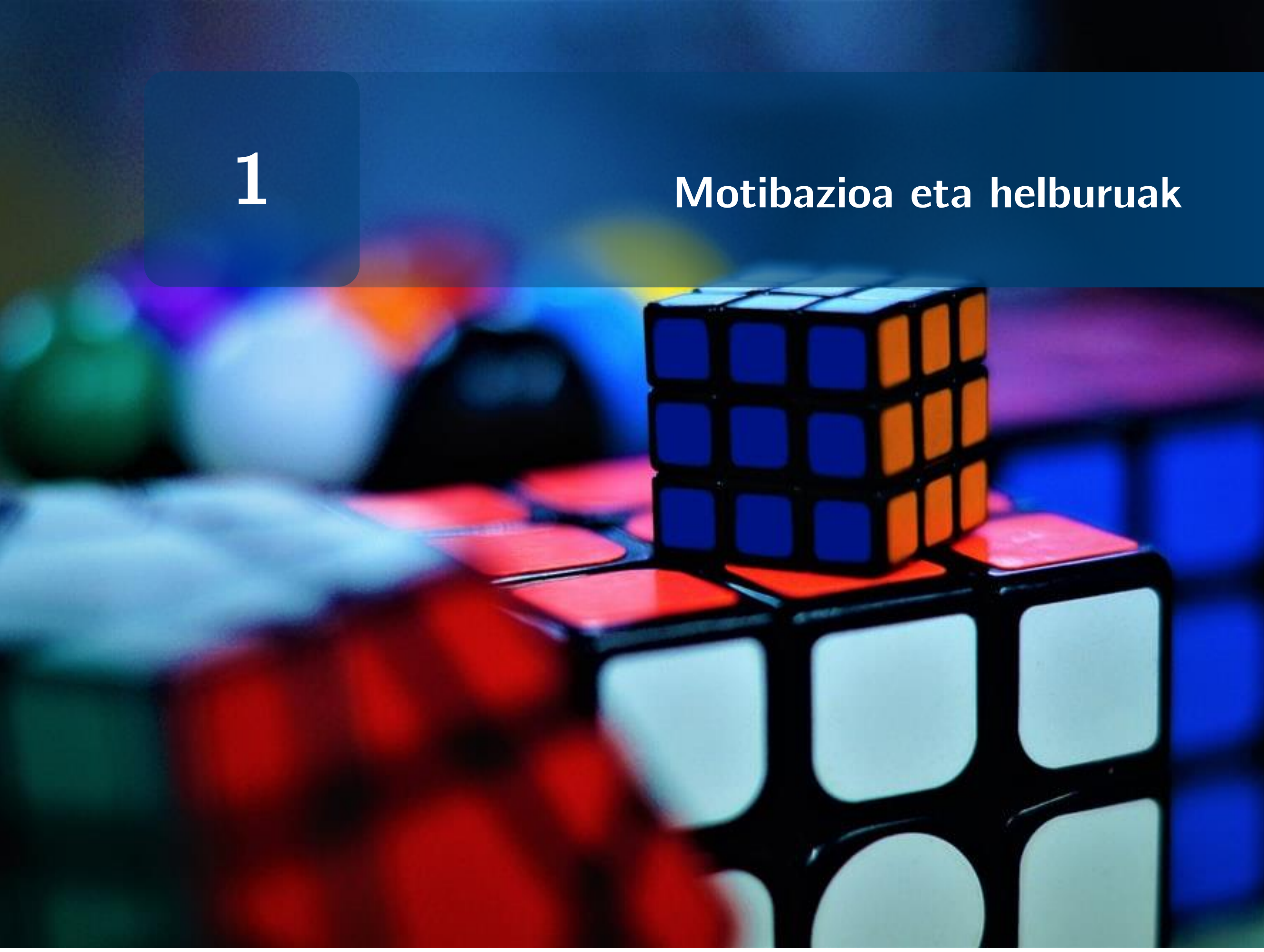
JARDUERA FISIKOA SAILKATU ETA ERORIKOAK DETEKTATZEKO PUNTA SENTSORIZATU BATEN GARAPENA

ASIER BRULL MESANZA

Doktorego Tesia - 2022

Zuzendariak Itziar Cabanes eta Asier Zubizarreta
Sistemen Ingeniaritza eta Automatika Saila

Contents/Aurkibidea



1 Motibazioa eta helburuak

Doktorego tesi hau **Asier Brull Mesanzak** garatu du *Euskal Herriko Unibertsitatea/Universidad del País Vasco (UPV/EHU)ko Kontrol Ingeniaritza, Automatizazioa eta Robotika Doktorego* programan, eta **Itziar Cabanes Axpe** eta **Asier Zubizarreta Pico** doktoreek gainbegiratu dute.

Doktorego tesian aurkezten den ikerketa *Euskal Herriko Unibertsitatea/Universidad del País Vasco (UPV/EHU)ko Bilboko Ingeniaritza Eskolako Sistemen Ingeniaritza eta Automatika* saileko *Virtual Sensorization (ViSens) Ikerketa Talderaen* barnean garatu da. Ikerketa hau, *Euskal Herriko Unibertsitatea/Universidad del País Vasco (UPV/EHU)* ko **PIF18/067** euskarri ekonomikoari esker eraman da aurrera.

Doktorego tesi hau, artikuluen bildumaren bidez aurkezten da. Zehazki, JCR-en indexatutako zientzia aipamen altua duten aldizkarietan publikatutako hiru artikulu aurkezten dira: **Sensorized Tip for Monitoring People with Multiple Sclerosis that Require Assistive Devices for Walking** (1. eranskinean [28]), **A Machine Learning Approach to Perform Physical Activity Classification Using a Sensorized Crutch**

Tip (2. eranskinean [126]) eta **Machine Learning based Fall Detector with a Sensorized Tip** (3. eranskinean [125]).

1.1 Motibazioa

Munduko Osasun Erakundea (MOE)ren arabera, lesio edo gaixotasun bat jasan ondoren errehabilitazioak garrantzi handia du pertsonen osaera prozesuan [140, 78, 59]. Mundu osoan, 2,4 milioi pertsona inguruk, errehabilitazioa behar duen osasun arazoren bat pairatzen dute [1]. Errehabilitazio premia handiena duten gaixotasunen artean, muskulo-eskeletoaren nahasmenduak nabarmentzen dira, gaur egun, 1,7 mila milioi pertsonek jasaten dute [41]. Azken 37 urteetan, pertsona hauek desgaitasuna jasaten duten urteen kopurua %66,2 hasi da [86]. Eta logikoa denez, desgaitasun denbora luzatzeak, errehabilitazio fisikoaren beharra handiagotzen du. Gainera, errehabilitazio behar hori oraindik eta gehiago areagotzen da populazioaren bilakaeraren ondorioz [78], izan ere, gero eta pertsona gehiagok dute funtzionamenduaren narriadura, eta, horren ondorioz, errehabilitazio egokia behar dute. Bestalde, adineko pertsonek erortzeko joera handiagoa dute, errehabilitazioa behar duen lesio bat jasateko probabilitatea handituz [48].

Bizi kalitatea eta autonomia izateko faktore nagusietako bat beheko gorputz-adarretan mugikortasun ona edukitzea da. Beharrezkoa den kasuetan, oso garrantzitsua da mugikortasun hau berreskuratzeko errehabilitazio egoki bat egitea. Bestalde, gaixotasun neurologikoek edo trauma lesioek, beheko gorputz-adarretan higidura galtzea eragin dezakete, hauek pairatzen dituztenen bizitza pertsonala mugatuz. Egoera honen aurrean, paziente bakoitzarentzako errehabilitazio-estrategia bat diseinatzerako orduan, gorputzeko atal garrantzitsu honen funtzioen berreskuratze partziala edo osoa lortzen saiatzea da helburu nagusietako bat da [63, 48, 82]. Mugikortasunean eragina duten eta errehabilitazio egokia behar duten gaixotasun neurologiko horien artean Esklerosis Anizkuna nabarmentzen da, 2,3 milioi pertsonari eragiten baitio, eragin sozial eta ekonomiko handia sortuz [60].

Errehabilitazio interbentzioak ahalik eta eraginkorrenak izateko, pazienteen ezaugarri indibidualera egokitu behar dira [101]. Gainera, ikerketa desberdinek erakutsi dute nola errehabilitazioa etxean egiteak eraginkortasuna lagungarria izan daitekeela pertsona bakoitzaren beharretara eta denboretara egokitzeko, errehabilitazioaren eraginkortasuna hobetuz [96, 184]. Gaixoaren egoera partikularrera egokitutako errehabilitazio prozesu honek azkarrago hobetzen lagun dezake, egindako ariketak pazientearen egoeraren araberakoak baitira. Terapiaren indibidualizazio hau pazientearen egoera partikularraren araberakoa da, pazientearen eguneroko jarduerak egiteko gaitasunarekin lotura zuzena duena [43]. Adibidez, egunero kilometro pare bat egiteko gai den paziente aktiboago batek horrelako jarduerarik egiten ez duenaren premia desberdinak izango ditu. Beraz, egunean zehar egindako Jarduera Fisikoa (JF) modu objektiboan kuantifikatzea tresna baliotsua izan daiteke terapia-plangintza eraginkorra egiteko. Kuantifikazioa honek, pazientearen beharrizan funtzionalei hobekien egokitzen zaien gailu lagungarria hautatzea ere ahalbidera dezake. Gaixoak bere kasa ibiltzeko gaitasuna galdu badu, gurpildun aulkia edo scooterra erabiltzea da aukerarik onena, baina ibiltzeko gai den bitartean makuluak edo kanaberak erabiltzea da gomendagarriena. Horregatik, terapeutak pazientearen egoera aldizka egiaztatu behar du, errehabilitazio prozesua eta gainerako beharrizanak bere egoerara moldatuz.

Gaixoaren egoera une oro indibidualizatu ahal izateko, ezin bestekoa da, pertsonaren egoera ulertzen lagun dezakeen etengabeko ebaluazio klinikoa egitea. Egiaztapen hau, establezimendu klinikoetan egindako proben bidez bildutako datuak erabiliz egiten da, normalean oso kontrolatuta daudenak. Maiz, ezarpen kliniko horiek ez dituzte kontuan hartzen egunerokoan gerta daitezkeen aldagaiak, ondorioz, ebaluazioak ez du islatzen pazienteak errealitatean duen egoera. Arrazoi honengatik, pazienteek egunean zehar gauzatutako Jarduera Fisikoa (JF) motak kontrolatzea gero eta garrantzitsuagoa da pazienteen ebaluazio funtzionalean, JF honela definitzen delarik: "Energia gastuetan sortzen diren muskulu eskeletikoek eragindako edozein gorputz-mugimendu"[31]. JFren ikuskapen honek pertsonaren autonomia-maila ezagutzea eta bere ebaluazio kliniko egokiagoa egitea ahalbidera dezake [90]. Gainera, pertsonaren egoera orokorra zein den ezagutzen lagun dezakeen informazio garrantzitsua lor daiteke mugitzeko moduari edo indarrari buruz. Osasunerako onurak ditu, eta, gainera, gaixotasun ez-kutsakorrak prebenitzen laguntzen du [176, 22]. Bestalde, JFren ikuskapenetik bildutako informazioaren bidez, aldian behingo proben emaitzak interpretatu ahal izango dira, horrela, pertsonaren osatze-prozesuari laguntzeko gomendio indibidualizatuak eta feedback-a egitea ahalbideratuz [19]. Hau ez da posible ohiko ebaluazio klinikoaren bidez, pazientearen momentu bateko egoera bakarrik ezagutzen baita [11, 151].

JFren etengabeko kontrolaren arazo nagusietako bat, terapeutak ezin egin ahal izatea da, ezinezkoa baita terapeutak gaixoari etengabe jarraitzea. Tradizionalki, indibidualizazio hori azterketa puntualen bidez egin da, eta tresna tradizional gehienek ez dute JF ebaluatzen eguneroko bizitzan zehar [84]. Gainera, errenta ertaineko estatu askotan, errehabilitaziorako gaitasuna duten 10 profesional baino gutxiago daude milioi biztanleko [1], indibidualtasuna zailduz. Hori dela eta, sentsore-teknologiaren alorrean egin diren aurrerapenei esker, gaur egun, zaintza hau, sentsoreen bitartez egiten hasi da, sentsoreak pazientearen eguneroko bizitzan txertatuz [174, 55]. Eguneroko bizitza sentsorizatzeari esker, pazienteen ibilera behatu ahal izango da, ezagutza hau, banakako errehabilitazioaren diseinuan faktore garrantzitsua delarik. Halaber, erabiltzaileak une oro zein egoera funtzional duen jakin daiteke, errehabilitazioaren indibidualizazio hobetuz. Sentsore hauen erabilerak datu kuantitatiboagoak eman ditzake, mugimenduari, indarrari eta abarri buruzko datuak eskainiz. Informazio kuantitatibo honek pazientearen egoera une oro hobeto ulertzeko aukera ematen die errehabilitazioko langileei, egoera horretara moldatzea ahalbidetuz.

JFren ikuskapena mota askotako sentsoreak erabiliz egiten da, sentsore hauek, jarduera desberdinak egiten direla jakiteko datu multzo bat ematen baitute. Sentsore ezberdinak erabiltzeak, haiek nahastuz, JF detektatzeko aldagai esanguratsu ezberdinak lortzeko gaitasuna ematen du, horrela gauzatzen ari den jardueraren deskribapen zehatzagoa lortuz.

Zaintza kasuistikoaren barruan, Ibiltzeko Laguntza Gailua (ILG), hala nola bastoiak edo makuluak, behar dituzten pazienteen zaintzan zentratutako soluzio multzo bat dago. Sentsoreek gaixoaren egoera kuantifikatzeko duten potentzialtasuna eta elementu desberdinetan txertatzeko gaitasunari esker, eguneroko laguntza gailuetan integratzeko interesa nabarmen hasi da. ILG bat behar dutenek etengabe mugitzen dira harekin, eta horrek erraztu egiten du eguneko aurrerapenei buruzko informazioa lortzea. Eremu honetan, bastoiak edo makuluak sentsorizatzea proposatu dute azterlan batzuek [25].

Hala ere, oraindik, ez da nahikoa sakondu, jarduera fisikoak identifikatzeko eta, horrela, errehabilitazioan hobetzeko, ILGk sentsore eramangarri gisa erabiltzea. Elementu horien erabilera interesgarria da zeregin horietarako; izan ere, ILG sentsorizatuak erabiltzeak abantaila nabarmenak ditu gorputzean sentsore jantziak sartzeari edo sentsoreak kameren antzera erabiltzeari dagokionez. Lehenik eta behin, sentsore horiek ez dute zarata parasitorik izango, gune zurrunetan jarriko baitira. Bigarrenik, ILGan finko jarri daitezke, ez baitira jantzi eta erantsi behar, horrela sentsoreen posizionamendua beti egokia izatea bermatuz. Azkenik, gorputzari erantsita ez doazenez, sentsoreek eta eskuratze-sistemek ez dute eragozpenik sortzen erabiltzailearen mugimenduan.

Banakoaren Sensorizazioak bi abantaila nagusi ditu. Alde batetik, Jarduera Fisikoa kontrolatzeko erabil daiteke, horrela pertsonen errehabilitazio indibidualizatuan lagunduz. Bestalde, erorketa detektatzeko sistema gisa erabil daiteke, erorikoak ekidinez eta errehabilitazioa behar dezaketen lesioak saihestuz.

Gorago esan bezala, jendea zahartu ahala, gero eta gehiago erortzen da. Pertsona heldu bat erortzeak edo arazo fisikoren bat izateak eragin handia izan dezake pertsona hori pairatzen duenarengan [143, 73]. Erorketaren kasuan ekintza azkarra funtsezkoa da, batez ere bakarrik bizi diren pertsonentzat, zenbat eta beranduago erreakzionatu gertakariari, orduan eta handiagoa da erikortasuna edo hilkortasun tasa [74, 192]. Horrek errehabilitazio beharra areagotu dezake, osasun arloko langileek errehabilitazioa gauzatzeko beharra areagotuz.

MOEren arabera [199, 164], 64 urtetik gorako biztanleen %28k gutxienez erorketa bat jasaten du urtean. Gainera, kontutan eduki behar da, talde hau, eroriko baten ondorioak jasateko talde sentiberenen artean dagoela. Ikerketa desberdinen arabera, erorikoak, lesio fisikoak eragin ditzake jasandako pertsonen %6an [179, 172], eta horietatik %14k zauri larriak izan ditzake [175]. Bestalde, erorketa batek ere ondorioak izan ditzake adineko pertsonen funtzionamenduan [172], %15 murrizten baitu etxetik kanpoko gizarte-jarduera.

Arrazoi hauengatik, oso garrantzitsuak dira bai erorketen prebentzioa, bai detekzio goiztiarra, bai ekintza. Hala ere, sarritan ezinezkoa da erorikoa gertatzen denean bizkor jokatzea. Kasu batzuetan, erorketak kontzientzia galtzea edo desorientazioa ekar dezake, hori ezinezko bihurtuz. Gainera, jende asko bakarrik egoten da erortzen den unean, eta ezin die inork lagundu. Bestalde, frogatuta dago ILGak erabiltzeak mugikortasun arazoak dituzten pertsonen erorketa kopurua murriztu dezakeela [116]. ILGren erabilerak erortzeak murrizten baditu ere, pertsona hauek oraindik mugitzeko zailtasunak dituzte, eta gainerako pertsonek baino erortzeko joera handiagoa dute [158].

Arrazoi hauengatik, beharrezkoa da erorketa bat atzeman eta horren arabera joka dezaketen irtenbide egokiak bilatzea. Honen aurrean, eguneroko bizitzan txertatutako sentsoreak gero eta gehiago erabiltzen ari dira, Adimen Artifiziala (AA)n oinarritutako metodologiekin batera, erorketaren bat gertatu den detektatzeko. Modu honetan, abisu goiztiarrak eman eta ekintza azkarrak har daitezke, horrela errehabilitaziora bideratutako ondorio posibleak saihestuz.

Eguneroko bizitzan ILG bat erabiltzen duten pertsonen erorketak detektatzea ez da asko sakondutako eremu bat. Hala ere, ikertzeko arlo garrantzitsu bat dela ikusten da, ILG bat behar dutenek berrerortzeko aukera handiagoa izan ohi baitute.

Aipatu moduan, sentsoreek Jarduera Fisikoa kuantifikatu eta errehabilitazioaren indibidualizazioan laguntzeaz gainera, erorketen detekzio goiztiarra ahalbidera dezakete. Gainera, beste sentsore mota batzuekin konparatuz, Ibiltzeko Laguntza Gailua elementu sentsore gisa erabiltzearen abantailak kontuan hartu behar dira. Arrazoi hauengatik, doktoretza tesi honek ILGra egokitzeko gai den sentsore-punta bat garatzea proposatzen du. Dispositibo honek, Machine Learning (ML) teknikak erabiliz, pazienteen JF ezagutu eta erorketak detektatzea ahalbideratuko du.

Laburbilduz, errehabilitazioa indibidualizatzea faktore garrantzitsua da pazienteen errehabilitazio prozesua hobetzeko. Indibidualizazio hau, Jarduera Fisikoa kontrolatuz lor daiteke, fisioterapeutei pazientearen bilakaera ebaluatzeko aukera emanez, errehabilitazio espezifikoko errutina sortzeko, hau lortzeko sentsoreak erabiltzea aukerarik onena delarik. Gaur egun, naiz eta desabantaila nabarmenak izan, horretarako erabiltzen diren sentsoreak sentsore jantziak izan ohi dira. Honen aurrean ikusten da, ILGn sentsoreak erabiltzeak sentsore jantziek aurkezten dituzten arazo asko ezaba ditzakeela. Ikuskapen honek pertsona baten eguneroko jardueraren ulermena eman dezake, baita gerta litezkeen erorketak detektatu eta ohartarazi, horrela erabiltzaileen bizitza hobetzen lagunduz.

1.2 Helburuak

Lehen aipatu den bezala, pertsonek egunean zehar egiten duten Jarduera Fisikoaren ikuskapenak errehabilitazio prozesua hobetu dezake. Horretarako, egunean zehar egiten den jarduera detektatzen duten sentsore eroso eta ez-inbaditzaileen multzo bat behar da. Beraz, tesi honen helburu nagusia **Jarduera Fisikoa kuantifikatzeko eta erorketak detektatzeko gai den sentsore-sistema adimentsu bat diseinatzea da**.

Helburu orokor hori azpihelburu hauetan banatzen da:

- **Ibiltzeko Laguntza Gailua (ILG) ezberdinetara egokitzen de punta sentsorizatu bat diseinatu**. Gorago aipatu denez, pazientearen datuak eman ditzakeen sentsore multzo bat erabiltzea funtsezkoa da Jarduera Fisikoa kontrolatzeko. Horregatik, zeregin hori burutzeko proposatu diren metodoak analizatu ondoren, ILGren puntan sartutako sentsore-sistema bat diseinatu behar da, enbarazurik egin gabe egindako mugimenduak detekta ditzakeena. Gainera, punta sentsorizatu hau trukagarria da, beraz, ILGz alda daiteke inolako konplexutasunik gabe.

- **Punta sentsorizatuaren neurketetan oinarrituz Jarduera Fisikoa (JF) sailkatzeko sistema diseinatu**. Datuak neurtzeko gai den sistema garatu ondoren, Jarduera Fisikoa behar bezala ikuskatu ahal izateko, jarduera horiek detektatzeko gai den sailkapen-tresna bat diseinatu behar da. Hau da, ILG erabiltzean egiten diren oinarrizko jarduera fisikoen artean ezberdintzeko gai den sistema bat diseinua behar da. Helburu hau lortzeko, Machine Learningren oinarritutako sailkapena aztertuko da, Jarduera Fisikoaren beste sailkapen sistema batzuetan arrakastaz erabili baita.

- **Punta sentsorizatuaren neurketetan oinarrituz erorketa detektagailu bat diseinatu**. Pertsonen bizi kalitatea hobetzeko, errehabilitazioa indibidualizatzea bezain garrantzitsua da erorketen aurrean azkar erreakzionatzea. Horregatik, JF detektatzeko sentsoreen erabilera aprobetxatuz, erorketak detektatzeko gai den sistema bat sortu da.

1.3 Egitura

Gainerako lana honela antolatuta dago: 2. kapituluak jarduera fisikoa sailkatzeko eta erorikoak detektatzeko teknologia eta gailuen azterketa aurkezten du; tesia artikuluen bildumen bidez aurkeztu denez, 3. kapituluak artikuluen laburpena aurkezten du (1. eranskina [28], 2. eranskina [126] eta 3. eranskina [125]); horietan Punta sentsorizatu bat diseinatu eta garatzen da, eta Jarduera Fisikoaren sailkatzaile bat eta erorikoen detektagailu bat sortzen da, Machine Learning teknikak eta Punta sentsorizatuak ematen dituen datuak erabiliz; azkenik, ondorio garrantzitsuenak, 3. kapituluan aurkezten dira.

2 Jarduera Fisikoak Detektatzea: artearen egoera

Helburu nagusia ILG erabiltzaileen jarduera fisikoak sailkatzeko gai den punta sentsorizatu bat garatzea denez, ezinbestekoa da erabilitako sentsore-sistemak eta haien ezaugarriak eta jarduera fisikoak sailkatzeko eta erorketak detektatzeko erabiltzen diren teknikak ezagutzea.

Arrazoi honegatik, 2.1. kapituluak ILGn erabiltzen diren sentsore-elementuen sarrera bat aurkezten du. Ondoren, 2.2. kapituluan, jarduera fisikoen sailkapena egiteko erabiltzen diren sistemak eta metodologiak aztertzen dira. 2.3. kapitulua erorketak detektatzeko erabiltzen diren sistemen eta metodoen analisiari eskainia dago. Azkenik, 2.4. kapituluak artearen egoeraren ideia nagusiak laburbildu eta ondorio garrantzitsuenak azaleratzen ditu.

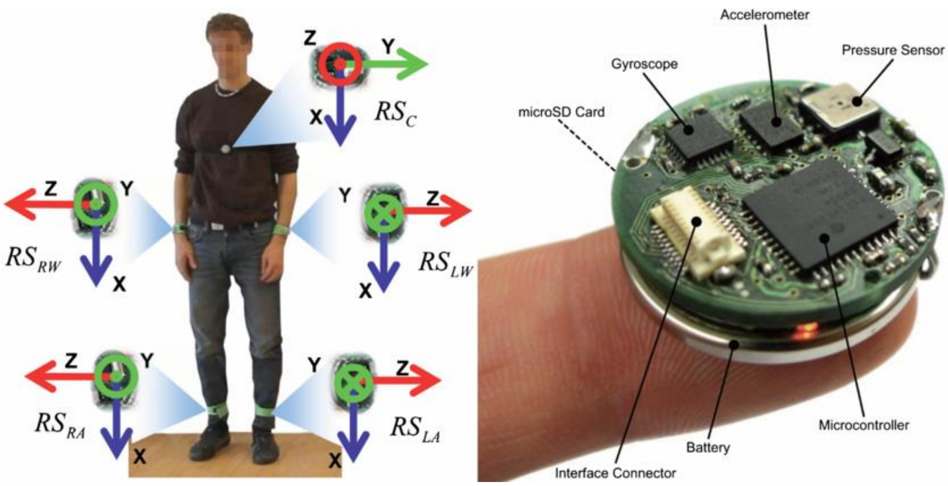
2.1 Jarduera fisikoa detektatzeko metodologiak

Pertsonen jarduera fisikoa detektatzeko erabiltzen diren sentsoreak mota askotarikoak dira [55]. Zuzenean aktibitate hau detektatzen duten sistemak aurki daitezke. Baina beste batzuek, beste helburu batzuetako sortutako sentsoreen gaitasunak aprobetxatzen dituzte lan hau egiteko.

Datuen irakurketa eta bilaketari dagokienez, irtenbide teknologiko desberdinak proposatu dira [155]. Teknologia hauen erabilerari esker, posible da pertsonaren mugimendua, indarra edo eguneroko jarduera ezberdinak identifikatzen laguntzen duten beste parametro batzuk ezagutzea.

Jarduera fisikoa detektatzeko, ikusmenean oinarritutako hainbat sistema aurkitu dira [178, 5, 147]. Hainbat autorek kameretan oinarritutako gailuak erabiltzea proposatu dute. Horien artean, pertsona baten ibilera ezagutzea ahalbideratzen duten Kinect kamerak dira erabilienak [81]. Beste batzuk, egunero bizitzeko jarduerak ezagutzeko gai dira, gela sentsorizatuen bidez [64]. Sistema mota hauek emaitza onak lortu dituzten arren jarduera fisiko ezberdinak sailkatzean, arazoak sor ditzakete kasu batzuetan pribatutasuna hausteagatik [21]. Gainera, normalean, ez dira kontrolik gabeko ingurunetan JF detektatzeko gai, ingurunean gertatzen diren aldaketen ondorioz interkonexio asko sor baitezakete. Bestalde, eginkizun bererako erabil daitezkeen beste sistemak baino garestiagoak dira.

Gaur egun, erabiltzen diren teknologia ezberdinen artean, ezagunenak gailu eramangarriak dira, hau da, gaixoaren gorputzera lotzen diren gailuak. Hauek, neurtu nahi den puntuan kokatu behar dira eta erabilienak Inertial Measurement Unit (IMU) dira [194, 70]. Gailu hauek mugimendua neurtzen dute, adibidez IMU erabiliz, [191, 72, 12, 16, 166, 127, 76, 190, 9, 187, 91, 110, 66, 118, 186, 139, 149, 188, 58] (ikusi 2.1. irudia). Gailu mota honek azelerazioa eta/edo abiadura adierazten du, uneoro egindako jarduera fisikoaren informazio eskainiz.



Irudia 2.1: IMU sentsorea (eskuina) eta gorputzean posizionamendua (ezkerra) [127].

Gailu eramangarri guztiak ez dira IMUn oinarritzen, horien barruan aurki daitezke jarduera fisikoaren datuak atzematen dituzten Electromyography (EMG) [133, 178] bezalako seinale biomedikoak neurtzen dituzten gailuak ere. Seinale mota honek aldaketa txikiak hautematen ditu giharren aktibitate elektrikoan, honela muskulu jakin baten mugimendua lortuz eta pertsonaren jarduera ezagutuz.

Soluzio horiek, gorputz-adarretan zuzen kokatzea eta mugatzea eskatzen dute ondo funtzionatzeko, eta honek, pazienteak hauek erabiltzera ukatzera eraman dezake. Desabantaila hauek murrizteko, smartwatch-etako eta telefono mugikorretako sentsore integratuen erabilera proposatu da [4, 117, 106, 85, 120, 95]. Azken gailu horiek ez dute kokapen espezifikorik izan behar, baina, kokatzeko malgutasun hori eta mugimendu parasitoek sartutako aldagarritasuna kontuan hartu behar dira datuak prozesatzerakoan.

Aplikatutako indarra irakurtzen duten elementuen erabilera gero eta ohikoagoa da jarduera fisikoa detektatzeko orduan. Horien artean, ibilera mota ezberdinak detektatzeko gai diren sentsore-matrizeetan oinarritutakoak daude [150]. Beste batzuek erresistentziak erabiltzen dituzte helburu bererako [200]. Alde batetik, elementu horiek une bakoitzean aplikatutako indarra neurtzeko aukera ematen dute, eta horrek pisu-kargaren banaketa ezagutzea ahalbidetzen du. Bestalde, elementu horiek mugitzeko zailak diren zeren eta espazio operatibo mugatua duten alfonbrak izaten dira.

Jarduera fisikoa antzemateko aipatutako gailu horien artean, hainbat tresna komertzial daude merkatuan, hala nola XSens [170], BioStampRC [173], Tracmor [76], FlexiForce [130] edo BioCapture [178].

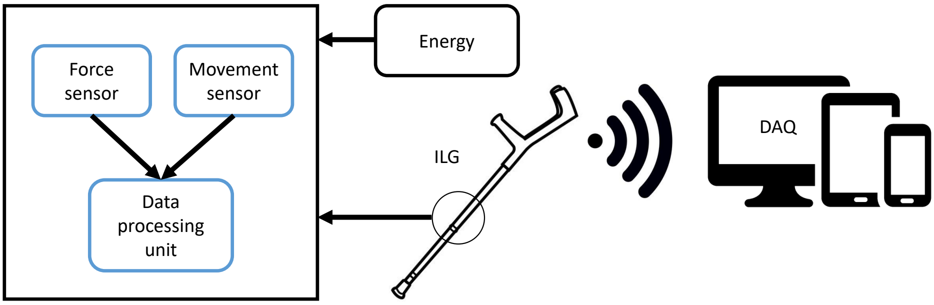
Amaitzeko, nahiz eta lehen aipatutako gailu guztiak gai izan JFren sailkapenari irtenbidea emateko, guztiak ez dira egokiak egun osoko jarduera detektatzeko. Horietako batzuek ezin dute egun osoan aktibitatea antzeman eta ez dira egokiak kontrolik gabeko eremuetan erabiltzeko. Beste batzuk, hala nola sentsore eramangarriak, datuak behar bezala neurtu ahal izateko kokatu beharreko eremuaren arabera, gogaikarriak izan daitezke. Arrazoi hauegatik, JF detektatzeko konponbiderik onenetakoa ibiltzeko laguntza gailu sentsorizatuak erabiltzea izan daiteke. Hauek behar dituztenek egun osoan erabiliko dituzte, gainera ez dira deserosoak eta ez dute behar etengabeko egokitasunik.

2.1.1 Ibiltzeko Laguntza Gailu (ILG) sentsorizatuen sentsoreak

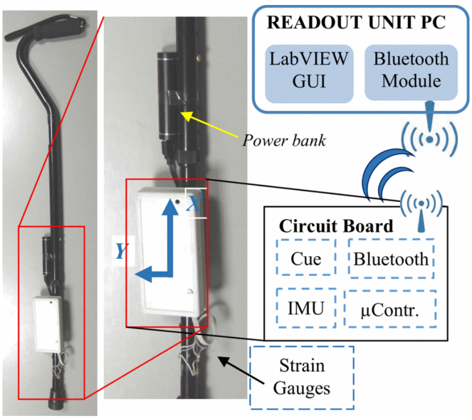
Ibiltzeko Laguntza Gailua (ILG)k, giza gorputzaren mugimenduari laguntza ematen dioten gailuak dira. Haien xedea, erabiltzailea zutik egotea eta mugitzeko gai izatea da. Gailu hauek mota ezberdinetan sailka daitezke: makuluak, multipodaleko kanak edo kanoak.

Azken urteetan, Ibiltzeko Laguntza Gailua (ILG) sentsorizatuei lotutako argitalpenen kopurua nabarmen hazi da (ikusi 2.1. taula). Gehienek eskema eragile berari jarraitzen diote (ikusi 2.2. irudia), non sentsoreak ILGn txertatzen diren eta datuak ordenagailu edo gailu mugikor batera bidaltzen diren irakurketa-sistema baten bidez.

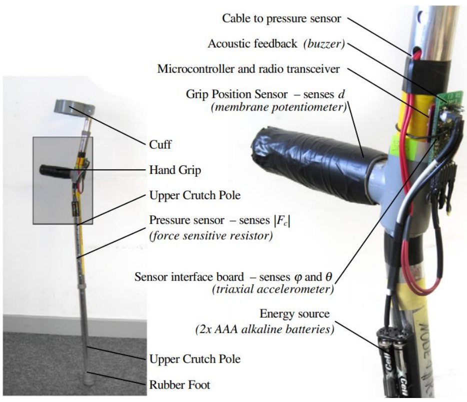
Eremu honetan zentratzen diren lan gehienek Laguntza Gailuari aplikatzen zaion indarra edo/eta mugimendua neurtzeko sistemak erabiltzea proposatzen dute [163, 47, 100, 180, 77, 122, 121, 165, 33, 49, 61, 123, 159, 168] (ikus 2.3 irudia). Zehazki, badira kirtenari aplikatutako indarra neurtzeko gai diren sentsoreak [124, 99, 132, 185, 123] edo objektuen hurbiltasuna detektatzeko gai direnak [185, 14].



Irudia 2.2: Sentsorizatutako ILGen eskema.



(a) F. Mekki et al



(b) G. Merrett et al

Irudia 2.3: Galga estentsometrikoak dituzten ILG [122, 124].

Taula 2.1: ILGren diseinu instrumentatuari buruzko azterlanen alderdi nagusiak. (A = Azelerometro, G = Giroscopio, M = Magnetometro, F = Indar).

Azterketa	Sentsoreak	Sentsoreen Kokapena
[13]	2x FSR	FSR puntan eta elektronika kutxa batean kanaberan.
[14]	Ultrasoinu, Ur Sentsorea, LDR, GPS	Kanaberan.

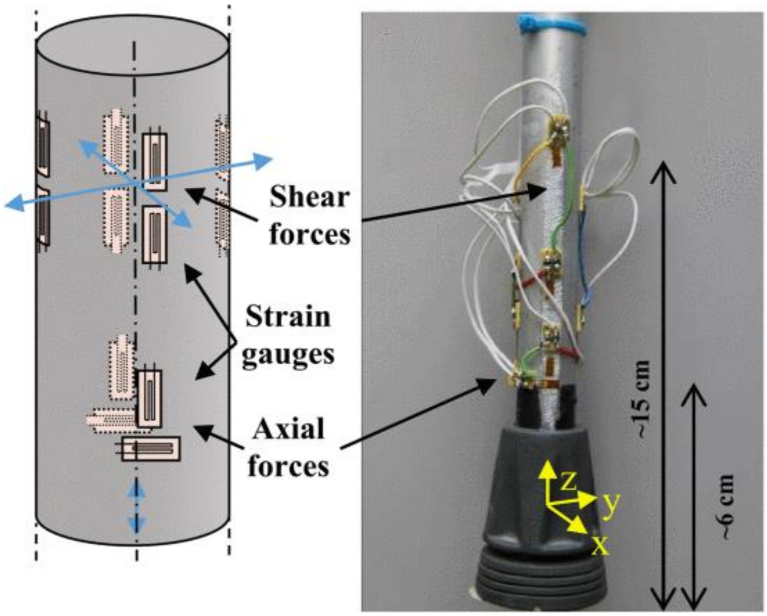
2.1. taularen jarraipena

Azterketa	Sentsoreak	Sentsoreek Kokapena
[33]	F zelula	F puntan eta elektronika makulu barruan.
[36]	2x galga, F zelula, 3-ardatz A, G, M	F puntan eta elektronika kanaberan.
[47]	F zelula, 2-ardatz G, 3-axis A, M	F puntan eta elektronika eta G, A, M kutxa batean kanaberan.
[49]	3x 3-ardatza A, G, M	Kanaberan
[62]	Uhin milimetrikoen radarra	Kanaberan
[61]	5x 3-ardatz A, G, M	Kanaberan
[65]	9x F zelula, 3-ardatz G	Kanabera barruan, era F puntan.
[68, 69]	4x galga, 3-axis A, G, M	Heldulekuaren barruan
[77]	3x FSR, 3-ardatz A, G, M	FSR punta barruan eta A, G, M eta elektronika kutxa batean.
[99]	2x F, 3-ardatza A, G	F bat puntan, bestea heldulekuan, eta A, G eta elektronika kutxa batean.
[100, 163]	3x galga, 3-ardatz A	Kanaberan
[121]	3-ardatz A, FSR	Elektronika eta F heldulekaun.
[122]	4x galga estesometrikoak, 3-ardatz A, G, M	F puntan eta elektronika eta A, G, M kutxa batean.
[123]	F zelula, 3-ardatz A	F heldulekuan eta elektronika eta A kutxa batean.
[124]	FSR, Mintz zuzenaren potentziometroa, 3-ardatz A	F heldukoan eta elektronika eta A kanaberan.
[132]	Galga, 3-ardatz A, G, M	F heldukoan eta elektronika eta A, G, M kutxa batean.
[159]	F	Kanabera barruan.
[165]	4x F, 2-ardatz A	F heldukoan eta elektronika eta A kutxa batean.
[168]	F	Kanaberan.
[180]	G, 2x FSR	F puntan eta elektronika eta G kutxa batean.
[185]	F zelula, 2x3-ardatz A 8x FSR (heldulekuan), 3-ardatz G, M, Ultrasoinu	F heldulekuan eta besteak eta elektronika kanaberan.
[196]	GPS, Argi Sentsoreak, Pultsu sentsorea	Kutxa batean.

2.1.1.1 Indarraren neurketa

Laguntza gailuari aplikatzen zaion indar axialaren neurketa erlatiboki zuzena da, beraz, lan gehienak neurketa hau barne hartzen dute. Literaturan, bi hurbilketa erabiltzen dira: indar integratuko sentsoreak eta tentsio-neurgailuak (ikusi Taula 2.1).

Indar integratuko sentsoreak [33, 47, 185, 36, 65] gailu komertzialak dira, sentsorean aplikatzen diren kargen neurketa axiala (edo triaxiala) ahalbidetzen dutenak. Oro har, barne-betetasunaren presio aldaketa detektatzean edo zelulak kargatzean oinarritu daitezke. Nahiz eta zehaztasun altua izan ohi duten, kostua ere altua izaten da, eta seinale egokitzaileren bat behar izaten da normalean. Elementu hauen forma zilindrikoaren ondorioz, laguntza teknikoko gailuetara egokitzeko gaitasun handiagoa dute.



Irudia 2.4: Zurtoian galburu estentsometrikoak dituzten ILG [100].

Tentsio-neurgailuek [124, 180, 100, 77, 163, 122, 121, 165, 13, 159, 168], indarreko sentsoreek baino kostu eta zehaztasun baxuagoa dute. Neurketa hobetzeko, askotan hainbat neurgailu sartzen dira dispositiboan, sistema konplexuagoa behar delarik. Gainera, elementu hauek normalean aurrekoak baino irakurketa sistema landuagoa behar dute, erresistentzia-balioaren aldaketa irakurtzeko gai den zirkuitu bat eta anplifikazio-sistema bat behar baita, hornitutako seinalea nahi dena baino askoz baxuagoa bada. Tentsioak lana neurtzen du efektu piezoresistikoari esker, zeinarekin elementu gidari baten deformazioa bere balio erresistenteari esker neur daitekeen. Bestalde, elementu hauek oso xaflakorrak dira, eta horrek oso interesgarri bihurtzen ditu indarrak neurtzeko, laguntza gailuaren egitura aldatu gabe. Literaturan, makulu edo kanalen deformazioak neurtzeko erabili izan dira [100] (ikus 2.4 irudia), baita laguntza gailuaren heldulekuari aplikaturiko indarra neurtzeko ere [124]. Xaflakortasun hori ere oztopo izan daiteke kokapen egonkorrerako, errazago mugi edo desager baitaitezke.

2.1.1.2 Mugimenduen neurketa

Indarra alde batera utzita, autore askok inkorporazio-sentsoreak erabiltzen dituzte mugimendua neurtzeko.

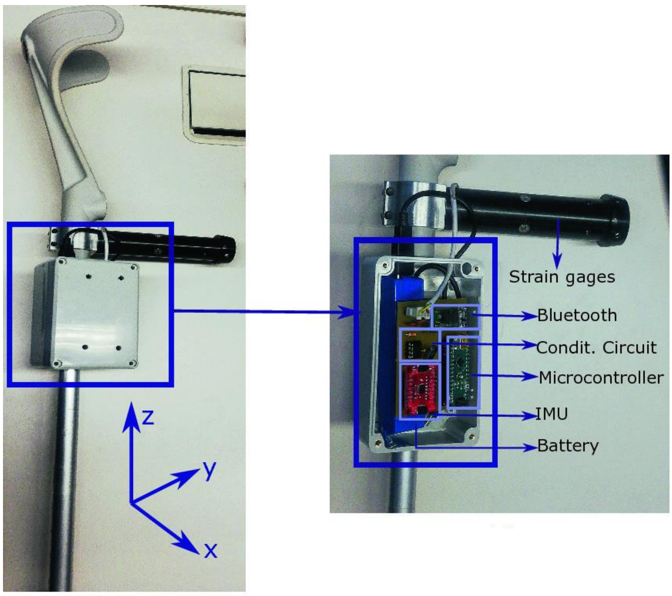
Mugimendua neurtzen duten autore gehienek Inertial Measurement Unit (IMU) [77, 47, 185, 122, 132, 68, 69, 61, 99, 49, 61] erabiltzen dute. Sentsore mota hauek aeronautika, automatizazioa edo nabigazioa bezalako alorretan erabiltzen dira. IMU gehienek azelerazio linealak eta abiadura angeluarrak neurtzen dituzte hiru ardatz espazialetan, hiru ardatzetako bakoitzean azeleragailua eta giroskopioa badituzte. Sentsorearen une bakoitzean abiadura eta azelerazioa ezagutzeko aukerari esker, gailu lagungarriaren mugimendua jakin daiteke. IMU baten abantaila nagusia datu guztiak fusionatu ahal izatea den arren, badira azeleragailuak [100, 163, 124, 121, 165, 123] edo giroskopikoak [180, 65] bakarrik erabiltzen dituzten lanak. Hala ere, elementu horiek desabantailak dituzte, adibidez erabiltzean zuzendu behar diren deribak. Bestalde, ILGekin ibiltzean egiten diren desplazamenduak ezagutzeko, beste autore batzuek Global Positioning System (GPS) neurketa erabiltzen dute [195, 14, 2].

Kontuan izan IMUaren (edo azeleragailuen edo giroskopioen) erabilerak ez duela zuzenean Ibiltzeko Laguntza Gailuaren orientazioa ematen, estimazio-teknika ezberdinak aplikatu behar dira sistemaren orientazio absolutua lortzeko. Metodo sinpleenetako bat giroskopioak eskaintzen duen abiadura errotazionalaren integrazio zuzenean oinarritzen da, metatutako errorea aldizka zuzenduz [180]. Aurreko soluzioak denboraren gaineko joera esanguratsua sortzen du, eta, beraz, beste autore batzuek ikuspuntu kuasi-estatiko bat erabiltzea proposatu dute, non orientazioa grabitate-bektoreak ardatz bakoitzean duen proiekziotik zehazten den [100, 124, 163, 185]. Azken hurbilketak ez ditu aintzat hartzen aurrerapen eta inpaktu dinamiko egokiak. Kalman iragazkietan oinarritutako soluzioak ere aurki daitezke [47, 88, 113]. Iragazki horiek hainbat sentsoreren informazioa elkartrukatzeko gai dira, sistemaren barne-eredu batean oinarritutako orientazio absolutuaren balioespena lortzeko. Kasu hauetan iragazki mota honek giroskopio eta azeleragailuek ematen duten irteera konbinatuz lan egiten du, baita magnetometro bat ere kobariantza multzo batekin batera. Horrela, laguntza gailuaren orientazioa definitzen duten Euler angeluen estimazioa lor daiteke. Azkenik, iragazki osagarrien erabileran oinarritutako azken soluzio multzo bat dago, eta horien abantaila nagusia, Kalman iragazkiaren alde, kostu konputazional txikia da. Iragazki honen adibide bat CAHRS da [51].

Amaitzeko, laguntza gailu gehienak gutxienez indar sentsore bat eta/edo sentsore inerte bat dute. Horrela, sentsore hauek pertsonaren mugimendua eta laguntza gailuari aplikatzen zaion indarra zehazteko erabil daitezke. Indar sentsoreen kasuan, tentsio neurgailuak eta karga zelulak erabiltzen dira. Tentsio neurgailuak arinagoak eta merkeagoak diren bitartean, normalean kokapen zehatzagoak eta eskuratze sistema konplexuagoa behar izaten dira. Indar sentsoreak, aldiz, astunagoak izanik, normalean sendoagoak eta errazagoak izaten dira gailu lagungarriei eusteko. Autore ezberdinek erabiltzen dituzten mugimendu-sentsoreak aztertzen, gehienek IMUak erabiltzen dituzte. Hau espazio berean sentsore ezberdinak edukitzearen ondorioz gertatzen da.

2.1.2 Sentsoreen posizioa

Autore bakoitzak, sentsoreak Ibiltzeko Laguntza Gailuan posizio desberdinetan kokatzen ditu 2.1 taulan ikusten den moduan. Autoreetako batzuk, Ibiltzeko Laguntza Gailuarentzat eraikitako kutxa batean jartzen dituzte [47, 77, 100, 122, 165, 132, 49, 13, 61]. Normalean kutxa hau makuluaren enborrari lotua egoten da eta zenbait egoeratan baldarra izan daiteke (ikus 2.5 irudia). Beste autore batzuek, elektronika enbor barruan sartu nahi izan dute, normalean hutsik dagoela aprobetxatuz. Indarra neurtzen duten sentsoreen kasuan [47, 100, 124, 163], hauetako asko puntan [77, 122, 165, 99, 13] edo egitura batean [185, 36] gehitzen dira. Sentsoreak modu honetan kokatzearen arazo nagusia, laguntza gailu desberdinen artean trukatzea saila dela da.



Irudia 2.5: ILG sistemak fabrikazio-kaxa propio dutenak [132].

Azken batean, sentsoreen kokapena garrantzitsua da ILG sentsore baten diseinuan. Autoreen artean ez dago adostasun argirik sentsoreen kokapenari buruz, eta horrek esan nahi du diseinatzailearen arabera leku ezberdinetan aurki daitezkeela. Gailu lagungarrietan dauden sentsore asko gerora kendu ezin diren lekuetan kokatzen dira, edo ahalegin gehiago behar dute horretarako. Horrek esan nahi du, gorago aipatu bezala, sentsoreak Ibiltzeko Laguntza Gailua bakar eta berari lotuta daudela, erabiltzaileak gailu batetik bestera erraz aldaraztea ezinezko eginez.

2.1.3 Datuak irakurri eta komunikatzeko sistemak

Aipaturiko sentsore guztiek modu desberdinetan bidaltzen dute informazioa. Balio analogikoa bidaltzen duten sentsoreetatik abiatuz, Inter-Integrated Circuit (I2C) edo Serial Peripheral Interface (SPI) bezalako komunikazio-metodo bat erabiltzen duten sentsoreetaraino. Hori dela eta, irakurketa sistema bat, Data Acquisition System (DAQ) bat, behar da datu hauek irakurri, egokitu, gorde edo/eta beste gailu batera bidaltzeko. Gailu hauek, barne diseinukoak izan ohi dira [36, 165, 185, 100, 163]. Nahiz eta aukera ezberdinak egon, Arduinoa da erabiliena [122]. Honen abantaila nagusiak, prozesadoreen kostu baxua eta programazioa errazten duten liburutegiak edukitzea dira. Azkenik, prototipo azkarretan oinarritutako DAQak aurki daitezke [122]. Hauek National Instrument edo beste enpresa batzuen sistema komertzialak dira. Hauek, normalean kostu handia izaten dute, baina haien fidagarritasuna eta gaitasuna besteena baino handiagoa izaten da sarri.

Irakurtze sistema hauek, normalean, datuak biltegiratzeko beste sistema batzuetara bidaltzen dituzte. Bi sistemen arteko komunikazioa gehietan haririk gabe egiten bada ere, badaude kable bidez egiten dutenak ere [180, 165]. Haririk gabeko datu-transferentziak egiteko erabiltzen diren metodoen artean, bi metodo nagusi aurkitzen dira: Bluetooth [47, 100, 163, 185, 122, 132, 99], gehien erabiltzen den metodoa dena, eta Wireless Fidelity (WIFI) [124, 36, 77]. Beste alde batetik, gailu batzuek oroimen birtualari buruzko informazioa gordetzen dute, hala nola Secure Digital (SD) txartelak [68, 69].

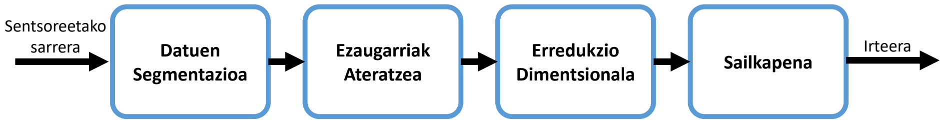
Laburbilduz, autoreen gehiengo zabalak, zalantzarik gabe, datuen eskuratze sistema propioa diseinatzen du. DAQen diseinu honek asko errazten du laguntza gailuan txertatzeko aukera, nahi diren neurrietara egokitzea ahalbidetuz.

Datuak bidaltzeko erabiltzen den metodoa Bluetooth da kasu gehienetan. Komunikazio sistema honen erabilera justifika daiteke bere oinatz elektroniko txikiagatik eta ez duelako behar antena handi bat martxan jartzeko. Horrez gain, Bluetooth-a informazioa bidaltzeko gai da distantzia egokietan haririk erabili gabe, eta, beraz, ez dago etengabe gailu hartzailetik hurbil egon beharrik eta handik metro batzuetara egon ahal izango da. Hala ere, teknologia honen eragozpen handienetako bat interferentziak izaten dira.

2.2 Jarduera fisikoak sailkatzeko metodologiak

Jarduera Fisikoa (JF) behar bezala monitorizatu ahal izateko, datuak atzematen dituen gailu sentsore bat edo gailu sentsore multzo bat edukitzeaz gainera, neurtutako datuak modu egokian landu behar dira. Hau da, proposatzen diren JFk bereizteko gai den sailkatzaile bat diseinatu behar da. Horretarako, lehenik eta behin, sentsoreetatik lortutako datuak prozesatu behar dira, sailkatzaileak sortzeko elementu gisa erabili ahal izateko.

Normalean, Jarduera Fisikoa sailkatzeko metodologia bat erabiltzen da [11, 151] (ikusi 2.6. irudia). Metodologia hori datuen egokitzapenetik abiatzen da, datuak leihoetan banatuz edo segmentatuz eta datuen ezaugarri ateraz. Erabiliko diren ezaugarriak identifikatu ondoren, garrantzitsuenak aukeratzen dira. Azkenik, jarduera fisikoen sailkatzailea sortzen da (ikusi 2.2. taula).



Irudia 2.6: Jarduera Fisikoak sailkatzeko egindako urratsen eskema.

2.2.1 Jarduera fisikoaren jarraipenari buruzko datuen segmentazioa eta tratamendua

JFren sailkapena lortzeko, nahi diren datuak neurtu ondoren, modu egokian tratatu behar dira erabili ahal izateko. Normalean, atzemandako datuak, denbora-tarte batez bereizten diren bektoreak izaten dira. Datu horiek hobeto kudeatu eta ezaugarriak lortzeko erabili ahal izateko, informazio-segmentu txikiagoetan banatu ohi dira.

2.2.1.1 Datuen segmentazioa

Osasun-diagnostikoko aplikazioetan soluzio teknologikoak inplementatzeko orduan, funtsezkoa da sentsoreetatik ateratako datuak prozesatzea. Datuen tratamenduaren helburua askotarikoa izan daiteke: ezaugarri jakin batzuk lor daitezke (abiadura azkarrena, indar handiena, distantzia...) [145, 30] edo datuak eskala kliniko estandarizatu batekin lotu daitezke [98]. Oro har, sailkapena da ezaugarri guztien helburua, eta hori interes bereziko eremua da pazienteen diagnostikoan, beraien egoera sailkatzea ahalbideratzen baitu.

Sailkapen hori egin aurretik, literaturan ohikoa da aurre-prozesamenduko lehen etapa bat egitea leiho tekniken edo segmentazioaren bidez. Teknika horietan, sentsoreetatik lortutako seinaleak denbora-segmentu askoz txikiagoetan banatzen dira, ILGren erabiltzaileak egindako ekintzak identifikatzen laguntzeko. Prozesamendu honi esker, informazioa segmentatzen da sailkapena errazagoa izan dadin.

Leiho horien sorrera, datuak osorik irakurri ondoren edo datu-bilketan zehar defini daiteke, datuak denbora errealean tratatuz gero. Leihoak sortzeko beharren arabera, horiek sortzeko metodo bat edo bestea erabiliko da.

Datuen sailkapenean, batez ere hiru leiho mota erabiltzen dira, bakoitza leihoak sortzeko metodo desberdina duelarik.

Leihoka lortzeko lehen metodoa *leiho irristakorra* da. Leiho mota honetan, atzemandako seinalea leiho finkoetan banatzen da, eta ez da leiho horien arteko espaziorik existitzen. Sailkapenaren beharren arabera, leiho tamaina desberdina erabili daitezke, hau da, denbora luzeagoa edo laburragoa izan dezakete [83, 15, 11, 151, 188, 127, 166]. Leiho irristakorrek ez dute seinalea prozesatzen; beraz, ezin hobeak dira denbora errealean erabiltzeko. Zatiketa mota hauek seinalearen maiztasuna oso konstantea denean erabil daitezke; zatitu beharreko seinaleek maiztasun konstantea ez badute, leihoak hainbesteraino bana daitezke, aztertu beharreko daturen bat leihoetatik kanpo geratzea probokatuz.

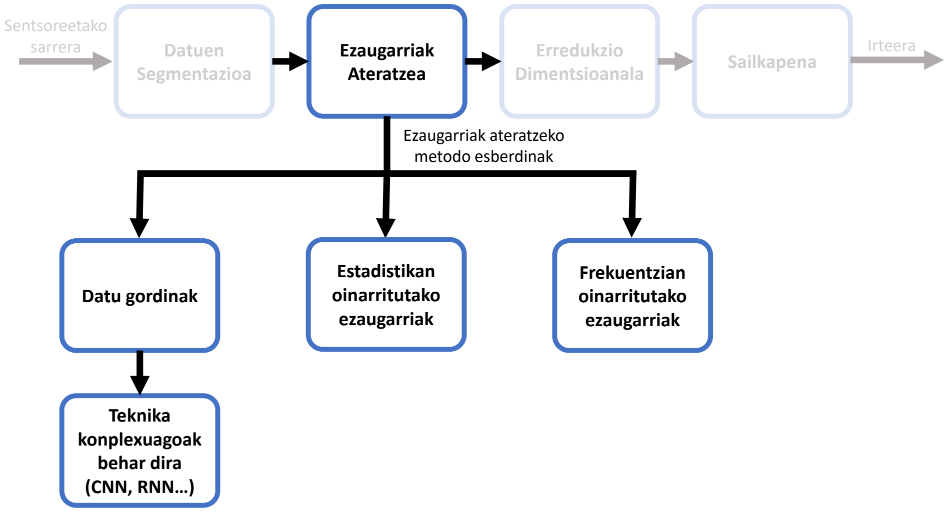
Bigarren metodoa *ekitaldi-leihoak* dira. Ekitaldi-leihoek aldez aurreko prozesamendua behar dute gertaera espezifiko bat aurkitzeko. Ekitaldiak leihoaren hasiera definitzen du, eta leihoak ez du tamaina zehatzik. Leihoaren amaiera bi modutara defini daiteke: gertaera beraren hurrengo errepikapen bat erabiliz, gertaera horrek egungo leihoaren amaiera eta hurrengoaren hasiera markatuz; edo hasierako gertaeratik independentea den beste gertaera mota bat erabiliz. Leihoaren hasiera markatzen duen gertaera lortzeko, beste sentsore bat erabil daiteke, adibidez lurraren aurkako inpaktua edo beste gertaera garrantzitsu bat detektatzeko gai den sentsorea [15, 190, 202]. Leiho horiek erabiltzeak, haien barruan datu multzo bat kapsulatzen laguntzen du. Datuak neurtzean gerta daitezkeen egoeretara egokitzeko duen gaitasunari esker, teknika hau da gehien erabiltzen dena leihoetan segmentatzeko. Adibidez, martxari buruzko datuak hartuz gero, nahiz eta pertsonak ibiltzeko erritmoa aldatu, leihoek pauso bana izaten jarraituko dute metodologia honi esker.

Erabilitako hirugarren leiho-teknika *jarduerek* zehaztutakoa da. Leihoak jarduerak bereizten diren puntuen arabera definitzen dira [138]. Teknika mota hori da leihoak sortzeko gutxien erabiltzen dena.

Laburbilduz, sentsoreekin neurtutako datuen segmentazioa garrantzi handiko faktorea da. Horretarako leihoak erabiltzea aukera egokia da, eta denbora errealean lan egin nahi bada, gertaeretan oinarritutako leihoak dira egokienak. Datuen segmentazioak, datuen dimentsionaltasuna murrizten laguntzen du; gainera, leihoak egiteak esanahi garrantzitsua izan dezake, adibidez, ibilbide-ziklo bakoitzerako leihoak bereiztea ahalbidera dezake.

2.2.1.2 Ezaugarriak ateratzea

Ibiltzeko Laguntza Gailuak ematen dituen datu gordinak segmentatu ondoren prozesatu egin behar dira, jarduera hobeto sailkatzeko. Lan batzuek, datu gordinak erabiltzen dituzten zuzenean, baina hauek gutxiengoak dira, ezaugarriak ateratzeko erabiltzen den aurreprozesamenduaren bidez sailkapena egiten dutenen aldean (ikusi 2.7. irudia).



Irudia 2.7: Ezaugarriak ateratzeko erabiltzen diren metodo ezberdinak.

Oro har, datu gordinak erabiltzen dituztenek, algoritmo konplexuagoak eta kostu konputazional handiagokoak behar dituzte, hala nola Convolutional Neural Network (CNN) [72], Recurrent Neural Network (RNN) [44] edo ezkutuko geruza ugari dituzten Multilayer Perceptron (MLP) sare neuronal tradizionalak [190]. Hori dela eta, ez da ohikoa zuzenean datu gordinak erabiltzea.

Hala ere, aurreko paragrafoan aipatu bezala, badira datu gordinak erabiltzen dituzten lanak, baina, dimentsionaltasuna murrizteko asmoz, badira leihoetan banatutako datuetan oinarrituta ezaugarriak ateratzen dituzten lan asko ere [11, 151, 152, 70]. Hauen artean daude kalkulu estatistikoetatik edo maiztasunean oinarrituta lortutakoak.

Arestian aipatu bezala, ezaugarri horiek kalkulu estatistikoetatik lor daitezke. Prozesamendu estatistikoen artean, ohikoenak hauek dira: segmentatutako leiho bakoitzeko datuen batez besteko karratuak, leihoetan aurkitutako gehieneko balioak, desbideratze estandarra edo punta-puntako balioa [9, 70, 188, 83, 149, 58]. Bestalde, badira ohikoenekin batera erabiltzen diren datu estatistiko konplexuagoak ere [151, 76, 127, 120, 166], hala nola, zurrosia, kuartilen arteko tartea edo pertzentilak. Datu mota hori, leiho bakoitzean datuek nola jokatzen duten adierazten duen informazio-balio bat izan daiteke, eta, beraz, aztertu beharreko ekintzen azterketa argiagoa izan daiteke.

Ezaugarriak ateratzeko beste modu bat maiztasunean oinarritutako datuak erabiltzea da [200, 111, 193, 83, 127], hala nola leiho bakoitzaren batez besteko oszilazio-zikloa kalkula daiteke. Analisia fasean erabiltzen dutenak [16] edo ezaugarri heuristiko batzuk sortzen dituztenak ere badaude [54]. Hala ere, ezaugarri hauek ez dira estatistikoak bezain ohikoak, beraien interpretazioa konplexuagoa baita.

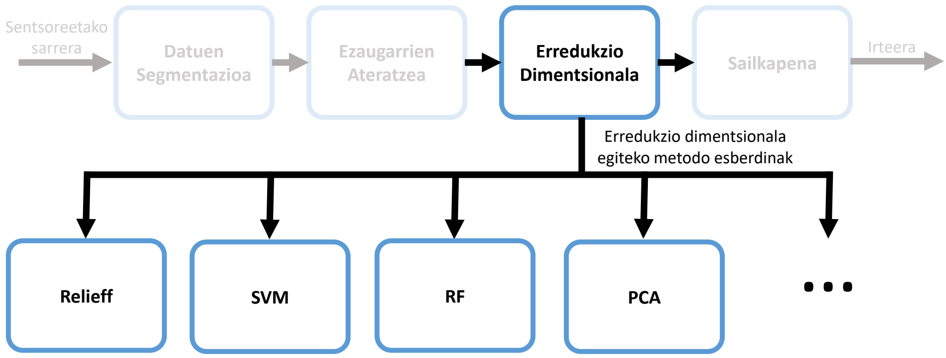
Literaturan, ibilera aztertzen laguntzen duten hainbat ezaugarri ere zehaztu dira, hala nola, distantzia jakin bat egiteko beharrezko urratsen kopurua, batez besteko abiadura edo urratsen arteko denbora [171]. Horrelako datuek pertsona bat zein abiaduratan mugitzen den adieraz dezakete, honela, pertsona hori nola mugitzen den zehatzago ezagutuz.

Indar axiala neurtzen duten Ibiltzeko Laguntza Gailuaetan zentratuz, hauek, pazientearen pisuarekiko karga maximoan [159, 168] edo karga ertainean [168] oinarritutako ezaugarriak sortzen dituzte. Analisi hau pertsona bakoitzarentzat egiten da, pertsona guztiek ezin baitute karga bera egin, pisutsuagoek pisu gutxiagokoek baino gehiago kargatuko dute.

Laburbilduz, jarduera sailkatzeko erabili beharreko ezaugarrien hautaketan barietate handia dagoen arren, orokorrean ohikoenak eta ezartzeko errazenak estatistikan oinarritutakoak dira. Hauek, jatorrizko datuen interpretazio erraza eta egokia eskain dezakete.

2.2.1.3 Ezaugarri garrantzitsuen hautaketa

Jarduera fisikoaren sailkapena egiterakoan ez da egokia sarrera gisa lor daitezkeen ezaugarri guztiak erabiltzea. Horregatik, leiho bakoitzeko ezaugarriak kalkulatu ondoren, horien artean garrantzitsuenak aukeratu behar dira [11, 151]. Hau da, erredukzio dimentsional bat egin behar da (ikusi 2.8. irudia).



Irudia 2.8: Ezaugarri garrantzitsuenak hautatzeko erabiltzen diren metodo ezberdinak.

Kasu batzuetan, ezaugarri garrantzitsuenak modu bisualean hauta daitezke, datuak datu-basean nola banatzen diren begiratuz. Hala ere, erabilera hori ez dago oso zabalduta, oso zaila baita sailkapenari lagun diezaioketen aldagaien arteko erlazioak aurkitzea, eta aldagai askoren kasuan, azterketa hori egiteko behar den denbora oso handia da.

Horregatik, helburu hori lortzeko aukera aurreratuagoak existitzen dira. Lan desberdinetan proposatutako aukera eta soluzioen aniztasuna oso handia da, eta metodologia askotan oinarritutako irtenbideak aurki daitezke [39]. Aukera horietako bat

Relieff-en oinarritutako ezaugarrien hautaketa da [12, 127, 93, 38]. Relieff-ek pisuak esleitzen dizkio ezaugarri bakoitzari, eta, horretarako, klase berdinetako eta desberdinetako datu-puntuak zein ondo bereiz ditzakeen balioesten du. Bi kasuetan, ezaugarri bakoitzerako pisu bat lortzen da, eta haren balio altuenak esan nahi du ezaugarriak garrantzi handiagoa duela.

Proposatutako beste aukerak dira Support Vector Machine (SVM) [105, 188], K-Means Clustering (KMCA) [83], Correlation based Feature Selection (CFS) [120, 39] edo Forward-Barckward Sequential Search sistemetan oinarritutako sistemak erabiltzea [149]. Horiek guztiek ezaugarrien dimentsionaltasuna nabarmen murriztea lortzen dute.

Beste aukera bat Random Forest (RF) algoritmoen erabilera da [177, 39]. RF, Decision Trees edo erabaki-zuhaitz ezberdinetatik abiatuta, sailkatzaile bat edo erregresio bat eraikitzeko metodo bat da. Zuhaitz bakoitza ausazko ezaugarrien bektore batek osatzen du. Eta erabaki-zuhaitza une jakin batean hartutako erabaki batetik sor daitezkeen gertaera guztiak irudikatzeko modu grafiko eta analitikoa da. Decision Trees horiek erabaki posible batzuen artean erabakirik onena hartzen laguntzen dute.

Hainbat metodo aurki daitezke RF-ren barruan. Metodo horien artean Decision Forest delakoa dago [89], hainbat Decision Trees konbinatuz funtzionatzen duena. Horrek sailkapen zehatzago bat edo atzera egiteko gai den sistema bat sor dezake. Teknika honen bidez, neurri handiagoan orokortu daiteke entrenamendu-datuen zehaztasuna mantenduz.

RF atalean sar daitezkeen beste teknika bat Bagging da [79, 23]. Teknika hori hainbat Decision Treesk osatzen dute; emaitza globala arbola guztien batez bestekoa eginda lortzen da.

Bagging-aren oso antzeko teknika da AdaBost-en teknika [154]. Berezitasun nagusia, entrenamendu multzoak ausaz ez aukeratze da, kasu honetan pisu-multzo bat erabiltzen dute entrenamendu-multzoko lagin bakoitzerako. Pisua zenbat eta handiagoa izan, orduan eta handiagoa izango da laginaren eragina. Sailkapen-akatsa ere pisu horien araberakoa izango da.

Teknika horiek guztiek, arazoak dituzte errorea orokortzeko [52]. Horregatik, arazo hori arintzeko gai diren teknika berriak proposatu dira, hala nola Random Forest-RI [24]. Metodo hori lehen aipatutako Bagging metodoan oinarritzen da, baina ausaz egiten da zuhaitz bakoitza eraikitzea, ordezkapen-laginen ausazkotzeaz gain, ezaugarriak ordeztu gabe. Metodo honek bi helburu izan ditzake: ausazko zuhaitz bat sortzea entrenamendukoak ez diren laginak sailkatzeko edo datu-base baten ezaugarrien arteko garrantzi erlatiboa neurtzeko.

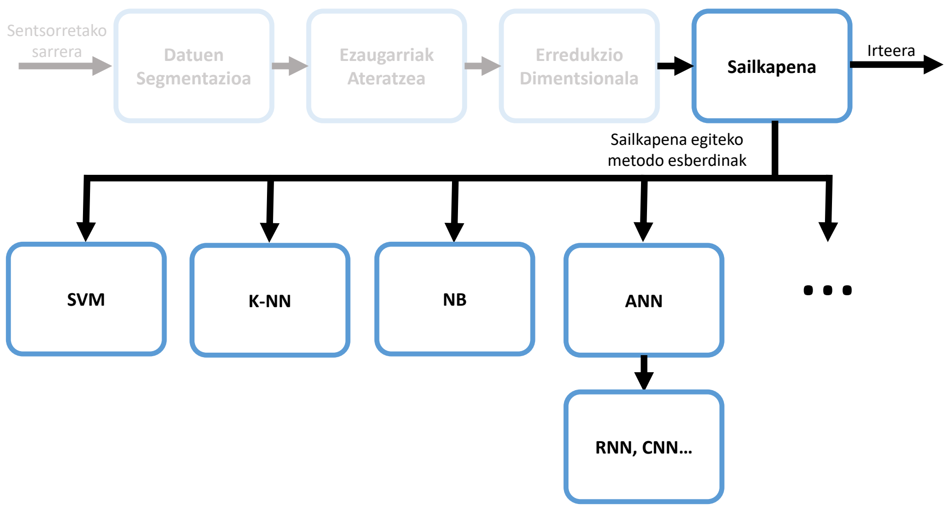
Ezaugarriak murrizteko metodologiak erabiltzeaz gain, ezaugarriak eraldatzeko metodoak ere proposatu dira [11]. Teknika mota horietan dimentsionaltasuna murrizten da ezaugarri kopuru txikiagoaren bidez. Teknika mota honen adibide bat Principal Component Analysis da [198, 112, 66, 64, 110, 150]. Metodo honek datu-multzorako koordenatu-sistema berri bat aukeratzen du, sistemaren dimentsionaltasuna sinplifikatuz. Sortzen diren aldagai berriak datuen bariantzetatik lortzen dira.

Lehen aipatu bezala, teknika honek ezaugarrien arteko korrelazioaren eragina ezagutzea ahalbidetzen du eta, beraz, ezaugarri bakoitzak rankingean duen pisua hobeto ezagutzea.

Ondorioz, ez dago adostasun orokorrik ezaugarri garrantzitsuenak identifikatzeko erabilitako metodologiaren aukeraketari buruz. Planteatutako metodo guztiek, ezaugarri garrantzizkoenak identifikatzen laguntzen dute, horrela arazoaren dimentsionaltasuna murriztuz eta sailkapen hobea ahalbidetuz.

2.2.2 Jarduera fisikoaren jarraipenari buruzko datuen sailkapena

Datuak segmentatu eta ezaugarri garrantzizkoenak hautatu ondoren, datuen sailkapen teknikak erabili ohi dira jarduera fisikoa sailkatzeko [11, 151] (ikusi 2.9. irudia).



Irudia 2.9: Sailkatzeko erabiltzen diren metodo ezberdinak.

Machine Learning (ML) tekniken erabilera gero eta hedatuago dago medikuntzaren eta errehabilitazioaren arloan [42]. Aplikazio desberdinetan erabiltzen diren era guztietako teknikak aurki daitezke. Sistema hauek, datu homogeneoetan talde atipikoak detektatzeko, pneumoniaren larritasuna 4 hantura-markatzaileren arabera sailkatzeko, farmako jakin batzuen eraginkortasuna aurreikusteko edo paziente batek bihotzekoa izateko duen arriskua aurreikusteko erabiltzen dira. Zeregin hauetarako hainbat ML teknika desberdin erabiltzen dira, Artificial Neural Networktik K-Nearest Neighborsra.

Teknika horiek, Jarduera Fisikoa (JF) sailkatzeko eta errehabilitazioan laguntzeko ere erabili dira [11, 151]. Jarduera Fisikoaren eremuan, erabilitako sailkapen-sistemek ondorengo informazioa ematen dute: eskailerak igotzen edo jaisten ari diren, pertsona oinez ari den edo geldirik dagoen, aldapan dabilen ala ez, etab. Eguneroko bizitzako jardueren sailkapen mota horrek, pazientearen portaera ulertzen lagun dezake. Portaera hori ezagututa, errehabilitazioko profesionalari informazio kuantitatiboa eman dakioke diagnostiko egokia egin edo/eta errehabilitazioa indibidualizatzeko.

Literaturan, sailkapena egiteko hainbat irtenbide aurki daitezke, estatistika-tekniken erabileratik teknika adimendunen erabileraraino aldatuz [161, 11, 151]. Kasu gehienetan, sailkapen sistemarako erabiltzen diren sentsoreak gorputzaren beheko gorputzadarretan jartzen dira.

Sailkatzaileak diseinatzeko orduan, metodo estatistikoak asko erabili dira ingeniaritzaren hainbat arlotan. Metodo estatistikoen artean atalasetan oinarritutako metodoak daude (thresholding). Teknika honek atalase jakin bat edo zenbait atalase erabiltzen ditu jarduera bat edo beste egiten ari den adierazteko. Sailkapen-mota honekin emaitza onak lortu dira erorikoak hautemateko [139, 46].

Erabilitako beste metodo estatistiko bat metodo hierarkikoak dira. Sailkapen hierarkikoko eskema bat aplikatzen dute, non egitura beste nodo batera eramaten duten erabaki bitarretan oinarritzen den. Elkarren segidako nodo batzuen bidez, kasuan kasuko erabakia hartzen da. Martxaren karakterizazioari dagokionez, metodo hau hainbat jarduera sailkatzeko erabiltzen [58], hala nola, eskailerak igotzen edo jaisten ari den detektatzeko. Decision Treesek, edo erabakitzeko zuhaitzek, metodo hierarkikoetan oinarritutako sailkapen-sistema bat erabiltzen dute. Egitura mota honek erabakiak hartzeko prozesua automatizatzen duten algoritmo zorrotzak eta arau multzo bat erabiltzen ditu, nodoetan erabakia konplexuagoa eginez [58, 120, 166, 111]. Kasu hierarkikoetan bezala, erabakitzeko zuhaitzek nahiko ondo funtzionatzen dute eguneroko martxako jarduerak sailkatzeko, hala nola, oinez ibiltzea edo aldapak igotzea. Hala ere, sistema hauekin lortutako emaitzak ez dira onenak, %70 zehaztasuna lortuz [166].

Jarduera fisikoa sailkatzen dituzten Naive Bayes (NB)n oinarritutako sistemak ere aurki daitezke [150, 120, 15, 193]. Naive Bayes (NB), Bayesen teoreman oinarritzen den sailkatzaile probabilistiko bat da. Aztertutako lanetan emaitza onak lortu dira, [150]-ren kasuan bezala, zehaztasuna %94 izanik.

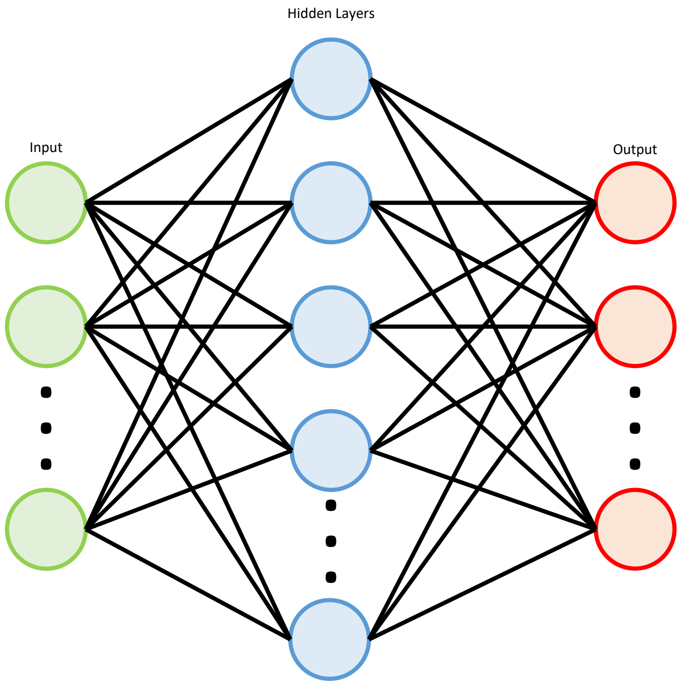
Sailkatzeko sistemen beste multzo handia Adimen Artifizialako tekniketan oinarritzen da. K-Nearest Neighbors (K-NN) Adimen Artifiziala barruan aurki daitekeen tekniketako bat da [127, 120, 150, 186, 166, 15, 38, 93, 108, 111, 149]. Metodo honek, ezaugarri multidimentsionalak dituen espazio bat eraikiz egiten du sailkapena. Entrenamendu-datu multzo batetik abiatuta, ezaugarrien espazioa sortzen da, eta hori erabiltzen da datuak entrenamendu-fasean markatutako kasuen artean sailkatzeko. Kasu honetan, JF sailkatzeko lortutako emaitzak askotarikoak dira: %73 [186], %80 [166] edo %90 [127], baina kontuan hartu behar da emaitza horiek erabilitako datuen araberakoak direla.

Aurki daitekeen beste Adimen Artifiziala teknika bat Support Vector Machine (SVM) da [66, 150, 107, 157, 64, 76, 17, 118, 188, 198, 105, 12, 38, 39]. Teknika hau, sailkatzaile linealen kategorian sar daitekeen gainbegiratutako ikaskuntza-algoritmo bat da. Entrenamendu-puntuen multzo bat edo horietako bakoitza kategoria posibleetako batekoa dela kontuan hartuta, puntu berri bat talde batekoa edo bestekoa den iragartzeko gai den eredu bat eraikitzen da teknika hau erabiliz. Metodo honek, laginak espazioan dituen puntuak irudikatzen ditu, banaketa-hiperplano baten bidez klaseak bi espazio ahalik eta zabalenetan banatuz. Datu berriak sartzen direnean, dagokien planoaren arabera, mota batean edo bestean sailkatzen dira.

K-NN-en emaitzen kasuan bezala, SVM-en emaitzak asko aldatzen dira erabilitako datuen arabera, JF sailkatzeko, %80 [107, 118] edo %98-ren [157] inguruko emaitza aurki daitezke.

Pertsona batek egiten duen jarduera fisikoa sailkatzeko erabiltzen den beste AAren metodoetako bat Fuzzic Logic (FL) da [162]. Metodo honek, gizakiok erabakiak hartzeko dugun modua imitatzen du, informazio zehaztugabea edo anbiguoa erabiliz. Teknika horri esker, zehaztasun falta handia duen informazioarekin lan egin daiteke.

Azkenik, teknika adimendunen artean, Artificial Neural Network (ANN) teknikak daude [80, 151, 76, 117, 81, 178, 17, 190, 72, 9, 187, 91, 110, 200, 150, 169, 133, 95, 148, 44, 188, 58, 157, 39, 149, 62]. Gaur egun gehien erabiltzen diren teknikak dira, mota honetako aplikazioetan emaitzarik hoberenak ematen dituztenak baitira. Teknika hauek, potentzialtasun handia dute diagnostikorako osasunaren arloetan [8], eta horregatik, nabarmen hazi dira azken urteotan [146]. Teknika hauen helburua, animalien nerbio-sistemaren funtzionamendua simulatzea da. Elkarrekin konektatutako neurona talde batzuk dira (ikusi 2.10. irudia). Emandako sarreraren eta aurreko entrenamenduan lortutako esperientziaren arabera, irteera-balio bat ematen dute. Adibidez, EMG sentsore batetik lortutako datuak eta Artificial Neural Network erabiliz, oin baten berme-faseak identifika daitezke (berme- eta kulunkatze-fasea) [133].



Irudia 2.10: ANN baten egitura.

ANN barietate handia dago, horien artean jarduera fisikoa sailkatzeko gehien erabiltzen dena Artificial Neural Network Multilayer FeedFordward edo Multilayer Perceptron (MLP) da [133, 108, 178, 95, 148, 188, 58, 157]. ANN mota hau gainbegiratutako entrenamendu-sareen taldearen barruan dago. MLP sareek sarrera eta irteera multzo bat dute, eta horiek elkarri konektatuta daude ezkutuko geruzen nodoen bitartez. Horrela, irteera-balioa, geruzen barruko transferentzia-funtzioaren eta nodoei esleitutako haztapenaren arabera lortzen da. Horrelako egiturek emaitza onak izaten dituzte: %90 [108] edo %97 [178] baino handiagoak.

Sailkapen mota hauek eguneroko bizitzako jarduerak sailkatzeko erabil daitezke. Adibidez, autore batzuek eguneroko jarduera konplexuak (jatea, lan egitea, erostea, etab.) ezagutzeko erabili dituzte [117]. Sailkapen mota hori egiteko, hainbat neurona-sareren egitura konplexua erabiltzen da. Sare neuronal horien irteerek honako hau elikatzen dute: Convolutional Neural Network (CNN) [72, 61] eta Recurrent Neural Network (RNN) [44]. Metodo hauek, jarduera konplexuak sailkatzen dituztelako erabiltzen dira; sistema horiek ez dira erabiltzen, oinez ibiltzea edo eskailerak igotzea bezalako eguneroko bizitzako jarduera sinpleagoak sailkatzeko.

Neurona-sareak gainbegiratuta "ikas"dezan, entrenamendu-algoritmo egokia behar da. Artificial Neural Network entrenamendurako erabilitako algoritmoen artean, Back-Propagation nabarmentzen dira [91, 190, 9, 187, 150, 148, 58, 157]. Halaber, ikaskuntza errazteko, aldaketak aplikatzen dira, adibidez, kasu batzuetan, sarearen pisua aldez aurretik abiarazten da [9].

Nahiz eta kasu gehienetan ezkutuko geruza bakarra izan, aplikazioaren arabera, geruza ezkutuen kopurua eta geruza bakoitzeko neuronen kopurua aldatu egiten da. Sarrera- eta irteera-geruzetako neuronak, berriz, aztertu beharreko datu-kopuruaren eta lortu nahi diren emaitzen araberakoak dira. Neurona kopuru txiki bat duten barne-geruzak erabil daitezke [9], baita neurona kopuru handi bat duten ezkutuko geruzak ere [72, 190].

Sailkatzeko erabili diren beste sare neuronal mota batzuk, memorian gordetako ereduak erabiltzen dituzten ANN probabilistikoak edo Spiking Neural Network (SNN)ak [183] dira. Hauek, informazioa sare neuronal biologikoen antzera prozesatzeko gai dira, baina abiadura handiagoa eskaintzen dute eta sarrera bitarrak onartzeko diseinatuta daude.

ANNrekin lortutako emaitzak, oro har, oso onak dira JFk sailkatzeko, erabilitako datuen arabera aldatzen direla kontuan hartuta. Oro har, %90-tik gorako balioak lortzen dira [76, 81, 178].

Azterlan batzuek hainbat tekniken arteko konparaketa egin dute. Adibidez, [150] kasuan, ANN, SVM, K-NN eta Naive Bayesen emaitzak alderatzen dira. Kasu honetan, emaitzarik onenak SVMk eta ANNk emandakoak dira, %90,6 eta %92 hurrenez hurren, beste kasuetan baino sentikortasun eta espezifikotasun handiagoarekin. SVM, K-NN eta DT lortutako emaitzen artean egindako beste azterlan konparatibo bat ageri da [166]n. Hemen ere, emaitzarik onenak SVMarekin lortzen dira, arrakasta-ehunekoa %89 delarik. Beste batek K-NN, RF, Logistic Regression (LR), Naive Bayes, ANN eta SVMren emaitzak alderatzen ditu [157], eta oso emaitza onak lortzen ditu ANN eta SVMrekin, %95tik gorakoak izanik. Beste lan batzuek ANN, SVM eta RF konparatzen dituzte, kasu guztietan antzerako emaitzak lortuz [39]: %88 ANNrentzat, %87,5 SVMrentzat eta %86,9 RFrentzat.

Sailkapen-sistemen artearen egoera aztertu ondoren, ondoriozta daiteke gaur egun batez ere Artificial Neural Network metodoa erabiltzen dela. Gehien erabiltzen den sistema izan arren, sailkatzeko beste Machine Learning sistema batzuk ere badaude, SVM adibidez. Pertsonen Jarduera Fisikoaren sailkapenari dagokionez, azterlan gehienek Jarduera Fisikoa normala sailkatzen dute, eta ez dute makulu edo makila gisa ILG erabiltzen. Bestalde, aztertutako ia lan guztiek, inbaditzaileak izan daitezkeen sentsore eramangarriak erabiltzen dituzte. Hau, makulua bezalako eguneroko elementuetan sentsoreak sartuz konpondu nahi da.

Beraz, egindako lanen emaitzek argi erakusten dute, errehabilitazioaren eta pazientearen egoeraren kuantifikazioaren esparruan, sailkatzaile gisa, teknika horiek duten ahalmena.

Taula 2.2: JF sailkatzeko buruzko azterlanen alderdi nagusiak. (A = Azelerometro, G = Giroskopio, M = Magnetometro, F = Indarra).

Azterketa	**Sentsoreak**	**Dimentsionaltasuna Murrizteko Metodoa**	**Sailkatzeko Metodoa**
[6]	3-ardatz A, GPS		RF
[9]	4x A		ANN
[12]	A, G	CFS, FCBF, Relieff	SVM
[15]	5x 3-ardatz A		Decision Tree, NB, K-NN, Decision Table
[16]	3-ardatz A, G, M		LDA, PV, PV+CS
[17]	Bideo Sistema		SVM, ANN
[32]	3-axis A	Murrizketa etaineko ezpurutasunen pruba, Greedy selekzioa	RF, Threshold
[38]	3-ardatz A	Relieff	K-NN, SVM
[39]	A	Relieff, RF, One-R, SFS, CFS eta abar	ANN, SVM, RF
[44]	3-ardatz A, G, M		RNN
[45]	3-ardatz A, G		RLE test
[46]	2x A		Threshold
[58]	3-axis A, GPS		Decision Tress, ANN, Hybrid modelua
[61]	Mukulu sentsorizatua		CNN
[64]	A, M, Kamera eta abar	PCA	SVM

2.2. taularen jarraipena

Azterketa	Sentsoreak	Dimentsionaltasuna Murrizteko Metodoa	Sailkatzeko Metodoa
[66]	A, G	PCA	SVM
[71]	3-ardatz A, G		RF
[72]	5x 3-ardatz G, A		CNN
[76]	3-ardatz A		Decision Trees, ANN, SVM, Gehiengoz bozkatzea
[81]	Kinect Sentsorea		ANN
[83]	3-ardatz A		K-means
[54]	3-ardatz A		Threshold
[91]	3-ardatz A		ANN
[93]	B, 3-ardatz A, G	Relieff, Rand Features	K-NN
[94]	3-ardatz A		Decision Trees
[95]	Smartphone A		ANN
[103]	A		RF, Gradient Boosting
[108]	Bisio sentsoreak		K-NN
[110]	A, G	PCA	ANN
[109]	A		Threshold
[111]	3-ardatz A, Mikrofonoa, Argi Sentsorea		K-NN, Decision Tree
[112]	3-ardatz A	PCA	Bayesian
[118]	3x 3-ardatz G, A		SVM
[120]	eWatch (A)	Correlation based, CFS	Decision Trees, NB, K-NN, Bayes Net
[117]	Multimodal sentsoreak	CNN	ANN
[127]	5x ReSense eramangarria (P, A, G)	Relieff	K-NN
[133]	EMG		ANN
[138]	1-ardatz A		Rand-en zuzenean espazio korrelazioa, onden koefiziente diadiko diskretua
[139]	A, B		Threshold

2.2. taularen jarraipena			
Azterketa	**Sentsoreak**	**Dimentsionaltasuna Murrizteko Metodoa**	**Sailkatzeko Metodoa**
[148]	Smartphone (A, G, M)		
[149]	2-ardatz A, G, F, Argi sentsorea, Bihotz erritmoa sentsorea, 3-ardatz A	Atzera eta aurrera bilaketa	K-NN, ANN
[150]	F alfonbra	PCA	ANN, SVM, K-NN, NB
[157]	3-ardatz A		SVM
[159]	Makila sentsorizatua		Metodo estadistikoak
[162]	2-ardatz A		Fuzzy Logic
[166]	3-ardatz A		Decision tree, K-NN, Ensemble metodoa
[169]	Bision, F		ANN
[178]	EMG, Bideo kamerak		ANN
[188]	A	SVM	ANN, SVM
[187]	3-ardatz A		ANN
[186]	A	LDA	K-NN
[190]	A, Oin etengailua		ANN
[193]	A, G, ECG		NB
[200]	F		RBF sareak
[202]	3-ardatz A		Threshold

2.3 Erorikoak detektatzeko metodologiak

Eroriko baten ondorioz gerta daitezkeen lesioek, errehabilitazio beharra sor dezakete. Hau prebenitzeko asmoarekin, gero eta ohikoagoa da eguneroko bizitza monitorizatzen duten sentsoreak erabiltzea (ikusi 2.3. taula). Sentsore hauei esker, erorketa bat gertatu dela detektatu eta osasun langileei edo senitartekoei abisatzen zaie, funtsezkoa izan daitekeen erreakzio azkar bat eraginez.

2.3.1 Erorikoak detektatzeko sentsoreak

Erorikoak detektatzeko, hainbat detekzio-gailu erabil daitezke. Gailu hauek, alarma-seinale bat sortzen dute eroriko gertatu dela zaintzaileei abisatzeko.

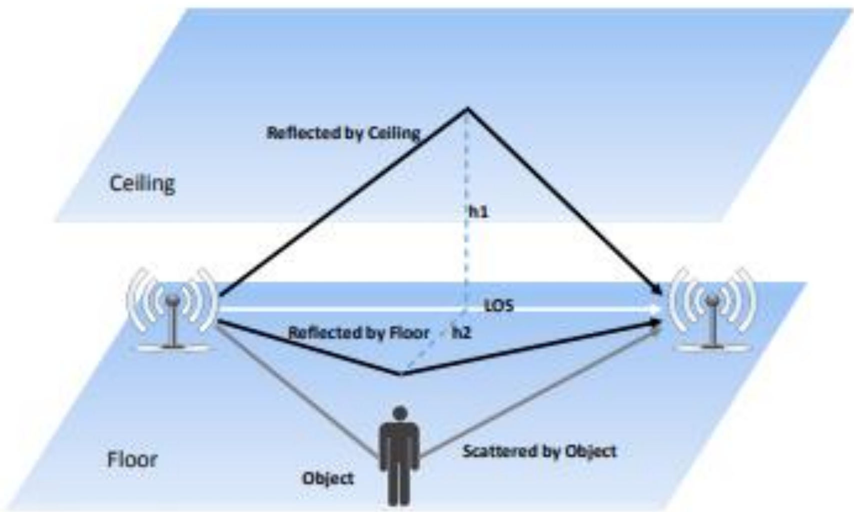
Literaturan aurki daitezkeen detekzio-sistemen artean, neurtzen dituzten aldagaien arabera 3 gailu-multzo bereiz daitezke [144, 129, 154]: 1) ikusmen-sistemak; 2) ingurunea detektatzeko sistemak; eta 3) sentsore jantzietan oinarritutako sistemak.

Erorketak detektatzeko sentsoreen lehen kategoriaren barruan, ikusmen-sistemetan oinarritzen direnak daude. Elementu horiek erorikoen detektagailu gisa erabiltzea nahiko zabalduta dago, eta zeregin hori egiten duten gailu ugari aurki daitezke [18, 50, 108, 115, 137, 156, 67, 167, 75]. Normalean, merkatuan aurki daitezkeen ohiko kamerak erabiltzen dira. Kasu batzuetan gauez (edo ilunetan) funtzionatzeko egokitzen dira. Neurketa egin ondoren, datu horiek prozesatu beharra dago [50, 115] (ikusi 2.11. irudia). Ikusmenean oinarritutako sistemek, arrakasta-tasa altua dute, %91 [156] eta %96 [50] bitartekoa, erorketen detekzioan. Gainera, eroritako pertsonaren irudi bat eman diezaiokete abisua jasotzen duenari, erori den pertsonaren egoera aldez aurretik ezagutzeko aukera emanez. Hala ere, sistema horiek hainbat eragozpen dituzte. Eragozpen aipagarriena, kameraren irismen txikia da (normalean gela jakin batera mugatzen da), honek detektagailu hauen aplikagarritasuna mugatzen baitu. Sistemaren irismena handitu daiteke sentsore kopurua gehituz, baina horrek sistemaren prezioa eta konplexutasuna handituko lituzke. Gainera, etengabe aktibo dauden ikusmen sistemak edukitzeak pribatutasun arazoak eta haienganako mesfidantza eragin ditzake [108, 21].

Irudia 2.11: Ikusmenean oinarritutako erorikoak detektatzeko sistema [50].

Erorikoak detektatzeko gailuen bigarren multzoan, ingurumen-seinaleen aldaketan oinarritzen diren sistemak daude [129]. Sistema hauek hainbat seinaleren neurketan oinarritzen dira: irrati-seinaleak [87, 189, 160], soinu-seinaleak [34, 201, 56] edo lurzoruaren bibrazioak [7].

Lehen taldea, abiadura-aldaketa bat dagoenean islatutako irrati-seinalearen maiztasunean izandako aldaketetan oinarritzen da [87]. Gailu hauek, erorketen %97a baino gehiago detektatzeko ahalmena dute. Beste ikuspegi komun bat, gorputzaren posizioa triangelatzeko irrati-seinaleak erabiltzea da (ikusi 2.12. irudia) [189]. Maiztasun-aldaketak detektatzen dituzten sentsoreen kasuan bezala, emaitza onak, %94 ingurukoak, lortzen dira erorikoak hautematean. Erorikoak behar bezala detektatzeko gai diren arren, erorketa bat beste ekintza mota batzuekin, adibidez posizio aldaketa batekin, nahastu dezakete, positibo faltsu ugari sortuz.



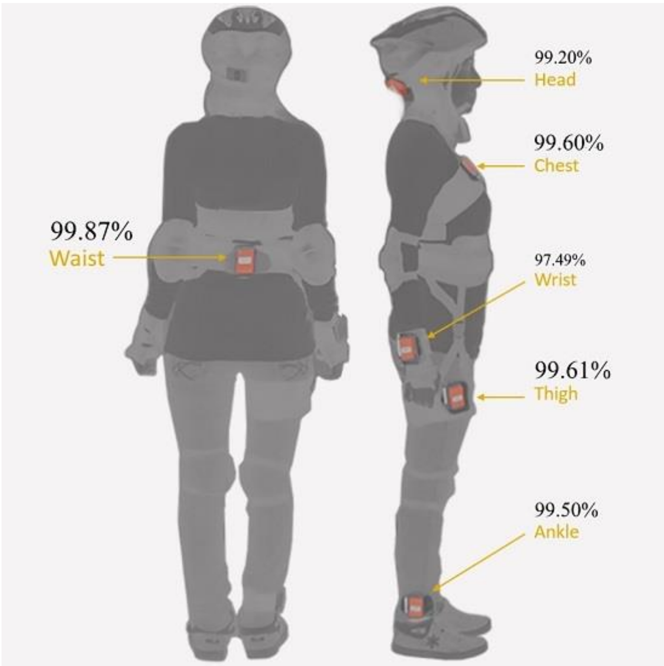
Irudia 2.12: Irrati bidezko posizionamendu-sistema [189].

Bigarren taldean, soinuan oinarritutako sistemek daude [34, 201]. Sentsore mota honen erabilerak %98 inguruko arrakasta-tasa dauka [34]. Gainera, sistema hauen inplementazioa nahiko erraza da eta mikrofono kopuru txikia eskatzen du. Hala ere, inguruneko eta kanpoko zaratek eragin diezaiokete, erorketen detekzioaren zehaztasuna txikituz. Gainera, ikusmen-sistemek bezala, pribatutasun-arazoak sor ditzakete.

Azkenik, bibrazioan oinarritutako sistemak, lurzoruko bibrazio-patroiak identifikatzen dituzte [7]. Sistema hauek, egoera kontrolatu batean izandako erorketen %100 detektatzea lortzen da. Gainera, ez du aurreko irtenbidearen pribatutasun-arazorik, baina kanpoko zaratek eta bibrazioek haren eraginkortasuna mugatzen dute.

Ingurumeneko seinaleak hautematean oinarritutako detektagailuek, ikusmenekoek baino kostu txikiagokoak izan arren, hauek ere, espazio espezifikoetara mugatuta daude.

Aurreko bi soluzioen arazoa konpontzeko, hirugarren soluzio multzo handia sentsore jantziak edo eramangarriak dira. Beraien tamaina txikiari esker, gorputzeko ia edozein ataletan jar daitezke. Multzo honetako gailu gehienak sentsore inertzialetan oinarritzen dira, bereziki azelerometroetan [197, 35, 37, 53, 57, 181, 182, 114, 97, 142, 10, 67, 131]. Era berean, lan batzuek IMUak erabiltzea proposatzen dute. Informazio gehiago lortzeko, beste sentsore batzuekin konbinatzen dira, hala nola giroskopioekin edo magnetometroekin, [153, 136, 141, 44] (ikusi 2.13. irudia).



Irudia 2.13: Sentsore eramangarrietan oinarritutako sistema: posizio bakoitzeko arrakasta-tasa [141].

Soluzio gehienak aurreko gailuetan oinarritzen badira ere, egile batzuek beste soluzio batzuk proposatu dituzte, hala nola, barometroen [20] edo smartphone eta smartwatchetan integratutako azelerometroen eta giroskopioen erabilera [3, 92, 119, 104, 128], edo mikrofonoarena [34].

Sentsore jantzien ezaugarririk garrantzitsuenetako bat pertsonak soinean eraman behar dituela da, eta horrek neurtzeko gaitasuna handitzen du. Hala ere, kontutan izan behar da, sentsoreak kokatzen den posizioak garrantzi handia duela, jasotako seinaleak posizio erlatibo horren arabera aldatuko baitira.

Egileen artean adostasun argirik ez dagoen arren, gehienek sentsoreak gerrian jartzea erabaki dute [35, 53, 114, 182, 20, 54]. Hala ere, badira eskumuturrean [197, 181, 67], oinean [57] eta bizkarrean [136] erabiltzea proposatzen duten autoreak ere. Azken ikerketetan, sentsoreen kokapen optimoa definitzen ahalegindu dira, orkatilekin, bularrarekin eta gerriarekin lotutako posizioak ebaluatuz [37], eta horiei burua, eskumuturrak eta izterra gehituz [141]. Bi ikerketek ondorioztatzen dute, erorikoak detektatzeko egokiena sentsorea gerrian kokatzea dela, nahiz eta emaitza ezin hobeak lortzen diren sentsorea bularrean jarrita ere [37, 10].

Smartphone-ak sentsore gisa erabiltzea proposatzen dutenek ere [44], aztertu dute erorketen detekziorako zein den posizio egokiena [3]. Kasu honetan, smartphone-a gerrikoan edo poltsikoan jartzea aztertu dute, kasu bietan antzeko emaitzak lortuz.

Laburbilduz, sentsore jantzien abantaila nagusia irismena da, berain erabilera ez baitago eremu jakin batera mugatuta. Hala ere, kokapenaren arabera, erabiltzailea gogaitu dezake, batez ere adinekoa bada. Gainera, sor daitezkeen zarata parasitoak ezabatzeko, kasu gehienetan, posizionamendu egokia eskatzen dute. Adibidez, Smartwatch eta smartphonen kasuan, gailuen mugimendu parasitoak poltsikoan edo eskumuturrean iragaztea oraindik irekita dagoen ikerketa-eremu bat da.

Bestalde, erorikoak detektatzeko asmoarekin, pixkanaka-pixkanaka sentsoreak ibiltzeko laguntza gailuetan gehitzen ari dira [195, 65, 99]. Horien artean daude makil instrumentatuetan [99, 195, 40] edo makuluetan [65] sentsoreak dituztenak. Horrelako elementuetan, askotan sentsore bat baino gehiago erabiltzen da erorikoak detektatzeko. Konbinazio tipikoen barruan sartzen dira indar-sentsoreak eta sentsore inertzialak erabiltzea [99, 65], edo GPSa duten sentsore inertzialak eta bihotz-sentsore bat konbinatzea [195]. Hauen abantaila nagusia, sentsoreak gailuan kokatuta daudela da, beraz, ILGaren erabiltzaileak ez litzateke posizionamendu zuzenaz arduratu beharko.

Laburbilduz, aipatutako gailu guztiak erorikoak detektatzeko gai diren arren, bakoitzak bere abantaila eta eragozpenak ditu, testuinguruaren eta erabiltzailearen arabera egokiagoak edo desegokiagoak egiten dituztenak. Ikusmen-sistemetan edo ingurumen seinaleetan oinarritutakoak, lan eremutik (gela kontrolatutik) aterata, eragina izateari uzten diote, gailu gehiago instalatzea eskatuz, eremu handiak estaltzeko. Gainera, berain erabilera, barnealdeetara mugatuta dago. Bestalde, ingurumen-seinaleen aldaketak detektatzen dituzten sistemei, zarata moduko kanpo perturbazioek eragin diezaiekete.

Zentzu horretan, sentsore jantziek erabilera eremua handiagoa dute, baina beraien inbasioa handiagoa da eta erabiltzaileei traba egin diezaiokete. Hori bereziki kritikoa da mugitzeko makuluak edo makilak behar dituzten pertsonentzat. Gailu hauen erabilera ezinbestekoak denez, erorikoak detektatzeko edo beste monitorizazio-jarduera batzuk egiteko sentsoreak hauetan kokatu daitezke. Modu honetan, erabilera eremua handitu daiteke, erabiltzaileri enbarazurik egin gabe. Abantaila ugari izan arren, oraindik irekita dagoen potentzial altuko ikerketa eremu bat dela ikusten da.

2.3.2 Erorikoak detektatzeko datuen prozesamendua

Erorikoak detektatzeko, aipatutako sentsoreek emandako datuak modu egokian prozesatu behar dira. Horretarako, bi ikuspegi nagusi daude. Lehenengoa, sentsoreek neurtutako datu gordinak erabiltzean datza [197, 181]. Datu horiek sare neuronaletan sartzean dira zuzenean. Planteamendu honek, kostu konputazional handiagoa du, eta soluzio suboptimoak eta ez oso interpretagarriak eskaintzen ditu.

Bigarren ikuspegia, denborazko seriearen informazioa metriketan definitzea eta arazoaren dimentsionaltasuna murriztea ahalbidetzen duten, ezaugarri garrantzitsuenak aukeratzean datza [57, 135, 141, 182, 119, 142, 102]. Ezaugarri gehienak denbora-leihoei estatistikoak aplikatuz lortzen dira (batez bestekoa, bariantza, zurrosia, autokorrelazioa...).

Datuak zatitu eta ezaugarri garrantzitsuenak definitu ondoren, sailkatzaile bat diseinatu behar da, eroriko bat egon den ala ez zehazteko. Sailkatzaile hau diseinatzeko, Machine Learning teknika aplikatu izan dira [134]. Teknika horien barruan, sailkatzaileak definitzeko teknika ugari aurki daitezke [154].

Erorikoak detektatzeko gehien erabiltzen den tekniketako bat Artificial Neural Network da [5, 136, 181, 182, 197, 141, 18, 34, 53, 114, 135, 137, 119, 87]. Artificial Neural Networkak hainbat motatakoak izan daitezke. Sare neuronalen soluzio klasikoenen artean MLP topologia da erabiliena [136, 135, 53, 181, 182, 141]. Teknika honetan, batez ere, sentsoreetako seinaleetatik ateratako ezaugarrietatik abiatuta sailkatzen dira erorketak. Neurona-sareen eraginkortasuna entrenamendu-prozesuaren araberakoa den arren, MLPen bitartez erorketen %98a detektatu daitekela frogatu da [182]. Ikerketa horretan, 11 erabiltzailek 11 erorketa desberdin simulatu dituzte. Neurketak egiteko erabiltzailen gerrian azelerometro triaxial bat kolokatu da.

Autore batzuek, erorikoak detektatzeko teknika konplexuagoak erabiltzen dituzte [87, 197, 119, 114, 137, 67, 160]. Horien artean dago RNN, azelerometroen neurketekin oinarrituz, erorikoak detektatzen dituena [114, 119]. Sistema mota honek, datu ugariko datu-basea behar du entrenatzeko. Gainera, lehen aztertutakoak ez bezala, neuronen irteerako datuen atzeraelikaduran oinarritzen dira, denbora-tarte jakin batean sailkapena lortzeko. Erabilitako beste teknika konplexuetako bat CNN da [137, 67, 160]. Teknika mota horretan oinarritutako sareak irudiak ezagutzeko erabiltzen dira normalean. Irudiak sarreratzat hartzen dituzte, eta irudietako elementu batzuei pisu bat ematen zaie. Honela, sareen ezkutuko geruzak irudiaren elementu horiek ezagutzeko gai dira. Geruza bakoitza ezagutza-mota batean espezializatzen da; horrela, ezkutuko geruza guztiak konbinatuz, forma konplexuagoak ezagutzeko gai da. Sare konplexu horiek denbora eta kontsumo konputazional handia eskatzen dute. Mota horretako sistemek, erorketen %94 [137] edo %100 [197] detekta ditzakete.

Neurona-sareez gain, Machine Learning teknikek, SVM moduko sailkapenera bideratutako beste teknika batzuk ere badituzte [136, 37, 57, 119, 141, 201, 97, 20, 142, 128, 56]. Teknika horiek, sailkatu beharreko klaseak dauden eskualdea mugatzen duten, bektoreak eraikitzen dituzte. Bektore horiek lortzeko, mota desberdinetako puntuak ematen dituzten entrenamenduak behar dira. MLP sareetan oinarritutako sistemen kasuan bezala, batez ere seinale prozesatuen ezaugarriekin lan egiten dute. Teknika hauekin oso arrakasta ona lortu dute, %98-tik gorakoa [57].

K-NN teknikak, saikapenerako asko erabili izan ohi diren beste Machine Learning teknika bat dira [50, 108, 142]. Teknika honek, SVMaren antzeko aplikazioa du, eta %96-ko asmatze-tasak lortu ditu erorketen detekzioan [50].

Azkenik, erorikoak detektatzeko gutxiago erabiltzen diren beste teknologia batzuk aurki daitezke. Besteak beste, erorketak detektatzeko, Thresholds, erorketak detektatzen dituzte parametroetako batek edo batzuek muga bat gainditu dutela detektatzen duena [7, 35, 153, 195, 104]; Naive Bayes, gainerakoen ezaugarrietako bakoitza independizatuz sailkatzen duena [119, 3, 141, 142]; Fuzzic Logic aldagaiak prozesatzeko ikuspegia duena [53]; Decision Trees [3, 99] eta Random Forest [189, 142] arauetan oinarritutako sistemak [92], Logistic Regression [18, 142] edo LSM oinarritutakoak [34, 141] erabiltzen dira.

Oro har, ez dago adostasunik teknika baten eta bestearen arteko egokitasunari buruz. Ildo horretan, zenbait autorek konparazioak proposatu dituzte tekniken eraginkortasuna ebaluatzeko. [3]n egileek K-NN, Decision Trees eta Naive Bayes alderatzen dituzte, eta emaitzarik onena DTk ematen duela erakusten dute, nahiz eta Naive Bayesk lortutako emaitzak antzekoak izan. [119]n SVM, Naive Bayes eta RNN alderatzen dituzte, eta emaitzarik onenak azken horretan lortu dituzte (%100), SVMren %93,45rekin alderatuta. [141]n hainbat teknologia konparatzen dira, sinuen posizionamendua eta K-NN, SVM, gutxieneko karratuak, erabaki bayestarrak hartzea, denbora-distortsio dinamikoa eta ANN. Emaitzarik onena K-NN erabiliz lortzen da, baina kasu guztietan zehaztasuna %90 baino handiagoa da.

Ondorioz, erorikoak detektatzeko erabiltzen diren tekniketan barietate handia dagoen arren, ANN edo SVMn oinarritutako sistemak erabiltzeko joera dago. Oro har, erorketak detektatzeko erabiltzen diren teknologia guztiek %90etik gorako arrakasta dute. Nahiz eta, RNN bezalako teknika batzuekin %100eko asmamena lortzen duten, teknika horiek kostu konputazional handiagoa dute eta lagin gehiago behar izaten dituzte ondo funtzionatzeko, detektagailu horien garapena garestituz.

Teknologia horiek beste arlo batzuetan erabili ohi dira, eta horrek ezagunagoak egiten ditu. Gainera, teknologia horiek aplikatzeko errazak dira eta ez dute datu-base handiegirik behar.

Taula 2.3: Erorketen detekzioari buruzko azterlanen alderdi nagusiak. (A = Azelerometro, G = Giroskopio, M = Magnetometro, F = Indarra).

Azterketa	Sentsoreak	Sentsore Posizioa	Detekzio Metodoa
[4]	Smartphone A	Poltsiko, Gerriko	Decision Trees, K-NN, NB
[5]	Bideo		ANN
[10]	A, G	Bular	Threshold
[18]	Bideo		SVM, ANN, LR
[34]	Smartphone audioa	Poltsiko	K-NN, SVM, LSM, ANN
[35]	A	Gerria	Threshold
[37]	3-ardatz A	Poltsiko, Bular, Gerria	SVM
[44]	Smartphone IMU	Poltsiko	RNN
[50]	Bideo		K-NN
[53]	A	Gerria	Fuzzy logic, ANN
[57]	A	Oina	SVM
[61]	IMU	Makulu sentsorizatua	Threshold, Gertaera
[65]	F, 3-ardatz G	Makulu sentsorizatua	Threshold
[87]	Radar		Deep Learning
[92]	Smartwatch	Eskumutur	Threshold
[99]	F, 3-ardatz A, G	Makulu sentsorizatua	Threshold
[108]	Bideo		K-NN
[114]	A	Gerria	RNN
[115]	Bideo		Fluxu optikoaren aldaketa
[119]	Smartwatch A	Eskumutur	SVM, NB, DL
[136]	3-ardatz A 2x G	Sorbalda, Gerriko	ANN, SVM
[137]	Bideo		CNN
[141]	6x 3-ardatz A, G, M	Burua, Orkatila, Gerria, Eskumutur, Bular, Izter	K-NN, SVM, LSM, BDM, ANN, DTW
[142]	Sentsore Inertziala	Sorbalda	SVM, K-NN, LR, NB, RF
[153]	A, G		ANN, Threshold
[181]	3-ardatz A	Eskumutur	ANN
[182]	3-ardatz A	Gerria	ANN
[189]	Radio seinalea		SVM, RF
[196]	GPSG, G, Bihotz erritmo sentsorea	Makulu sentsorizatua	Angulu identifikazioa
[197]	3-ardatz A	Eskumutur	ANN

2.4 Ondorioak

Kapitulu honetan aipatu den bezala, Jarduera Fisikoa sailkatzeko eta erorikoak detektatzeko sentsoreak erabiltzeak abantaila ugari ekar ditzake. Ikerketa-arlo honetan aurrerapen nabariak egin badira ere, oraindik hobetu beharreko hainbat alderdi daude.

2.1. kapituluan adierazi den moduan, sentsore mota jakin batzuen erabilerak eragozpen asko izan ditzake. Gehien erabiltzen diren sentsoreak, sentsore jantziak eta ikusmenean oinarritutakoak, erabiltzaileentzako ezerosoak dira edo pribatutasun-arazoak dituzte. Nahiz eta sentsore jantziak emaitza onak lortu helburu jakin baterako erabiltzen direnean, behar bezala jartzeko zailtasunak neurketan akatsak eragin ditzake. Gainera, zarata parasitoak sor ditzakete, arropa edo gorputzaren gainean jartzen direlako, eta horrek sailkapen okerra eragin dezake. Egoera honen aurrean, sentsoreak ILG kokatzeak onura nabarmenak ekar ditzakeela ikusi da. Sentsoreak ILGn integratzea erabaki duten ikertzaileek, hainbat sentsore mota erabiltzen dituzte. Gehienek, sentsore inertzialak erabiltzen dituzte egindako mugimendua neurtzeko, eta erabiltzaileak egindako indarra, indar-sentsoreen bidez neurtzen dute.

Laguntza gailu sentsorizatu asko aurki daitezkeen arren, gehienak ILGren menpe daude, hau da, erabiltzaileak ILG bat bera erabili behar du aldioro. Hau arazo bat izan daiteke, pertsona bakar batentzat egokia den Ibiltzeko Laguntza Gailuak ez baitu zertan beste pertsona batentzat funtzionatzen duenaren berdina izan behar. Gainera, Ibiltzeko Laguntza Gailuako sentsore askok inpraktikoak egiten dituzte erabiltzeko. ILGra egokitzeko gai diren sentsore-sistemak erabiltzea ustiatu gabeko eremua da. ILGra egokitzeko moduko sentsore-sistemak diseinatzea azterketa-eremu interesgarria da, aukera ematen baitu sentsoreak erabiltzailearentzat erosoena den ILGra egokitzeko. Horregatik, doktore tesi honetan, **ILGen artean egokitzeko eta trukatzeko gai den punta sentsorizatu bat diseinatzen da**.

2.2. kapituluan azaldu denez, lortutako datuen tratamendua eta sailkapenerako erabilitako metodologia ere garrantzi handikoa da. Jarduera fisikoak sailkatzeko jarraitutako metodologia honela banatu ohi da: datuak egokitzeko fasea, ezaugarriak sortzeko fasea, ezaugarriak murrizteko fasea eta, azkenik, sailkapen-fasea. Aztertutako lan gehienek egitura hori jarraitzen duten arren, horretarako erabilitako metodoak askotarikoak dira. Datuen egokitzapenaren kasuan, leihoak zatitzean oinarritutako metodologiak aurkeztu ohi dira, leiho mota kasu bakoitzaren beharren arabera aldatuz. Ezaugarriak sortzeko prozesua aztertuz gero, gehienek kalkulu estatistikoetan oinarritutako ezaugarriak erabiltzen dituzten arren, beste ezaugarri batzuk erabiltzen dituzten lanak ere aurki daitezke. Ezaugarrien dimentsionaltasuna murrizteari dagokionez, estrategia ugari erabiltzen dira, ia guztiak emaitza onak ematen dituztelarik. Sailkapenerako erabilitako metodologiak aztertuta, barietate handia aurki daiteke, baina kasu gehienetan Machine Learning oinarritutako metodologiak erabiltzen dira, SVM, K-NN edo ANN bezala. Horregatik guztiagatik, doktorego-tesi honek, ILGari akoplatutako punta sensorizatuak neurtutako datuetan oinarrituta, **Jarduera Fisikoakoa sailkatzaileko sistema adimenduna** garatzea proposatzen du.

2.3. kapituluan adierazi den moduan, esan behar da erorikoak detektatzeko erabiltzen diren elementu gehienak sentsore eramangarriak direla. Sentsore hauek ingurune desberdinetan erorikoak detektatzeko gai badira ere, eragozpen ugari dituzte, beti behar bezala kokatuta egon behar dira eta gogaikarriak izan daitezke erabiltzaileentzat. Nahiz eta gaur egunean gutxi landutako alor bat izan, irtenbide praktiko eta egokienetako bat Ibiltzeko Laguntza Gailuan erorikoak detektatzeko gai diren sentsoreak gehitzea izan daiteke. Horregatik, doktorego-tesi honek, punta sentsorizatua erabiliz **erorikoen detektagailu** bat diseinatzea proposatzen du, eroriko baten ondorioengatik errehabilitazio beharra murrizteko. Bestalde, erorikoak detektatzeko gehien erabiltzen diren metodoak Machine Learning sistemetan oinarritzen dira, batez ere ANN eta SVM sistemetan.

Hurrengo ataletan tesian egindako garapenak azalduko dira. Hau da, kapitulu honetan aztertu eta hauteman diren arazoei irtenbide berriak emango zaizkie.

3 Jarduera fisikoa sailkatu eta erorikoak detektatzeko Punta sentsorizatua

Kapitulu honetan, Jarduera Fisikoa (JF) monitorizatzeko/kuantifikatzeko eta erorketak detektatzeko punta sentsorizatu adimenduna garatzeko egindako lanaren laburpena aurkezten. Doktorego tesi hau, artikuluen bildumaren bidez aurkezten denez, atal honetan, 1. eranskinean [28], 2. eranskinean [126] eta 3. eranskinean [125] egindako lanak laburbiltzen dira. Artikulu horietan aurkitu daiteke egindako lanaren inguruko informazio zehatzagoa.

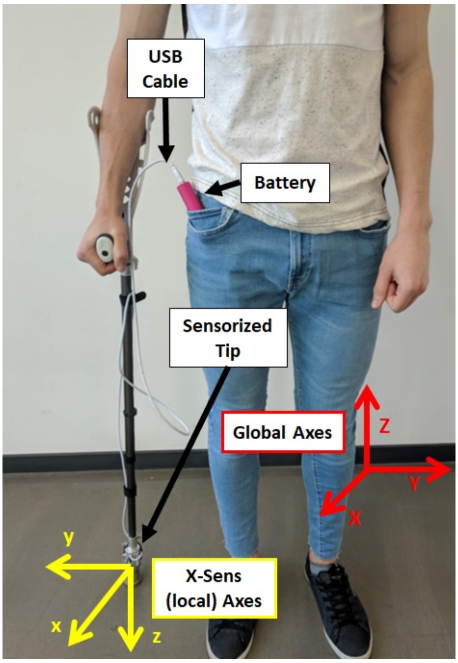
3.1 Ibiltzeko Laguntza Gailurako Punta sentsorizatua

Atal honetan, Jarduera Fisikoa monitorizatzeko diseinatutako punta sensorizatu aldagarriaren diseinua laburbiltzen da. Atal honen azalpen zehatza 1. eranskinean [28] aurki daiteke. Artikulu hau, *Sensors* izeneko sarbide irekiko aldizkarian argitaratu da.

2.1. kapituluan, jarduera fisikoa detektatzeko Ibiltzeko Laguntza Gailua (ILG) desberdinetan txertatutako sentsoreak aztertu ondoren, Punta sensorizatu bat garatzea erabaki zen. Punta sensorizatu honen garapenaren helburua ILG bat daramaten pertsonen Jarduera Fisikoa neurtu ahal izatea da. Hainbat ILGetara egokitu daitekeen Punta sensorizatu baten bidez, gaur egunean JF monitorizatzeko erabiltzen diren sentsoreen arazo nagusie erantzuna eman nahi zaie.

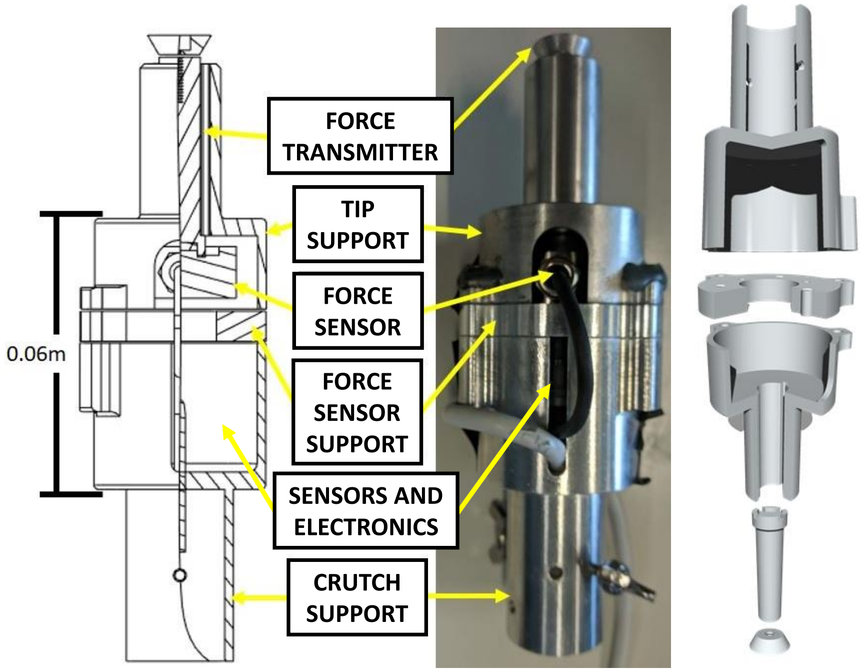
3.1.1 Punta sentsorizatuaren prototipoa

Puntu sentsorizatu hau osatzen duen sistemak bi elementu nagusi ditu (ikusi 3.1. irudia): 1) sentsoreak eta sentsoreetatik lortutako datuak prozesatzeko eta bidaltzeko elektronika dituen Punta sensorizatua; 2) Punta sentsorizatuaren elektronika guztia elikatzen duen 5V-ko USB bateria estandar bat. 2.1. kapituluan aipatutako beste ILG sensorizatu ez bezala, Punta sensorizatu hau edozein ILG-i (makulu, makila...) akoplatzeko diseinatuta dago, atxikitze-sistema sinple baten bidez.



Irudia 3.1: Sistemaren elementuak eta erreferentzia-ardatzak.

Punta Sentsorizatuaren egitura, diseinu propiokoa da (patentearen zain), eta barnean, sentsoreak, datu-prozesadorea eta bidalketa-sistema ditu. Egitura hau aluminioz diseinatuta dago eta pisua baxukoa da. Punta sensorizatuaren pisua (sentsoreak barne eta kanpoko bateria kontutan eduki gabe) 180g da. Bere luzera (0,06m), makuluaren altuera doitzeko hautatu da, izan ere, makulu estandar batean, hiru posizioren arteko distantzia 0,06m baita. Punta Sentsorizatuaren egiturak 5 zati ditu (ikusi 3.2. irudia): makuluaren euskarria; sentsore gehienak eta prozesadorea ILGren zurtoinera lotzen dituen euskarria; indar-sentsorea eta honen euskarria; indar-sentsoreari indar axiala transmititzen dion indar-transmisorea; eta indar-sentsoreari eusten dion euskarria.



(a) (b)

Irudia 3.2: Punta sentsorizatuaren egitura mekanikoa.

Punta Sensorizatuak JFko hainbat aldagai neurtzen dituzten sentsore desberdinak ditu. 2.1. kapituluan aipatu bezala, aldagai garrantzizkoenak ILGren mugimendua eta erabiltzaileak ILGn aplikatutako indarra dira. Lan desberdinetan erabilitako elementuak kontuan hartuta, kasu honetan, 3 ardatzeko azelerometroa, 3 ardatzeko giroskopioa eta 3 ardatzeko magnetometroa dituen, X-Sens Inertial Measurement Unit (IMU) MTi-1 bat inplementatuko da. IMU horrek, adierazitako sentsoreen datuez gain, Roll-Pitch-Yaw angelu absolutuen balioa ere ematen du. Bestalde, indar axiala neurtzeko, HBMko C9C sentsorea erabiltzen da. Indar-sentsore horren irteera-seinalea egokitzeko, seinalea anplifikatzeko zirkuitu bat gehitu da. Azkenik, Boshek garatutako BMP280 sentsore barometrikoa du.

Sentsore horiek neurtutako datuak prozesatzeko unitate baten bitartez irakurtzen dira. Unitate horrek, datuak prozesatu eta Bluetooth bidez datuak eskuratzeko kanpoko sistema batera bidaltzen ditu. Datuak prozesatzeko unitate hau, nRF52 IC prozesadore batean oinarritutako BLE Nano v2 bat da. IMUak eta barometroak I2C komunikazioaren bidez bidaltzen dituzte datuak BLE Nanora; indar-sentsoreak, berriz, BLE Nanoaren sarrera analogikoetako bat erabiltzen du. BLE Nano prozesadoreak, eskuratutako datuak Bluetooth Low Energy (BLE) bidez bidaltzen ditu. BLEren energia-kontsumo txikiari esker, punta sentsorizatuak ez du bateria asko kontsumitzen. Zehatzago esanda, energia-kontsumoa 0,225Wkoa da 5Vra.

Taula 3.1: BLE paketeen datuak

Lehenengo Paketea	**20 Bytes**	**Bigarren Paketea**	**20 Bytes**
	Bits Zenbakia		*Bits Zenbakia*
Iterazioa	**4**	Iterazioa	**4**
Indarra	**16**	Azelerometroa	**45**
Altuera	**32**	Y ardatza	20
Euler Anguluak	**78**	Z ardatza	25
Roll	26	Giroscopio	**60**
Pitch	26	X ardatza	20
Yaw	26	Y ardatza	20
Azelerometro	**30**	Z ardatza	20
X ardatza	25	Magnetometro	**48**
Y ardatza	5	X ardatza	16
		Y ardatza	16
		Z ardatza	16

BLE Nanok sentsoreetatik eskuratutako datuak Bluetooth bidez ordenagailu edo smathphone batera bidali eta bertan gordetzen dira. Bidali beharreko datuak bi paketetan sartu eta 50Hz-ko maiztasunarekin bidaltzen dira. 3.1. taulan agertzen den moduan, guztira 40 byte bidaltzen dira laginketa-aldi bakoitzean.

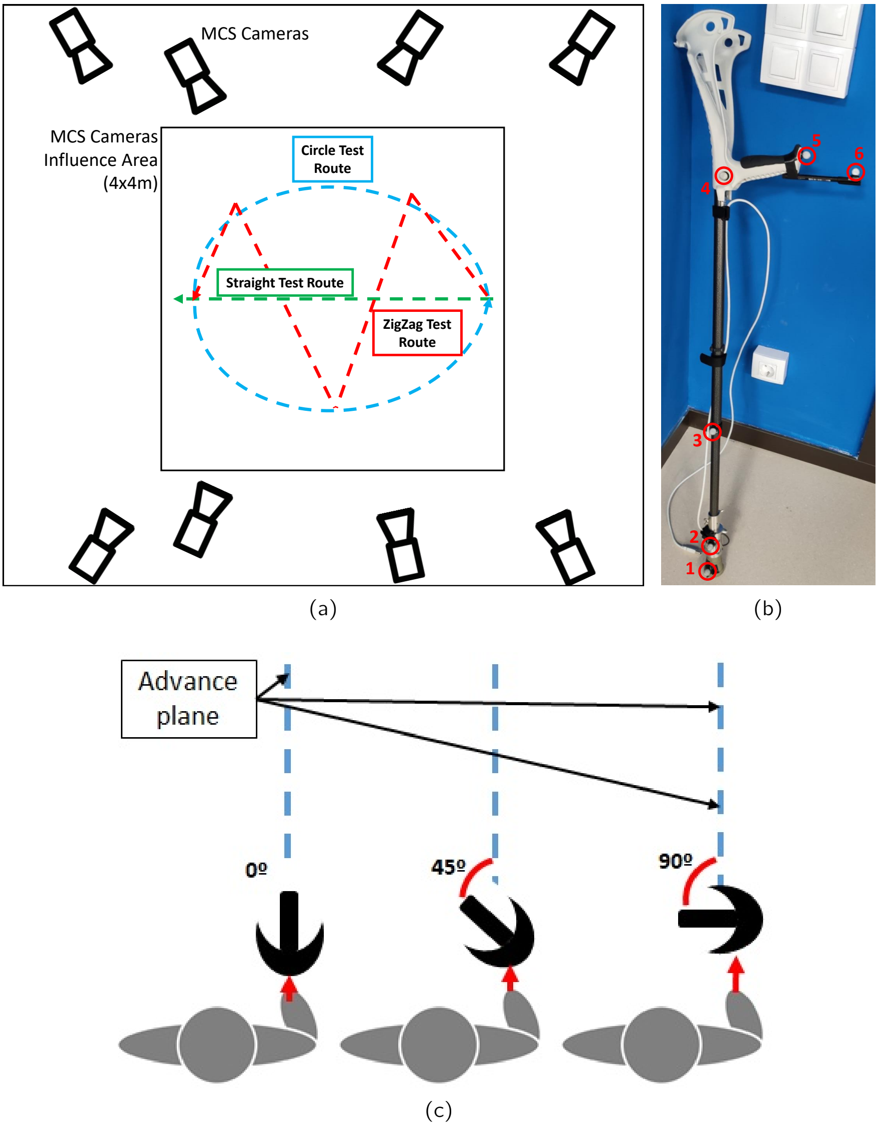
3.1.2 Neurketa-erroreen karakterizazioa

Puntu sentsorizatuaren zehaztasuna ezagutzeko, atal honetan, erabilitako sentsoreen errorea analisatzen da.

X-Sens sentsoreak emandako Eulerren angeluak baliozkotzeko, Punta sentsorizatuak neurtutako datuak, UPV/EHUn instalatutako 3D VICON mugimendua atzemateko sistemak emandakoekin alderatzen dira. Sistema honek, 4x4 m-ko eremua estaltzen duten 8 kamera ditu (ikusi 3.3a. irudia). Kamera-sistema honekin neurtu ahal izateko, 6 markatzaile islatzaile gehitzen dira Punta sensorizatuarekin erabiltzen den makuluan (ikusi 3.3b. irudia).

Eulerren angeluak baliozkotzeko hainbat proba desberdin diseinatu dira. Bost ibilbide hartu dira kontuan (ikusi 3.3a. irudia): lerro zuzenean 4m egiteko hiru proba, makuluaren heldulekuaren orientazio desberdinekin (gutxi gorabehera 0°, 45° eta 90° errotaziokoak) (ikusi 3.3c. irudia); sigi-sagako ibilbide bat (0° errotaziokoa) eta ibilbide zirkular bat (0° errotaziokoa).

Probak egin ondoren, emaitzek erakusten dute, Punta sentsorizatuak 1,5°-tik beherako errorea duela Roll eta Pitch angeluetan (ikusi 3.2. taula). Yaw angeluaren kasuan errorea handiagoa 4,3° (ikusi 3.2. taula). Balio horiek literaturan proposatutakoen antzekoak dira, beraz, aplikazio honetarako onargarriak direla esan daiteke.

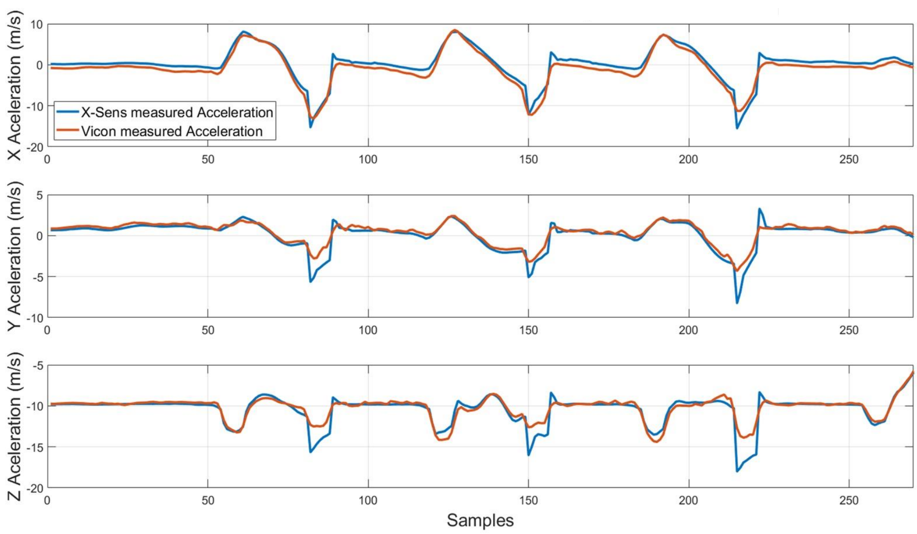


Irudia 3.3: (a) 3Dko mugimendua neurtzeko laborategiaren eskema kamerekin, neurtze-eremua eta definitutako proba-ibilbideak. (b) Markatzaile islatzaileen banaketa erabilitako makuluan (markatzaileak zenbakiekin identifikatzen dira). (c) Makuluaren heldulekuaren posizioa aitzinamendu-planoarekiko, X-Sens sistemak emandako Eulerren angeluak baliozkotzeko probetan.

Taula 3.2: X-Senseko Eulerren angeluen estimazio-errorea.

		RMS Errorea		
Froga	**Helduleku Orientazioa**	**Roll (°)**	**Pitch (°)**	**Yaw (°)**
Ibili 4 metro zuzen	0°	0.5439	1.0971	2.3457
Ibili 4 metro zuzen	45°	0.8482	0.7325	2.1725
Ibili 4 metro zuzen	90°	0.5429	1.0984	2.3404
Sigi-saga	0°	0.6736	0.8693	4.3096
Zirkulua	0°	0.935	1.5278	4.3099
Batezbesteko		0.7267	1.0777	3.4688

VICON sistema bera erabiliz, X-Sensen sentsore azelerometrikoaren zehaztasuna balioztatzen da. Horretarako, 4m-ko proba erabiltzen da (0°-ko orientazioa). Lortutako emaitzen erroreak 1,4m/s^2-tik beherakoak dira 3 ardatzetan. 3.4. irudian ikus daitekeenez, VICON sistemak eta X-Sens sentsoreak neurtutako kurba oso antzekoak dira, lurzoruaren aurkako inpaktu bat jasaten denean izan ezik, efektu horrek azelerazio handiagoa baitu.



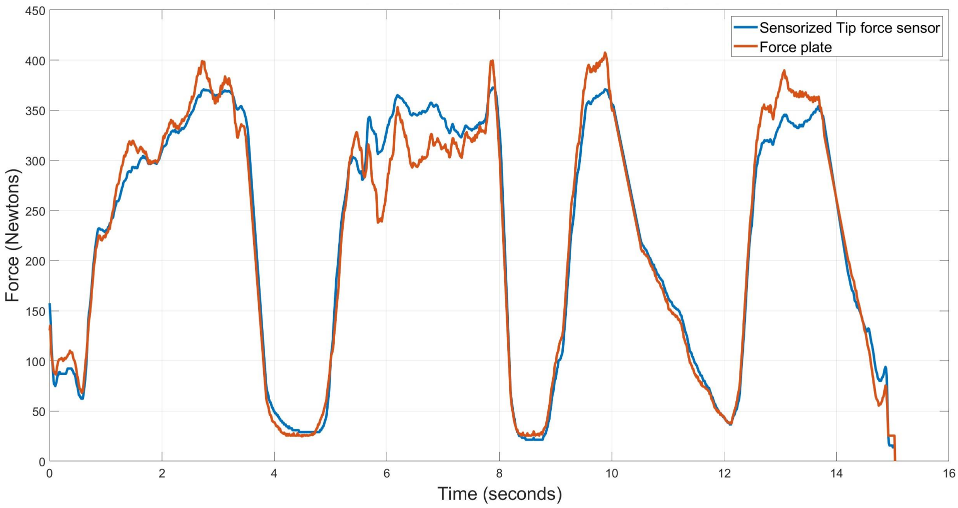
Irudia 3.4: X-Sens eta Vicon bidez neurtutako azelerazioen konparaketa.

X-Sens sentsoreekin amaitzeko, 3 ardatzeko giroskopioa baliozkotzen da. Horretarako, Punta sentsorizatuta birarazten da serbomotor batekin. 3 abiadura desberdinetan birarazten da: 100°/s, 200°/s eta 300°/s. Errorea handitu egiten da motorraren errotazio-abiadura handitu ahala. Hala ere, egiaztatu da pertsona osasuntsu baten ILGaren abiadura angeluarra 180°/s-tik beherakoa dela x eta y ardatzetan eta 220°/s-tik beherakoa z ardatzean. Beraz, abiadura-tarte horretan, akatsa 1°/stik beherakoa izango da.

Erabilitako C9C indar-sentsorea baliozkotzeko, Bertec 4060-15 indar-plaka batek neurtutako datuekin alderatzen da. Lehenik eta behin, kurbaren funtzioa kalkulatzen da, puntari pisua gehituz kg-ko gehikuntzetan.

$$y = -230.71x^2 + 797.3736x - 285.6619 \tag{3.1}$$

Funtzio hori lortu ondoren, indar axial desberdinak egiten dira eta sentsorearen neurriak indar-plataformaren emaitzekin alderatzen dira. Ateratzen diren kurbak 3.5. irudian ikus daitezke. Lortutako emaitzak onargarriak dira mota honetako aplikazioetarako (21.1N RMS errorearekin).

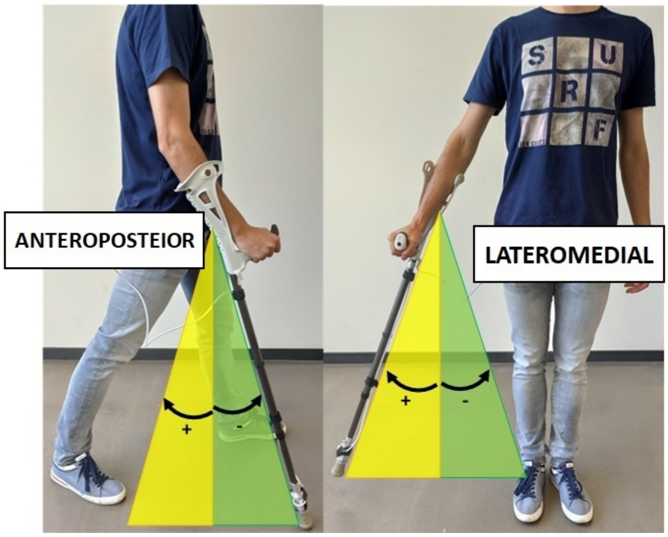


Irudia 3.5: Kalibrazio ondoren indar-sentsoreak ematen dituen datuak eta baskulatik neurtutako datuak.

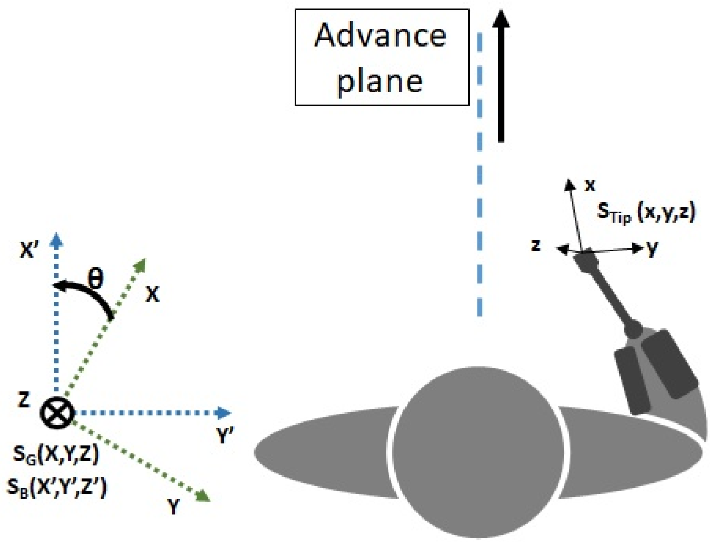
Azkenik, BMP280 barometroaren zehaztasuna egiaztatzen da. Horretarako, proba erraz bat egin da erreferentzia gisa eskailera multzo bat erabiliz. Proba, 12 eskailerako (2,04m-ko) lau zatitan banatu da. Denbora-bilakaeran eskailera-tarte bakoitzari lotutako eremu lauak kontuan hartuta, RMS errorea 0,2716m lortzen da, eta batez besteko errorea, berriz, -0,0466m da. Kontuan izan fabrikatzailearen datuekin bat datorrela, 0,12hPa-ko zehaztasun erlatiboa ematen baitu.

3.1.3 Gailuaren orientazioaren estimazioa

Erabilitako gailuaren kasuan, Kalman-iragazki batean oinarritutako algoritmo propio baten bidez, Mti-1 sentsore integratuak, Eulerren orientazio-angeluak ematen ditu. Angelu hauek, Punta sensorizatuaren erreferentzia lokala, $S_{tip}(x, y, z)$, erreferentzia globalarekin, $S_G(X, Y, Z)$, erlazionatzen dute.



(a)



(b)

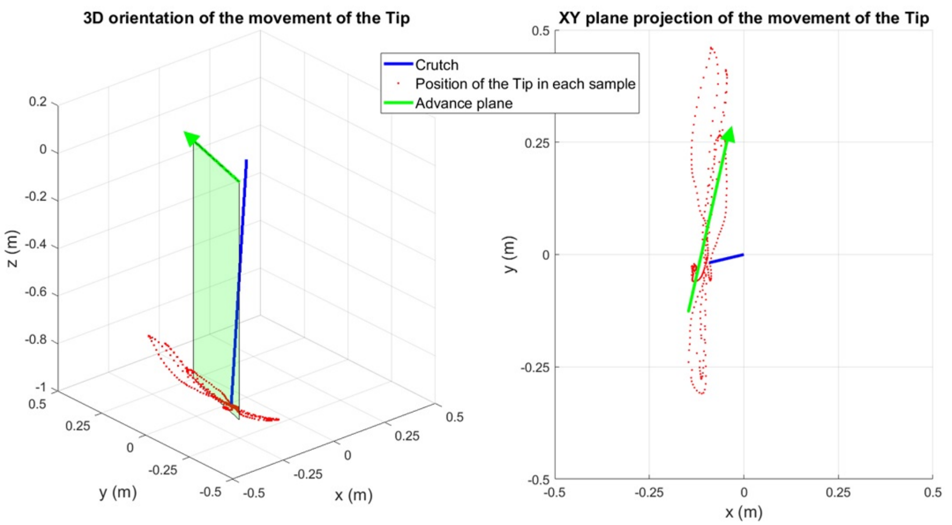
Irudia 3.6: (a) Angelu Anteroposteriorra eta Lateromediala. (b) Erreferentzia orokorreko, gorputzeko eta punta sentsorizatuko ardatzak.

Hala ere, aplikazio honetan, pazientearen gorputzarekiko Ibiltzeko Laguntza Gailuaren mugimendu erlatiboa behar da. Hau da, angelu Anteroposteriorra eta Lateromedialak, 3.6a. irudian ikusten den bezala.

Angelu horiek kalkulatzeko, bi urrats egin behar dira. Lehenik eta behin, sentsoreak emandako datuetatik abiatuta, gorputzaren erreferentzia-sistema eta aurrerapen-planoa lortzen dira. Bigarrenik, angelu Anteroposteriorra eta Lateromedialak kalkulatzen dira.

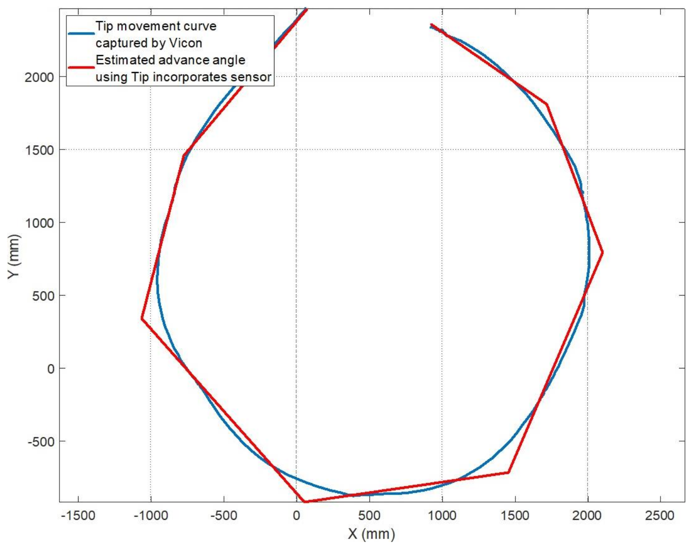
Gorputzaren erreferentzia-sistema, MTi-1 sentsoreak sortzen duen erreferentzia-sistema globalaren Z ardatzarekin lerrokatutzat hartzen da. Bere X' ardatzak gorputzaren mugimenduaren norabidean apuntatzen du, honela, $X'Z'$ aurrerapen-planoa definituz. Beraz, erreferentzia globala eta gorputzaren erreferentzia sistema, Z ardatz globalarekiko θ-ren errotazioaren bidez erlazionatuta daude (ikusi 3.6b. irudia). Erreferentzia-sistema hori lortzeko, mugimenduaren norabidea definitu behar da erreferentzia-sistema globalaren planoan (XY). Horretarako, kontuan izan behar da MTi-1en erreferentzia-esparru globalak Z ardatza baino ez duela finkatzen, eta ILG erabiltzen duten pertsonek angelu ugariko heldulekua har dezaketela.

Horrela, aurrerapen-planoa ezagutzeko, lehenik eta behin, indar-sentsorea erabilita, urratsen faseak definitzen dira (euskarri-fasea eta kulunka-fasea). Fase horiek ezagututa, laguntza-fasearen prozesuan Eulerren angeluak biltegiratzen dira eta ILGaren 3D orientazioa irudikatzen da (ikusi 3.7. irudia). Neurtutako Euler-angeluen multzo bakoitzerako, detekzio-puntaren erreferentzi-sistema lokala eta $MTi-1$en erreferentzi-sistema globala erlazionatzen dituen, errotazio-matrize bat defini daiteke. Punta Sentsorizatuaren Z ardatz lokala Punta Sentsorizatuaren ardatzarekin lerrokatuta dagoenez, posible da Z ardatz lokalari lotutako ${}^{G}\mathbf{u}_z$ bektore unitarioaren irudikapena definitzea hirugarren zutabe globalaren esparruan $\mathbf{R}_{rpy}$.



Irudia 3.7: Sentsorizatutako puntaren 3D orientazioa eta planoaren proiekzioa (XY).

Puntu Sentsorizatuaren sentsoreen kasuan bezala, proposatutako algoritmoa egiaztatzen da. Kasu honetan, heldulekuaren orientazioa aldatzen duten hainbat ibilbide egiten dira. Lortutako emaitzak konparatu ahal izateko, proba horiek VICON ingurunean egiten dira. Lortutako errorea 5° baino txikiagoa da kasu guztietan, zirkuluetan ibiltzen denean izan ezik, non errorea 8° ingurukoa den (ikusi 3.8. irudia). Errore hori mugimendu zirkularraren ezaugarriengatik gertatzen da, kasu honetan ez baitago aurrerapen-plano finkorik urratsetan zehar. Hala ere, 3.8. irudian ikus daitekeen bezala, kalkulatutako aurrerapen-planoak egindako ibilbide zirkularrera nahiko ongi hurbiltzen dira.



Irudia 3.8: Proba zirkularreko aurrerapen-planoaren kalkulua (eszenatoki okerrena) eta benetako ibilbidearen konparaketa.

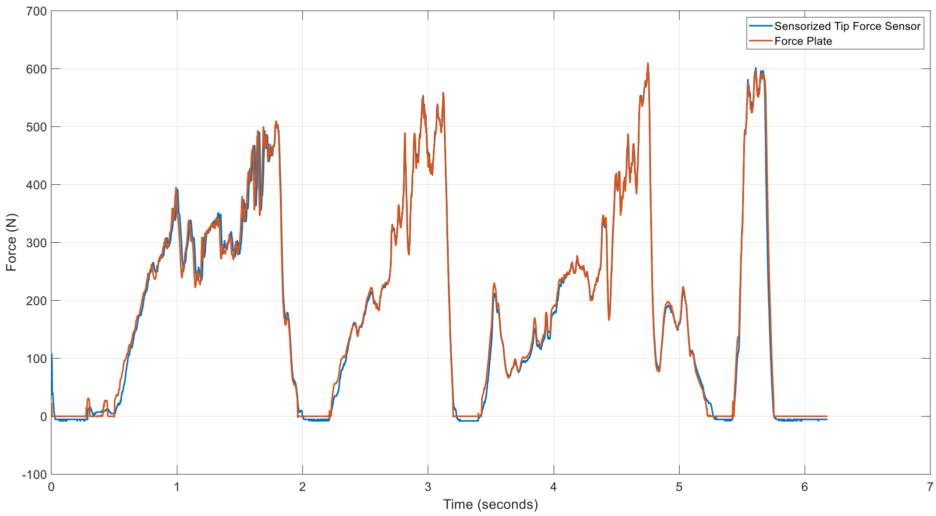
Azkenik, angelu Anteroposteriorra eta Lateromediala kalkulatzen dira. Horretarako, Sentsorizatutako puntaren erreferentzia-ardatzetako z ardatzaren proiekzioa erabiltzen da, gorputzaren erreferentzia-ardatzekiko.

3.1.4 Punta sentsorizatuaren bertsio berria

Indar-sentsorearen zehaztasuna hobetzeko eta ILGn egindako indar axiala modu errealistagoan transferitu ahal izateko, Punta sentsorizatuaren diseinu mekanikoa hobetu da (ikusi 3.10. irudia). Aldaketak bakarrik Punta sentsorizatuaren egitura mekanikoan egin dira, hau da, gainerako elementuak aurreko bertsioko berdinak dira.

Egin den aldaketetako bat, ILGra Punta sentsorizatua finkatzeko sistema aldatzea izan da. Lehengo bernoetan oinarritutako sistema, besarkaderetan oinarritutako sistemagatik aldatu da. Hobekuntza horrek Punta sensorizatuaren finkatzea errazagoa eta sendoagoa izatea ahalbideratzen du.

Irudia 3.9: Punta sentsorizatu berria.



Irudia 3.10: Sentsorizatutako punta berriaren indar-sentsorearen kalibrazio-kurba eta indar baskulatik lortutako datuak.

Bestalde, indar-sentsorera transmititzen duen pieza aldatu da. Diseinu berriarekin, puntaren elementu desberdinen arteko marruskadura txikitu da. 3.10. irudian ikus daitekeenez, indar-sentsoreak neurtutako kurba eta baskulak emandakoak ia berdinak dira. Ikusten denez, aurreko bertsiorekin alderatuta (3.5. irudia), askoz ere zehaztasun handiagoa du bertsioa berri honek (11.4N RMS errorearekin).

3.1.5 Ondorioak

Atal honetan, edozein ILG-i egokitu dakiokeena Punta sensorizatu bat aurkezten da. Punta sensorizatu honek, ILG erabiltzen duten pertsonen jarduera monitorizatzeko gaitasuna du. Integratu zaizkion sentsoreei esker, ILGren mugimendua eta erabiltzaileak egindako indarra neurtzeko gai da. Gainera, Bluetooth bidez datua transmititzeko eta ahalik eta gutxien pisatzeko diseinatu da.

Proba desberdinen bidez, Punta sentsorizatuaren errorea kalkulatu da. Horretaz gainera, ILGren angelu lateromediala eta anteropostiorra kalkulatzeko algoritmo bat diseinatu da. Lortutako emaitzek erakusten dutenez, lortutako erroreak txikiak eta onargarriak dira. Beraz, diseinatutako Punta sensorizatua egokia da ILG erabiltzen duten pertsonen jarduera monitorizatzeko.

Gainera, gailuaren bertsio berri bat diseinatu da, lortutako emaitzak hobetzeko.

3.2 Jarduera fisikoaren sailkatzailea

Atal honetan, Jarduera Fisikoaren sailkatzailearen diseinua laburbiltzen da. Sailkatzaile hau, Punta sentsorizatuaren sentsoreek neurtutako datuetan oinarrituta garatu da. Diseinuaren informazioa zehatzagoa 2. eranskineko [126] artikuluan aurkitu daiteke. Artikulu hau, sarbide irekiko *IEEE Access* aldizkarian argitaratu da.

Jarduera Fisikoa monitorizatzeko gai den Punta sentsorizatua garatu ondoren, egindako jarduera fisikoak sailkatzeko gai den metodologia bat behar da. 2.2. kapituluan aipatu den bezala, JF sailkatzeko sistema gehienek metodologia bera jarraitzen dute. Sentsoreen bitartez datuak bildu ondoren, datuak segmentu txikiagoetan banatzen dira; ondoren, ezaugarriak identifikatzen dira; ostean, sortutako ezaugarriak murrizten dira garrantzitsuenak aukeratuz; eta, azkenik, sailkatzailea diseinatzen da. 2.2. kapituluan pausu bakoitzerako teknika desberdinak analizatu dira.

3.2.1 Datuak atzemateko entseguak

Punta sensorizatuan oinarritutako JFren sailkatzaile bat garatzeko, lehenik eta behin, datu-base bat sortu behar da. Horretarako, zer jarduera sailkatu nahi diren hautatu, eta jarduera horiek dituzten entsegu desberdinak egin behar dira. Kasu honetan, 5 jarduera fisiko desberdin sailkatuko dira:

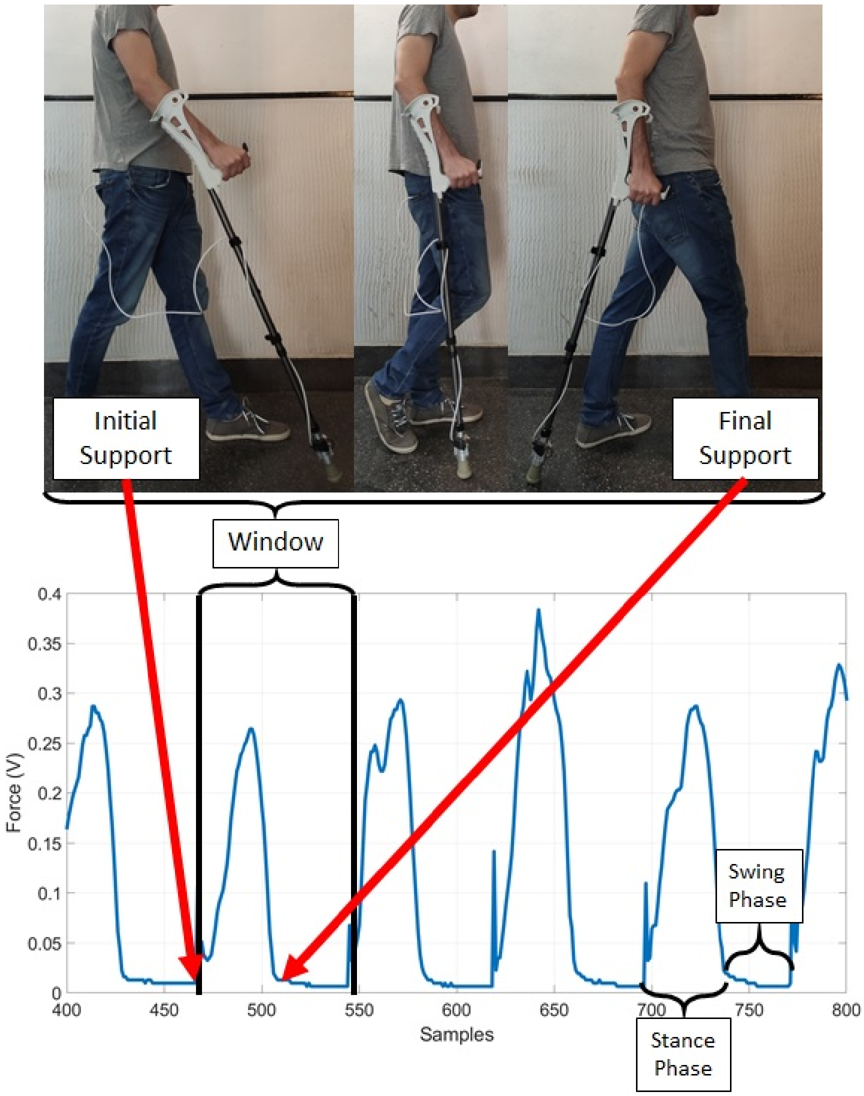
- Lerro zuzenen 30m ibili abiadura arruntean.
- Lerro zuzenen 30m ibili normaletik gorako abiaduran (gutxi gorabehera %30 azkarrago).
- 10 segundo inguru geldirik egon.
- 11 mailako eskailera igo.
- 11 mailako eskailera jaitsi.

Entseguak 11 pertsona desberdinek egin dituzte (ikusi 2. eranskinean datu zehatzagoak), eta partaide bakoitzak hiru aldiz errepikatu ditu proba guztiak.

3.2.2 Datuen segmentazioa

Entseguen bidez datuak neurtu ondoren, datuak segmentatu behar dira. Segmentazio hori egiteko, 2.2. kapituluan ikusitako aukera desberdinak aztertu dira eta leihoak ekitaldien arabera sortzea erabaki da. Leiho bakoitzak, ILGaren erabilera ziko edo fase oso bat (oreka-fasea eta kulunka-fasea) izango du (ikusi 3.11. irudia). Zatiketa hori lortzeko, Punta sentsorizatuan integratutako indar-sentsorea erabiltzen da. Leihoaren hasiera oreka-fasearen hasierak definitzen du, eta leihoaren amaiera, berriz, kulunka-fasearen amaierak. Aurreko entseguetan lortutako leihoen kopurua 3.3. taulan laburbiltzen da.

JFaren sailkatzailea garatzeko, datuak bi multzotan banatzen dira, bata MLn oinarritutako sistemen entrenamendurako erabiliko da eta bestea sortutako sakailatzaileak



Irudia 3.11: ILG baten erabilera-zikloa eta haren faseak. Leihoetan datu segmentazioa, indar-sentsoretik eskuratutako datuak erabilita.

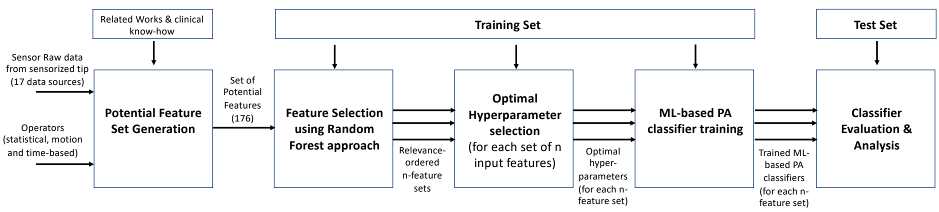
Taula 3.3: Jarduera Fisikoa (JF)ko datuen leiho kopurua. Entrenamendurako eta testerako datuak.

JF Mota	Leiho Kopurua	Entrenamendu Datuak	Test Datuak
Normal Ibili	724	254	123
Azkar Ibili	528	264	118
Eskailerak Igo	360	251	109
Eskailerak Jaitsi	357	251	106
Geldirik Egon	329	218	111
Guztira		1238	567

ondo funtzionatzen duela egiaztatzeko edo testatzeko. Zatiketa hori egiteko, datuen %70 inguru entrenamendurako erabiltzen dira, eta gainerakoak testatzeko uzten dira (ikusi 3.3. taula).

3.2.3 Ikaskuntza automatikoan oinarritutako JFkoaren sailkatzaileak diseinatzeko metodologia

Datuak leihoetan banatu ondoren, datu-basea egokitzen da, eta azkenik, JFkoaren sailkatzailea garatzen. 2.2. kapituluan aipatutako metodologiari jarraituz (ikusi 3.12. irudia), datuak zatitu ondoren, ezaugarri potentzialen multzo bat sortu behar da. Ostean, ezaugarrien dimentsionaltasuna murriztu behar da garrantzitsuenak hautatuz. Azkenik, jarduera fisikoak bereizteko sailkatzailea garatzen da.



Irudia 3.12: Jarduera Fisikoa sailkatzailea sortzeko jarraitutako metodologia.

3.2.3.1 Ezaugarri potentzialen sorkuntza

JFren sailkatzailea garatzeko lehen urratsa leiho bakoitzaren ezaugarri potentzialak sortzea da. 2.2. kapituluan aipatu den bezala, egindako lan gehienetan kalkulu estatistikoetan oinarritutako ezaugarriak erabiltzen dira. Doktorego-tesi honetan, estatistikan oinarritutakoez gainera, mugimenduan eta denboran oinarritutako ezaugarri batzuk erabiltzea proposatzen da. Ezaugarri horiek, sentsoreetatik lortutako 17 neurriei aplikatzen zaizkie, leiho bakoitzeko 176 ezaugarri lortuz (ikusi 3.4. taula).

Taula 3.4: Sentsorizatutako puntak emandako datuetatik sortutako ezaugarriak (R = Roll, P = Pitch, Y = Yaw, A = Anteroposterior, L = Lateromedial).

Ezaugarria / **Datuen Iturria**	Azelerometroa (X, Y, Z)	Giroskopioa (X, Y, Z)	Magnetometroa (X, Y, Z)	Anguluak (R, P, Y)	Anguluak (A, L)	Barometroa (Filtroarekin)	Barometroa (Filtro gabe)	Indar Sentsorea
Mean	X	X	X	X	X	X	X	X
Standard Deviation	X	X	X	X	X	X	X	X
Variance	X	X	X	X	X	X	X	X
Kurtosis	X	X	X	X	X	X	X	X
Corr. Coef. XY	X	X	X					
Corr. Coef. XZ	X	X	X					
Corr. Coef. YZ	X	X	X					
Corr. Coef. RP				X				
Corr. Coef. RY				X				
Corr. Coef. PY				X				
Corr. Coef. AL					X			
25th Percentile	X	X	X	X	X	X	X	X
50th Percentile	X	X	X	X	X	X	X	X
75th Percentile	X	X	X	X	X	X	X	X
Area	X	X	X	X	X	X	X	X
Interquartile Range	X	X	X	X	X	X	X	X
Stance Start Value					X			
Value at Max. Force					X			
Stance End Value					X			
Amplitude					X			
Cycle time								X
Stance Ph. %								X
Ezaugarri Kopurua	30	30	30	30	27	9	9	11

3.2.3.2 Ezaugarri garrantzitsuenak hautatzea

Leiho bakoitzaren 176 ezaugarriak JFren sailkatzailea garatzeko erabil daitezkeen arren, baliteke garapen horretarako ezaugarri guztien erabilera oso eraginkorra ez izatea. Ezaugarri guztiak erabiltzeak, sailkatzailearen kostu konputazionala handituko luke, eta gainera, litekeena da sailkapenaren eraginkortasunean eragin negatiboa izatea. Horregatik, ezaugarrien dimentsionaltasuna murrizteko metodologia bat proposatzen da.

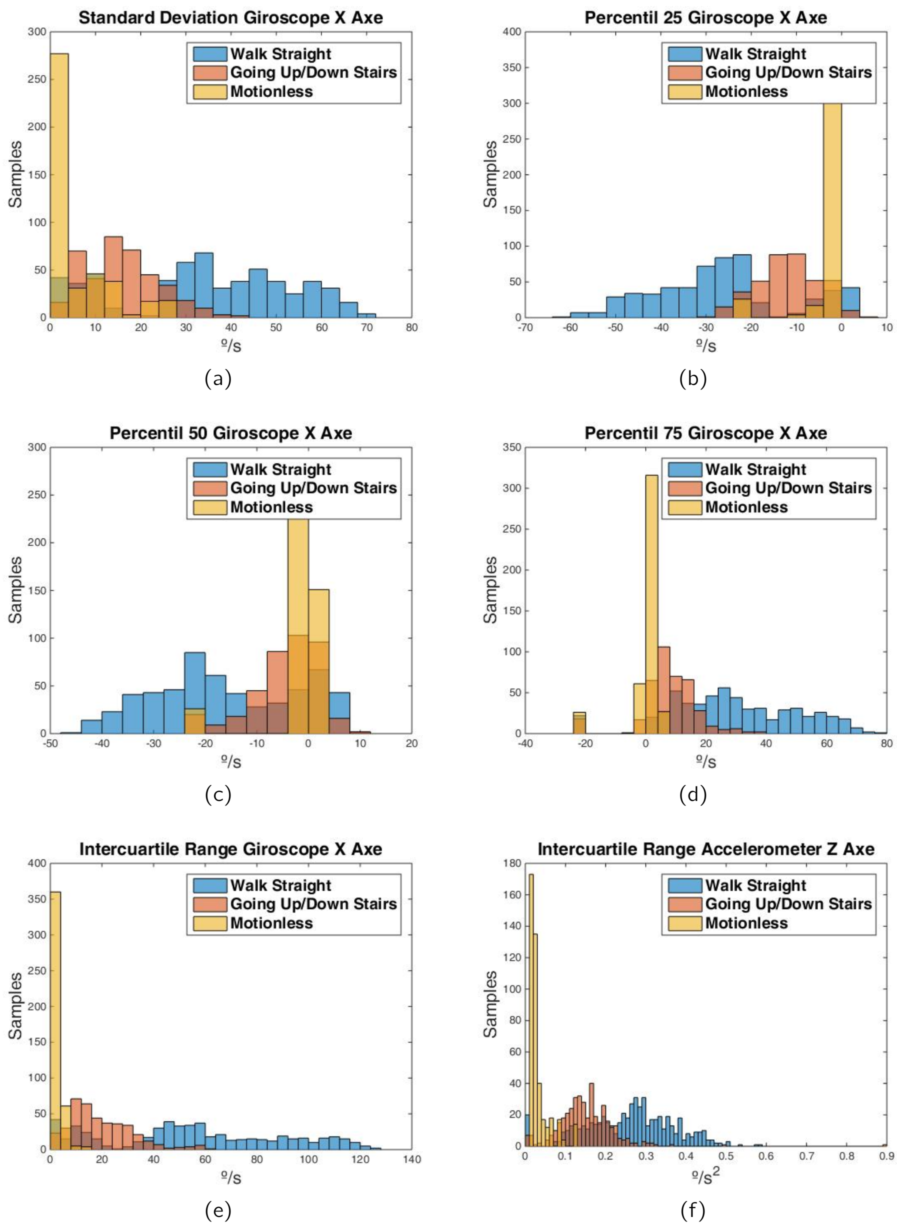
2.2. kapituluan aipatu bezala, dimentsionaltasuna murrizteko metodologia desberdinak erabili dira. Dimentsionaltasuna murrizteko moduetako bat hautatutako ezaugarrien analisi bisuala egitea da. Metodologia hau egokia izan daiteke, jardueren sailkatzaile sinpleago batentzat, adibidez, 3 JFko bakarrik sailkatzen diren kasuetan. [26] modu horretan murrizten da ezaugarrien dimentsionaltasuna. Kasu honetan, 3 jardueren bereizketa, ezaugarrien banaketa histografikoa aztertuz egiten da. Horrela, histogramaren banaketan alderik handiena hauteman den ezaugarriak (6) erabiltzen dira (ikusi 3.13. irudia).

[29] jarduera fisikoen sailkatzaile bera proposatzen da, baina kasu honetan, [26] hautatutako ezaugarriak erabiltzeaz gain, beste hiru gehitu dira (zikloko denbora, ziklo bakoitzeko laguntza-fasearen ehunekoa eta z ardatzaren azelerazio ertaina).

Ezaugarrien dimentsionaltasuna bisualki murriztu badaiteke ere, aukeratutako ezaugarriak ez dira zertan egokienak izan. Gainera, ezin dira bistara ikusi ezaugarrien arteko korrelazio posibleak. Horregatik, kasu honetan Random Forest (RF) erabiltzea proposatzen da helburu hori lortzeko (metodologia hau, 2. eranskinean [126] eta [27] erabili da). Horretarako, *entrenamendu-multzoko* datuak bakarrik erabiltzen dira. Proposatutako RF ondorengo hiperparametroak kontuan hartuta inplementatu da, esperimentalki hautatua:

- Basoko zuhaitzen kopurua 5000ra egokitu da.
- Ordezpen-estrategia duen lagin bat hautatu du.
- Nodo baten tamaina zehaztu zen.
- Zatiketa bakoitzean ausaz aukeratutako aldagaien kopurua ($mtry$) $\sqrt{M}$-ra doitu da, non Maldagaien guztizko kopurua den.
- Ezaugarri korrelatiboek eragindako asaldurak saihesteko, erabilitako aurresarea interakzio-kurbadura izan da.

3.5. taulak garrantzitsuentzat jotako lehen 30 ezaugarrien emaitzak erakusten ditu. Kontuan izan behar da RFk esleitutako ezaugarri bakoitzak duen pisua ematen duela; horrela, lortutako balioa zenbat eta handiagoa izan, orduan eta garrantzi handiagoa izango du ezaugarri horrek jardueraren sailkapenean. Lortutako emaitzak aztertuta, Random Forestren arabera, Yaw-angeluaren kurbaren azpiko eremua da ezaugarririk garrantzitsuena.



Irudia 3.13: Ikusizko analisitik lortutako ezaugarri garrantzitsuenen histograma.

Taula 3.5: Ezaugarrien garrantzia eta pisu erlatiboa, Random Forest prozeduraren arabera. (Magne = Magnetometroa, Accel = Azelerometroa, AUtC = Kurbaren Azpiko Area, 25P = 25th Pertzentila, 50P = 50th Pertzentila, 75P = 75th Pertzentila, IR = Kuartien Arteko Tartea, SD = Desbideratze Estandarra, Corr. Coef. = Korrelazio Koefizientea, Antero = Anteromedial Angulua, Latero = Lateromedial Angulua, WoF = Iragazki Gabe, WF = Iragazkiarekin, n = Posizioa).

n	Ezaugarria	Pisua	n	Ezaugarria	Pisua
1	AUtC Yaw	2.276	*16*	Antero SD	1.213
2	Cycle Time	2.242	*17*	Antero Variance	1.178
3	Accel SD X	2.216	*18*	Accel 25P Z	1.159
4	Accel Variance X	2.002	*19*	Gyro IR Y	1.131
5	Magne 75P X	1.992	*20*	SD Pitch	1.126
6	Gyro 25P Y	1.978	*21*	Accel SD Z	1.103
7	Antero IR	1.766	*22*	Variance Pitch	1.087
8	Magne Mean X	1.698	*23*	Accel Variance Z	1.078
9	Accel Mean Z	1.671	*24*	Gyro 75P X	1.063
10	IR Pitch	1.635	*25*	Accel IR Y	1.060
11	Magne AUtC X	1.582	*26*	Accel AUtC Z	1.022
12	Accel IR Z	1.527	*27*	Accel 50P X	1.021
13	Accel 25P Y	1.507	*28*	Accel Mean X	1.003
14	Magne 50P X	1.503	*29*	Gyro 50P Y	0.966
15	Magne 25P X	1.402	*30*	Accel 75P X	0.942

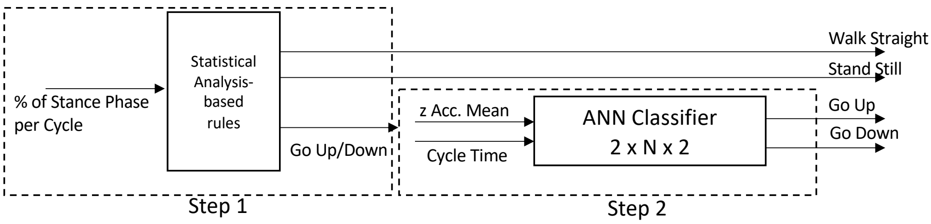
3.2.3.3 Sailkatzaileak sortzea

Ezaugarriak jarduera fisikoa sailkatzeko duten garrantziaren arabera ordenatu ondoren, dagokion sailkatzailea diseinatzen da. Sailkatzailearen helburua jarduera fisikoak bereiztea da. [26] eta [29] kasuan, 4 jarduera fisikoren artean bereizteko (ibiltzea, eskailerak igotzea, eskailerak jaistea eta geldirik egotea) sailkatzaile bat diseinatu da. Bestalde, 2. eranskinean [126], 5 jarduera fisiko desberdin detektatzen dituen sailkatzaile bat proposatzen da: normal ibiltzea, azkar ibiltzea, eskailerak igotzea, eskailerak jaistea eta geldirik egotea.

[26] eta [29] sortutako sailkatzailearen kasuan, 4 irteera desberdin izango dituzte. Eta 2. eranskinaren [126] kasuan, sailkatu beharreko jarduera fisikoen gorakada dela eta, 5 irteera izango ditu sailkatzaileak, hau da, aipatutako jarduera bakoitzari lotutako irteera bat.

Hiru sailkatzaileen sarrera-kopurua aldatu egiten da. [26] kasuan, bisualki hautatutako 6 ezaugarri baino ez dira erabiltzen. [29], 3 ezaugarri gehiago gehitzen zaizkie aurretik hautatutako 6 ezaugarriei. Azkenik, 2. eranskinean [126], sarreren kopurua aldatzen joan da, erabiliko diren ezaugarrien kopuru optimoa aurkitzeko. Horrela, sarrera kopurua aldatuz, ezaugarrien kopurua adina sailkatzaile garatu dira. Lehenengo sailkatzailea, sarrera bakarra erabiliz diseinatu da, sarrera hori, RFren arabera ezaugarririk garrantzitsuena dena izan da (Yaw angelu-kurbaren azpiko eremua). Bigarren sailkatzaileak, bi sarrera izan ditu, hauek, RFren arabera pisurik handiena duten bi ezaugarriak izan dira. Hirugarren sailkatzailean, hiru ezaugarri garrantzitsuenak erabili dira sarrera gisa. Eta metodologia hau erabiliz, sailkatzaile desberdinak garatu dira, aurretik proposatutako n ezaugarrietara iritsi arte.

Doktorego-tesi honetan sailkapena egiteko, Machine Learning (ML)n oinarritutako metodologiak erabili dira. Kasu honetan, 2.2. kapituluan aztertutako metodologietatik, ohikoenak aukeratzea erabaki da, K-Nearest Neighbors (K-NN), Support Vector Machine (SVM) eta Artificial Neural Network (ANN). [26] eta [29], ANNetan oinarritutako sailkatzaileak inplementatu dira. Gainera, [29] kasuan zehatzean, sailkatzailea bi urratsetan sortu da (ikusi 3.14. irudia). Bertan, eskailerak igotzen edo jaisten, geldirik edo oinez ari den sailkatzen da lehendabizi, eta ondoren ANN sailkatzaile bat erabiltzen da eskailerak igotzearen eta jaistearen artean bereizteko.



Irudia 3.14: 4 Jarduera Fisikoa sailkatzeko, ANNn oinarritutako bi urratseko sailkatzailea.

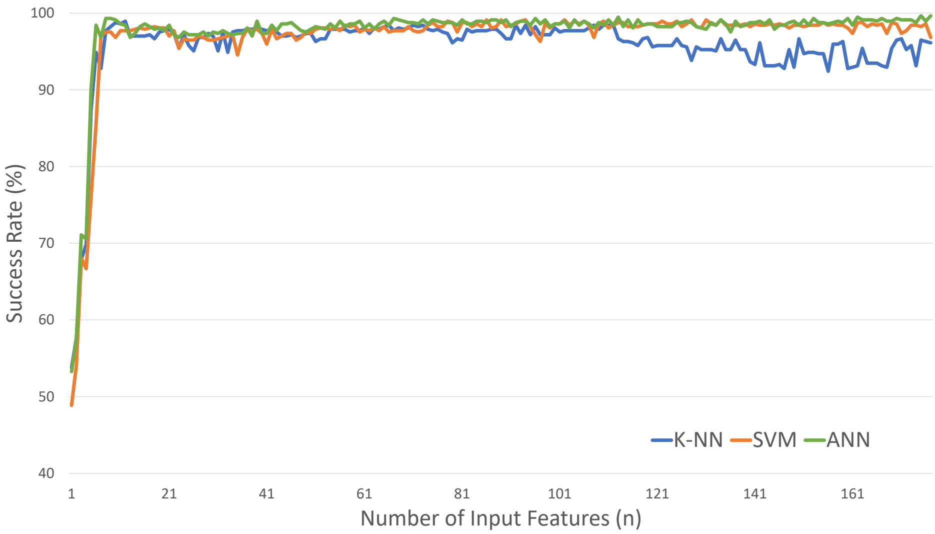
Bestalde, MLn oinarritutako sailkatzaile bakoitzerako hiperparametroen azpimultzo optimoa aurkitu behar da. Horretarako, K-fold baliozkotze gurutzatuko ikuspegi bat proposatzen da $K = 5$-rekin. Ikuspegi horri esker, MLn oinarritutako hainbat ereduren ebaluazio eraginkorra egin daiteke. SVM eta K-NN kasuan, Matlab Toolbox Static and Machine Learning erabiltzen da sailkatzaile bakoitzerako hiperparametrorik onenak hautatzeko. ANNren kasuan, ezkutuko geruza bakarra duen Multilayer Perceptron (MLP) sare bat erabiltzea aukeratzen da. Lehen aipatu den bezala, irteerako neuronen kopurua 5 da, eta sarrerako neuronen kopurua n izango da. Bestalde, ezkutuko geruzetako neurona kopuru optimoa hautatzeko, sare desberdinak entrenatu dira, 1 eta 10 arteko neurona kopuruarekin, eta emaitza onenak eman dituena aukeratu da.

3.2.4 Analisi konparatiboa

Atal honetan, aurreko atalean proposatutako metodologia aplikatzetik lortutako emaitzen analisi konparatiboa egiten da.

[26] eta [29], proposaturiko 4 jarduera fisikoen artean bereizteko gai diren sailkatzaileak lortzen dira. [26] kasuan, %90 inguruko arrakasta-tasa lortzen da 4 jarduerak sailkatzerakoan, baina eskailerak igotzen edo jaisten ari den desberdintzeko garaian, %80 soilik igarri dira. Hala ere, [29] proposatutako bi urratseko sailkatzaileari esker, emaitzak %97 igo dira.

Emaitzak hobetzeko, 2. eranskinean [126] jarraitutako metodologia erabili da da. Lehen aipatu bezala, saikatzailea garatzeko orduan, 3 ML ikuspegi desberdin erabiltzen dira (SVM, K-NN eta ANN). Denetan hoberena zein de jakiteko, 3 tekniketatik lortutako emaitzak konparatu dira. Gainera, lehen aipatu bezala, entrenamendua sarrera kopurua handituz egiten da (RFk emandako ordenaren arabera); horrela, ikuspegi bakoitzean, ezaugarri kopuru optimoa zein den aztertuz.



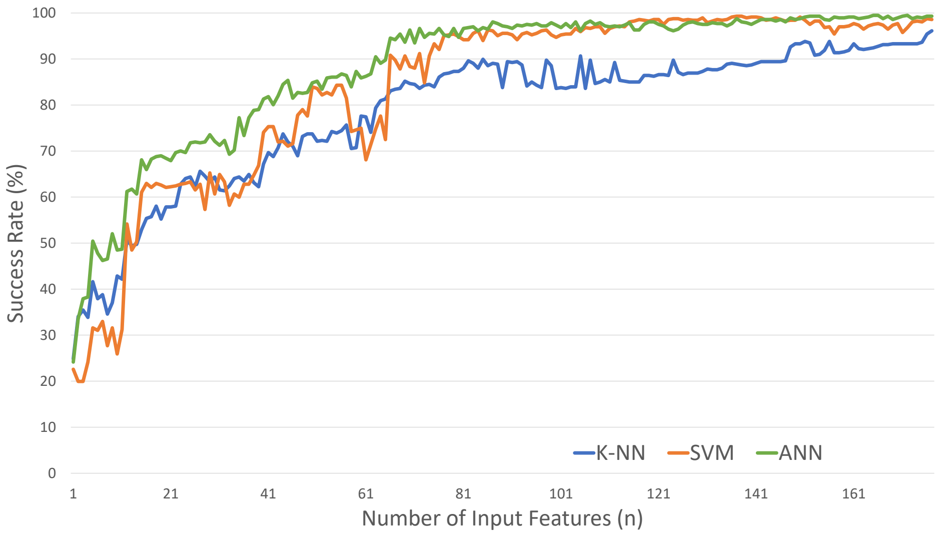
Irudia 3.15: K-NN, SVM eta ANNn oinarritutako sailkatzaileen arrakasta-tasa, RFren arabera ordenatutako *n* ezaugarri garrantzitsuennei dagokionez.

3.15. irudian lortutako emaitzak ikus daitezke, non sailkatzaile bakoitzaren arrakasta-tasa globala adierazten den. Ikus daitekeenez, 7 ezaugarri garrantzitsuenak erabiliz gero, arrakasta-tasa %90etik gorakoa da hiru kasuetan (%92,8 K-NN, %97 SVM eta %96,8 ANN). Arrakasta-tasarik onena 66 ezaugarrirekin lortzen da K-NNren kasuan (%98,4), 87 ezaugarrirekin SVMren kasuan (%99,1) eta 174 ezaugarrirekin ANNren kasuan (%99,6).

3.15. irudian ikus daitekeen bezala, SVM eta ANNren kasuan, 7 ezaugarri baino gehiago erabiltzen badira ere, arrakasta-tasa ea ez da handitzen. Hortik ondorioztatzen da ezaugarriak behar bezala hautatu direla. Kasu zehatz honetan, esan daiteke 7 ezaugarri garrantzitsuenak erabiliz, %95etik gorako arrakasta-tasa duten emaitzak lortuta kostu konputazional txikiarekin.

Beste alde batetik, lehen aipatu bezala, ANNrako neurona kopuru egokia ezagutzeko, ezkutuko geruzan 1etik 10era bitarteko neuronak dituzten sailkatzaileak garatu dira. Emaitzak aztertuta, ikusten da emaitzarik onenak 9 neuronekin lortzen direla.

Ezaugarrien garrantziaren aukeraketa zuzena egiaztatzeko, aurreko prozedura errepikatzen da, baina kasu honetan ezaugarriak garrantzi txikienekotik garrantzitsueneraino ordenatuz. Hau da, 176 ezaugarriko multzo bat aztertzen da berriro: lehenik,



Irudia 3.16: K-NN, SVM eta ANNn oinarritutako sailkatzaileen arrakasta-tasa, RFren arabera ordenatutako *n* ezaugarri ez garrantzitsuenari dagokionez.

garrantzi gutxien duen ezaugarria sarrera gisa erabiliz, gero garrantzi gutxien duten bi ezaugarriak sartuz, eta horrela hurrenez hurren. Emaitzak 3.16. irudian azter daitezke, eta horrek erakusten du arrakastaren ehunekoa nola handitzen den Random Forestren arabera ezaugarri garrantzitsuagoak gehitu ahala.

3.2.5 Ondorioak

Atal honetan, Punta sentsorizatua erabiliz JF desberdinak detektatzeko gai den sailkatzaile bat aurkezten da. Sailkatzaile hori garatzeko, Machine Learningn oinarritutako metodologia bat erabili da. Sailkapena egin aurretik, hurbilketa bat proposatzen da, non entseguetatik lortutako datuak zatitu eta ezaugarri multzo bihurtzen diren. Dimentsionaltasuna murriztu eta lortutako ezaugarriak garrantziaren arabera ordenatzeko, RFn oinarritutako teknika bat aplikatu da.

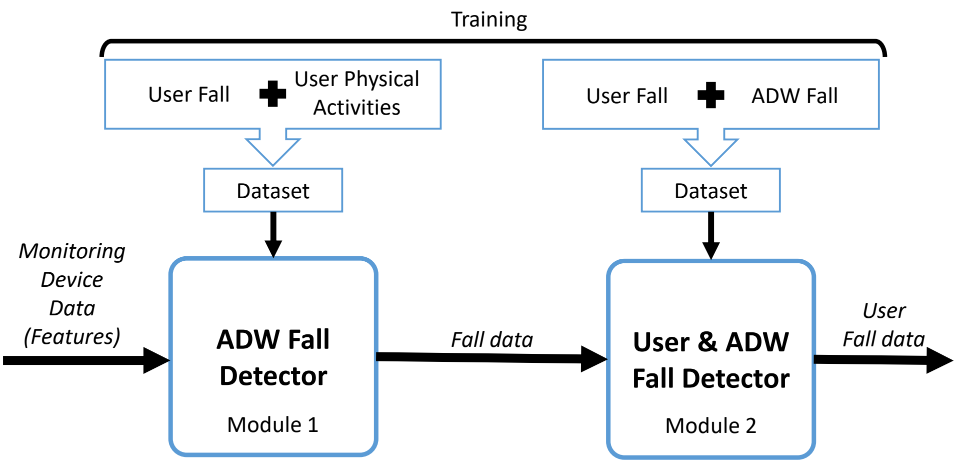
Erabilitako metodologia baliozkotzeko, ML oinarritutako hiru teknika desberdin erabiliz, SVM, K-NN eta ANN, JFko hiru sailkatzaile desberdin garatu dira. Kasu guztietan, %92 eta %97 arteko arrakasta-tasa lortu da, RFren arabera aukeratutako 7 ezaugarri garrantzitsuenak erabiliz.

3.3 Erorikoen detektagailua

Atal honetan, diseinatutako Punta sentsorizatuan oinarrituta garatu den erorketen detektagailua laburbiltzen da. Garapen honen inguruko informazio zehatzagoa, sarbide irekiko *IEEE Access* aldizkarian argitaratutako 3. eranskinean [125] aurki daiteke.

Erorikoak goiz detektatu eta erantzun berantiar baten ondorioak saihesteko, erorketen detektagailu bat garatu da. 2.3. kapituluan aipatu den bezala, erorketak detektatzeko, posizio desberdinetan kokatzen diren mota askotako sentsoreak aurki daitezke. Ikerketa honetan, merkatuan aurki daitezkeen sentsoreen desabantailei erantzuna eman nahian, erorketen detektagailua diseinatzeko, garatu den Punta sentsorizatua erabiltzea aukeratu da. Bestalde, 2.3. kapituluan, erorketak detektatzeko erabilitako metodologiak aztertu ondoren, detekzio era desberdinak daudela ikusi da. Kasu honetan, JFren sailkatzailea garatzeko jarraitutako metodologiaren antzeko prozedura bat proposatzen da.

Doktorego-tesi honetan, erorketen detektagailua garatzeko, bi modulutan oinarrituta prozesura bat erabiltzea proposatzen da (ikusi 3.17. irudia). Lehenengo modulua ILGaren erorketa hautemateaz arduratzen da; bigarren moduluak, berriz, erorketen datuak erabiltzen ditu erabiltzailea ILGarekin batera erori den edo ez ebaluatzeko. Bigarren modulu hau, ILGaren erorketen ondorioz sortu daitezkeen positibo faltsuak saihesteko diseinatuta dago.



Irudia 3.17: Bi modulutan banatutako erorikoak detektatzeko metodologia.

Modulu bakoitzean, datu-multzo desberdinak erabiltzen dira. Lehen moduluko datu multzoa, ILGarekin erabiltzaileak izandako erorketek eta ILGarekin egindako jarduera fisikoen multzo batek osatzen dute. Bigarren moduluak, erabiltzaileak ILGarekin izandako erorikoen datuak (lehen moduluan erabilitakoak), erabiltzailerik gabeko ILGaren erorketekin konbinatzen ditu.

Jarduera Fisikoaren sailkatzailean bezala, behar diren datuak aukeratu ondoren, metodologia bati jarraitzen zaio. Lehenik eta behin, erorketak zehazteko ezaugarri multzo bat sortzen da. Bigarrenik, ezaugarrien dimentsionaltasuna murrizten da. Azkenik, Machine Learningn oinarritutako erorketa-detektagailua sortzen da, zehatzago esateko, SVMn oinarritutako detektagailua. Proposatutako ikuspegia ebaluatzeko, emaitzak datu-multzoekin alderatuko dira.

Diseinatutako erorketa detektagailua egiaztatzeko, Punta sentsorizatutik lortutako emaitzak, sentsore jantziekin lortutakoekin konparatzen dira. Horretarako, eskumuturrean, gerrian, bizkarrean eta poltsikoan kokatutako, 4 GENEActiv azelerometro erabiltzen dira. Sentsore hauek, erorketak simulatzerakoan ez ezik, beste hainbat jarduera fisikotan erabiltzen dira. GENEActivetik neurtutako datuekin erorikoen detektagailu bat garatu da, Punta sensorizatuaren eta GENEActiven lortutako emaitzak alderatzeko.

3.3.1 Protokolo esperimentala eta datuak atzematea

Erorketen detektagailua garatzeko, datu-base egokia behar da. Datu horiek lortzeko, 12 pertsona osasuntsuk esperimentu desberdinak egin dituzte (3. eranskinean informazio gehiago aurki daiteke). Esperimentu horiek Bolognako Unibertsitateko 149960 Etika Batzordearen onespenarekin egin dira. Erorikoen ondorioz sortu daitezkeen lesioak saihesteko, koltxoi bat erabili da.

Lehen aipatu den bezala, 3 datu-multzo desberdin sortu dira: 1) Erabiltzailea ILG baliatuz erortzea (erabiltzailearen erorketen datu-multzoa); 2) ILG erabiliz jarduera fisiko desberdinak egitea (erabiltzailearen Jarduera Fisikoaren datu-multzoa); 3) Erabiltzailerik gabe ILG erortzea (ILGren erorketen datu-multzoa).

Erabiltzailearen erorketen datu-basearen kasuan, pertsonen erorketen simulazioak ILG erabiliz egiten dira. Databrary datu-baseko bideoen erorketak aztertu ondoren, 16 agertoki desberdin hartzen dira kontuan:

1. Geldi egonda, pauso bat ematen saiatu eta ILGarekin estropezu egin eta erortzea.
2. Aurrerantz erortzea.
3. Atzeraka erortzea, zorabio bat simulatuz.
4. Atzerantz erortzea.
5. 90º eskuinera biratu eta eskuinerantz erortzea.
6. Eskuinerantz erortzea.
7. 90º ezkerrera biratu eta ezkerrerantz erortzea.
8. Ezkerrerantz erortzea.
9. Koltxoirantz doala, ILGarekin estropezu egin eta aurrerantz erortzea.
10. Koltxoirantz doala, objektu batekin estropezu egin eta aurrerantz erortzea.

11. Koltxoirantz doala, objektu batekin estropezu egin eta ezkerrerantz erortzea.
12. Koltxoirantz doala, objektu batekin estropezu egin eta eskuinerantz erortzea.
13. Koltxoirantz doala, objektu batekin estropezu egin eta atzerantz erortzea.
14. Oreka galdu, metro batzuk aurrera eginez berreskuratzen saiatu eta aurrerantz erortzea.
15. Oreka galdu, metro batzuk atzera eginez berreskuratzen saiatu eta bizkarrez erortzea.
16. Joan etorrian dabilela eta atzerantz erotzea.

Erabiltzailearen Jarduera Fisikoaren datu multzoaren kasuan, 7 jarduera fisiko desberdin simulatzen dira:

1. Erritmo normalean ibiltzea: definitutako zirkuitu batetan, lerro zuzenean ibiltzeaz gainera, bira desberdinak egin dira, norabide desberdinetan ibiliz.
2. Azkar ibiltzea: aurretik egindako zirkuitu bera errepikatzen da, baina abiadura %30 azkartuz.
3. Zutik egotea: 30 segundoz geldirik egotea.
4. Eskailerak igo eta jaistea: eskailerak behin eta berriz igo eta jaitsi dira.
5. Aulki batean eseri eta jaiki: makuluaren laguntzaz, aulki batetik altxatu eta aulki berean eseri; hau, 30 segundoz errepikatu da.
6. Objektu bat lurretik jasotzeko gelditu eta zutik jarri; hau, 30 segundoz errepikatu da.
7. Oreka-galera laburra (ia erorita), oreka 4 aldiz berreskuratu da.

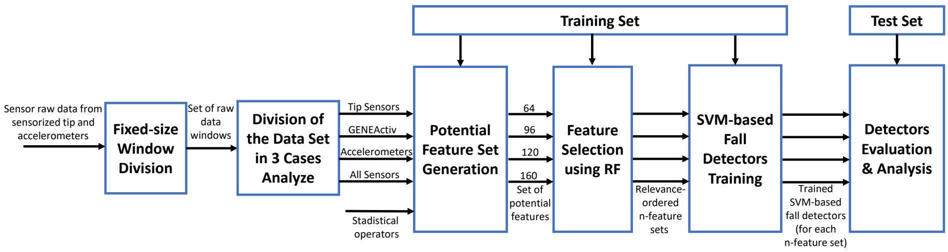
Azkenik, zenbait proba egiten dira ILG erabiltzailerik gabe erortzen utziz:

1. Makulua lurrean posizio estatiko desberdinetan jarrita edo leku batean bermatuta.
2. Erabiltzailea geldirik dagoela edo oinez doala makulua erortzea. Makuluaren 80 erorketa egingo dira (40 kasu bakoitzeko).

Guztira, ILGren erabiltzaileen 192 erorketa lortzen dira; boluntario bakoitzeko, 9 minutuko jarduera fisikoa atzematen da; eta erabiltzaile bakoitzeko, 5 minutuko tartean egindako ILGren posizio estatiko desberdinetik erortzeak eta makuluaren 80 erorketa neurtzen dira.

3.3.2 Metodologia

Datu-multzoak sortu ondoren, 3.17. irudian proposatutako bi modulutan banatutako algoritmoak diseinatzen dira. Lehen aipatu bezala, lehen modulua (ILGaren erorketen detektagailua) erorketak detektatzeko diseinatuta dago, eta bigarren moduluak (erabiltzailearen eta ILGaren erorketen detektagailua) ILGarekin batera erabiltzailea erori den zehazten du. Lehen esan bezala, bi moduluek sarrera-datu desberdinak erabiltzen dituzte. Hala ere, bi moduluak diseinatzeko erabilitako metodologia antzekoa da; metodologia honek 3.18. irudian azaldutako egiturari jarraitzen du.



Irudia 3.18: Machine Learningn oinarritutako erorketak detektatzeko moduluak diseinatzeko jarraitutako metodologia.

3.3.2.1 ILGren erorketa-detektagailuaren garapena

Modulu hau, ILGren erorketak detektatzeaz arduratzen da. Modulu honetan, erabiltzailearen erorketari buruzko datuak eta erabiltzailearen Jarduera Fisikoako datu-multzoa erabiltzen dira.

Taula 3.6: Datu-multzoaren banaketa eta datu-kopuruaren doikuntza.

			Leihoak		
			Train	**Test**	**Guztira**
Partaideak			8	4	12
Erorketen Detektagailuaren Datuak	*Ez Estutua*	Erorketak	2770	1216	3986
		Ez Erorketak	5805	2600	8405
	Estutua	Erorketak	759	382	1141
		Ez Erorketak	866	433	1299
Pertsonen Erorketa Detektatzeko Datuak		Pertsonen Erorketak	128	64	192
		ILG Erorketak	50	30	80

Lehenik eta behin, datuak leiho irristakorretan banatzen dira. Leihoen tamaina 100 laginekoa da (2s), eta leihoen hasiera 20 laginek banatzen dute (0,4s). 100eko leiho-tamaina aukeratu da, egindako esperimentuak aztertzetik ondorioztatu delako, hau dela pertsona batek erortzeko behar duen batez besteko denbora-tartea. Segmentazio hori egin ondoren, lortutako leihoetatik zeintzuk diren erorketei dagozkionak adierazi da, erorketarik ez dituztenak kenduz (%50 inguru). Lortutako datuak entrenamenduko datu multzo batean eta probako edo testeko datu multzo batean banatu dira, entrenamendurako 8 boluntarioren datuak eta probarako beste 4renak erabiliz (ikusi 3.6. taula).

Bigarrenik, datuak leihoetan segmentatu ondoren, leiho bakoitza definitzen duten ezaugarriak hautatu dira. Kasu honetan, estatistika-operadoreetan oinarritutako ezaugarriak aukeratu dira:

- Batez bestekoa (MEAN).
- Desbideratze estandarra (STD).
- Bariantza (VAR).
- Kurtosia (KUR).
- Kuartilen arteko ibiltarte (IR).
- Kurbaren azpiko seinalea (AUS).
- Leihoaren gehienezko balioa (MAX).
- Leihoaren gutxieneko balioa (MIN).

Estatistika operazio horiek, datu-multzoaren leiho bakoitzari aplikatu zaizkio. Leiho bakoitza sentsoreen datu hauek osatzen dute: Punta sentsorizatuaren indar-sentsorea, Punta sentsorizatuaren giroskopioa (x, y, z), Punta sentsorizatuaren azelerometroa (x, y, z) eta Punta sentsorizatuaren inklinazio-angelua (α). Kasu honetan, leiho bakoitzeko 64 ezaugarri lortzen dira guztira.

Hirugarrenik, ezaugarririk garrantzitsuenak hautatzen dira, dimentsionaltasuna murriztuz. Dimentsionaltasun-murrizketa hori, ezaugarri bakoitzari esleitutako pisu bat ematean datza. 2.3. kapituluan aipatu bezala, literaturan metodologia desberdin asko daude zeregin honetarako. Lan honetan, Relief eta RF ikuspegien arteko alderaketa egiten da, ordenarik onena ematen duena aukeratzeko. Garrantziaren ordena eta 15 ezaugarri garrantzitsuenen pisuak 3.7. taulan ikus daitezke.

Azkenik, erorikoen detektagailua sortzen da. Kasu honetan, sarrera-kopurua aldatzen joan da, sarrera-kopuru optimoa zehazteko. Horrela, lehenik eta behin, detektagailu bat egiten da sarrera bakar batekin, hori ezaugarririk garrantzitsuena izanik; gero, beste detektagailu bat sortzen da, bi sarrerarekin; bi ezaugarri garrantzitsuenak erabiliz, eta horrela hurrenez hurren, ezaugarri guztiak sartu arte. Erorketen detektagailua SVM ikuspegi batekin egin da, eta hiperparametroak K-Fold balidazio gurutzatua erabiliz optimizatuko dira, $K = 10$ batekin.

Taula 3.7: RF eta Relief emandako ezaugarrien pisua. (α = IGL inklinazio angelua, accel = azelerometroa, gyro = giroskopioa)

Random Forest			**Relieff**		
n	*Ezaugarria*	*Pisua*	*n*	*Ezaugarria*	*Pisua*
1	α MAX	3.587	*1*	Punta indarra AUS	0.086
2	Punta gyro MIN Z axis	2.803	*2*	Punta gyro KUR X axis	0.057
3	Punta gyro KUR X axis	2.788	*3*	α MAX	0.048
4	α MEAN	2.631	*4*	Punta accel AUS Y axis	0.038
5	Punta gyro MIN X axis	2.545	*5*	Punta accel AUS X axis	0.028
6	α STD	2.485	*6*	Punta accel MEAN X axis	0.026
7	Punta gyro KUR Y axis	2.395	*7*	Punta accel KUR Z axis	0.016
8	α VAR	2.380	*8*	α STD	0.015
9	α AUS	2.348	*9*	Punta indarra MIN	0.014
10	Punta accel MEAN Z axis	2.342	*10*	α MEAN	0.013
11	Punta gyro MIN Y axis	2.168	*11*	α AUS	0.013
12	Punta accel AUS Z axis	2.165	*12*	Punta gyro KUR Y axis	0.010
13	Punta accel MAX Z axis	2.095	*13*	Punta gyro MAX Y axis	0.010
14	Punta accel KUR Z axis	1.947	*14*	α KUR	0.008
15	Punta indarra MEAN	1.915	*15*	Punta gyro MEAN Y axis	0.006

3.3.2.2 Erabiltzailearen erorketa-detektagailuaren garapena

Modulu hau, ILG erabiltzailearekin edo erabiltzailerik gabe erori den detektatzeaz arduratzen da. Erabilitako metodologia lehenengo moduluaren antzekoa da. Hala ere, modulu honetan, leihoen banaketa modu desberdinean egin da. Aurreko moduluan ILG erori dela detektatu den eremua baino ez da erabiltzen leiho gisa. Horren ondorioz, erabiltzailearekin 192 erorketa eta erabiltzailerik gabeko ILGren 80 erorketa erabili dira (ikusi 3.6. taula).

Hautatutako ezaugarri-multzoa, lehen moduluko bera da, baita dimentsionaltasuna murrizteko metodoa ere. Azkenik, beste moduluan bezala, detektagailua sortzeko K-Fold balidazio gurutzatua duen SVM erabili da.

3.3.3 Emaitzak eta analisi konparatiboa

Atal honetan, aurretik azaldutako metodologiari jarraituta lortutako emaitzak aztertzen dira. Gainera, Punta sentsorizatuan oinarritutako detektagailuarekin lortutako emaitzak, beste sentsore batzuekin lortutakoekin konparatzen dira. Lau sentsore talde desberdin erabiltzea konparatu da (ikusi 3.8. taula): 1) Punta sentsorizatu; 2) GENEActive sentsore jantziak; 3) Azelerometro posible guztiak (Punta sentsorizatuaren barne-azelerometroa eta lau GENEACtiv azelerometro); eta 4) Sentsore guztiak. Konparaketa egokia egin ahal izateko, lau ikuspegietan metodologia berbera jarraitu da.

Taula 3.8: Sentsorearen sarrera kontuan hartuta aztertutako kasuak. (Accel = Azelerometro, Gyro = Giroscopio, α = Inklinazio Angulua)

Device	**Sensors**	**Analisiak egiteko modu desberdinak**			
		Sensorized Tip	**GENEActiv Sensors**	**Accel. Sensors**	**All Sensors**
Sensorized Tip	α	X			X
	3 axis Gyro.	X			X
	Force Sensor	X			X
	3 axis Accel.	X		X	X
4x GENEActiv Accel.	3 axis Accel.		X	X	X

3.3.3.1 ILGren erorketa-detektagailuaren ebaluazioa

3.7. taulan lortutako ordenan oinarrituta, aurretik azaldutako prozedura jarraituz, detektagailu desberdinak garatu dira, emaitza onena ematen duena zein den aukeratzeko. Bi metodoekin antzeko emaitzak lortzen diren arren, apur bat hobeagoak dira Random Forestk hautatutako ezaugarriekin. Beraz, teknika hori erabili da lau kasuetarako.

Dimentsionaltasuna murrizteko metodoa hautatu ondoren, konparatuko diren 4 kasuei aplikatu zaie. Punta sentsorizatuaren sentsoreak bakarrik erabiliz gero, ezaugarririk garrantzitsuena gehieneko inklinazio-angelua da. GENEACtiv sentsoreek emandako emaitzei erreparatuz, ezaugarri garrantzitsuena gehieneko inklinazio-angelua dela eta hiru ezaugarri garrantzitsuenak erabiltzailearen bizkarrean dagoen sentsoretik eratortzen direnak (bereziki X ardatza, bertikala) direla ikusi da. Azelerometro erabilgarri guztiak kontuan hartzen badira (GENEACtiv eta Punta sentsorizatuaren azelerometroa), Puntaren azelerometroa eta bizkarraren GENEACtiv sentsorea dira ezaugarririk garrantzitsuenak. Sentsore guztiak erabiltzen direnean, berriz ere egiaztatzen da ezaugarririk garrantzitsuena inklinazio-angelu maximoarekin erlazionatutakoa dela.

Ezaugarrien garrantzia ezagutu ondoren, SVMn oinarritutako detektagailua sortzen da. Lehen esan bezala, sarrera-ezaugarrien kopurua handituz entrenatuko dira, RFk emandako ordenaren arabera.

Taula 3.9: SVMn oinarritutako erorikoen detektagailuetan aztertutako kasuen emaitzak (No. In = Sarrera zenbakia sailkatzaile bakoitzeko, P = Zehaztasuna, Sp = Espezifikotasuna, Se = Sentsibilitatea, F = F-score).

	Punta sentsorizatua				**GENEActive**			
No. In	*P*	*SP*	*Se*	*F*	*P*	*SP*	*Se*	*F*
1	0.982	0.984	1.000	0.991	0.941	0.945	0.984	0.962
2	0.986	0.988	1.000	0.993	0.956	0.960	1.000	0.978
3	0.980	0.982	1.000	0.990	0.957	0.960	1.000	0.978
4	0.982	0.984	1.000	0.991	0.957	0.961	1.000	0.978
5	0.983	0.985	1.000	0.991	0.953	0.957	0.999	0.976
6	0.983	0.984	1.000	0.991	0.969	0.972	1.000	0.984
7	0.987	0.988	1.000	0.993	0.978	0.980	1.000	0.989
8	0.982	0.983	1.000	0.991	0.971	0.973	1.000	0.985
9	0.982	0.984	1.000	0.991	0.970	0.973	0.999	0.985
10	0.982	0.984	1.000	0.991	0.974	0.977	0.997	0.986
	Azelerometroak				**Sentsore Guztiak**			
No. In	*P*	*SP*	*Se*	*F*	*P*	*SP*	*Se*	*F*
1	0.979	0.982	0.979	0.979	0.970	0.972	1.000	0.985
2	0.979	0.982	0.981	0.980	0.986	0.988	1.000	0.993
3	0.982	0.984	0.989	0.985	0.986	0.988	1.000	0.993
4	0.984	0.985	1.000	0.992	0.982	0.984	1.000	0.991
5	0.980	0.982	1.000	0.990	1.000	1.000	1.000	1.000
6	0.990	0.991	1.000	0.995	1.000	1.000	1.000	1.000
7	0.997	0.998	1.000	0.999	1.000	1.000	1.000	1.000
8	0.981	0.983	1.000	0.991	1.000	1.000	1.000	1.000
9	0.984	0.986	1.000	0.992	0.992	0.993	1.000	0.996
10	0.982	0.983	1.000	0.991	0.989	0.991	1.000	0.995

Emaitza horiek aztertuta, ikus daiteke, Punta sentsorizatua soilik erabilita 0,99tik gorako F-Score lortzen dela kasu guztietan (ikusi 3.9. taula). Gainera, kasu honetan ezaugarrien kopurua ez da garrantzitsua, emaitza onak lor baitaitezke ezaugarri bakarra erabilita ere. Hala ere, emaitzarik onenak bi ezaugarri erabiliz lortzen dira.

Punta sentsorizatuko sentsore guztiak erabiltzen ez diren bi kasuetan, emaitza txarragoak lortzen dira, nahiz eta onak izaten jarraitzen duten. GENEACtiv bakarrik erabilita, emaitzarik onena 0,989ko F-Score da eta 7 ezaugarri garrantzitsuenak erabiliz lortzen da (ikusi 3.9. taula). Bestalde, azelerometro guztiak erabiliz, 7 ezaugarrirekin ere, 0,999ko F-Score lortzen da (ikusi 3.9. taula). Emaitzarik onenak, sentsore guztiak erabiltzean lortzen dira, 5 ezaugarri dituen 1eko F-Score batekin (ikusi 3.9. taula). Hala ere, esan daiteke aztertutako 4 kasuekin emaitza oso ona lortzen direla, kasurik txarrenean ere, 0,98 F-Scorea baino balio handiagoa lortuz.

3.3.3.2 Erabiltzailearen erorketa-detektagailuaren ebaluazioa

Aurreko detektagailuak, ILGren erorketa bat hautematen badu, ILGrekin batera erabiltzailea erori den edo ez esaten duen detektagailua erabili behar da. Lehen aipatu bezala, detektagailu honen garapenerako erabilitako datu-multzoa ez da aurrekoa bezalakoa, ondorioz, dimentsionaltasuna murriztu da berriro. Horretarako, lehen bezala RF aplikatu da; kasu honetan, 5 ezaugarri garrantzitsuenak Puntaren indar-sentsoreari lotutakoak dira. Izan ere, pertsona bat ILGarekin erortzen denean, ez erortzen saiatzen da indar gehiago eginez.

Ezaugarrien garrantzi-ordena lortu ondoren, lehen SVMa kalkulatzeko erabilitako metodologia bera aplikatzen da. Emaitzak 3.10. taulan laburbiltzen dira. Kasu guztietan, 0,89tik gorako F-Score balioak ikusten dira, emaitzarik onena 6 ezaugarri garrantzitsuenak erabiliz lortzen direlarik.

Taula 3.10: ILG erabiltzailearekin edo gabe erori den hautematen duen detektagailuaren emaitzak (No. In = Sarrera zenbakia detektagailu bakoitzeko, P = Zehaztasuna, Sp = Espezifikotasuna, Se = Sentsibilitatea, F = F-score).

No. In	*P*	*Sp*	*Se*	*F*
1	0.876	0.717	0.936	0.905
2	0.880	0.733	0.917	0.898
3	0.888	0.757	0.906	0.897
4	0.880	0.737	0.906	0.893
5	0.940	0.867	0.984	0.962
6	0.943	0.873	0.984	0.963
7	0.940	0.867	0.984	0.962
8	0.930	0.843	0.969	0.949
9	0.926	0.833	0.967	0.946
10	0.943	0.873	0.981	0.962

3.3.4 Ondorioak

Atal honetan, ILG desberdinetara akoplatu daitekeen Punta sentsorizatu bat erabiltzen duen erorikoen detektagailu bat garatu da. Erorikoak detektatzeko, bi modulutan oinarritutako metodologia inplementatu da. Lehenengo modulua ILGren erorikoak hautemateaz arduratzen da. ILGren erorikoa detektatzen badu, bigarren modulua, ILGrekin batera erabiltzailea erori den edo ez detektatzeaz arduratuko da. Bi moduluak SVMn oinarrituta daude. Gainera, RF erabili da ezaugarri garrantzitsuenak aukeratu eta dimentsionaltasuna murrizteko.

Erorketa-detektagailutik, oso emaitza onak lortu dira, ILGen erorketen detektagailuak 0.993 F-Scorea du eta erabiltzaileen erorketen detektagailuak 0.963 F-Scorea. Gainera, sentsore eramangarriak erabiliz, sentsore desberdinen konparazio bat egin da (ikusi 3.9. taula). Punta sentsorizatuarekin emaitza hobeak lortuz eta sarrea gutxiago behar izanez. Punta sentsorizatuarekin bakarrik bi sarrerarekin 0.993 F-Scorea lortzen da, eta sentsore eramangarriekin, 0.989 F-Scorea ematen du 7 sarrera aukeratuta.

4 Ondorioak

Atal honetan, doktorego-tesi honen barnean garatutako lanaren ondorioak aurkezten dira, egindako ekarpen teknologikoak azpimarratuz. Garatutako lanaren argitalpenak ere zehazten dira (eragin handiko JCR aldizkarietan eta nazioarteko biltzarretako Springer liburuetan argitaratutako artikuluak). Euskal Herriko Unibertsitatea/Universidad del País Vasco (UPV/EHU)ko doktorego-legerian definitzen den bezala, argitalpen hauei esker, tesi hau argitalpenen bilduma gisa aurkeztu da. Azkenik, atal honetan, etorkizuneko lanak adierazten dira, doktorego-tesi honen eremuan etorkizunerako irekita egon daitezkeen ikerketa-ildoak erakutsiz.

Azken hamarkadetan, errehabilitazioa behar duten pertsonen bizi-kalitatea hobetu nahian, errehabilitazioaren indibidualizazioa areagotu da. Sentsorizazioaren arloko aurrerapenei esker, eta bereziki giza sentsorizazioari esker, errehabilitazio prozesu horretan laguntzeko gai diren sentsore-sistemak proposatzen hasi dira. Hala ere, sentsore mota horiek eragozpen ugari dituzte. Eragozpen horiei irtenbidea eman nahian, azken aldian, ikerketa desberdinek, sentsoreak ILGetan ezartzea proposatu dute. Hala ere, ILGk sentsorizatzea ez da lan erreza, eta aurki daitezkeen lan gehienak fabrikatuta dauden ILGetara baino ez dira egokitzen. Horretaz gainera, errehabilitazioaren indibidualizazio hori lortzeko, oso garrantzitsua da pertsona batek zer Jarduera Fisikoa egiten duen jakitea. Hori dela eta, pertsonen eguneroko bizitzan sentsore desberdinak integratzen hasi dira, beraien jarduera fisikoak ezagutzeko. Bestalde, pertsonen sentsorizazioa aprobetxatuz, lan askok erorikoak detektatzea proposatzen dute, eroriko baten eraginez errehabilitazio gehiago behar ez izateko. Egoera horren aurrean, doktore tesi honek ILGren sentsorizazioan sakondu nahi du.

Erronka hori lortzeko, tesia hiru ekarpen nagusitan egituratu da.

Lehenengo ekarpena, merkatuko **ILG desberdinetara egokitzeko gai den Punta sentsorizatua** diseinatzean eta baliozkotzean oinarritzen da. Bertan, JF ezagutzeko neurtu beharreko aldagai garrantzitsuenak aztertu ondoren, aldagai horiek neurtzeko sentsore egokiak hautatu dira. Ondoren, Punta sentsorizatuaren egitura egokia diseinatu da, sentsoreak ILGetan txertatu ahal izateko. Ondoren, datuak eskuratzeko sistema programatu da, Bluetooth Low Energy (BLE) bidez sentsoreen datuak biltzeko. Horrela, hainbat ILGetara egokitzeko gai den Punta sentsorizatu bat lortu da. Punta sentsorizatu hori, ILGari aplikatutako indarra, dagoen altuera eta ILGaren mugimenduak neurtzeko gai da. Azkenik, erabilitako sentsoreak VICON kamera-sistema batean baliozkotu dira, oso emaitza onak lortuz.

> *Punta sentsorizatu bat garatu da, merkatuan dauden Ibiltzeko Laguntza Gailua (ILG)etara egokitzeko gaitasuna duena (makuluak, makilak...). Puntu sentsorizatu hau garatzeko, metodologia honi jarraitu zaio. Lehenik eta behin, neurtu beharreko aldagai garrantzitsuenak aztertu dira. Analisi honek sentsoreen konfiguraziorik onena identifikatzen laguntzen du, hau da, indar axiala neurtzen duen indar-sentsore bat, Punta sentsorizatuaren mugimendua neurtzen duten 3 ardatzeko azelerometro bat, 3 ardatzeko giroskopio bat eta 3 ardatzeko magnetometro bat, eta altitude-aldaketak neurtzen laguntzen duen barometro bat. Bigarrenik, puntaren egituraren diseinua optimizatu da, baita datuak bildu eta biltegiratuko dituen elektronikaren programazioa ere. Diseinatzerako orduan, kontuan hartu da ahalik eta arinena izan dadila eta ILG desberdinen artean trukagarria izatea. Autonomia handia izateko, eskuratze-sistemaren eta sentsoreen datuak biltzen dituen prozesadorearen arteko komunikazioa Bluetooth Low Energy (BLE) bidez egin da. Hirugarrenik, hainbat algoritmo garatu dira pertsonaren aurrealdeko planoa ILGaren bidez balioetsi eta angelu anteroposteriorrak eta lateromediala lortzeko. Azkenik, hainbat proba esperimental egiten dira garatutako Punta sentsorizatua baliozkotzeko helburuarekin.*
>
> *Beraz, ondorioztatu daiteke, proposatutako metodologiarekin* **garatutako Punta sentsorizatua** *egokia dela* **Jarduera Fisikoa monitorizatu eta erorikoak**

detektatzeko.

Bigarren ekarpena, diseinatutako Punta sentsorizatuan integratutako **5 jarduera fisiko desberdinen sailkatzaile bat garatzea** izan da. Sailkatzaile hau, Adimen Artifizialaren teknikak erabiliz garatu. Jarduera Fisikoaren sailkatzaile hori lortzeko, ILG bat erabiliz, jarduera horiek simulatzen dituzten hainbat proba diseinatu dira. Lortutako datuekin, datuak egokitzeko eta ezaugarri estatistikoak ateratzeko prozesu bat egin da. Ondoren, lortutako datuekin, ezaugarri garrantzitsuenak aukeratu eta dimentsionaltasuna murrizten da, Random Forestn oinarrituta. Azkenik, 3 sailkatzaile ezberdin inplementatzen dira, K-NN, SVM eta ANN oinarrituta.

Sailkatzailearen garapenerako metodologia hau jarraitu da. Lehen urratsa, sailkatu beharreko jarduerak hautatzea da: ibiltzea, azkarrago ibiltzea, eskailerak igotzea, eskailerak jaistea eta geldirik egotea. Jarduera horiek simulatzeko hainbat esperimentu egin dira Punta sentsorizatua integratuta duen ILG bat erabiliz. Bigarren urratsa, entseguetatik lortutako datuak zikloak irudikatzen dituzten leihoetan zatitu, eta leiho bakoitzerako ezaugarriak lortzean datza. Hirugarren urratsean, Random Forest bidez, Jarduera Fisikoaren sailkapena egin ahal izateko ezaugarri garrantzitsuenak hautatzen dira. Azkenik, MLn oinarritutako sailkatzaileak garatu da. Kasu honetan, 3 metodologia erabili dira: K-NN, SVM eta ANN. Eta erabilitako 3 sailkapen-metodologien artean lortutako emaitzak alderatu dira. Analisi honetatik frogatu da, RF bidez lortutako dimentsionaltasun-murrizketa egokia dela. 7 ezaugarri garrantzitsuenak erabiliz, %96tik gorako arrakasta-tasa lortu da SVM eta ANNrekin.

Beraz, ondorioztatu daiteke, Machine Learning erabiliz eta Punta sentsorizatuan oinarrituta garatu den **Jarduera Fisikoakoaren sailkatzailea egokia dela definitutako 5 jarduera desberdinak bereizteko.**

Azkenik, doktorego-tesiaren hirugarren ekarpena diseinatutako Punta sentsorizatuan oinarritutako **erorketa detektagailu** adimentsu bat garatzea izan da. Erorketa-detektagailu hori SVMn oinarrituta dago, eta **ILGa sentsorizatua erabiltzailearekin edo gabe erortzen den detektatzen du**. Zenbait proba esperimental egin, eta horietatik lortutako datuak egokitu dira. Datu horietatik abiatuta, hainbat ezaugarri lortu eta beraien dimentsionaltasuna murriztu da. Azkenik, Machine Learningn oinarritutako, bi modulutan banatutako erorketen detektagailu berritzailea inplementatu da.

Erorikoen detektagailu berriak metodologia hau jarraitu du. Lehenik eta behin, erorketa eta jarduera fisiko desberdinak simulatzeko esperimentuak diseinatu dira. Entsegu hauek, diseinatutako Punta sentsorizatua integratuta duen Ibiltzeko Laguntza Gailua bat erabiliz egin dira. Bigarrenik, Machine Learningn oinarritutako, bi modulutan banatutako, detektagailua garatu da. Lehenengo moduluak, ILGa erori den detektatzen du. Bigarrenak berriz, ILGa erabiltzailearekin edo erabiltzailerik gabe erori den detektatzen du, hau da, positibo faltsuak detektatzen ditu. Bi moduluak, SVMn oinarritutako detektagailua dira, eta horiek diseinatzeko Jarduera Fisikoaren sailkatzailean jarraitutako metodologia *bera erabili da. Azkenik, lortutako emaitzak, sentsore eramangarrietan oinarritutako erorketa-detektagailu batekin konparatu dira. Lehen moduluan, 0,99 F-Score baino emaitza hobeak lortu dira. Bestalde, bigarren moduluan, 0,96 F-Score-ko emaitzak eskuratu dira.*

Beraz, ondorioztatu daiteke, garatutako Punta Sentsorizatuan oinarrituta, **ILGa erabiltzailearekin edo erabiltzailerik gabe erori den detektatzeko gai den, erorketen detektagailu bat diseinatu dela.**

4.1 Ekarpenak: argitalpenak

Doktorego-tesi honetan deskribatutako ekarpenen ondorioz, hainbat emaitza argitaratu dira. Lan hauek, eragin-indize altua duten aldizkarietan eta ikerketa-arloan ospe handia duten nazioarteko kongresuetan aurkeztu dira. Egindako lanek argitalpen hauek ekarri dituzte.

JCR aldizkarietan publikatutako artikuluak (argitalpenen bilduma gisa erabiltzen dira):

- Asier Brull, Asier Zubizarreta, Itziar Cabanes, and Ana Rodriguez-Larrad. Sensorized Tip for Monitoring People with Multiple Sclerosis that Require Assistive Devices for Walking. *Sensors*, 20(15):4329, aug 2020.

  doi: https://doi.org/10.3390/s20154329 JCR2020: 3.576 (Q1)

  1. eranskina

- Asier Brull Mesanza, Sergio Lucas, Asier Zubizarreta, Itziar Cabanes, Eva Portillo, and Ana Rodriguez-Larrad. A Machine Learning Approach to Perform Physical Activity Classification Using a Sensorized Crutch Tip.*IEEE Access*,8:210023–210034, 2020.

  doi: https://doi.org/10.1109/ACCESS.2020.3039885 JCR2020: 3.367 (Q2)

  2. eranskina

- Asier Brull Mesanza, Ilaria D'Ascanio, Asier Zubizarreta, Luca Palmerini, Lorenzo Chiari, and Itziar Cabanes. Machine Learning based Fall Detector with a Sensorized Tip. *IEEE Access*, pages 1–1, dec 2021.

  doi: https://doi.org/10.1109/ACCESS.2021.3132656 JCR2020: 3.367 (Q2)

  3. eranskina

Springer Booksen nazioarteko konferentzien aktetan argitaratutako lanak:

- Asier Brull, Aitor Gorrotxategi, Asier Zubizarreta, Itziar Cabanes, and Ana Rodriguez-Larrad. Classification of Daily Activities Using an Intelligent Tip for Crutches. *Advances in Intelligent Systems and Computing*, 1093 AISC:405–416, nov 2019.

  doi: https://doi.org/10.1007/978-3-030-36150-1_33

- Asier Brull, Asier Zubizarreta, Itziar Cabanes, Jon Torres-Unda, and Ana Rodriguez-Larrad. A Smart Crutch Tip for Monitoring the Activities of Daily Living Based on a Novel Neural-Network Intelligent Classifier. pages 113–122. *Springer*, Cham, sep 2021.

  doi: 10.1007/978-3-030-57802-2_11

- Asier Brull, Sergio Lucas, A. Zubizarreta, Eva Portillo, and Itziar Cabanes. A Random Forest Based Methodology for the Development of an Intelligent Classifier of Physical Activities. *Biosystems and Biorobotics*, 28:85–89, oct2020.

  doi: https://doi.org/10.1007/978-3-030-70316-5_14

4.2 Etorkizuneko lanak

Doktorego-tesi honetan egindako lanari esker, etorkizuneko ikerketa-lanetarako hainbat interes-ildo hauteman dira:

- Doktorego-tesi honetan, Jarduera Fisikoa monitorizatzeko eta erorikoak detektatzeko Punta sentsorizatu bat aurkeztu da. Hala ere, haren erabilera erosoagoa izan dadin, bai egitura mekanikoa bai elektronikoa alda daitezke, bateria puntan txertatuz. Gainera, integratu diren sentsore komertzialen ordez, garapen propioko sentsoreak erabil litezke, sistemaren dimentsioak murriztuz.

- Punta Sentsorizatu berritzaile hau, taka-taka bat bezalako, ILG konplexuagoetan inplementatzeko, komenigarria litzateke, martxaren monitorizazioa sinkronizatzeko bi Punta sentsorizaturen arteko komunikazio-sistema garatzea.

- Doktorego-tesian, 5 jarduera desberdin bereizteko gai den JFaren sailkatzaile bat aurkeztu da. Hala ere, eguneroko bizitzan jarduera fisiko gehiago aurki daitezke. Egoera horretan, komenigarria litzateke sailkatzaileak bereiz ditzakeen jarduera fisikoak areagotu ahal izatea. Hori egin ahal izateko, sailkatu beharreko jarduera fisiko berri horien analisia egin, esperimentu batzuk diseinatu eta sailkatzailea birsortu beharko litzateke.

- Errehabilitazio klinikoko inguruneetan, Punta Sentsorizatua ezartzea egokia litzateke. Horrela, garatutako sistemak ematen duen eguneroko jarduerari buruzko informazio kuantifikatuari buruzko profesionalen iritzia lortzea posible izango litzateke.

- Garatutako erorketa-detektagailua hobetzeko, jarduera fisikoen eta erorketen multzo zabalagoa simulatu liteke, honela, erorikoak detektatzeko ahalik eta kasu gehien bilduz. Horretarako, aztertu beharreko kasu berriak bilduko lituzkeen esperimentu multzo bat diseinatu eta detektagailua berriro sortu beharko litzateke.

- Sailkatzailea eta erorikoen detektagailua hobetzeko, denbora errealean ezar litezke datuak eskuratzeko sisteman integratuz. Horrez gain, datuak hodeian gorde ahal litezke. Horrela, unean bertan egindako Jarduera Fisikoaren berri eman ahal izango da, eta, eroriz gero, osasun-langileei horren berri eman ahal izango diete.

List of Tables/Taulen Zerrenda

List of Figures/Irudien Zerrenda

Bibliography/Bibliografia

[1] Rehabilitation. 2, 3

[2] Adam, Lauren B Sherar, James P Sanders, Paul W Sanderson, and Dale W Esliger. Technologies That Assess the Location of Physical Activity and Sedentary Behavior: A Systematic Review. *J Med Internet Res 2015;17(8):e192 https://www.jmir.org/2015/8/e192*, 17(8):e4761, aug 2015. 13

[3] Bruno Aguiar, Tiago Rocha, Joana Silva, and Inês Sousa. Accelerometer-based fall detection for smartphones. In *IEEE MeMeA 2014 - IEEE International Symposium on Medical Measurements and Applications, Proceedings*. IEEE Computer Society, 2014. 30, 31, 33

[4] Bruno Aguiar, Joana Silva, Tiago Rocha, Susana Carneiro, and Ines Sousa. Monitoring physical activity and energy expenditure with smartphones. In *2014 IEEE-EMBS International Conference on Biomedical and Health Informatics, BHI 2014*, pages 664–667. IEEE Computer Society, 2014. 9, 34

[5] Laila Alhimale, Hussein Zedan, and Ali Al-Bayatti. The implementation of an intelligent and video-based fall detection system using a neural network. *Applied Soft Computing Journal*, 18:59–69, may 2014. 8, 32, 34

[6] Hoda Allahbakhshi, Lindsey Conrow, Babak Naimi, and Robert Weibel. Using Accelerometer and GPS Data for Real-Life Physical Activity Type Detection. *Sensors 2020, Vol. 20, Page 588*, 20(3):588, jan 2020. 25

[7] M. Alwan, P.J. Rajendran, S. Kell, D. Mack, S. Dalal, M. Wolfe, and R. Felder. A Smart and Passive Floor-Vibration Based Fall Detector for Elderly. pages 1003–1007. Institute of Electrical and Electronics Engineers (IEEE), oct 2006. 29, 33

[8] Filippo Amato, Alberto López, Eladia María Peña-Méndez, Petr Vaňhara, Aleš Hampl, and Josef Havel. Artificial neural networks in medical diagnosis, 2013. 23

[9] K. Aminian, Ph Robert, E. Jéquier, and Y. Schutz. Estimation of speed and incline of walking using neural network. In *Conference Proceedings - 10th Anniv., IMTC 1994: Advanced Technologies in I and M. 1994 IEEE Instrumentation and Measurement Technology Conference*, pages 160–162. Institute of Electrical and Electronics Engineers Inc., 1994. 8, 18, 23, 24, 25

[10] Kamiar Aminian and Bijan Najafi. Capturing human motion using body-fixed sensors: Outdoor measurement and clinical applications. *Computer Animation and Virtual Worlds*, 15(2):79–94, may 2004. 30, 31, 34

[11] Akin Avci, Stephan Bosch, Mihai Marin-Perianu, Raluca Marin-Perianu, and Paul Havinga. Activity Recognition Using Inertial Sensing for Healthcare, Wellbeing and Sports Applications: A Survey. In *23th International Conference on Architecture of Computing Systems 2010*, pages 1–10, 2010. 3, 16, 17, 18, 19, 21, 22, 20

[12] Muhammad Awais, Lorenzo Chiari, Espen Alexander F. Ihlen, Jorunn L. Helbostad, and Luca Palmerini. Physical Activity Classification for Elderly People in Free-Living Conditions. *IEEE Journal of Biomedical and Health Informatics*, 23(1):197–207, jan 2019. 8, 20, 23, 25, 22

[13] Joaquin Ballesteros, Alberto Tudela, Juan Rafael Caro-Romero, and Cristina Urdiales. Weight-Bearing Estimation for Cane Users by Using Onboard Sensors. *Sensors (Basel, Switzerland)*, 19(3), feb 2019. 10, 12, 14

[14] Malti Bansal, Saurabh Malik, Mohit Kumar, and Nikita Meena. Arduino based Smart Walking Cane for Visually Impaired People. In *Proceedings of the 4th International Conference on Inventive Systems and Control, ICISC 2020*, pages 462–465. Institute of Electrical and Electronics Engineers Inc., jan 2020. 10, 13

[15] Ling Bao and Stephen S. Intille. Activity recognition from user-annotated acceleration data. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 3001:1–17, 2004. 17, 22, 25

[16] Harrison L Bartlett and Michael Goldfarb. A Phase Variable Approach for {IMU}-Based Locomotion Activity Recognition. *{IEEE} Transactions on Biomedical Engineering*, 65(6):1330–1338, jun 2018. 8, 19, 25, 18

[17] Rezaul K. Begg, Marimuthu Palaniswami, and Brendan Owen. Support vector machines for automated gait classification. *IEEE Transactions on Biomedical Engineering*, 52(5):828–838, may 2005. 23, 26, 22, 25

[18] Michael Belshaw, Babak Taati, Jasper Snoek, and Alex Mihailidis. Towards a single sensor passive solution for automated fall detection. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, pages 1773–1776, 2011. 28, 32, 33, 34

[19] Hansen BH, Kolle E, Dyrstad SM, Holme I, and Anderssen SA. Accelerometer-determined physical activity in adults and older people. *Medicine and Science in Sports and Exercise*, 44(2):266–272, feb 2012. 3

[20] Federico Bianchi, Stephen J. Redmond, Michael R. Narayanan, Sergio Cerutti, and Nigel H. Lovell. Barometric pressure and triaxial accelerometry-based falls event detection. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 18(6):619–627, dec 2010. 30, 33, 32

[21] Michael Boyle, Christopher Edwards, and Saul Greenberg. The Effects of Filtered Video on Awareness and Privacy. *Proceedings of the 2000 ACM conference on Computer supported cooperative work - CSCW '00*, 2000. 8, 28

[22] Mirko Brandes, Ralph Schomaker, Gunnar Möllenhoff, and Dieter Rosenbaum. Quantity versus quality of gait and quality of life in patients with osteoarthritis. *Gait and Posture*, 28(1):74–79, jul 2008. 3

[23] Leo Breiman. Bagging predictors. *Machine Learning*, 24(2):123–140, 1996. 20

[24] Leo Breiman. Random forests. *Machine Learning*, 45(1):5–32, oct 2001. 20

[25] Giampaolo Brichetto, Ludovico Pedullà, Jessica Podda, and Andrea Tacchino. Beyond center-based testing: Understanding and improving functioning with wearable technology in MS. *Multiple sclerosis (Houndmills, Basingstoke, England)*, 25(10):1402–1411, sep 2019. 4

[26] Asier Brull, Aitor Gorrotxategi, Asier Zubizarreta, Itziar Cabanes, and Ana Rodriguez-Larrad. Classification of Daily Activities Using an Intelligent Tip for Crutches. *Advances in Intelligent Systems and Computing*, 1093 AISC:405–416, nov 2019. 51, 53, 55, 56

[27] Asier Brull, Sergio Lucas, A. Zubizarreta, Eva Portillo, and Itziar Cabanes. A Random Forest Based Methodology for the Development of an Intelligent Classifier of Physical Activities. *Biosystems and Biorobotics*, 28:85–89, oct 2020. 53

[28] Asier Brull, Asier Zubizarreta, Itziar Cabanes, and Ana Rodriguez-Larrad. Sensorized Tip for Monitoring People with Multiple Sclerosis that Require Assistive Devices for Walking. *Sensors*, 20(15):4329, aug 2020. 1, 6, 37

[29] Asier Brull, Asier Zubizarreta, Itziar Cabanes, Jon Torres-Unda, and Ana Rodriguez-Larrad. A Smart Crutch Tip for Monitoring the Activities of Daily Living Based on a Novel Neural-Network Intelligent Classifier. pages 113–122. Springer, Cham, sep 2021. 53, 55, 56

[30] Ilaria Carpinella, Davide Cattaneo, and Maurizio Ferrarin. Quantitative assessment of upper limb motor function in Multiple Sclerosis using an instrumented

Action Research Arm Test. *Journal of NeuroEngineering and Rehabilitation*, 11(1):67, 2014. 16

[31] C J Caspersen, K E Powell, and G M Christenson. Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research. *Public Health Reports*, 100(2):126, 1985. 3

[32] Marzia Cescon, Divya Choudhary, Jordan E. Pinsker, Vikash Dadlani, Mei Mei Church, Yogish C. Kudva, Francis J. Doyle, and Eyal Dassau. Activity detection and classification from wristband accelerometer data collected on people with type 1 diabetes in free-living conditions. *Computers in Biology and Medicine*, 135:104633, aug 2021. 26, 25

[33] Gema Chamorro-Moriana, José Sevillano, and Carmen Ridao-Fernández. A Compact Forearm Crutch Based on Force Sensors for Aided Gait: Reliability and Validity. *Sensors*, 16(6):925, jun 2016. 10, 11, 12

[34] Michael Cheffena. Fall Detection Using Smartphone Audio Features. *IEEE Journal of Biomedical and Health Informatics*, 20(4):1073–1080, jul 2016. 29, 30, 32, 33, 34

[35] Jay Chen, Karric Kwong, Dennis Chang, Jerry Luk, and Ruzena Bajcsy. Wearable sensors for reliable fall detection. In *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, volume 7 VOLS, pages 3551–3554. Institute of Electrical and Electronics Engineers Inc., 2005. 30, 33, 34

[36] Yongqi Felix Chen, Danielle Napoli, Sunil K. Agrawal, and Damiano Zanotto. Smart Crutches: Towards Instrumented Crutches for Rehabilitation and Exoskeletons-Assisted Walking. In *Proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics*, volume 2018-Augus, pages 193–198. IEEE Computer Society, oct 2018. 11, 12, 14, 15

[37] Wen Chang Cheng and Ding Mao Jhan. Triaxial accelerometer-based fall detection method using a self-constructing cascade-AdaBoost-SVM classifier. *IEEE Journal of Biomedical and Health Informatics*, 17(2):411–419, 2013. 30, 31, 33, 34, 32

[38] Nour Cherif, Youssef Ouakrim, Amel Benazza-Benyahia, and Neila Mezghani. Physical activity classification using a smart textile. *2018 IEEE Life Sciences Conference, LSC 2018*, pages 175–178, dec 2018. 20, 22, 23, 26, 25

[39] Joana Chong, Petra Tjurin, Maisa Niemelä, Timo Jämsä, and Vahid Farrahi. Machine-learning models for activity class prediction: A comparative study of feature selection and classification algorithms. *Gait & Posture*, 89:45–53, sep 2021. 20, 23, 25, 26, 19, 22

[40] Hsi-Chiang Chou and Kai-Yu Han. Developing a smart walking cane with remote electrocardiogram and fall detection. *Journal of Intelligent & Fuzzy Systems*, 40(4):8073–8086, jan 2021. 31

[41] Alarcos Cieza, Kate Causey, Kaloyan Kamenov, Sarah Wulf Hanson, Somnath Chatterji, and Theo Vos. Global estimates of the need for rehabilitation based on the Global Burden of Disease study 2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet*, 396(10267):2006–2017, dec 2020. 2

[42] Ton J. Cleophas and Aeilko H. Zwinderman. *Machine Learning in Medicine - a Complete Overview*. Springer International Publishing, 2015. 21

[43] Jeffrey A Cohen, Stephen C Reingold, Chris H Polman, and Jerry S Wolinsky. Disability outcome measures in multiple sclerosis clinical trials: current status and future prospects. *The Lancet Neurology*, 11(5):467–476, 2012. 2

[44] Paul Compagnon, Grégoire Lefebvre, Stefan Duffner, and Christophe Garcia. Learning personalized ADL recognition models from few raw data. *Artificial Intelligence in Medicine*, 107:101916, jul 2020. 18, 23, 24, 26, 30, 31, 34, 25

[45] Alessia Cristiano, Alberto Sanna, and Diana Trojaniello. Daily Physical Activity Classification using a Head-mounted device. In *2019 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, pages 1–7, 2019. 26, 25

[46] Karen M. Culhane, G. M. Lyons, D. Hilton, P. A. Grace, and D. Lyons. Long-term mobility monitoring of older adults using accelerometers in a clinical environment. *Clinical Rehabilitation*, 18(3):335–343, may 2004. 22, 26, 25

[47] Peter R. Culmer, Peter C. Brooks, Daniella N. Strauss, Denise H. Ross, Martin C. Levesley, Rory J. Oconnor, and Bipin B. Bhakta. An instrumented walking aid to assess and retrain gait. *IEEE/ASME Transactions on Mechatronics*, 19(1):141–148, feb 2014. 10, 11, 12, 13, 14, 15

[48] Luciani D, Cadossi M, Mazzotti A, Chiarello E, and Giannini S. The importance of rehabilitation after lower limb fractures in elderly osteoporotic patients. *Aging clinical and experimental research*, 25 Suppl 1(1 SUPPL.), oct 2013. 2

[49] Duc Cong Dang and Young Soo Suh. Walking Distance Estimation Using Walking Canes with Inertial Sensors. *Sensors (Basel, Switzerland)*, 18(1), jan 2018. 10, 11, 13, 14

[50] Koldo de Miguel, Alberto Brunete, Miguel Hernando, and Ernesto Gambao. Home Camera-Based Fall Detection System for the Elderly. *Sensors*, 17(12):2864, dec 2017. 28, 33, 34, 32, iii, iv

[51] Michael del Rosario, Stephen Redmond, and Nigel Lovell. Tracking the Evolution of Smartphone Sensing for Monitoring Human Movement. *Sensors*, 15(8):18901–18933, jul 2015. 13

[52] Thomas G. Dietterich. Experimental comparison of three methods for constructing ensembles of decision trees: bagging, boosting, and randomization. *Machine Learning*, 40(2):139–157, aug 2000. 20

[53] Christoph Dinh and Matthias Struck. A new real-time fall detection approach using fuzzy logic and a neural network. In *Proceedings of the 6th International Workshop on Wearable, Micro, and Nano Technologies for Personalized Health: "Facing Future Healthcare Needs", pHealth 2009*, pages 57–60. IEEE Computer Society, 2009. 30, 32, 33, 34

[54] Karantonis DM, Narayanan MR, Mathie M, Lovell NH, and Celler BG. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. *IEEE transactions on information technology in biomedicine : a publication of the IEEE Engineering in Medicine and Biology Society*, 10(1):156–167, jan 2006. 19, 26, 30, 18

[55] Lucas Medeiros Souza Do Nascimento, Lucas Vacilotto Bonfati, Melissa La Banca Freitas, José Jair Alves Mendes Junior, Hugo Valadares Siqueira, and Sergio Luiz Stevan. Sensors and Systems for Physical Rehabilitation and Health Monitoring—A Review. *Sensors 2020, Vol. 20, Page 4063*, 20(15):4063, jul 2020. 3, 8

[56] Charalampos Doukas and Ilias Maglogiannis. Advanced patient or elder fall detection based on movement and sound data. In *Proceedings of the 2nd International Conference on Pervasive Computing Technologies for Healthcare 2008, PervasiveHealth*, pages 103–107, 2008. 29, 33, 32

[57] Charalampos Doukas, Ilias Maglogiannis, Philippos Tragas, Dimitris Liapis, and Gregory Yovanof. Patient fall detection using support Vector Machines. In *IFIP International Federation for Information Processing*, volume 247, pages 147–156. Springer, Boston, MA, 2007. 30, 32, 33, 34

[58] Miikka Ermes, Juha Pärkkä, Jani Mäntyjärvi, and Ilkka Korhonen. Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions. *IEEE Transactions on Information Technology in Biomedicine*, 12(1):20–26, jan 2008. 8, 18, 22, 23, 24, 26, 25

[59] Gimigliano F and Negrini S. The World Health Organization "Rehabilitation 2030: a call for action". *European journal of physical and rehabilitation medicine*, 53(2):155–168, apr 2017. 2

[60] Multiple Sclerosis International Federation. The Atlas of Multiple Sclerosis. Technical report, 2013. 2

[61] Ibai Gorordo Fernandez, Siti Anom Ahmad, and Chikamune Wada. Inertial Sensor-Based Instrumented Cane for Real-Time Walking Cane Kinematics Estimation. *Sensors*, 20(17):4675, aug 2020. 10, 11, 13, 14, 24, 26, 34, 25

[62] Ibai Gorordo Fernandez and Chikamune Wada. Cane with millimeter wave radar for base of support measurement. *2019 IEEE 1st Global Conference on Life Sciences and Technologies, LifeTech 2019*, pages 133–136, mar 2019. 11, 23

[63] Peter Flachenecker. Clinical Implications of Neuroplasticity – The Role of Rehabilitation in Multiple Sclerosis. *Frontiers in Neurology*, 6(MAR):36, mar 2015. 2

[64] Anthony Fleury, Michel Vacher, and Norbert Noury. SVM-based multimodal classification of activities of daily living in health smart homes: Sensors, algorithms, and first experimental results. *IEEE Transactions on Information Technology in Biomedicine*, 14(2):274–283, mar 2010. 8, 21, 23, 26, 20, 22, 25

[65] Leonardo Frizziero, Giampiero Donnici, Alfredo Liverani, Giulia Alessandri, Grazia Chiara Menozzi, and Emma Varotti. Developing Innovative Crutch Using IDeS (Industrial Design Structure) Methodology. *Applied Sciences*, 9(23), 2019. 11, 12, 13, 31, 34

[66] Matteo Gadaleta, Luca Merelli, and Michele Rossi. Human authentication from ankle motion data using convolutional neural networks. In *2016 {IEEE} Statistical Signal Processing Workshop ({SSP})*. IEEE, jun 2016. 8, 21, 23, 26, 20, 22

[67] Yves M. Galvão, Janderson Ferreira, Vinícius A. Albuquerque, Pablo Barros, and Bruno J.T. Fernandes. A multimodal approach using deep learning for fall detection. *Expert Systems with Applications*, 168:114226, apr 2021. 28, 30, 32

[68] Satinder Gill, Jason Hearn, Graeme Powell, and Erik Scheme. Design of a multi-sensor IoT-enabled assistive device for discrete and deployable gait monitoring. In *2017 IEEE Healthcare Innovations and Point of Care Technologies, HI-POCT 2017*, volume 2017-Decem, pages 216–220. Institute of Electrical and Electronics Engineers Inc., dec 2017. 11, 13, 15

[69] Satinder Gill, Nitin Seth, and Erik Scheme. A Multi-Sensor Cane Can Detect Changes in Gait Caused by Simulated Gait Abnormalities and Walking Terrains. *Sensors*, 20(3):631, jan 2020. 11, 13, 15

[70] A. Godfrey, R. Conway, D. Meagher, and G. ÓLaighin. Direct measurement of human movement by accelerometry. *Medical Engineering and Physics*, 30(10):1364–1386, dec 2008. 8, 18

[71] Walid Gomaa, Reda Elbasiony, and Sara Ashry. ADL Classification Based on Autocorrelation Function of Inertial Signals. In *2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA)*, pages 833–837, 2017. 26

[72] Jiaqi Gong, Myla D. Goldman, and John Lach. Deepmotion: A deep convolutional neural network on inertial body sensors for gait assessment in multiple sclerosis. In *2016 IEEE Wireless Health, WH 2016*, pages 164–171. Institute of Electrical and Electronics Engineers Inc., dec 2016. 8, 18, 23, 24, 26

[73] Clare Griffiths, Cleo Rooney, and Anita Brock. Leading causes of death in england and wales–how should we group causes. *Health statistics quarterly*, 28(9), 2005. 4

[74] R. Jan Gurley, Nancy Lum, Merle Sande, Bernard Lo, and Mitchell H. Katz. Persons Found in Their Homes Helpless or Dead. *New England Journal of Medicine*, 334(26):1710–1716, jun 1996. 4

[75] Jesús Gutiérrez, Víctor Rodríguez, and Sergio Martin. Comprehensive Review of Vision-Based Fall Detection Systems. *Sensors 2021, Vol. 21, Page 947*, 21(3):947, feb 2021. 28

[76] Illapha Cuba Gyllensten and Alberto G. Bonomi. Identifying types of physical activity with a single accelerometer: Evaluating laboratory-trained algorithms in daily life. *IEEE Transactions on Biomedical Engineering*, 58(9):2656–2663, sep 2011. 8, 9, 18, 23, 25, 26, 22, 24

[77] Modar Hassan, Hideki Kadone, Kenji Suzuki, and Yoshiyuki Sankai. Wearable gait measurement system with an instrumented cane for exoskeleton control. *Sensors (Switzerland)*, 14(1):1705–1722, jan 2014. 10, 11, 12, 13, 14, 15

[78] Allen W. Heinemann, Michael Feuerstein, Walter R. Frontera, Steven A. Gard, Leonard A. Kaminsky, Stefano Negrini, Lorie Gage Richards, and Catherine Vallée. Rehabilitation Is a Global Health Priority. *BMC Health Services Research 2020 20:1*, 20(1):1–3, feb 2020. 2

[79] Tin Kam Ho. The random subspace method for constructing decision forests. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(8):832–844, 1998. 20

[80] Kur Hornik, Maxwell Stinchcombe, and Halber White. "Multilayer feedforward networks are universal approximators". Technical report. 23

[81] A. S.M. Hossain Bari and Marina L. Gavrilova. Artificial Neural Network Based Gait Recognition Using Kinect Sensor. *IEEE Access*, 7:162708–162722, 2019. 8, 23, 25, 26, 24

[82] Benjamin W. Hoyt, Gabriel J. Pavey, Paul F. Pasquina, and Benjamin K. Potter. Rehabilitation of Lower Extremity Trauma: a Review of Principles and Military Perspective on Future Directions. *Current Trauma Reports 2015 1:1*, 1(1):50–60, jan 2015. 2

[83] Tâm Huynh and Bernt Schiele. Analyzing features for activity recognition. In *ACM International Conference Proceeding Series*, volume 121, pages 159–164, 2005. 17, 18, 19, 20, 26

[84] Guirao-Goris JA, Cabrero-García J, Moreno Pina JP, and Muñoz-Mendoza CL. [Structured review of physical activity measurement with questionnaires and scales in older adults and the elderly]. *Gaceta Sanitaria*, 23(4):334.e1–334.e17, jul 2009. 3

[85] Ankita Jain and Vivek Kanhangad. Human Activity Classification in Smartphones Using Accelerometer and Gyroscope Sensors. *IEEE Sensors Journal*, 18(3):1169–1177, feb 2018. 9

[86] Tiago S. Jesus, Michel D. Landry, and Helen Hoenig. Global Need for Physical Rehabilitation: Systematic Analysis from the Global Burden of Disease Study 2017. *International Journal of Environmental Research and Public Health 2019, Vol. 16, Page 980*, 16(6):980, mar 2019. 2

[87] Branka Jokanovic and Moeness Amin. Fall Detection Using Deep Learning in Range-Doppler Radars. *IEEE Transactions on Aerospace and Electronic Systems*, 54(1):180–189, feb 2018. 29, 32, 34

[88] David Jurman, Marko Jankovec, Roman Kamnik, and Marko Topič. Calibration and data fusion solution for the miniature attitude and heading reference system. *Sensors and Actuators A: Physical*, 138(2):411–420, 2007. 13

[89] Tin kam Ho, Jonathan J. Hull, and Sargur N. Srihari. Decision Combination in Multiple Classifier Systems. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 16(1):66–75, 1994. 20

[90] Sidney Katz, Amasa B Ford, Roland W Moskowitz, Beverly A Jackson, and Marjorie W Jaffe. Studies of Illness in the Aged: The Index of ADL: A Standardized Measure of Biological and Psychosocial Function. *JAMA*, 185(12):914–919, 1963. 3

[91] A M Khan, Y K Lee, and T S Kim. Accelerometer signal-based human activity recognition using augmented autoregressive model coefficients and artificial neural nets. *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference*, 2008:5172–5, 2008. 8, 23, 24, 26

[92] Samad Khojasteh, José Villar, Camelia Chira, Víctor González, and Enrique de la Cal. Improving Fall Detection Using an On-Wrist Wearable Accelerometer. *Sensors*, 18(5):1350, apr 2018. 30, 33, 34

[93] Jens Kirchner, Samira Faghih-Naini, Pinar Bisgin, and Georg Fischer. Sensor Selection for Classification of Physical Activity in Long-Term Wearable Devices. *Proceedings of IEEE Sensors*, 2018-Octob, dec 2018. 20, 22, 26

[94] Michał Kos, Małgorzata Bogdan, Nancy W. Glynn, and Jaroslaw Harezlak. Classification of human physical activity based on raw accelerometry data via spherical coordinate transformation. *Statistics in Medicine*, 39(22):2901–2920, sep 2020. 26

[95] Jennifer R. Kwapisz, Gary M. Weiss, and Samuel A. Moore. Activity recognition using cell phone accelerometers. *ACM SIGKDD Explorations Newsletter*, 12(2):74–82, mar 2011. 9, 23, 26, 24

[96] Widén Holmqvist L, de Pedro-Cuesta J, Holm M, and Kostulas V. Intervention design for rehabilitation at home after stroke. A pilot feasibility study. *Scandinavian Journal of Rehabilitation Medicine*, 27(1):43–50, mar 1995. 2

[97] Chin Feng Lai, Sung Yen Chang, Han Chieh Chao, and Yueh Min Huang. Detection of cognitive injured body region using multiple triaxial accelerometers for elderly falling. *IEEE Sensors Journal*, 11(3):763–770, 2011. 30, 33, 32

[98] Olivier Lambercy, Serena Maggioni, Lars Lünenburger, Roger Gassert, and Marc Bolliger. Robotic and wearable sensor technologies for measurements/-clinical assessments. In *Neurorehabilitation Technology, Second Edition*, pages 183–207. Springer International Publishing, jan 2016. 16

[99] Mars Lan, Ani Nahapetian, Alireza Vahdatpour, Lawrence Au, William Kaiser, and Majid Sarrafzadeh. SmartFall: An automatic fall detection system based on subsequence matching for the smartcane. In *BODYNETS 2009 - 4th International ICST Conference on Body Area Networks*. ICST, nov 2011. 10, 11, 13, 14, 15, 31, 33, 34

[100] Matteo Lancini, Mauro Serpelloni, and Simone Pasinetti. Instrumented crutches to measure the internal forces acting on upper limbs in powered exoskeleton users. In *Proceedings - 2015 6th IEEE International Workshop on Advances in Sensors and Interfaces, IWASI 2015*, pages 175–180. Institute of Electrical and Electronics Engineers Inc., aug 2015. 10, 11, 12, 13, 14, 15, iii, iv

[101] Amy E Latimer-Cheung, Lara A Pilutti, Audrey L Hicks, Kathleen A Martin Ginis, Alyssa M Fenuta, K Ann MacKibbon, and Robert W Motl. Effects of Exercise Training on Fitness, Mobility, Fatigue, and Health-Related Quality of Life Among Adults With Multiple Sclerosis: A Systematic Review to

Inform Guideline Development. *Archives of Physical Medicine and Rehabilitation*, 94(9):1800—-1828.e3, sep 2013. 2

[102] Tuan Le Minh, Ly Van Tran, and Son Vu Truong Dao. A Feature Selection Approach for Fall Detection Using Various Machine Learning Classifiers. *IEEE Access*, 2021. 32

[103] Kangjae Lee and Mei Po Kwan. Physical activity classification in free-living conditions using smartphone accelerometer data and exploration of predicted results. *Computers, Environment and Urban Systems*, 67:124–131, jan 2018. 26

[104] R. Y. W. Lee and A. J. Carlisle. Detection of falls using accelerometers and mobile phone technology. *Age and Ageing*, 40(6):690–696, nov 2011. 30, 33

[105] Guo-Zheng Li, Jie Yang, Guo-Ping Liu, and Li Xue. Feature Selection for Multi-class Problems Using Support Vector Machines. *Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science)*, 3157:292–300, 2004. 20, 23, 22

[106] Pengfei Li, Yu Wang, Yu Tian, Tian Shu Zhou, and Jing Song Li. An Automatic User-Adapted Physical Activity Classification Method Using Smartphones. *IEEE Transactions on Biomedical Engineering*, 64(3):706–714, mar 2017. 9

[107] Wan Yin Lin, Chun Hsien Chen, Yi Ju Tseng, Yu Ting Tsai, Ching Yu Chang, Hsin Yao Wang, and Chih Kuang Chen. Predicting post-stroke activities of daily living through a machine learning-based approach on initiating rehabilitation. *International Journal of Medical Informatics*, 111:159–164, mar 2018. 23, 22

[108] Chien Liang Liu, Chia Hoang Lee, and Ping Min Lin. A fall detection system using k-nearest neighbor classifier. *Expert Systems with Applications*, 37(10):7174–7181, oct 2010. 22, 23, 26, 28, 33, 34, 24, 32

[109] Jian Liu, Jeehoon Sohn, and Sukwon Kim. Classification of Daily Activities for the Elderly Using Wearable Sensors. *Journal of Healthcare Engineering*, 2017, 2017. 26

[110] Lei Liu, Peng Yang, Zuojun Liu, Yanli Geng, and Jun Zhang. Leg amputees motion pattern recognition based on principal component analysis and BP network. In *2013 25th Chinese Control and Decision Conference, CCDC 2013*, pages 3802–3804, 2013. 8, 21, 23, 26, 20

[111] Clemens ; Lombriser, Nagendra Bharatula, ; Bhargava, Daniel ; Roggen, Gerhard Tröster, Clemens Lombriser, Nagendra B Bharatula, and Daniel Roggen. On-body activity recognition in a dynamic sensor network. 2007. 19, 22, 26, 18

[112] Xi Long, Bin Yin, and Ronald M. Aarts. Single-accelerometer-based daily physical activity classification. *Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009*, pages 6107–6110, 2009. 21, 26, 20

[113] H. J. Luinge and Peter H. Veltink. Measuring orientation of human body segments using miniature gyroscopes and accelerometers. *Medical and Biological Engineering and Computing*, 43(2):273–282, mar 2005. 13

[114] Francisco Luna-Perejon, Javier Civit-Masot, Isabel Amaya-Rodriguez, Lourdes Duran-Lopez, Juan Pedro Dominguez-Morales, Anton Civit-Balcells, and Alejandro Linares-Barranco. An automated fall detection system using recurrent neural networks. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 11526 LNAI, pages 36–41. Springer Verlag, jun 2019. 30, 32, 34

[115] Xiaomu Luo, Tong Liu, Jun Liu, Xuemei Guo, and Guoli Wang. Design and implementation of a distributed fall detection system based on wireless sensor networks. *Eurasip Journal on Wireless Communications and Networking*, 2012(1):1–13, mar 2012. 28, 34

[116] Clare Luz, Tamara Bush, Xiaoxi Shen, and Rachel Pruchno. Do Canes or Walkers Make Any Difference? NonUse and Fall Injuries. *The Gerontologist*, 57(2):211–218, apr 2017. 4

[117] Mingqi Lv, Wei Xu, and Tieming Chen. A hybrid deep convolutional and recurrent neural network for complex activity recognition using multimodal sensors. *Neurocomputing*, 362Lv, M.,:33–40, oct 2019. 9, 23, 24, 27, 26

[118] Andrea Mannini, Diana Trojaniello, Andrea Cereatti, Angelo Sabatini, Andrea Mannini, Diana Trojaniello, Andrea Cereatti, and Angelo M. Sabatini. A Machine Learning Framework for Gait Classification Using Inertial Sensors: Application to Elderly, Post-Stroke and Huntington's Disease Patients. *Sensors*, 16(1):134, jan 2016. 8, 23, 27, 22, 26

[119] Taylor Mauldin, Marc Canby, Vangelis Metsis, Anne Ngu, and Coralys Rivera. SmartFall: A Smartwatch-Based Fall Detection System Using Deep Learning. *Sensors*, 18(10):3363, oct 2018. 30, 32, 33, 34

[120] Uwe Maurer, Anthony Rowe, Asim Smailagic, and Daniel Siewiorek. Location and activity recognition using eWatch: A wearable sensor platform. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 3864 LNAI, pages 86–102. Springer Verlag, 2006. 9, 18, 20, 22, 27, 26

[121] Rajesh Kannan Megalingam, M. G. Greeshma, and Soumya S. Pillai. Design and implementation of intelligent crutches for medical applications. In *Proceedings of the 2019 IEEE International Conference on Communication and Signal Processing, ICCSP 2019*, pages 926–929. Institute of Electrical and Electronics Engineers Inc., apr 2019. 10, 11, 12, 13

[122] Feriel Mekki, Michela Borghetti, Emilio Sardini, and Mauro Serpelloni. Wireless instrumented cane for walking monitoring in Parkinson patients. In *2017 IEEE International Symposium on Medical Measurements and Applications, MeMeA 2017 - Proceedings*, pages 414–419. Institute of Electrical and Electronics Engineers Inc., jul 2017. 10, 11, 12, 13, 14, 15, iii, iv

[123] Joseph Mercado, Gemmilyn Chu, Erika Jane Imperial, Kelvin George Monje, Rae Mart Pabustan, and Angelito Silverio. Smart cane: Instrumentation of a quad cane with audio-feedback monitoring system for partial weight-bearing support. *2014 IEEE International Symposium on Bioelectronics and Bioinformatics, IEEE ISBB 2014*, 2014. 10, 11, 13

[124] Geoff V Merrett, Mohamed A Ettabib, Christian Peters, Georgina Hallett, and Neil M White. Augmenting forearm crutches with wireless sensors for lower limb rehabilitation. *Measurement Science and Technology*, 21(12):124008, oct 2010. 10, 11, 12, 13, 14, 15, iii, iv

[125] Asier Brull Mesanza, Ilaria D'Ascanio, Asier Zubizarreta, Luca Palmerini, Lorenzo Chiari, and Itziar Cabanes. Machine Learning based Fall Detector with a Sensorized Tip. *IEEE Access*, pages 1–1, dec 2021. 2, 6, 37, 59

[126] Asier Brull Mesanza, Sergio Lucas, Asier Zubizarreta, Itziar Cabanes, Eva Portillo, and Ana Rodriguez-Larrad. A Machine Learning Approach to Perform Physical Activity Classification Using a Sensorized Crutch Tip. *IEEE Access*, 8:210023–210034, 2020. 2, 6, 37, 49, 53, 55, 56, 57

[127] A. Moncada-Torres, K. Leuenberger, R. Gonzenbach, A. Luft, and R. Gassert. Activity classification based on inertial and barometric pressure sensors at different anatomical locations. *Physiological Measurement*, 35(7):1245–1263, 2014. 8, 17, 18, 19, 20, 22, 23, 27, 26, iii, iv

[128] Seyed Amirhossein Mousavi, Fatemeh Heidari, Ehsan Tahami, and Mahdi Azarnoosh. Fall detection system via smart phone and send people location. *European Signal Processing Conference*, 2021-January:1605–1607, jan 2021. 30, 33, 32

[129] Muhammad Mubashir, Ling Shao, and Luke Seed. A survey on fall detection: Principles and approaches. *Neurocomputing*, 100:144–152, jan 2013. 28

[130] Alvaro Muro-de-la Herran, Begonya Garcia-Zapirain, and Amaia Mendez-Zorrilla. Gait Analysis Methods: An Overview of Wearable and Non-Wearable

Systems, Highlighting Clinical Applications. *Sensors*, 14(2):3362–3394, feb 2014. 9

[131] Md Jaber Al Nahian, Tapotosh Ghosh, Md Hasan Al Banna, Mohammed A. Aseeri, Mohammed Nasir Uddin, Muhammad Raisuddin Ahmed, Mufti Mahmud, and M. Shamim Kaiser. Towards an Accelerometer-Based Elderly Fall Detection System Using Cross-Disciplinary Time Series Features. *IEEE Access*, 9:39413–39431, 2021. 30

[132] Marien Narváez and Joan Aranda. Gait patterns monitoring using instrumented forearm crutches. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 12377 LNCS, pages 402–410. Springer Science and Business Media Deutschland GmbH, sep 2020. 10, 11, 13, 14, 15, iii, iv

[133] Nurhazimah Nazmi, Mohd Azizi Abdul Rahman, Shin Ichiroh Yamamoto, and Siti Anom Ahmad. Walking gait event detection based on electromyography signals using artificial neural network. *Biomedical Signal Processing and Control*, 47:334–343, jan 2019. 9, 23, 27, 24, 26

[134] N. Noury, A. Fleury, P. Rumeau, A. K. Bourke, G. Ó Laighin, V. Rialle, and J. E. Lundy. Fall detection - Principles and methods. In *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, pages 1663–1666, 2007. 32

[135] B. T. Nukala, N. Shibuya, A. I. Rodriguez, J. Tsay, T. Q. Nguyen, S. Zupancic, and D. Y.C. Lie. A real-time robust fall detection system using a wireless gait analysis sensor and an Artificial Neural Network. In *2014 IEEE Healthcare Innovation Conference, HIC 2014*, pages 219–222. Institute of Electrical and Electronics Engineers Inc., feb 2014. 32

[136] Bhargava Teja Nukala, Naohiro Shibuya, Amanda Rodriguez, Jerry Tsay, Jerry Lopez, Tam Nguyen, Steven Zupancic, and Donald Yu-Chun Lie. An Efficient and Robust Fall Detection System Using Wireless Gait Analysis Sensor with Artificial Neural Network (ANN) and Support Vector Machine (SVM) Algorithms. *Open Journal of Applied Biosensor*, 03(04):29–39, feb 2014. 30, 32, 33, 34

[137] Adrián Núñez-Marcos, Gorka Azkune, and Ignacio Arganda-Carreras. Vision-based fall detection with convolutional neural networks. *Wireless Communications and Mobile Computing*, 2017, 2017. 28, 32, 33, 34

[138] M. N. Nyan, F. E H Tay, K. H W Seah, and Y. Y. Sitoh. Classification of gait patterns in the time-frequency domain. *Journal of Biomechanics*, 39(14):2647–2656, 2006. 17, 27, 26

[139] Yasuaki Ohtaki, Mitsutoshi Susumago, Akihiro Suzuki, Koichi Sagawa, Ryoichi Nagatomi, and Hikaru Inooka. Automatic classification of ambulatory movements and evaluation of energy consumptions utilizing accelerometers and a barometer. In *Microsystem Technologies*, volume 11, pages 1034–1040. Springer, aug 2005. 8, 22, 27, 26

[140] World Health Organization and Others. *Rehabilitation in health systems*. World Health Organization, 2017. 2

[141] Ahmet Özdemir. An Analysis on Sensor Locations of the Human Body for Wearable Fall Detection Devices: Principles and Practice. *Sensors*, 16(8):1161, jul 2016. 30, 31, 32, 33, 34, iii, iv

[142] Luca Palmerini, Jochen Klenk, Clemens Becker, and Lorenzo Chiari. Accelerometer-Based Fall Detection Using Machine Learning: Training and Testing on Real-World Falls. *Sensors*, 20(22):6479, nov 2020. 30, 32, 33, 34

[143] Pietro Pasquetti, Lorenzo Apicella, and Giuseppe Mangone. Pathogenesis and treatment of falls in elderly. *Clinical Cases in Mineral and Bone Metabolism*, 11(3):222–225, sep 2014. 4

[144] Mubarak Patel, Aleksandar Pavic, and Victoria A. Goodwin. Wearable inertial sensors to measure gait and posture characteristic differences in older adult fallers and non-fallers: A scoping review, feb 2020. 28

[145] O R Pearson, M E Busse, R W M van Deursen, and C M Wiles. Quantification of walking mobility in neurological disorders. *QJM: An International Journal of Medicine*, 97(8):463–475, 2004. 16

[146] Niels Peek, Carlo Combi, Roque Marin, and Riccardo Bellazzi. Thirty years of artificial intelligence in medicine (AIME) conferences: A review of research themes, sep 2015. 23

[147] Alex Pentland. Looking at people: Sensing for ubiquitous and wearable computing. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(1):107–110, 2000. 8

[148] Ivan Miguel Pires, Nuno M. Garcia, Nuno Pombo, Francisco Flórez-Revuelta, Susanna Spinsante, and Maria Canavarro Teixeira. Identification of activities of daily living through data fusion on motion and magnetic sensors embedded on mobile devices. *Pervasive and Mobile Computing*, 47:78–93, jul 2018. 23, 24, 27

[149] Susanna Pirttikangas, Kaori Fujinami, and Tatsuo Nakajima. Feature Selection and Activity Recognition from Wearable Sensors. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 4239 LNCS:516–527, oct 2006. 8, 18, 20, 22, 23, 27

[150] Cauchy Pradhan, Max Wuehr, Farhoud Akrami, Maximilian Neuhaeusser, Sabrina Huth, Thomas Brandt, Klaus Jahn, and Roman Schniepp. Automated classification of neurological disorders of gait using spatio-temporal gait parameters. *Journal of Electromyography and Kinesiology*, 25(2):413–422, apr 2015. 9, 21, 22, 23, 24, 25, 27, 20

[151] Stephen J. Preece, John Y. Goulermas, Laurence P.J. Kenney, Dave Howard, Kenneth Meijer, and Robin Crompton. Activity identification using body-mounted sensors - A review of classification techniques, 2009. 3, 16, 17, 18, 19, 21, 22, 23

[152] Stephen J. Preece, John Yannis Goulermas, Laurence P.J. Kenney, and David Howard. A comparison of feature extraction methods for the classification of dynamic activities from accelerometer data. *IEEE Transactions on Biomedical Engineering*, 56(3):871–879, mar 2009. 18

[153] Anagha Purushothaman, K. V. Vineetha, and Dhanesh G. Kurup. Fall Detection System Using Artificial Neural Network. In *Proceedings of the International Conference on Inventive Communication and Computational Technologies, ICICCT 2018*, pages 1146–1149. Institute of Electrical and Electronics Engineers Inc., sep 2018. 30, 33, 34

[154] J R Quinlan. Bagging, Boosting, and C4.5. Technical report. 20, 28, 32

[155] Akilesh Rajavenkatanarayanan, Varun Kanal, Konstantinos Tsiakas, Diane Calderon, Michalis Papakostas, Maher Abujelala, Marnim Galib, James Ford, Glenn Wylie, and Fillia Makedon. A Survey of Assistive Technologies for Assessment and Rehabilitation of Motor Impairments in Multiple Sclerosis. *Multimodal Technologies and Interaction*, 3(1):6, feb 2019. 8

[156] Henry Rimminen, Juha Lindström, Matti Linnavuo, and Raimo Sepponen. Detection of falls among the elderly by a floor sensor using the electric near field. *IEEE Transactions on Information Technology in Biomedicine*, 14(6):1475–1476, nov 2010. 28

[157] Daniel Rodríguez-Martín, Albert Samà, Carlos Pérez-López, Joan Cabestany, Andreu Català, and Alejandro Rodríguez-Molinero. Posture transition identification on PD patients through a SVM-based technique and a single waist-worn accelerometer. *Neurocomputing*, 164:144–153, sep 2015. 23, 24, 25, 27, 22

[158] Tine Roman De Mettelinge and Dirk Cambier. Understanding the relationship between walking aids and falls in older adults: a prospective cohort study. *Journal of geriatric physical therapy (2001)*, 38(3):127–132, jul 2015. 5, 4

[159] Rebecca L. Routson, Marcus Bailey, Isabelle Pumford, Joseph M. Czerniecki, and Patrick M. Aubin. A smart cane with vibrotactile biofeedback improves

cane loading for people with knee osteoarthritis. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, volume 2016-Octob, pages 3370–3373. Institute of Electrical and Electronics Engineers Inc., oct 2016. 10, 11, 12, 19, 27

[160] Hamidreza Sadreazami, Miodrag Bolic, and Sreeraman Rajan. Contactless Fall Detection Using Time-Frequency Analysis and Convolutional Neural Networks. *IEEE Transactions on Industrial Informatics*, 17(10):6842–6851, oct 2021. 29, 32

[161] Khaled Safi, Ferhat Attal, Samer Mohammed, Mohamad Khalil, and Yacine Amirat. Physical activity recognition using inertial wearable sensors - A review of supervised classification algorithms. *2015 International Conference on Advances in Biomedical Engineering, ICABME 2015*, pages 313–316, nov 2015. 22

[162] Arash Salarian, Heike Russmann, François J.G. Vingerhoets, Pierre R. Burkhard, and Kamiar Aminian. Ambulatory monitoring of physical activities in patients with Parkinson's disease. *IEEE Transactions on Biomedical Engineering*, 54(12):2296–2299, dec 2007. 23, 27

[163] Emilio Sardini, Mauro Serpelloni, and Matteo Lancini. Wireless Instrumented Crutches for Force and Movement Measurements for Gait Monitoring. *IEEE Transactions on Instrumentation and Measurement*, 64(12):3369–3379, dec 2015. 10, 11, 12, 13, 14, 15, 9

[164] Nishant K. Sekaran, Hwajung Choi, Rodney A. Hayward, and Kenneth M. Langa. Fall-Associated Difficulty with Activities of Daily Living in Functionally Independent Individuals Aged 65 to 69 in the United States: A Cohort Study. *Journal of the American Geriatrics Society*, 61(1):96–100, jan 2013. 4

[165] Çağlar Seylan and Uluc Saranli. Estimation of ground reaction forces using low-cost instrumented forearm crutches. *IEEE Transactions on Instrumentation and Measurement*, 67(6):1308–1316, jun 2018. 10, 11, 12, 13, 14, 15

[166] Bo Sheng, Oscar Moroni Moosman, Borja Del Pozo-Cruz, Jesus Del Pozo-Cruz, Rosa Maria Alfonso-Rosa, and Yanxin Zhang. A comparison of different machine learning algorithms, types and placements of activity monitors for physical activity classification. *Measurement: Journal of the International Measurement Confederation*, 154:107480, mar 2020. 8, 17, 18, 22, 23, 25, 27, 24

[167] Francy Shu and Jeff Shu. An eight-camera fall detection system using human fall pattern recognition via machine learning by a low-cost android box. *Scientific Reports 2021 11:1*, 11(1):1–17, jan 2021. 28

[168] M. Simic, K. L. Bennell, M. A. Hunt, T. V. Wrigley, and R. S. Hinman. Contralateral cane use and knee joint load in people with medial knee osteoarthritis: The effect of varying body weight support. *Osteoarthritis and Cartilage*, 19(11):1330–1337, nov 2011. 10, 11, 12, 19

[169] Saaveethya Sivakumar, Alpha Agape Gopalai, King Hann Lim, and Darwin Gouwanda. Artificial neural network based ankle joint angle estimation using instrumented foot insoles. *Biomedical Signal Processing and Control*, 54:101614, sep 2019. 23, 27

[170] R. I. Spain, R. J. St. George, A. Salarian, M. Mancini, J. M. Wagner, F. B. Horak, and D. Bourdette. Body-worn motion sensors detect balance and gait deficits in people with multiple sclerosis who have normal walking speed. *Gait and Posture*, 35(4):573–578, apr 2012. 9

[171] Gina Sprint, Diane J. Cook, and Douglas L. Weeks. Quantitative assessment of lower limb and cane movement with wearable inertial sensors. In *3rd IEEE EMBS International Conference on Biomedical and Health Informatics, BHI 2016*, pages 418–421. Institute of Electrical and Electronics Engineers Inc., apr 2016. 19

[172] V. S. Stel, J. H. Smit, S. M. F. Pluijm, and P. Lips. Consequences of falling in older men and women and risk factors for health service use and functional decline. *Age and Ageing*, 33(1):58–65, jan 2004. 4

[173] Ruopeng Sun, Yaejin Moon, Ryan S. McGinnis, Kirsten Seagers, Robert W. Motl, Nirav Sheth, John A. Wright, Roozbeh Ghaffari, Shyamal Patel, and Jacob J. Sosnoff. Assessment of Postural Sway in Individuals with Multiple Sclerosis Using a Novel Wearable Inertial Sensor. *Digital Biomarkers*, 2(1):1–10, jan 2018. 9

[174] Kristin Taraldsen, Sebastien F.M. Chastin, Ingrid I. Riphagen, Beatrix Vereijken, and Jorunn L. Helbostad. Physical activity monitoring by use of accelerometer-based body-worn sensors in older adults: A systematic literature review of current knowledge and applications. *Maturitas*, 71(1):13–19, jan 2012. 3

[175] Mary E. Tinetti, John Doucette, Elizabeth Claus, and Richard Marottoli. Risk Factors for Serious Injury During Falls by Older Persons in the Community. *Journal of the American Geriatrics Society*, 43(11):1214–1221, nov 1995. 4

[176] Figen Tokucoglu. Monitoring physical activity with wearable technologies. *Archives of Neuropsychiatry*, 55(Suppl 1):S63, oct 2018. 3

[177] Laura Tolo¸si, Tolo¸ Tolo¸si, and Thomas Lengauer. Data and text mining Classification with correlated features: unreliability of feature ranking and solutions. *Bioinformatics*, 27(14):1986–1994, 2011. 20

[178] Joko Triloka, S. M. N. Arosha Senanayake, and Daphne Lai. Neural computing for walking gait pattern identification based on multi-sensor data fusion of lower limb muscles. *Neural Computing and Applications*, 28(S1):65–77, dec 2017. 8, 9, 23, 25, 27, 24

[179] A. M. Tromp, J. H. Smit, D. J.H. Deeg, L. M. Bouter, and P. Lips. Predictors for falls and fractures in the longitudinal aging study Amsterdam. *Journal of Bone and Mineral Research*, 13(12):1932–1939, 1998. 4

[180] Naoaki Tsuda, Akane Hayashi, Motoi Tounai, and Susumu Akutagawa. Visualization system of crutch walking based on internal sensors. In *IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM*, pages 19–24, 2010. 10, 11, 12, 13, 15

[181] Javier Alexis Urresty Sanchez and Daniel M. Muñoz. Fall detection using accelerometer on the user's wrist and artificial neural networks. In *IFMBE Proceedings*, volume 70, pages 641–647. Springer Verlag, 2019. 30, 32, 34, 31

[182] Marcela Vallejo, Claudia V. Isaza, and Jose D. Lopez. Artificial Neural Networks as an alternative to traditional fall detection methods. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, pages 1648–1651, 2013. 30, 32, 34

[183] Kristof Van Laerhoven and Hans Werner Gellersen. Spine versus Porcupine: A study in distributed wearable activity recognition. In *Proceedings - International Symposium on Wearable Computers, ISWC*, pages 142–149, 2004. 25, 24

[184] Lena von Koch, Annica Wohlin Wottrich, and Lotta Widén Holmqvist. Rehabilitation in the home versus the hospital: The importance of context. *https://doi.org/10.3109/09638289809166095*, 20(10):367–372, 2009. 2

[185] Joshua W. Wade, Robert Boyles, Patricia Flemming, Arpan Sarkar, Michael De Riesthal, Thomas J. Withrow, and Nilanjan Sarkar. Feasibility of Automated Mobility Assessment of Older Adults via an Instrumented Cane. *IEEE Journal of Biomedical and Health Informatics*, 23(4):1631–1638, jul 2019. 10, 11, 12, 13, 14, 15

[186] Jeen Shing Wang, Fang Chen Chuang, and Ya Ting C. Yang. A wearable physical activity sensor system: Its classification algorithm and performance comparison of different sensor placements. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 6839 LNAI, pages 447–454. Springer, Berlin, Heidelberg, 2011. 8, 22, 23, 27

[187] Ning Wang, Eliathamby Ambikairajah, Nigel H. Lovell, and Branko G. Celler. Accelerometry based classification of walking patterns using time-frequency analysis. In *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, pages 4899–4902, 2007. 8, 23, 24, 27

[188] Shuangquan Wang, Jie Yang, Ningjiang Chen, Xin Chen, and Qinfeng Zhang. Human activity recognition with user-free accelerometers in the sensor networks. *Proceedings of 2005 International Conference on Neural Networks and Brain Proceedings, ICNNB'05*, 2:1212–1217, 2005. 8, 17, 18, 20, 23, 27, 22, 24

[189] Yuxi Wang, Kaishun Wu, and Lionel M. Ni. WiFall: Device-Free Fall Detection by Wireless Networks. *IEEE Transactions on Mobile Computing*, 16(2):581–594, feb 2017. 29, 33, 34, iii, iv

[190] T. Watanabe, S. Yamagishi, H. Murakami, N. Furuse, N. Hoshimiya, and Y. Handa. Recognition of lower limb movements by artificial neural network for restoring gait of hemiplegic patients by functional electrical stimulation. In *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, volume 2, pages 1348–1351, 2001. 8, 17, 18, 23, 24, 27

[191] Madeline Weikert, Yoojin Suh, Abbi Lane, Brian Sandroff, Deirdre Dlugonski, Bo Fernhall, and Robert W. Motl. Accelerometry is associated with walking mobility, not physical activity, in persons with multiple sclerosis. *Medical Engineering and Physics*, 34(5):590–597, jun 2012. 8

[192] Deidre Wild, U. S.L. Nayak, and B. Isaacs. How dangerous are falls in old people at home? *British Medical Journal (Clinical research ed.)*, 282(6260):266–268, jan 1981. 4

[193] Winston H. Wu, Alex A.T. Bui, Maxim A. Batalin, Lawrence K. Au, Jonathan D. Binney, and William J. Kaiser. MEDIC: Medical embedded device for individualized care. *Artificial Intelligence in Medicine*, 42(2):137–152, feb 2008. 19, 22, 27, 18

[194] Che-Chang Yang and Yeh-Liang Hsu. A Review of Accelerometry-Based Wearable Motion Detectors for Physical Activity Monitoring. *Sensors 2010, Vol. 10, Pages 7772-7788*, 10(8):7772–7788, aug 2010. 8

[195] Jiaye Yang, Yanjun Liu, Yanjun Chen, Huiyang Nie, Zhanqiu Wang, Xu Liu, Muhammad Ali Imran, and Wasim Ahmad. Assistive and Monitoring Multi-functional Smart Crutch for Elderly. In *2019 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech)*, pages 397–401, 2019. 13, 31, 33

[196] Zhongliang Yang, Yumiao Chen, Jianping Wang, and Hugh Gong. Recognizing the breathing resistances of wearing respirators from respiratory and sEMG signals with artificial neural networks. *International Journal of Industrial Ergonomics*, 58:47–54, mar 2017. 11, 34

[197] SunGil Yoo and Dongik Oh. An artificial neural network–based fall detection. *International Journal of Engineering Business Management*, 10:184797901878790, jan 2018. 30, 32, 34, 31

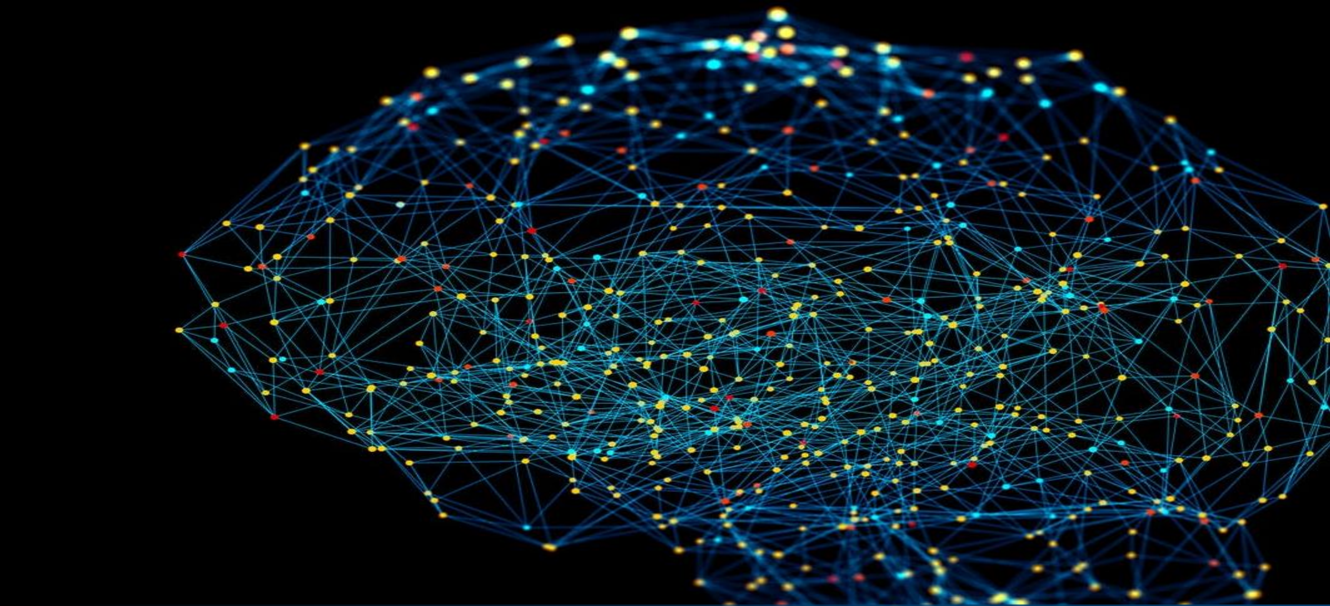
[198] Hyunjin Yoon, Kiyoung Yang, and Cyrus Shahabi. Feature subset selection and feature ranking for multivariate time series. *IEEE Transactions on Knowledge and Data Engineering*, 17(9):1186–1198, sep 2005. 21, 23, 20, 22

[199] S Yoshida. A global report on falls prevention: Epidemiology of falls. Geneva: World Health Organization, 2007. 4

[200] Wei Zeng and Cong Wang. Classification of neurodegenerative diseases using gait dynamics via deterministic learning. *Information Sciences*, 317:246–258, oct 2015. 9, 19, 23, 27, 18

[201] Xiaodan Zhuang, Jing Huang, Gerasimos Potamianos, and Mark Hasegawa-Johnson. Acoustic fall detection using Gaussian mixture models and GMM supervectors. In *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, pages 69–72, 2009. 29, 33, 32

[202] Wiebren Zijlstra. Assessment of spatio-temporal parameters during unconstrained walking. *European Journal of Applied Physiology*, 92(1-2):39–44, jun 2004. 17, 27



Appendix 1
1. eranskina

Asier Brull, Asier Zubizarreta, Itziar Cabanes, and Ana Rodriguez-Larrad. Sensorized Tip for Monitoring People with Multiple Sclerosis that Require Assistive Devices for Walking. *Sensors*, 20(15):4329, aug 2020. *doi: https://doi.org/10.3390/s20154329*
JCR2020: 3.576 (Q1)

sensors

MDPI

Article

Sensorized Tip for Monitoring People with Multiple Sclerosis that Require Assistive Devices for Walking

Asier Brull [1], Asier Zubizarreta [1,*], Itziar Cabanes [1] and Ana Rodriguez-Larrad [2]

[1] Department of Automatic and Control Systems, University of the Basque Country UPV/EHU, Faculty of Engineering of Bilbao, Ingeniero Torres Quevedo Square, 48013 Bilbao, Biscay, Spain; asier.brull@ehu.eus (A.B.); itziar.cabanes@ehu.eus (I.C.)

[2] Department of Physiology, University of the Basque Country UPV/EHU, Faculty of Medicine and Nursing, Barrio Sarriena, s/n, 48940 Leioa, Biscay, Spain; ana.rodriguez@ehu.eus

* Correspondence: asier.zubizarreta@ehu.eus

Received: 24 June 2020; Accepted: 1 August 2020; Published: 3 August 2020

Abstract: Multiple Sclerosis (MS) is a neurological degenerative disease with high impact on our society. In order to mitigate its effects, proper rehabilitation therapy is mandatory, in which individualisation is a key factor. Technological solutions can provide the information required for this purpose, by monitoring patients and extracting relevant indicators. In this work, a novel Sensorized Tip is proposed for monitoring People with Multiple Sclerosis (PwMS) that require Assistive Devices for Walking (ADW) such as canes or crutches. The developed Sensorized Tip can be adapted to the personal ADW of each patient to reduce its impact, and provides sensor data while naturally walking in the everyday activities. This data that can be processed to obtain relevant indicators that helps assessing the status of the patient. Different from other approaches, a full validation of the proposed processing algorithms is carried out in this work, and a preliminary study-case is carried out with PwMS considering a set of indicators obtained from the Sensorized Tip's processed data. Results of the preliminary study-case demonstrate the potential of the device to monitor and characterise patient status.

Keywords: sensorized tip; patient monitoring; multiple sclerosis; wearable sensors; rehabilitation

1. Introduction

It is estimated that 2.3 million people in the world suffer from Multiple Sclerosis (MS) [1]. This neurological disease has an important impact on society, as it is a chronic degenerating disease with no cure that appears in young people [2]. This implies not only an important economic impact on the health system, but also in the active population, as the physical decline causes inability to work at early ages [3].

MS is an autoimmune disease that affects the Central Nervous System, more specifically the brain and spinal cord. Although its symptoms vary depending on the area affected by the disease, some of the most common ones are fatigue and motor dysfunction. After 15 years from diagnosis, most of the patients require Assistive Devices for Walking (ADW) such as crutches or canes to maintain their autonomy [4]. This work focuses on providing solutions for the needs of these patients.

At present there is no cure for MS. Hence, the treatment focuses on the prevention of new attacks and alleviating the symptoms [5]. In this task, rehabilitation plays a key role, as it has demonstrated to be effective for reducing the effect of the symptoms caused by the disease [6,7], and therefore being central for maintaining the highest possible level of independence as the disease progresses. However, in order to be effective, therapies have to be adapted to each patient [8], which is not a trivial task.

Technological solutions can provide the information required for this purpose, by monitoring patients and extracting relevant indicators to assess their status. Some of the most popular devices for this purpose are *wearable sensors*, which are based on inertial sensors (accelerometers, gyroscopes) that allow to monitor limb motion [9–12]. For this purpose, wearable sensors are usually attached to the body of the patient. Although these devices are widely used in a range of applications, this latter requirement may generate rejection on PwMS that require ADW, as they have difficulties to move and are very sensitive to any external attachment to their limbs.

Hence, in order to provide a contactless monitoring approach some works have proposed the use of the internal sensors of smartphones to capture the motion of the lower limb once placed in a pocket of the trousers [13,14]. However, the data processing is more complex, as the mobile phone is not fixed and parasitic motions arise.

To overcome these aforementioned issues, recent studies [15] have proposed to include sensors in passive, daily-use Assistive Devices for Walking, such as canes or crutches, as they can provide more reliable monitoring data. Most of the works in this area [16–24] propose devices capable of measuring the load applied, as well as their motion, which can be used to define indicators that could provide relevant information regarding the modality of use of the ADW. To better characterize this use some works also include sensors that measure the force applied to the handle [25] or sensors to detect nearby objects [26].

The measurement of the applied axial load, is typically carried out considering a force sensor [17,24,26,27], which is usually expensive but provides an accurate measurement. Other authors propose the use of strain gauges [16,18–23,25], whose cost is lower, as well as their accuracy. The motion of the device is traditionally measured by the use of IMUs (Inertial Motion Units), which include accelerometers and gyroscopes. These devices, however, do not provide directly the orientation of the crutch or cane, and different techniques have to be applied to estimate them. One of the most simple approaches is based on the direct integration of the gyroscope rotational speed, and the periodical correction of the accumulated errors [19]. However, most authors use either a quasi-static approach, determining the orientation from the projection of the gravity vector on each acceleration axis [16,18,25,26]; or different filters such as Kalman [17,28,29] or CAHRS [30]. The aforementioned data is captured by an on-board Data Adquisition Device (DAQ), which is typically self-designed [18,23,26,27,31], although there are approaches based on Arduino or rapid-prototyping devices [21].

The raw data captured by the sensors of the device, however, is not generally useful for the therapist without further processing. Hence, in the literature, different indicators based on the raw data are defined. This way a change in these can be used to detect changes in the status of the patient. In the case of ADW, most of the indicators are related to the axial force, such as the maximum [32,33] or average load [33] with respect to the weight of the patient. For people that do not require these devices, on the other hand, the number of steps required for a given distance, the average speed or the time between steps [34] are some of the most used.

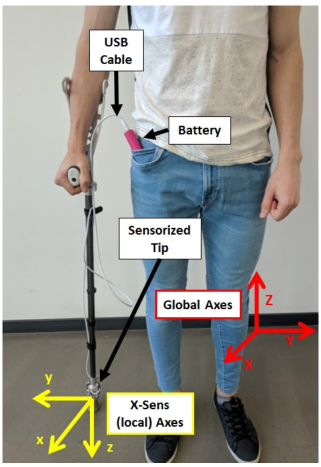
As previously analysed, currently there are a number of works that have proposed instrumented crutches and canes, with different sensor solutions and indicators extracted. However, this is still an open area, where further research is required—first, only a few of the proposed devices have been validated, characterising their measurement error [17,20,23,24,26,27]; second, only some of the works evaluate (preliminary) the proposed device with patients, defining indicators from the sensor data and demonstrating some kind of correlation between the proposed indicators and the patient status [17,21,24,26]; third, due to the complexity of the device orientation estimation, most of the indicators proposed are related with the applied axial load, although the former variables could be used to characterise the pattern of use of the sensorized ADW; and finally, all the aforementioned monitoring systems are part of a generic assistive device, and cannot be adapted to the personal ADW of each patient, which is usually personalized to his/her needs.

Hence, in this work a novel monitoring device is proposed, with four main contributions—1) the proposed device is a universal Sensorized Tip that can be fit to the patient's own personalised ADW, which minimizes the impact of the solution and consequently, improves its acceptability; 2) a complete and thorough validation of the device's monitoring capabilities is presented, detailing the algorithms used to estimate relevant parameters and validating them experimentally; 3) a novel procedure to estimate relevant orientation angles for the tip with respect to the body motion is proposed; and 4) the patient status assessing capabilities of the device are demonstrated by carrying out a preliminary/exploratory use-case study with PwMS. Note however, that the goal of this latter contribution is not to perform a thorough correlation analysis, but to demonstrate the potential of the device.

The rest of the work is structured as follows—Section 2 details the proposed Sensorized Tip and its capabilities; Section 3 characterises the measurement errors of the proposed device; Section 4 details the procedure to estimate the angles of motion of the Sensorized Tip; Section 5 illustrates the use of both raw sensor and estimated orientation data to define a set of indicators to perform a preliminary analysis of the capabilities of the device to assess PwMS status in a exploratory use-case study; finally, the most important ideas are summarised in Section 6.

2. Sensorized Tip Prototype

The general structure of the developed Sensorized Tip is detailed in Figure 1a. The overall system is composed by two main elements: the Sensorized Tip, whose structure is made in aluminium and integrates the sensors and the Data Acquisition (DAQ) device; and an external standard USB based 5 V battery. The Tip is designed to be attached in any crutch or cane to monitor its motion by means of a couple of screws. Moreover, it is designed so that it can be easily repaired if damaged. The weight of the Sensorized Tip prototype, without taking into account the external battery that is attached, is 180 g.



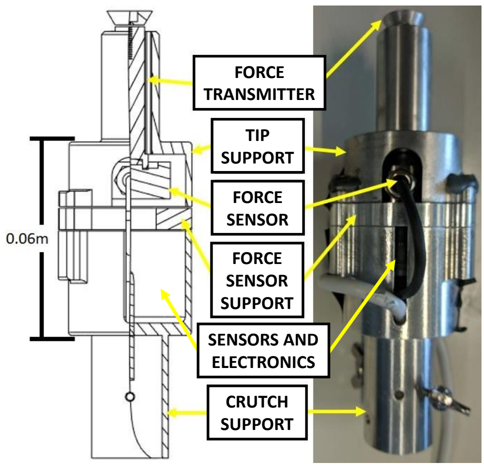


Figure 1. (**a**) System elements and reference axes. (**b**) Sensorized Tip mechanical structure.

The Sensorized Tip integrates three sensors in its structure: a force sensor, a barometer and an Inertial Motion Tracking Module, whose specifications will be detailed in Section 2.1. The data provided by these sensors is processed by a low cost B;uetooth Low Energy (BLE) Nano v2 board based on the nRF52 IC processor, which is able to communicate with Bluetooth 4.0 Low Energy (BLE) protocol with an external acquisition system, such as a PC or a mobile phone.

The battery is based on a 5 V 2600 mAh power bank typically used to charge mobile phones with a mass of 75 g. The use of standard USB-A based connectors was selected to simplify the design and increase compatibility. The decision to put the battery outside the Tip is motivated by the need to reduce the mass of the Tip and minimize its impact on the patient. Note that PwMS usually present progressive physical deterioration and high risk of falling, and incorporating even a small mass into the ADW can notably difficult their mobility. The cable connecting the sensor tip to the battery is attached to the crutch or cane by means of straps.

Next, each of the elements composing the Sensorized Tip are detailed.

2.1. Integrated Sensors

As analysed in Section 1, the most important basic variables that define the use of crutches or canes are the motion (acceleration, speed, angles, altitude) and the overall force applied on the walking support device. Based on this, three sensors have been selected.

The MTi-1 by X-Sense is an Inertial Measuring Unit (IMU) that integrates a 3-axis accelerometer (range ± 156.96 m/s^2), gyroscope (range $\pm 2000\ ^\circ/s$) and magnetometer (range $\pm 0.8\ G$) with an algorithm that provides Attitude and Heading Reference System (AHRS) functionalities. Hence in addition to the linear acceleration and rotational speed with respect to the local axes (Figure 1a), it provides the absolute Roll-Pitch-Yaw angles of the Tip in a Global Reference Frame with a relative low error (Roll and Pitch dynamic error of 0.5°, and Yaw dynamic error 1°), providing a 3D representation of the Tip orientation in real-time.

For the measurement of the force applied to the longitudinal axis of the crutch, a C9C force sensor manufactured by HBM is used. This element is designed to measure static and dynamic compression forces of up to 1 kN (0.2% precision). Due to the mechanical disposition of the sensor (see Section 2.2) a preload is required to ensure that low forces are measured. In addition, as the sensor is of piezoelectric nature, a conditioning circuit based on a INA118 amplifier is used to amplify the generated voltage to a suitable level.

Finally, the measurement of altitude is carried out using a low cost BMP280 sensor manufactured by Bosch, which communicates using I2C protocol with the Sensorized Tip's processing unit. This sensor allows to determine if the patient is going up or down stairs or slopes.

Although these sensors are commercial, a calibration procedure has been carried out in Section 3 in order to quantify the measurement error once implemented in the Sensorized Tip.

2.2. Mechanical Structure

The Sensorized Tip's structure has been self-designed to integrate the aforementioned sensors and the BLE Nano processing unit. The structure has been manufactured in aluminium to reduce its weight. In addition, its longitudinal size (0.06m) has been selected to minimize the need of adjusting the crutch height, as 0.06m are equal to three discrete positions in the length adaptability of a standard crutch.

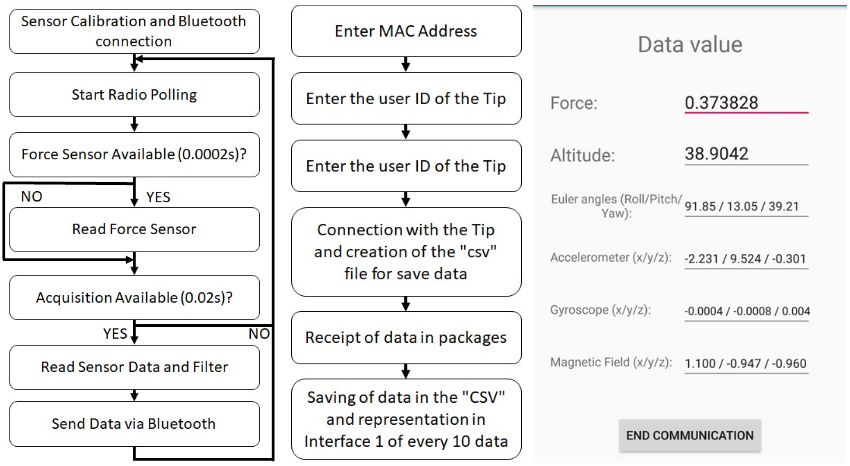
The elements composing the structure and their disposition are detailed in Figure 1b. The Data Processing Unit and the required electronics are placed in the upper part of the Tip, housed by an aluminium enclosure (Crutch support). The force sensor is placed in the lower part, attached to a stiff aluminium support (Force sensor support). The axial force applied on the Tip is transmitted by the Force transmitter, which is a mobile part which can transmit force axially. The rubber Tip of the crutch or cane is attached to the Tip support. Note that this element is dependant on the particular one selected by the patient for his/her needs.

As stated before, a preload is required to ensure proper operation of the force sensor. For that purpose, the set of screws that join the Crutch Support, Force Sensor Support and Tip Support parts are tightened to a desired preload and fixed with nordlock washers.

2.3. Data Processing Unit

The selected data processing unit is a BLE Nano board, which is based on the nRF52 microcontroller. This integrated circuit provides Data Acquisition (DAQ) capabilities and Bluetooth 4.0 Low Energy (BLE) connectivity with a very low energy consumption, which allows the system to work for a whole day with a small battery.

The tasks performed by the BLE Nano are summarised in Figure 2a. After the initialisation of the Bluetooth connection and the calibration of the sensors, it performs several tasks periodically: first, it captures the data from the aforementioned sensors; second, it compacts the data and sends it using BLE protocol with 50Hz rate to an external logging device (PC or mobile phone). Note that this frequency is enough to capture the walking data with assistive devices [35]. The capture process is analysed next.



(**a**) (**b**) (**c**)

Figure 2. (**a**) Operation scheme of the Bluetooth Low Energy (BLE) Nano V2 software, responsible for capturing the data coming from the sensors and sending them via Bluetooth. (**b**) Scheme of operation of the PC/Mobile Phone interface. (**c**) Representation of one of the screens of the smartphone application developed for the storage of the data received from the Sensorized Tip.

The sensor data is captured using two different approaches depending on the nature of the sensor output. This way, both the barometer and the MTi-1 module are connected using I2C communication protocol, hence, their measurements are requested each 20ms by the processing unit and stored in memory prior to sending them. The force sensor, on the other hand, is read using an analog input. As the measurement of the force sensor can be noisy, the force sensor is measured at 5 kHz rate, and its data is filtered prior to storing its value in memory.

The sensor data stored internally in the processing unit memory is sent periodically using Bluetooth 4.0 Low Energy to a logging device. The Attribute Protocol (ATT) is used so that once the Sensorized Tip and the logging device have been paired, communication is carried between both devices. This way, each 20ms (50Hz), 38 bytes of sensor data are sent in two packets (20 bytes each). Package data is summarized in Table 1.

Note that the Sensorized Tip is designed so that an external logging device is required to store the data. For that purpose, any device that supports BLE protocol can be used. The developed prototype provides a PC based logging system and an Android-based mobile phone app (Figure 2c) to perform these tasks. The logging programs developed in both devices follow the steps defined in Figure 2b. As it can be seen, the data is stored in a *csv* file. In order to detect possible package losses in the wireless transfer, the *iteration* bits are used to identify them (Table 1).

Table 1. BLE package data.

First Package	20 Bytes	Second Package	20 Bytes
	Number of Bits		Number of Bits
Iteration	**4**	Iteration	**4**
Force	**16**	Accelerometer	**45**
Altitude	**32**	Y axis	20
Euler Angles	**78**	Z axis	25
Roll	26	Gyroscope	**60**
Pitch	26	X axis	20
Yaw	26	Y axis	20
Accelerometer	**30**	Z axis	20
X axis	25	Magnetometer	**48**
Y axis	5	X axis	16
		Y axis	16
		Z axis	16

3. Characterization of the Measurement Errors

The aim of this section is to characterize the measurement errors associated to each of the three integrated sensors: the Inertial Motion Processing Unit (velocities, accelerations and angles), the barometer and the force sensor. This will allow to validate the accuracy of the proposed Sensorized Tip to measure crutch motion.

In order to achieve this goal, a series of calibration and measurement tests have been carried out with the Sensorized Tip at the research facilities of the University of the Basque Country (UPV/EHU). In particular, the high-fidelity measuring equipment of both the Automatic Control Laboratory and the 3D Body Motion Capture Laboratory were used to evaluate the measurements provided by the Sensorized Tip.

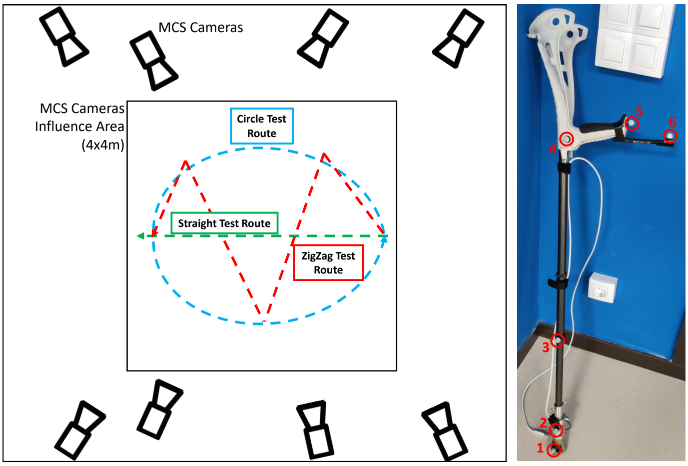
Next, each test is described, detailing the used equipment to characterize the measurement errors associated to each data source of the Sensorized Tip.

3.1. Euler Angles

The Mti-1 sensor from X-Sens integrated in the Sensorized Tip has an internal algorithm that provides an estimation of its orientation in a global reference frame (see Figure 1a). Using the internally estimated Euler angles, the real-time orientation of the crutch in 3D space can be estimated, as it will be detailed in Section 4.

In order to validate the estimations provided by the Mti-1 sensor, a series of tests were carried out comparing these with the data provided by the VICON 3D Motion Capture System installed in the 3D Motion Capture Laboratory. This facility provides a wide empty area with a flat soil where eight high fidelity Vicon Motion Capture System (MCS) cameras and a high precision Bertec 4060-15 force platform can be placed to capture accurately 3D motion data in a predefined working area.

For the error characterization measurements defined in this section, the eight cameras were placed to cover an area of 4x4m in the center of the lab, which was free of obstacles as seen in Figure 3a. To capture the motion of the crutch, and extract its 3D motion, 6 reflective markers were placed in a standard crutch (Figure 3b). Note that as the global reference system of both the Mti-1 sensor and the MCS were not the same, a calibration procedure was first executed to calculate the appropriate transformation matrices that relate both reference systems. In addition, in order to synchronize the data captured by both devices (Sensorized Tip and MCS), an initial vertical blow over the MCS force plate was executed to indicate the start of each measurement.



(**a**) (**b**)

Figure 3. (**a**) 3D Motion Capture Laboratory Schematic with camera placements, capture area and defined test trajectories. (**b**) Reflective marker distribution on the tested crutch (the markers are identified with numbers).

In order to characterize the measuring error of the Sensorized Tip, the way patients use ADW was considered. For instance, depending on the ADW, patients tend to grab its handle with an angle with respect to the advance plane (Figure 4). This way, to analyze the measurement errors in different scenarios, five trajectories were considered: three 4m straight walking tests, with different crutch handle orientations (more or less 0°, 45° and 90° rotation), a zig-zag trajectory (0° rotation) and a circular trajectory (0° rotation). These trajectories were marked in the floor as reference, as seen in Figure 3a.

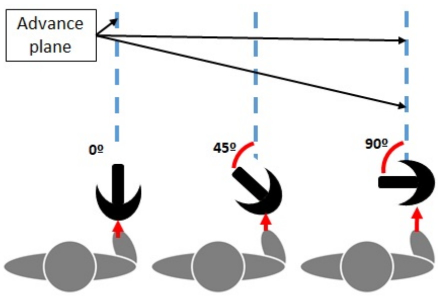


Figure 4. Position of the crutch handle with respect to the advance plane, in the different validation tests of Euler angles provided by the X-Sens.

Two members of the research group executed the tests, executing each trajectory twice at a normal pace (always in the same direction), once the required synchronizing initial vertical blow over the MCS force plate was executed. Data from the researchers is provided in Table 2.

Table 2. Volunteer data for Sensorized Tip Laboratory Validation.

Volunteer	Sex	Age	Height	Weight
1	Male	24	1.84 m	75 kg
2	Male	26	1.80 m	73 kg

Results of the measurement RMS (Root Mean Square) error in the MTi-1 reference system are summarized in Table 3. It can be seen that the Sensorized Tip provides a reduced estimation error for the Roll and Pitch angles (below 1.5 degrees RMS), while the error is slightly higher in the Yaw angle (up to 4.3 degrees RMS). The dynamic error specifications are higher than those specified by the manufacturer (0.5º for pitch/roll and 2º for yaw), although similar to other approaches proposed in the literature and acceptable for the required application. This can also be seen in Figure 5, which shows the time evolution of roll/pitch/yaw angles for both the Mti-1 and Vicon MCS measurements for the zig-zag trajectory experiments.

Table 3. X-Sens Euler angles estimation error.

Test	Handle Orientation	RMS Error Roll (°)	Pitch (°)	Yaw (°)
Walk straight 4 meters	0º	0.5439	1.0971	2.3457
Walk straight 4 meters	45º	0.8482	0.7325	2.1725
Walk straight 4 meters	90º	0.5429	1.0984	2.3404
Zigzag	0º	0.6736	0.8693	4.3096
Circle	0º	0.935	1.5278	4.3099
Mean		0.7267	1.0777	3.4688

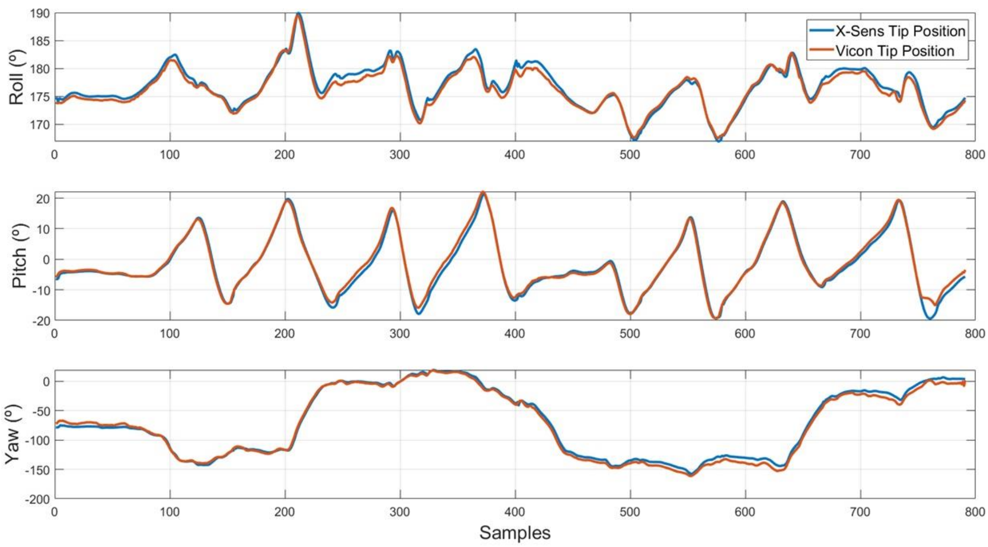


Figure 5. Euler angles of Vicon Motion Capture System (MCS) and X-Sens comparison in zigzag test.

3.2. Gyroscope

The Mti-1 by X-Sens integrates a gyroscope and accelerometer, whose raw data can also be captured. In this section, the gyroscope measurements will be analyzed and the measurement errors characterised. It is to be noted that the Mti-1 internally performs a calibration each time it is activated. However, it is widely known gyroscopes present a drift with time, which X-Sens ensures it is below 10 $^{\circ}/h$ and will not be analyzed in this section.

In order to determine the angular speed measurement error, an AKD21C servomotor configured in speed mode with a high precision encoder was used. The Sensorized Tip was attached to the axis of the servomotor using a 3D printed base, which allows to position the device so that each of the three local axes of the Mti-1 sensor (x, y, z) (Figure 1a) are aligned with the rotation axis of the motor. Each axis measurement is tested at three different constant angular speeds: 100 °/s, 200 °/s and 300 °/s. These speeds were verified with an external tachometer at the Automatic Control Laboratory.

Results are detailed in Table 4. As it can be seen, errors are low at 100 °/s, increasing with higher speeds, with the exception of the speed of 300 °/s in the z axis in which the error decreases. In general, error in z axis is higher than in the rest due to slight misalignment in the location of the MTi-1 sensor with respect to the center of the Sensorized Tip.

However, it has been experimentally checked that an average healthy person generates angular speeds on the walking assist system less than 180 °/s in x and y axes and 220 °/s in the z axis. Hence, an error less than 1 °/s is guaranteed in this range, which is acceptable for this application.

Table 4. X-Sens rotational speed measurement error summary.

	Gyroscope Error		
Motor Speed	x axis (°/s)	y axis (°/s)	z axis (°/s)
100°/s	–0.1463	–0.5159	–0.6127
200°/s	–0.1944	–0.9729	–1.0299
300°/s	–1.2977	–3.3778	–0.2363

3.3. Accelerometer

In order to characterize the accelerometer data provided by the Mti-1, first the calibration procedure proposed in Reference [28], which uses the gravity vector as a reference, is applied, and the accelerations in the global reference frame are calculated. Then, the data provided by the accelerometer is compared with the acceleration data obtained by the Vicon MCS system.

The 4 meter walking test (0° rotation) dataset defined in the Section 3.1 is used to perform this characterization, whose time evolution is depicted in Figure 6. Note that the captured accelerations are first filtered using a low pass filter.

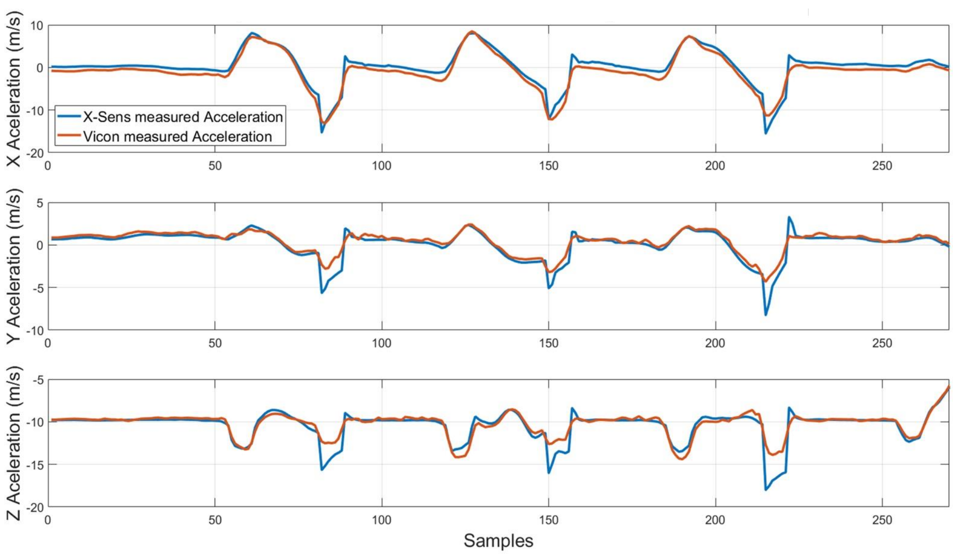


Figure 6. Comparison of acceleration measured by X-Sens and Vicon.

Table 5 summarizes the RMS and average errors in the global reference frame for each axis. As it can be seen, the RMS estimation error is generally less than 1.4 m/s^2, which is acceptable for the monitoring application. In addition, note that, as seen in Figure 6, the acceleration measurements along the experiment have good quality, except when the Sensorized Tip impacts the ground, in which higher accelerations appear due to this effect.

Table 5. X-Sens acceleration measurement error summary.

	x (m/s^2)	y (m/s^2)	z (m/s^2)
RMS Error	1.1365	0.3963	0.4574
Mean Error	0.9674	-0.3103	−0.1704

3.4. Force Sensor

In order to characterize the force sensor measurement, its measurements were compared with the ones given by the Bertec 4060-15 force plate integrated in the 3D Motion Capture Laboratory, as previously detailed.

It is important to note that, due to the Sensorized Tip design, the force sensor measures the force transmitted by the rubber Tip to the *force transmitter* part (Figure 1b). Hence, friction and damping effects appear, requiring to calibrate the force sensor prior to its use. For that purpose, the Sensorized Tip was placed vertically over the force plate using a 3D printed support, and a set of constant loads in the 0–100 kg (approximately 0–1 kN) range were progressively applied to it. Using the measurements of both the force plate and the Sensorized Tip force sensor the following calibration curve was obtained,

$$y = -230.71x^2 + 797.3736x - 285.6619. \tag{1}$$

Once calibrated, the Sensorized Tip was attached to a crutch and different loads were applied after placing it on the Bertec 4060-15 force plate. A particular test is shown in Figure 7. As it can be seen the negative and positive force gradients match, but there exist a measurement error when the maximum force is applied to the crutch due to the force transmission mechanism of the design and the existing friction. An average error of –0.0425 N is obtained from this sensor, with an RMS of 21.1104 N, which is considered acceptable for this application.

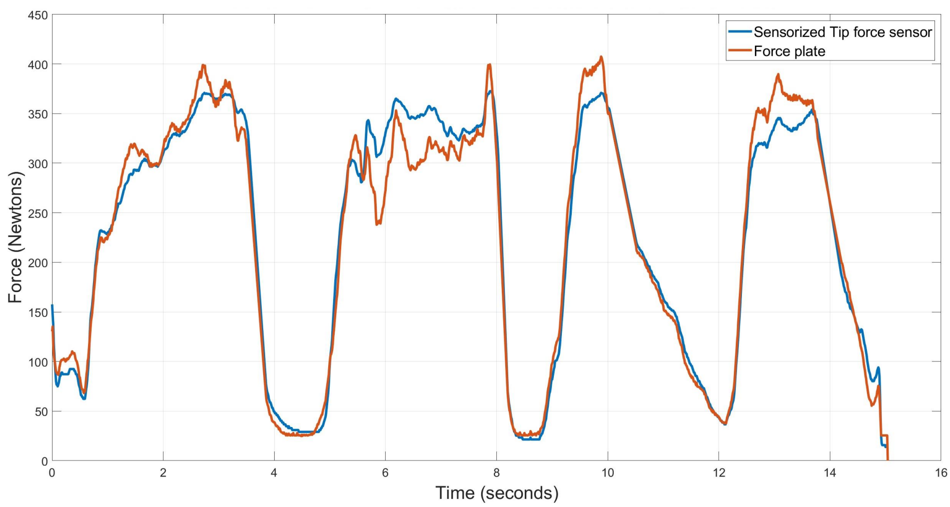


Figure 7. Force sensor after calibrate curve and data obtained from the scale.

3.5. Barometric Sensor

Finally, the Sensorized Tip includes a BMP280 barometer which allows to calculate the relative height based on the atmospheric pressure. In order to determine the measurement accuracy of the sensor, a simple test was carried out, consisting on using a stair set as a reference. It was divided into four flights, with 12 stairs per flight and a total of 2.04 m between flights.

Results are shown in Figure 8, in which the starting floor was considered as the 0 height value. If the *flat* areas associated to each flight of stairs are considered in the time evolution, the RMS error is 0.2716 m, while the average error is –0.0466 m. Note that this fits the data from the manufacturer, which offers a relative precision of 0.12 hPa.

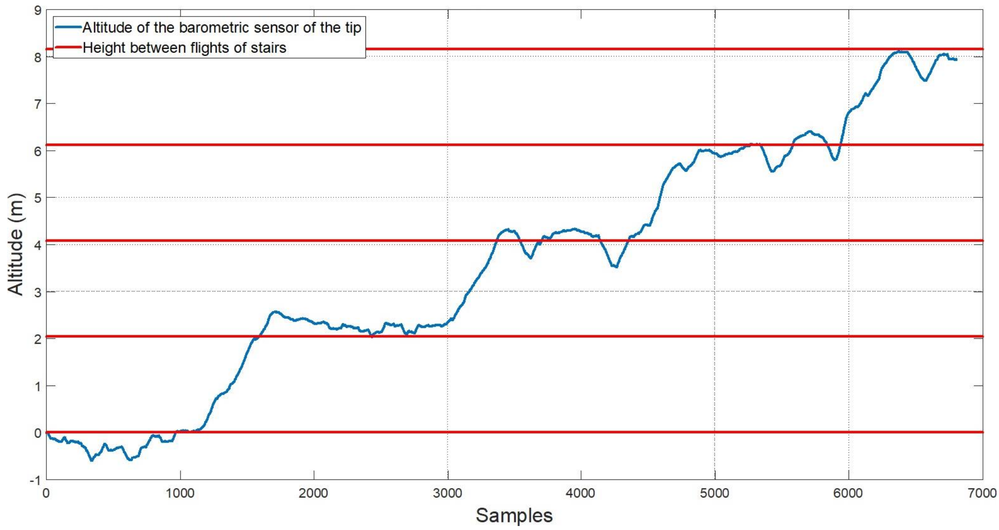


Figure 8. Comparison and validation of the altitude provided by the barometric sensor and the real altitude.

4. Estimation of the Orientation of the Device

As detailed in the introduction, orientation of the ADW can be used to define indicators related to the patterns of use of the device, which are related to the status of the patient.

However, the measurement of the orientation is not a trivial task, and as analysed previously, different approaches exist. In the particular case of the proposed device, the integrated Mti-1 sensor provides, using a proprietary algorithm based on a Kalman Filter, the Euler orientation angles that relate the local Sensorized Tip reference system $S_{tip}(x, y, z)$ with a global reference system $S_G(X, Y, Z)$.

However, for the specific application of the Sensorized Tip, the relative motion of the assistive device with respect to the body of the patient is required. This is, the lateromedial and anteroposterior angles, as seen in Figure 9a.

The calculation of these angles is not trivial and a two step procedure has been defined to estimate them. First, a *body reference system* ($S_B(X', Y', Z')$) has to be inferred from the data provided by the Sensorized Tip (Figure 9b). Second, the calculation of the lateromedial and anteroposterior angles is carried out by projecting the Sensorized Tip reference system into what will be named *advance plane*, that is, the $X'Z'$ plane of the body reference system, related to the direction of movement of the patient. This procedure will be detailed next.

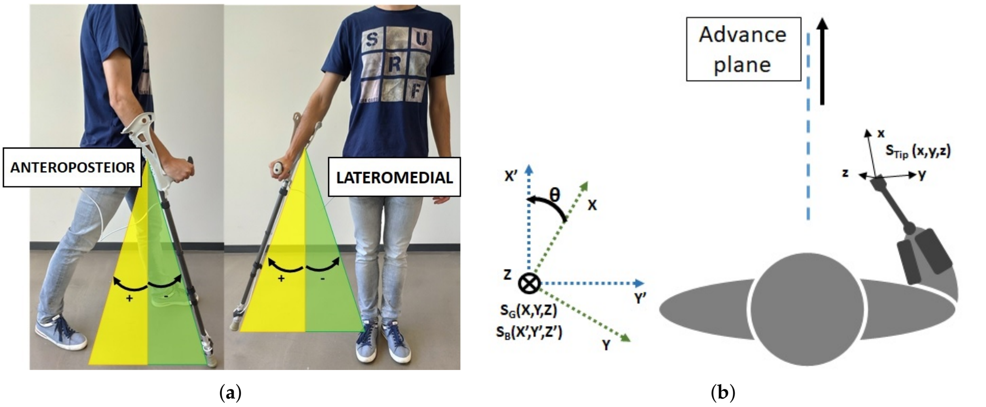


Figure 9. (**a**) Anteroposterior and Lateromedial angles. (**b**) Global, Body and Sensorized Tip reference frames.

4.1. Estimation Algorithm for the Body Reference System and the Advance Plane

The *body reference system* is considered aligned with the Z axis of the global reference system of the Mti-1, but its X' axis always points in the direction of the body motion, which defines the advance plane $X'Z'$. Hence, as seen in Figure 9b, the global and body reference systems are related by rotation of θ with respect to the global Z axis.

Hence, in order to define the *body reference system*, the motion direction in the (XY) plane of the global reference system has to be defined. Note that this is not a trivial tasks as—1) the global reference system of the Mti-1 only ensures the Z axis, but the X depends on an internal magnetometer which is affected by electromagnetic noise; and 2) as seen in Section 3.1, patients may grab the handle of the ADW with multiple angles, or even place the Sensorized Tip misaligned with the crutch.

In this work a novel approach is proposed to estimate the motion direction, and thus, the advance plane and body reference system, based on the *predominant* direction defined by the projection of the Sensorized Tip motion in the XY plane. The basic idea is to project on this plane the vector defined by the Euler angles provided by the Mti-1, creating a set of points in which a linear regression is applied to detect the main direction (Figure 10a).

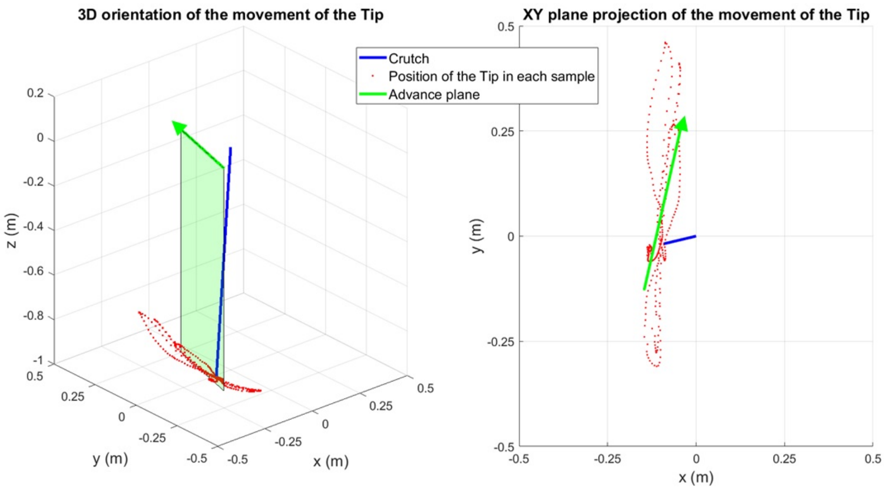
The proposed procedure is applied to each ADW cycle (see Figure 10b). When using a crutch or cane, in each cycle two phases can be differentiated if the load force is considered—the stance phase, in which the patient applies load to the assistive device; and the swing phase, in which no contact with the ground exists and the device is moved through the air to the next stance phase start.

This way, when the Sensorized Tip detects that the stance phase has started, the absolute orientation data (Euler angles) is captured within this phase. When the stance phase ends, the captured Euler Angles (α, β, γ) are used to represent in 3D the orientation of the ADW. For each set of Euler angles captured, the following rotation matrix can be defined,

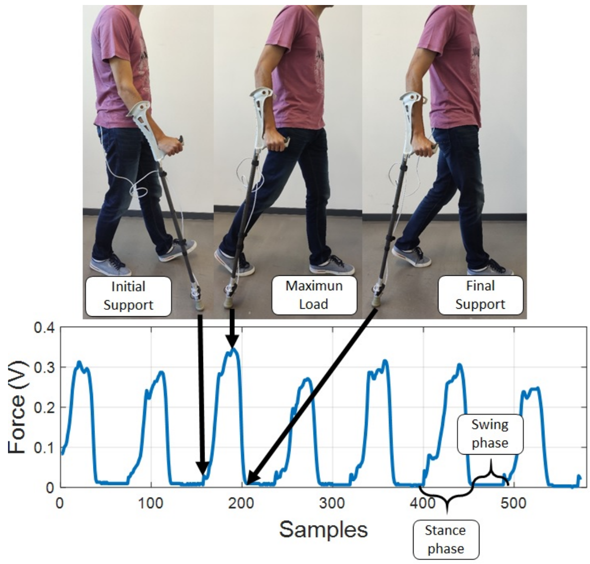
$$ {}^{G}\mathbf{R}_{tip} = \mathbf{R_z}(\alpha)\,\mathbf{R_y}(\beta)\,\mathbf{R_y}(\gamma) = \mathbf{R_{rpy}}, \tag{2} $$

which relates the Sensorized Tip local reference system and the global reference system of the Mti-1. As the Sensorized Tip local Z axis is aligned with the Sensorized Tip / assistive device axis, it is possible to define the representation of unitary vector ${}^{G}\mathbf{u_z}$ associated to the local Z axis in the global reference frame by extracting the third column of $\mathbf{R_{rpy}}$,

$$ \mathbf{R_{rpy}} = \left[\ {}^{\mathrm{G}}\mathbf{u_x} \quad {}^{\mathrm{G}}\mathbf{u_y} \quad {}^{\mathrm{G}}\mathbf{u_z}.\ \right] \tag{3} $$



(**a**)



(**b**)

Figure 10. (**a**) 3D Orientation of the Sensorized Tip and (XY) plane projection. (**b**) Stance and Swing Phases.

The projection of ${}^{G}\mathbf{u_z}$ in the XY plane of the Global Reference System reflects the motion of the Sensorized Tip in this reference system. Hence, if a particular stance phase is evaluated, cloud of points is obtained, which reflects the motions carried out in that particular cycle (Figure 10a).

Considering that no turns are carried out within an stance phase, a linear regression is applied to the projected points in the XY plane, obtaining the *predominant* direction of the body in that stance phase. Thus, the angle of this line with respect to the global reference system X axis defines θ (Figure 9b), and the *body reference system* can be calculated as,

$$^{G}\mathbf{R}_B = \mathbf{R_z}(\theta). \tag{4}$$

In order to validate this approach, the data of the tests carried out in Section 3.1 are used, in which five different trajectories were tested: 4m walking straight with different crutch handle orientations (0°, 45° and 90°), zig-zag trajectory and circular trajectory. The data from the Vicon MCS system was used to evaluate both body and crutch motions.

Results are summarized in Table 6, while the circular trajectory and the advance plane identification for each cycle are shown in Figure 11. As it can be seen, the proposed approach provides results with a RMS value of less than 5.6° in the case of linear motion (45° rotation in the handle), while the error increases up to 8° when the trajectory is circular. This is due to the fact that the estimation plane is calculated in each step assuming that the steps are carried out linearly. Hence, this is considered a worst case scenario that reflects sharp turns while walking.

Table 6. Body Reference System θ offset estimation error.

Test	Handle Orientation	RMS Error	Mean Error
Walk straight 4 meters	0°	5.4556	1.7311
Walk straight 4 meters	45°	5.605	5.4886
Walk straight 4 meters	90°	2.4038	1.5265
Zigzag	0°	4.4965	–2.0318
Circle	0°	7.9843	–5.8093

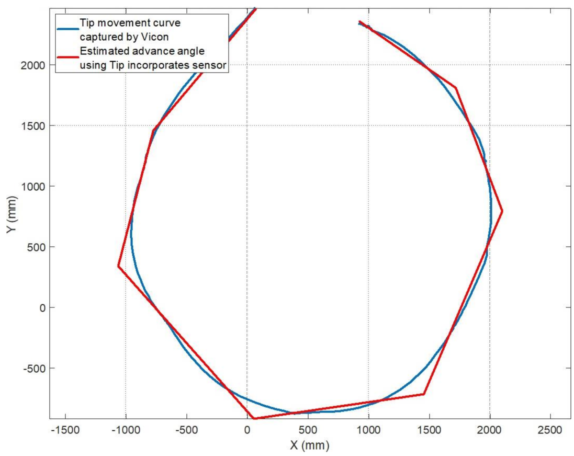


Figure 11. Advance plane estimation in the circular test (Worst Case Scenario) with respect to the real trajectory.

4.2. Anteroposterior and Lateromedial Angle Estimation

Once the body reference system $S_B(X', Y', Z')$ has been estimated, the anteroposterior and lateromedial angles can be calculated. As seen in the previous section,

$$ {}^{B}\mathbf{R}_{tip} = \mathbf{R}_z(\theta)\,\mathbf{R}_{rpy} = \begin{bmatrix} {}^{\mathbf{B}}\mathbf{u_x} & {}^{\mathbf{B}}\mathbf{u_y} & {}^{\mathbf{B}}\mathbf{u_z} \end{bmatrix}, \tag{5} $$

where ${}^{\mathbf{B}}\mathbf{u_z} = \begin{bmatrix} u_{z_x} & u_{z_y} & u_{z_z} \end{bmatrix}^T$ is the unitary directional vector of the z axis of the Sensorized Tip reference frame in the body reference frame. The time evolution of this vector, represents the motion of the assistive device with respect to the body reference frame.

Hence, projecting this vector in the $X'Z'$ and $Y'Z'$ planes, the anteroposterior θ_{ant} and lateromedial θ_{lat} angles can be obtained,

$$ \theta_{ant} = atan\left(\frac{u_{z_x}}{u_{z_z}}\right) \qquad \theta_{lat} = atan\left(\frac{u_{z_y}}{u_{z_z}}\right). \tag{6} $$

5. Study Case to Evaluate Device Potential with Pwms

The developed Sensorized Tip aims to monitor PwMS and provide objective and relevant data that can be used to assess patient function and progression. However, as stated in the introduction, the raw sensor and estimated orientation data defined in the previous sections should be further processed.

In this section, a set of indicators will be defined from the data provided by the Sensorized Tip (analyzed in Sections 3 and 4). Then, the results of a exploratory study-case with PwMS will be analyzed to study the potential of the proposed device to assess patient status. Please note that this is not an exhaustive study to correlate indicators and patient status and that further thorough clinical trials are required for this latter purpose.

5.1. Exploratory Study-Case Setup

In order to perform the preliminary analysis, the study case was approved by the Basque Country Clinical Research Ethics Committee (CEIm) (Code PS2018017), and was carried out in collaboration with ADEMBI (Multiple Sclerosis patient Association of Biscay). This Association is exclusively dedicated to the treatment of PwMS, and provided constant supervision for the patients during the tests.

Three PwMS that required ADW, each with different functional disability status (but EDSS >4.5), volunteered for this study-case. The data of each patient is shown in Table 7, including their weight, their level of disability measured by the standarized EDSS (Expanded Disability Status Scale) [36,37] and the time to perform the TUG (Timed Up and Go) [38] standardized test.

Each patient was explained the test thoroughly, and then asked to perform a standardised *10 meter walking test* (10MWT) walking at a normal and comfortable pace. The test was repeated twice, one in each direction. Note that the first meter is reserved to accelerate, while the last one to decelerate and stop. Hence, for the analysis only the middle 8 meters are considered. In order to detect these limits, two photoelectric cell gates (Polidemo, Micrgate, Italy) were placed in meters 1 and 9, allowing also to capture the average speed (see Figure 12).

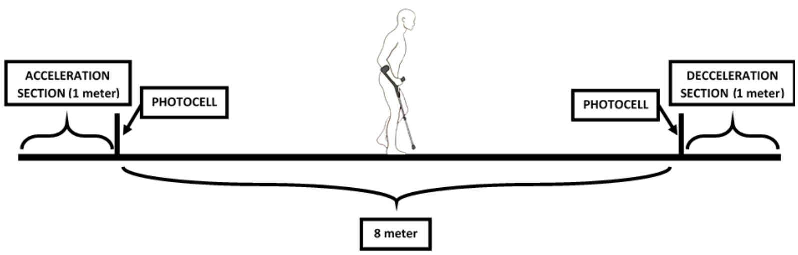


Figure 12. Ten meter walking test setup.

Table 7. Selected People with Multiple Sclerosis (MS) for the exploratory study-case.

	Weight (kg)	EDSS	TUG (s)	Assistive Device for Walking
Patient 1	86.4	4.5	14.1	Cane
Patient 2	78	6.5	22.97	Crutch
Patient 3	56.8	7.5	49.29	Crutch

5.2. Defined Indicators

As stated in the introduction, different indicators have been proposed in the literature based on monitoring data related to gait or ADW. In this work, some of the most relevant ones have been selected in order to demonstrate the potential of the proposed Sensorized Tip:

- The maximum load, which defines the maximum load that the user applies on the assistive device during the test (Figure 10b).
- The maximum load with respect to the weight (in percentage) [32,33], reflecting the maximum percentage of body weight the patient applies on the ADW during the stance phase.
- The average load with respect to the weight (in percentage) [33], reflecting the percentage of body weight the patient is applying on the assistive device .
- The average of two steps time [34], which represents the average time a patient requires for each cycle; this is, both the stance phase and the swing phase (Figure 10b).
- Number of cycles [34], defined by the number of cycles (stance/swing) the patient requires to complete the test.

The aforementioned indicators can be extracted from the force sensor data, as shown in Figure 10b. In addition, a set of indicators related to the orientation of the Sensorized Tip have been also defined, with the aim to define the pattern of use of the device. In this way, the anteroposterior and lateromedial angles estimated using the algorithms defined in Section 4 have been captured in three critical positions (Figure 10b): the initial contact point, the point of maximum load, and the final contact point of the stance phase.

5.3. Results and Discussion

Results for the three PwMS on the *10 meter walking test* are summarized in Table 8. Note that as previously noted, the aim of this work is not to carry out an exhaustive correlation analysis, but to demonstrate the potential of the use of the Sensorized Tip to assess patient functionality.

Table 8. Exploratory Study-Case results.

	Patient 1	**Patient 2**	**Patient 3**
Timed Up and Go (TUG) (s)	14.1	22.97	49.29
Expanded Disability Status Scale (EDSS)	4.5	6.5	7.5
Avgerage Speed (m/s)	0.82	0.46	0.61
Maximum Load (Kg)	6.69	10.44	11.09
Maximun Load with Respect Weight (%)	7.74	13.38	19.52
Mean Load (Kg)	5.55	7.78	6.74
Mean Load with Respect Weight (%)	6.42	9.97	11.86
Average Two Step Time (s)	1.49	1.65	1.31
Number of Cycles	6.5	10.5	10
Anteroposterior Angle Amplitude (°)	35.75	20.74	24.79
Anteroposterior Angle in Initial Support (°)	1.40	−24.00	−20.92
Anteroposterior Angle in Maximum Load (°)	7.12	−14.72	−4.36
Anteroposterior Angle in Final Support (°)	27.40	−5.52	−2.30
Lateromedial Angle Amplitude (°)	4.50	3.67	5.39
Lateromedial Angle in Initial Support (°)	6.78	10.40	6.96
Lateromedial Angle in Maximum Load (°)	8.29	9.93	4.91
Lateromedial Angle in Final Support (°)	6.17	8.74	7.60

From these data several initial guidelines can be extracted. If the exerted load is considered, note that the load value can give potential information regarding patient performance only if the value is normalized with respect to the body weight. In this case, the data shows that the percentage of body weight the patient applies on the sensorized assistive device increases with the degree of disability given by the Expanded Disability Status Scale (EDSS). A similar tendency is shown if the Timed Up and Go (TUG) time is considered.

If the number of cycles is considered, note that there are significant differences between Patient 1 and 2/3. This can be related also with the anteroposterior angle amplitude, as for the same distance, a less number of steps will imply greater assistive device motions (greater anteroposterior angles).

Note however, that the number of steps, or even the step time between two steps, which may be used to estimate also the average speed, potentially do not provide significant data to assess patient status. For instance, patient 3, which has a high degree of disability, presents similar number of steps than patient 2, which has a moderate degree. Even more, if speed metrics are derived, it can be seen that patient 3 is quicker than patient 2, although his EDSS (and TUG) is higher. This is consistent with the high heterogeneity within PwMS.

On the other hand, an analysis of the assistive device motion can be carried out by analyzing the proposed indicators for the estimated anteroposterior and lateromedial angles. These data can be used to analyze the way the patient uses the device through the day, and to detect if changes have arised, as proposed by the authors. For instance, patient 1 uses the cane to take impulse, as it first contacts the ground almost vertically (1.4°), moves the cane back while taking impulse (the maximum load is exerted in 7.12°, that is, with the cane behind the body) up to 27.4°. Patient 2, on the other hand, requires increased crutch support to move, starts the gait cycle by placing the crutch in front of the body (−24°) and using it to take impulse while pivoting (maximum force exerted at −14.7°) until reaching a near vertical position (−5.5°). Finally, patient 3, starts the cycle by placing the crutch in front of the body similar to patient 2 (−20.9°), but pivotes with both crutches applying increased load until reaching a near vertical position, where the maximum load is applied (−4.36°), finishing the cycle almost there.

In addition to the anteroposterior angle, the lateromedial angle can also be used to complete the use-pattern of the assistive device. Note that greater lateromedial angle may be related with a greater requirement for support area. This way, patient 1 places the cane near the vertical first, and opens the angle while taking impulse. Patient 2, places the crutch with a broader angle to ensure balance prior to taking impulse, and maintains it while pivoting (note that in this case, the crutch always moves in front of the patient, as previously detailed). Finally, patient 3 places the sensorized crutch almost vertically, as the patient uses it to take impulse while pivoting.

In summary, the exerted load with respect to the body weight and the proposed orientation angles are potential indicators to be considered to analyze patient status, while parameters related to the average speed seem to have less potential for the aforementioned purpose. These guidelines demonstrate the potential of the proposed device, and define the starting point for further tests with PwMS in order to perform a full correlation analysis on the data provided by the developed device.

6. Conclusions

Individualized rehabilitation is mandatory for achieving the highest possible level of independence in people with Multiple Sclerosis (PwMS). For that purpose, proper monitoring devices are required, which provide objective data that allow designing patient-centered therapy.

In this work a Sensorized Tip that can be attached to any crutch or cane is proposed to monitor PwMS that require Assistive Devices for Walking (ADW) within the day. Different from other approaches, the proposed device is designed to minimize the impact on the patient and allows to collect the axial load and the ADW 3D motion data. The proposed Sensorized Tip integrates a motion processing unit that provides acceleration, rotation and inclination data, a barometer for altitude estimation and a force sensor. The device is designed to be lightweight and allows wireless communication using Bluetooth protocol.

The novel Sensorized Tip measurement errors are characterized in a series of tests, concluding that the device's accuracy is enough to monitor PwMS. In addition, an algorithm to estimate relevant orientation data is defined. Moreover, the potential of the device to provide data to perform patient status assessments is analyzed in a exploratory case study with PwMS. Preliminary results demonstrate that the proposed device allows to extract important information regarding not only their status, but also the use given to the ADW, which has clinical repercussion.

However, the reported work presents some limitations that will be handled in future works. First, the study-case with PwMS was not carried out in 3D Motion Capture facilities due to the risks involved for the patients. Second, the weight and design of the device can be further optimized based on patient's feedback. Finally, the proposed study case is a preliminary analysis with a reduced number of patients, and select indicators that, although demonstrates an area of research with great potential, also emphasizes the need for further research.

In this sense, future work will include working in the aforementioned limitations, being the most relevant one the need to perform a wider longitudinal study with a represenative sample of PwMS (with an N > 20) to analyze correlations between the parameters offered by the Sensorized Tip and validated clinical tests (EDSS, TUG test data). This analysis could allow to give more insight into the validity of the approach to assess patients, and determine if the different indicators are able to detect changes in the patient status as the disease evolves.

Author Contributions: Conceptualization, methodology, formal-analysis, funding acquisition and supervision by A.Z., I.C. and A.R.-L.; data collection and investigation by A.B. and A.R.-L.; validation, writing-original draft-preparation, by A.B. and A.Z.; software by A.B., writing-review and editing, by I.C., A.Z. and A.R.-L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the University of the Basque Country (UPV/EHU) grants number PIF18/067, by the UPV/EHU under project number GIU19/045 (GV/EJ IT1381-19) and by the Ministerio de Ciencia e Innovación (MCI) under grant number DPI2017-82694-R (AEI/FEDER, UE).

Acknowledgments: The authors would also like to thank Multiple Sclerosis Patient Association ADEMBI for their invaluable help.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

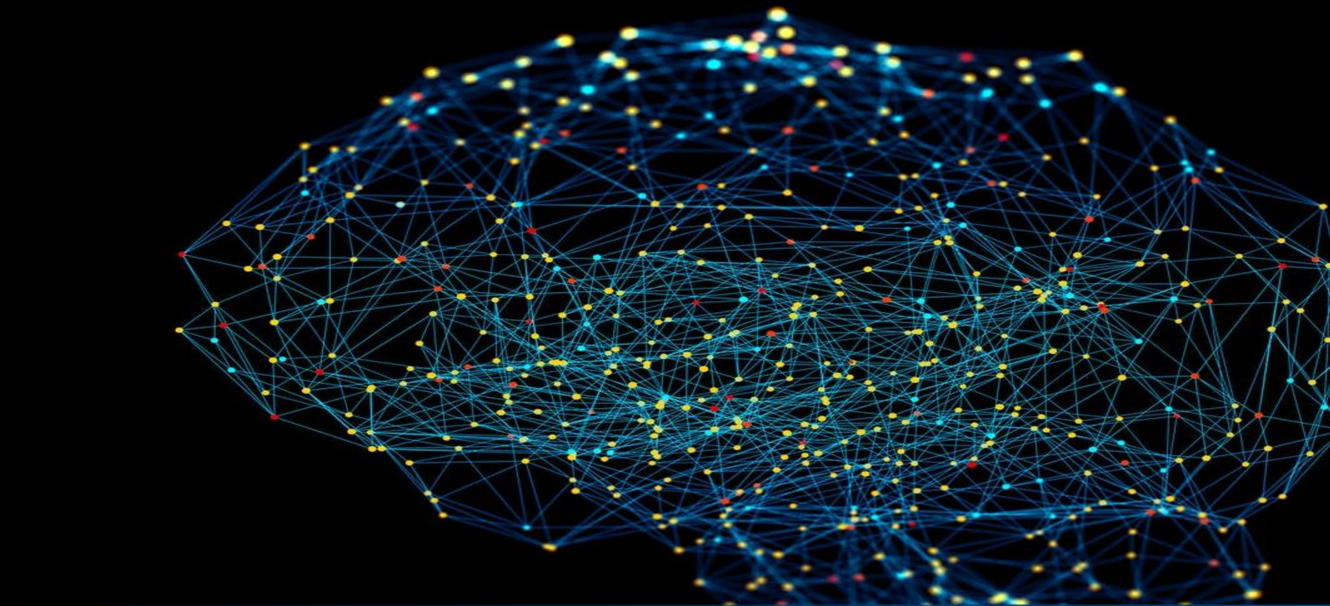
MS	Multiple Sclerosis
PwMS	People with Multiple Sclerosis
ADW	Assistive Devices for Walking
IMU	Inertial Measurement Unit
DAQ	Data Acquisition System
BLE	Bluetooth 4.0 Low Energy
ATT	Attribute Protocol
MCS	Motion Capturing System
RMS	Root Mean Square
EDSS	Expanded Disability Status Scale
TUG	Timed Up and Go

References

1. Federation, M.S.I. *The Atlas of Multiple Sclerosis*; Technical report; WHO Press: Geneva, Switzerland, 2008.
2. Organization, W.H. *Neurological disorders: Public health challenges*; Technical report; WHO Press: Geneva, Switzerland, 2006.
3. (FELEM), F.E.d.L.c.l.E.M. *Esclerosis múltiple en España: Realidad, necesidades sociales y calidad de vida*; Technical report; Real Patronato sobre Discapacidad: Madrid, Spain, 2007.
4. Souza, A.; Kelleher, A.; Cooper, R.; Cooper, R.A.; Iezzoni, L.I.; Collins, D.M. Multiple sclerosis and mobility-related assistive technology: Systematic review of literature. *J. Rehabil. Res. Dev.* **2010**, *47*, 213. [CrossRef] [PubMed]
5. Flachenecker, P. Clinical Implications of Neuroplasticity – The Role of Rehabilitation in Multiple Sclerosis. *Front. Neurol.* **2015**, *6*, 36–40. [CrossRef] [PubMed]
6. Jones, D.E.; Armstrong, M.J.; Sutliff, M.H.; Halper, J.; Brown, T.R.; Haselkorn, J.K.; Kraft, G.H.; Narayanaswami, P. Summary of comprehensive systematic review: Rehabilitation in multiple sclerosis: Report of the Guideline Development, Dissemination, and Implementation Subcommittee of the American Academy of NeurologyAuthor Response. *Neurol.* **2016**, *87*, 646. [CrossRef] [PubMed]

7. National Collaborating Centre for Chronic Conditions (Great Britain) and Chartered Society of Physiotherapy (Great Britain). *Multiple sclerosis: National clinical guideline for diagnosis and management in primary and secondary care*; Technical Report; Royal College of Physicians: London, UK, 2004.
8. Latimer-Cheung, A.E.; Pilutti, L.A.; Hicks, A.L.; Ginis, K.A.M.; Fenuta, A.M.; MacKibbon, K.A.; Motl, R.W. Effects of exercise training on fitness, mobility, fatigue, and health-related quality of life among adults with multiple sclerosis: A systematic review to inform guideline development. *Arch. Phys. Med. Rehabil.* **2013**, *94*, 1800–1828. [CrossRef] [PubMed]
9. Shull, P.B.; Jirattigalachote, W.; Hunt, M.A.; Cutkosky, M.R.; Delp, S.L. Quantified self and human movement: A review on the clinical impact of wearable sensing and feedback for gait analysis and intervention. *Gait Posture.* **2014**, *40*, 11–19. [CrossRef]
10. Gong, J.; Goldman, M.D.; Lach, J. Deepmotion: A deep convolutional neural network on inertial body sensors for gait assessment in multiple sclerosis. In Proceedings of the 2016 IEEE Wireless Health, WH 2016, Bethesda, MD, USA, 25–27 October 2016; pp. 164–171. [CrossRef]
11. Gyllensten, I.C.; Bonomi, A.G. Identifying types of physical activity with a single accelerometer: Evaluating laboratory-trained algorithms in daily life. *IEEE Trans. Biomed. Eng.* **2011**, *58*, 2656–2663. [CrossRef]
12. Moncada-Torres, A.; Leuenberger, K.; Gonzenbach, R.; Luft, A.; Gassert, R. Activity classification based on inertial and barometric pressure sensors at different anatomical locations. *Physiol. Meas.* **2014**, *35*, 1245–1263. [CrossRef]
13. Shoaib, M.; Bosch, S.; Durmaz Incel, O.; Scholten, H.; Havinga, P.J. Fusion of smartphone motion sensors for physical activity recognition. *Sensors.* **2014**, *14*, 10146–10176. [CrossRef]
14. Aguiar, B.; Silva, J.; Rocha, T.; Carneiro, S.; Sousa, I. Monitoring physical activity and energy expenditure with smartphones. In Proceedings of the IEEE Computer Society, Valencia, Spain, 28 July 2014; pp. 664–667. [CrossRef]
15. Brichetto, G.; Pedullà, L.; Podda, J.; Tacchino, A. Beyond center-based testing: Understanding and improving functioning with wearable technology in MS. *Mult. Scler.* **2019**, *25*, 1402–1411. [CrossRef]
16. Sardini, E.; Serpelloni, M.; Lancini, M. Wireless instrumented crutches for force and movement measurements for gait monitoring. *IEEE Trans. Instrum. Meas.* **2015**, *64*, 3369–3379. [CrossRef]
17. Culmer, P.R.; Brooks, P.C.; Strauss, D.N.; Ross, D.H.; Levesley, M.C.; Oconnor, R.J.; Bhakta, B.B. An instrumented walking aid to assess and retrain gait. *IEEE/ASME Trans. Mechatron.* **2014**, *19*, 141–148. [CrossRef]
18. Lancini, M.; Serpelloni, M.; Pasinetti, S. Instrumented crutches to measure the internal forces acting on upper limbs in powered exoskeleton users. In Proceedings of the 2015 6th International Workshop on Advances in Sensors and Interfaces (IWASI), Gallipoli, Italy, 18–19 June 2015; pp. 175–180. [CrossRef]
19. Tsuda, N.; Hayashi, A.; Tounai, M.; Akutagawa, S. Visualization system of crutch walking based on internal sensors. In Proceeding of IEEE/ASME International Conference on Advanced Intelligent Mechatronics, Montreal, QC, Canada, 6–9 July 2010; pp. 19–24. [CrossRef]
20. Hassan, M.; Kadone, H.; Suzuki, K.; Sankai, Y. Wearable Gait Measurement System with an Instrumented Cane for Exoskeleton Control. *Sensors* **2014**, *14*, 1705–1722, doi:10.3390/s140101705. [CrossRef] [PubMed]
21. Mekki, F.; Borghetti, M.; Sardini, E.; Serpelloni, M. Wireless instrumented cane for walking monitoring in Parkinson patients. In Proceedings of the 2017 IEEE International Symposium on Medical Measurements and Applications (MeMeA), Rochester, MN, USA, 20 July 2017; pp. 414–419. [CrossRef]
22. Megalingam, R.K.; Greeshma, M.G.; Pillai, S.S. Design and implementation of intelligent crutches for medical applications. In Proceedings of 2019 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 25 April 2019; pp. 926–929. [CrossRef]
23. Seylan, Ç.; Saranli, U. Estimation of ground reaction forces using low-cost instrumented forearm crutches. *IEEE Trans. Instrum. Meas.* **2018**, *67*, 1308–1316. [CrossRef]
24. Chamorro-Moriana, G.; Sevillano, J.; Ridao-Fernández, C. A Compact forearm crutch based on force sensors for aided gait: Reliability and validity. *Sensors.* **2016**, *16*, 925. [CrossRef] [PubMed]
25. Merrett, G.V.; Ettabib, M.A.; Peters, C.; Hallett, G.; White, N.M. Augmenting forearm crutches with wireless sensors for lower limb rehabilitation. *Meas. Sci. Technol.* **2010**, *21*, 124008. [CrossRef]
26. Wade, J.W.; Boyles, R.; Flemming, P.; Sarkar, A.; De Riesthal, M.; Withrow, T.J.; Sarkar, N. Feasibility of automated mobility assessment of older adults via an instrumented cane. *IEEE J. Biomed. Health Inf.* **2019**, *23*, 1631–1638. [CrossRef]

27. Chen, Y.F.; Napoli, D.; Agrawal, S.K.; Zanotto, D. Smart crutches: Towards instrumented crutches for rehabilitation and exoskeletons-assisted walking. In Proceedings of 2018 7th IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob), Enschede, The Netherlands, 11 October 2018; pp. 193–198. [CrossRef]
28. Jurman, D.; Jankovec, M.; Kamnik, R.; Topič, M. Calibration and data fusion solution for the miniature attitude and heading reference system. *Sens. Actuat. A Phys.* **2007**, *138*, 411–420. [CrossRef]
29. Luinge, H.J.; Veltink, P.H. Measuring orientation of human body segments using miniature gyroscopes and accelerometers. *Med. Biol. Eng. Comput.* **2005**, *43*, 273–282. [CrossRef]
30. del Rosario, M.; Redmond, S.; Lovell, N. Tracking the Evolution of Smartphone Sensing for Monitoring Human Movement. *Sensors* **2015**, *15*, 18901–18933. [CrossRef]
31. Sardini, E.; Serpelloni, M.; Lancini, M.; Pasinetti, S. Wireless instrumented crutches for force and tilt monitoring in lower limb rehabilitation. *Procedia Eng.* **2014**, *87*, 348–351. [CrossRef]
32. Routson, R.L.; Bailey, M.; Pumford, I.; Czerniecki, J.M.; Aubin, P.M. A smart cane with vibrotactile biofeedback improves cane loading for people with knee osteoarthritis. In Proceedings of2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, USA, 18 October 2016; pp. 3370–3373. [CrossRef]
33. Simic, M.; Bennell, K.L.; Hunt, M.A.; Wrigley, T.V.; Hinman, R.S. Contralateral cane use and knee joint load in people with medial knee osteoarthritis: The effect of varying body weight support. *Osteoarthr. Cartil.* **2011**, *19*, 1330–1337. [CrossRef] [PubMed]
34. Sprint, G.; Cook, D.J.; Weeks, D.L. Quantitative assessment of lower limb and cane movement with wearable inertial sensors. In Proceeding of 2016 IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI), Las Vegas, NV, USA, 21 April 2016; pp. 418–421. [CrossRef]
35. Slavens, B.A.; Bhagchandani, N.; Wang, M.; Smith, P.A.; Harris, G.F. An upper extremity inverse dynamics model for pediatric Lofstrand crutch-assisted gait. *J. Biomech.* **2011**, *44*, 2162–2167. [CrossRef] [PubMed]
36. Kurtzke, J.F. Rating neurologic impairment in multiple sclerosis: An expanded disability status scale (EDSS). *Neurology* **1983**, *33*, 1444–1452. [CrossRef] [PubMed]
37. Meyer-Moock, S.; Feng, Y.S.; Maeurer, M.; Dippel, F.W.; Kohlmann, T. Systematic literature review and validity evaluation of the expanded disability status scale (EDSS) and the multiple sclerosis functional composite (MSFC) in patients with multiple sclerosis. *Bmc Neurol.* **2014**, *14*, 58–68. [CrossRef]
38. Cattaneo, D.; Regola, A.; Meotti, M. Validity of six balance disorders scales in persons with multiple sclerosis. *Disabil. Rehabil.* **2006**, *28*, 789–795. [CrossRef]



Appendix 2
2. eranskina

Asier Brull Mesanza, Sergio Lucas, Asier Zubizarreta, Itziar Cabanes, Eva Portillo, and Ana Rodriguez-Larrad. A Machine Learning Approach to Perform Physical Activity Classification Using a Sensorized Crutch Tip. *IEEE Access*, 8:210023–210034, 2020. *doi: https://doi.org/10.1109/ACCESS.2020.3039885* JCR2020: 3.367 (Q2)

IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received November 11, 2020, accepted November 18, 2020, date of publication November 24, 2020, date of current version December 3, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3039885

A Machine Learning Approach to Perform Physical Activity Classification Using a Sensorized Crutch Tip

ASIER BRULL MESANZA[1], SERGIO LUCAS[1], ASIER ZUBIZARRETA[1], ITZIAR CABANES[1], EVA PORTILLO[1], AND ANA RODRIGUEZ-LARRAD[2]

[1]Department of Automatic Control and Systems Engineering, Faculty of Engineering of Bilbao, University of the Basque Country (UPV/EHU), 48013 Bilbao, Spain
[2]Department of Physiology, Faculty of Medicine and Nursing, University of the Basque Country (UPV/EHU), 48940 Leioa, Spain

Corresponding author: Asier Brull Mesanza (asier.brull@ehu.eus)

This work was supported in part by the University of the Basque Country [University of the Basque Country (UPV/EHU)] under Grant PIF18/067, in part by the UPV/EHU under Project GIU19/045 (GV/EJ IT1381-19), and in part by the Ministerio de Ciencia e Innovación (MCI) under Grant DPI2017-82694-R (AEI/FEDER, UE).

ABSTRACT In recent years, interest in monitoring Physical Activity (PA) has increased due to its positive effect on health. New technological devices have been proposed for this purpose, mainly focused on sports, which include Machine Learning algorithms to identify the type of PA being performed. However, PA monitoring can also provide data useful for assessing the recovery process of people with impaired lower-limbs. In this work, a Machine-Learning based Physical Activity classifier design procedure is proposed, which makes use of the data provided by a Sensorized Tip that can be adapted to different Assistive Devices for Walking (ADW) such as canes or crutches. The procedure is based on three main stages: 1) defining a wide set of potential features to perform the classification; 2) optimizing the number of features by a Random-Forest approach, detecting the most relevant ones to classify five relevant activities (walking at a normal pace, walking fast, standing still, going up stairs and going down stairs); 3) training the ML-based classifiers considering the optimized feature set. A comparative analysis is carried out to evaluate the proposed procedure, using three ML-based classifier (Support Vector Machines, K-Nearest Neighbour and Artificial Neural Networks), demonstrating that the proposed approach can provide very high success rates if proper feature selection is carried out. This work presents four relevant contributions to the PA monitoring area: 1) the approach is focused on people that require ADW, which are not considered in other approaches; 2) an analysis of the features to characterize gait in people that require ADW is carried out; 3) a design procedure to optimize the number of features using a Random-Forest approach is used, avoiding a typical "brute force" procedure; and 4) a comparative analysis is carried out to demonstrate the validity of the approach.

INDEX TERMS Instrumented crutch, rehabilitation, machine learning, physical activity classification, random forest, artificial neural network, support vector machine, K-nearest neighbor.

I. INTRODUCTION

Lower-limb mobility plays an important role on autonomy and quality of life. Neurological diseases or trauma injuries that affect the mobility of the lower-limb have a great impact on the lives of people suffering from them. Hence, trying to fully or partly recover this function is one of the main goals when designing a rehabilitation strategy for these patients [1].

The associate editor coordinating the review of this manuscript and approving it for publication was Tyson Brooks.

In order to be effective, rehabilitation interventions must be adapted to the status of the patient during the whole rehabilitation process [2]. This also includes the selection of the assistive device that better fits patient needs according to her/his functionality. If the patient has lost the ability to walk autonomously, the use of wheel chairs or scooters is the better option, while crutches or canes are typically used when the gait function is maintained. Hence, therapist are required to assess patient status periodically to monitor the evolution on the status of the patient.

Patient assessment is typically performed using the data collected through tests carried out in clinical settings. However, monitoring the types of Physical Activity (PA) the patient performs throughout the day is becoming increasingly important in the functional assessment of patients, due to the well-known benefits it has on their health and its contribution to the prevention of non-communicable diseases [3], [4]. It also allows interpreting the results of the periodic clinical tests and giving individualized recommendations and feedback on how much and how to perform these activities in order to aid in the recovery process.

In order to perform PA identification, three main steps are typically carried out: 1) data related to the patient is captured by a monitoring device; 2) a set of features that allow characterizing PA is extracted from the raw sensor data; and, 3) the set of features are processed by a classifier, which detects the particular PA being executed. The main works related to each step will be summarized next.

Regarding the data capture and monitoring, different technological solutions have been proposed [5]. The most popular ones are *wearable* devices, which have to be attached to specific places of the lower-limb of the patient, and typically capture motion data using Inertial Measurement Units (IMUs) [6]–[10] or biomedical signals such as EMG [11], [12]. A number of commercial devices exist on the market, such as XSens [13], BioStampRC [14], Tracmor [15]), FlexiForce [16], BioCapture [12]). These solutions require to be properly placed and attached to the limbs, and may generate rejection on patients. In order to reduce the impact of monitoring devices the use of the integrated sensors of smartwatches and mobile phones has been proposed [17]–[20]. These latter devices do not have a specific placement in the body, but, on the other side, this positioning flexibility and the variability introduced by parasitic motions are issues to be considered when processing the data.

Once the raw data has been captured by the monitoring device, the second step is to extract a set of features that will allow to characterize the different PA. For this purpose, the use of time-series segmentation using time-windows is a common approach, as it allows to reduce the number of data to be processed [21], [22]. In the case of gait monitoring, the selected window typically matches a *step*. Hence, features of different nature that allow to characterize each step can be extracted from these windows. Statistic (mean, standard deviation,...) [10], [15], [23]–[25], frequency [19], [26] or phase [9] operations are typically applied to the captured variables for this purpose. In addition, in the particular case of gait, features such as the average speed, time between steps or the number of steps [27] have also been proposed. It is to be noted that there is no standarized approach to define these features, and that in general, a *brute force* approach is used in which a wide set of features is defined so that the classifier to be designed has enough input data to perform its job.

Finally, in the third step, using the set of selected features, the PA identification or classification is performed. Machine Learning (ML) techniques such as K-Nearest Neighbour (K-NN) [10], [24], [28], Support Vector Machine (SVM) [29]–[31] and Artificial Neural Networks (ANN) [15], [32]–[34] are the preferred solution for gait-related PA classification due to their flexibility and capability of generalization, which provide acceptable results with a success rate up to 91% [15]. Note that all these approaches are of supervised nature, and require a set of properly designed training data in which the selected features are the input, and the type of PA to be identified are the outputs. In the case of gait-related PA the proposed classifiers typically identify if the patient is walking (at an habitual or normal speed or faster, i.e. running), going up and down stairs or standing still [9], [15], [28], [32], [35].

The three-step procedure detailed previously provides a general methodology for PA classification. However, it is to be noted that there is no standarized approach to be followed in each step, and that different open research areas still exist. In particular, the feature selection procedure is typically carried out using a *brute force* approach, in which a wide set of possible features are proposed as inputs to the ML-based Physical Activity classifier, so that it can have enough data to perform the classification. This approach, however, leads to non-optimal classifiers, which typically use more features than required leading to oversized solutions, as the relative importance of each feature is not usually analyzed.

Moreover, all the aforementioned works are designed for people that do not require Assistive Devices for Walking (ADW) such as crutches or canes. However, several parameters change significantly in the case of people that use ADW, as they present non-symmetrical gait and parameters such as the load applied to the ADW might be relevant. These differences have to be considered in the three-step procedure. Recent works have demonstrated that patients that require ADW in their rehabilitation process require specific monitoring approaches [36], being sensorized ADW devices the best option for this population [37]–[41]. Hence, the set of features to be defined also has to consider ADW data.

Based on the previous analysis, in this work, a novel approach for the development of Physical Activity classifiers for patients that require ADW is proposed. The proposed approach aims to give some insight into the previously cited issues, with four relevant contributions: 1) The approach is focused on people that require ADW, which are not considered in other works; 2) A comprehensive set of features to classify five relevant types of Physical Activity is proposed and analyzed ; 3) A Feature Selection methodology based on a Random-Forest approach is proposed; and, 4) A thorough comparative analysis using three ML approaches (K-NN, SVN and ANN) is carried out to validate the proposed approach.

The rest of the work is structured as follows. Section II presents the Sensorized Tip and its sensorization capabilities. Section III details the set of tests carried out to generate the database used to develop the ML-based PA classificators. In Section IV a thorough analysis of the potential features proposed in the literature for gait monitoring is carried out, and the proposed methodology to select the most relevant features and train three different ML-based PA classificators using K-NN, SVN and ANN approaches is detailed. Finally, in Section V, a comparative analysis is carried out to evaluate the approach. Finally, the most important ideas are summarized in Section VI.

II. SENSORIZED TIP FOR GAIT MONITORING

In order to monitor the performance of people that require ADW, different approaches can be used, as analyzed in Section I. Wearable devices, although widely used, present some drawbacks for this population, as they may generate rejection due to the need of attaching the sensors to the limbs, and do not consider the interaction force between the ADW and the patient, which provides relevant monitoring data. Smartphones and watches, on the other hand, present parasitic motions that have to be considered.

Hence, several works have proposed to sensorize ADW, providing a noninvasive approach that provides accurate measurements of both ADW motion and interaction force [37]–[41]. In particular, in this work the Sensorized Tip proposed in [41] (Figure 1) is used to capture gait data. Different from the other cited approaches in which a sensorized crutch or cane is designed, the proposed Sensorized Tip can be attached to the personal crutch or cane used by the patient, which is typically adapted to his/her needs.

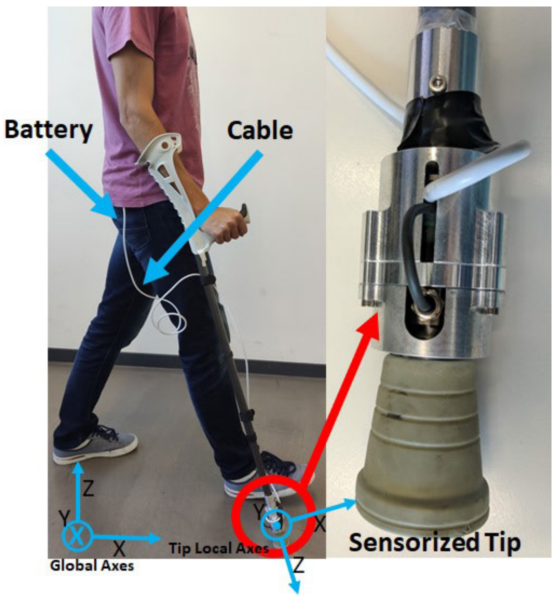


FIGURE 1. Sensorized Tip to Capture Gait Data.

The Sensorized Tip integrates three sensors in its aluminum enclosure. A 9 degrees-of-freedom Inertial Measurement Unit MTi-3 by XSens provides linear acceleration data, angular speed and magnetic field in the local (x, y, z) axes.

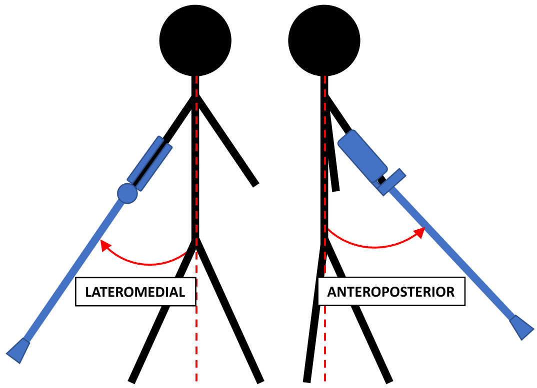


FIGURE 2. Lateromedial and Anteroposterior angles in the ADW.

In addition, this device integrates a proprietary algorithm based on a Kalman filter that allows to estimate the roll-pitch-yaw Euler angles in the global reference frame (Roll and Pitch dynamic error of 0.5°, and Yaw dynamic error 1°). The aforementioned data can also be used to estimate the anteroposterior and lateromedial crutch angles (see Figure 2). A BMP280 barometer provides information on atmospheric pressure, which allows to estimate the relative height of the device (relative precision of 0.12hPa). Finally, a C9C piezoelectric force sensor by HBM, with 1 kN range, provides information on the axial load exerted by the patient. The overall weight of the Tip is 160g.

The 16 sources of data provided by the aforementioned sensors are captured by a nRF52832 microprocessor, which adds a timestamp and sends the processed data with a 20ms period to a mobile phone device using the Bluetooth Low Energy (BLE) protocol. The data is stored in the phone using a self-developed app, so that it can be processed later. The capturing system is powered by a standard 5V powerbank, which is placed externally to the Tip in order to minimize the weight of the device (Figure 1).

The full characterization of the measurement errors and the integrated algorithms for the Sensorized Tip can be found at [41].

III. DATA BASE FOR CLASSIFIER DESIGN

In order to develop a Physical Activity classifier using Machine Learning approaches, a proper data base is required, in which the selection of the types of PA to be identified is a key issue.

As analyzed in Section I, when considering gait-related PA classifier five types of PA are typically considered [9], [15], [28], [32], [35]: walking at a normal pace; walking at a fast pace (approximately 30% faster than normal pace); going up stairs; going down stairs; and standing still. The identification of these types of PA will allow to monitor the activity of a patient through its daily life, defining patterns of activity, sedentariness, etc,... This data can be used by the therapist to provide individualized recommendations or to detect possible modifications in the patient functional status [26], [42].

In order to capture relevant data for the classifier design, a total of five tests have been carried out using a crutch in which the Sensorized Tip detailed in Section II was attached:

- Walking 30m in a straight line at the normal speed.
- Walking 30m in a straight line at a speed higher than normal (approximately 30% faster).
- Standing still for approximately 10 seconds.
- Going up an 11-step flight of stairs.
- Going down an 11-step flight of stairs.

The tests were carried out by 11 healthy volunteers from the research group of the authors (4 women and 7 men, ranging between 24-48 years), at the facilities of the Faculty of Engineering of Bilbao UPV/EHU. Each test was repeated three times for each volunteer.

In order to generate the database, a segmentation procedure was followed [28]. This procedure is carried out by considering each cycle of use of the crutch, which is composed by a stance phase (in which the crutch is in contact with the ground), and the swing phase (in which the crutch is lifted though the air and no contact exists). This way, the raw data provided by each sensor is divided in sequential windows, each associated to a crutch cycle. The initial point of each window is defined at the very first start of the stance phase, in which the crutch tip contacts the ground. This can be easily detected by considering the force sensor signal, as seen in Figure 3, as no force exist in the swing phase. The total number of segmented windows generated in the aforementioned tests are summarized in Table 1.

TABLE 1. Number of Windows per Physical Activity (PA). Test and Training Sets.

Type of PA	Number of Windows	Training Set	Test Set
Walk Normal	724	254	123
Walk Fast	528	264	118
Go Up Stairs	360	251	109
Go Down Stairs	357	251	106
Standing Still	329	218	111
Total		1238	567

Note that in the case of *Standing Still*, the aforementioned approach is no longer valid, as no crutch cycles exist. In these scenarios a *virtual step* is considered as a fixed segmentation window of 1.8s, which is slightly longer than the average cycle time for the cycles considered in the *walking at normal pace* scenario.

Once the database is defined, it will be divided into two balanced sets (Training and Test), as required by the design procedure of supervised ML-based approaches [43]. The Training set will be used to train the proposed ML-based PA classificators. For that purpose, a balanced set has been defined, with approximately the same number of windows considered for the different identified types of PA. This allows to train the classifier with the same relative importance for each type of PA. The Test set, in the other hand, will be

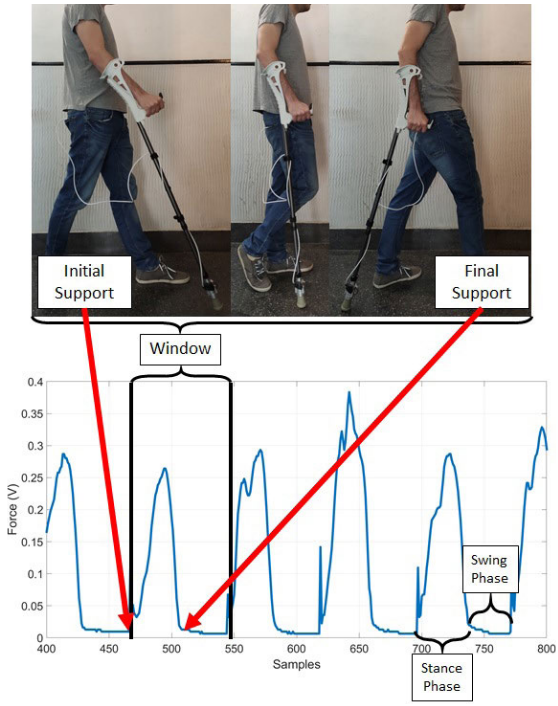


FIGURE 3. Cycle of use of an ADW and its phases. Data Segmentation in windows by using the data acquired from the force sensor.

used to test the designed classifiers. Hence, Test data will not be used in the PA classifier design procedure, but for the validation analysis carried out Section V. Note that in this latter case, a balanced window selection has also been carried, so that the tested classification success rates can be similar in nature for each type of PA to be identified [44], [45].

IV. MACHINE LEARNING-BASED PA CLASSIFIER DESIGN METHODOLOGY

The use of segmentation allows to define discrete units of data, one for each crutch cycle, from which a series of features can be extracted. These features, which may be diverse in nature (statistical, frequency based,...) can be used to characterize each cycle, and be used as inputs for the PA classification system to be developed. In this section, a methodology is detailed to select the most appropriate features and design the ML-based PA classificator.

The proposed methodology is summarized in Figure 4: First, a set of potential features based on the ones proposed in the literature is proposed (Section IV-A). This set is defined with a high number and variety of features, so that the maximum amount of information can be considered. Then, in a second step, a Random-Forest approach is used to determine the relative importance of each feature, allowing to order the potential feature set considering the relevance of each feature (Section IV-B).This ordered set will be used

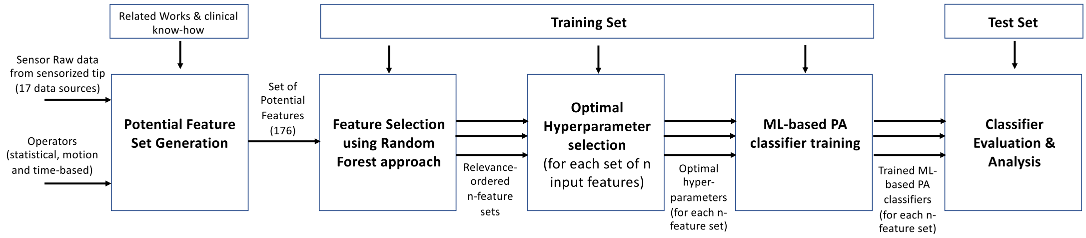


FIGURE 4. Feature selection methodology.

to design the ML-based classifier. In a third step, the set of optimal hyperparameters will be calculated for each set of n features to be considered as inputs. Finally, using the selected hyperparameters and the set of n features selected (based on their relevance), the ML approach will be trained (Section IV-C). An analysis and evaluation of the procedure will be carried out in Section V.

A. POTENTIAL FEATURES SET GENERATION

Features are related to the data sources available, as they are used to extract, using a simpler metric, a particular characteristic of the signal contained in the segmented window. For the particular case detailed in this work, 17 sources of data are considered based on the data provided by the Sensorized Tip (Section II): 9 associated to the raw IMU data (x, y, z components of acceleration, angular speed and magnetic field in the local axes); 5 related to the processed IMU data (RPY Euler Angles, and crutch anteroposterior and lateromedial angles); 1 related to the force sensor value, which is filtered; and, 2 associated to the barometer signal (filtered and unfiltered).

For each segmented window, the time evolution of these 17 data sources can be processed to extract a feature. This is carried out by applying an operator, which may be of different nature (statistical, time-based,...). Although the particular case of people that require ADW has not been analyzed in the literature, based on the operators proposed in the related works and the clinical experience of the authors, the following set of operators are proposed:

- Statistic-based operators: They are widely used in gait characterization works, as they are easily applied to any data source. *Mean value*, *standard deviation*, *variance*, *kurtosis*, *correlation coefficients XY* (i.e., between X and Y signals), *percentiles*, *area under each curve* and *interquartile ranges* [15], [23]–[25] have been selected to be applied to the data provided by all sensors. In the particular case of correlation coefficients, the correlation between the different angles/axes values provided by a sensor are considered, i.e. correlation between the accelerometer x and y signals, correlation between roll and pitch Euler Angles, etc.
- Motion-based operators: The values of motion-related sources of data in specific events allows to define features related to the use of the ADW. In particular, the values associated to the start of the stance phase (*Stance Start Value*), the end of the stance phase (*Stance End Value*) and the value associated to the maximum support (*Value at Max. Force*) are of particular interest. The *Amplitude*, defined as the absolute difference between the maximum and minimum values of a motion variable is also defined.
- Time-based operators: Measuring the time between specific events allows to obtain spatio-temporal features. In the case of ADW, *cycle time*, this is, the time between consecutive starts of the stance phase, allows to define speed-related features [27]. The use of the ADW can also be defined by comparing the relative percentage of the cycle time the patient uses the device for support, this is, the time of the stance phase with respect to the cycle time (*Stance Phase %*) [11].

By combining the set of data sources and the defined operators, a full set of 176 features can be defined. All are summarized in Table 2, where an *X* defines a feature (or features) that has been obtained by applying a particular operator (row) to a data source (column). Note that this set of 176 features is extracted for each ADW cycle, following the segmentation procedure detailed in Section III.

B. FEATURE SELECTION USING RANDOM-FOREST APPROACH

The aforementioned set of 176 features can be used to develop ML-based PA classifiers. This way, the set of features will be considered as the input to the classifier, which will identify a type of PA for each ADW cycle as seen in Figure 4.

However, this brute force approach, which is typical in the works cited in the introduction is not an efficient one. First, a high number of features increases the computational cost of the classifier. Second, the feature selection impacts the performance of the classifier, as some features may be not be related to the types of PA considered, or even some are correlated one with the other. Hence, in order to optimize the PA classifier design, proper feature selection approaches must be used.

Detecting the best feature set to design an PA classifier is not a trivial task. In recent years, Machine Learning approaches have demonstrated their ability to analyze the relative importance of different features when analyzing

TABLE 2. Features generated from the data provided by the sensorized tip (R=Roll, P=Pitch, Y=Yaw, A=Anteroposterior, L=Lateromedial).

Data Source→ Operations↓	Accelerometer (X, Y, Z)	Gyroscope (X, Y, Z)	Magnetometer (X, Y, Z)	Angle (R, P, Y)	Angles (A, L)	Barometer (With Filter)	Barometer (Without Filter)	Force Sensor
Mean	X	X	X	X	X	X	X	X
Standard Deviation	X	X	X	X	X	X	X	X
Variance	X	X	X	X	X	X	X	X
Kurtosis	X	X	X	X	X	X	X	X
Corr. Coef. XY	X	X	X					
Corr. Coef. XZ	X	X	X					
Corr. Coef. YZ	X	X	X					
Corr. Coef. RP				X				
Corr. Coef. RY				X				
Corr. Coef. PY				X				
Corr. Coef. AL					X			
25th Percentile	X	X	X	X	X	X	X	X
50th Percentile	X	X	X	X	X	X	X	X
75th Percentile	X	X	X	X	X	X	X	X
Area	X	X	X	X	X	X	X	X
Interquartile Range	X	X	X	X	X	X	X	X
Stance Start Value					X			
Value at Max. Force					X			
Stance End Value					X			
Amplitude					X			
Cycle time								X
Stance Ph. %								X
Feature Number	30	30	30	30	27	9	9	11

a classification or regression problem. One of the most interesting approach in this field is the Random Forest (RF) [46], [47] approach, which consists on the generation of a wide set (*forest*) of different decision trees for classification purposes. The trees are generated using a set of random samples and features, so that in the training procedure, different features can be tested. This technique has been used in different application fields such as diagnosis [48], mineral process industries [49] or DNA analysis [50], to estimate the relative importance of each feature. This way the most relevant ones can be identified, and the ones that are redundant or unimportant eliminated.

Hence, in this work, a Random-Forest approach is proposed to analyze the relative feature significance to the PA classification. For that purpose, only the samples contained into the *Training Set* defined in Section III have been used. The proposed RF has been implemented using Matlab's Statistics and Machine Learning Toolbox [51] and experimentally tuned considering the following set of hyperparameters: the number of trees in the forest has been tuned to 5000; a sample with replacement strategy has been selected; a node size of 1 was defined; the number of variables randomly chosen at each split (*mtry*) has been tuned to $\sqrt{M}$, where M is the total number variables; and the predictor used has been the *interaction-curvature* to avoid the disturbances caused by correlated features.

The obtained results from this procedure are summarized in Table 3, in which all the potential features have been sorted in decreasing order of decreasing relative significance according to the RF approach. Note that the RF approach orders the features by considering their relative *weight* or contribution to the desired classification process, being the *Area Under the Curve of the Yaw angle* and the *Cycle Time* some of the most relevant features for the proposed study-case.

It is to be noted that if all weights for the 176 features are analyzed, all present a positive weight with the exception of the last two, related to the Barometer Interquartile Range. This means that following the RF analysis, the features with positive weight contribute (or add information) to the PA classification. However, the relative importance of the most significant one *Area Under the Curve Yaw* is more than 50 times higher with respect to the less significant ones. Hence, designing an PA classifier using only some of the most relevant ones should provide better results than the use of the less relevant ones. In the next section, a comparative analysis will be carried out to analyze the effect of the proposed feature selection.

C. CLASSIFIER HYPERPARAMETER SELECTION AND TRAINING

Once the potential set of features has been ordered according to its relevance, a subset of n features can be selected to design a PA classifier. The goal of the classifiers is to be able to detect five relevant PA: Walking normal, Walking fast, Going up and down stairs and standing still. Hence, all classifiers will be implemented with 5 outputs/classes, one associated to each PA type.

In this work, the three most commonly used approaches in related works have been selected, so that a comparative analysis can be carried out in the next section: Support Vector Machine (SVM), K-Nearest Neighbor (K-NN) and Artificial Neural Network (ANN).

As detailed in Figure 4, for a given set of n relevance-ordered input features, first the optimal subset of

TABLE 3. Feature significance and their relative weight according to Random-Forest procedure. (Magne=Magnetometer, Accel=Accelerometer, AUtC=Area Under the Curve, 25P=25th Percentile, 50P=50th Percentile, 75P=75th Percentile, IR=Intercuartile Range, SD=Standard Deviation, Corr. Coef.=Correlation Coefficient, Antero=Anteromedial Angle, Latero=Lateromedial Angle, WoF=Without Filter, WF = With Filter, n=Position).

n	Feature	Weight	n	Feature	Weight	n	Feature	Weight
1	AUtC Yaw	2.276	60	Magne 50P Y	0.538	119	Latero Mean	0.310
2	Cycle Time	2.242	61	Gyro Kur X	0.538	120	AUtC R	0.307
3	Accel SD X	2.216	62	Latero Value at Max. Force	0.537	121	Corr. Coef. AnteroLatero	0.306
4	Accel Variance X	2.002	63	Magne AUtC Y	0.535	122	Latero 25P	0.304
5	Magne 75P X	1.992	64	25P Pitch	0.534	123	50P Roll	0.301
6	Gyro 25P Y	1.978	65	Magne SD X	0.530	124	Magne Kur X	0.296
7	Antero IR	1.766	66	Antero Kur	0.530	125	Baro Variance WOutF	0.295
8	Magne Mean X	1.698	67	Corr. Coef. RollYaw	0.529	126	Accel 75P Y	0.288
9	Accel Mean Z	1.671	68	Accel SD Y	0.516	127	Gyro Mean X	0.287
10	IR Pitch	1.635	69	Gyro Variance Z	0.515	128	Accel 50P Y	0.287
11	Magne AUtC X	1.582	70	Magne AUtC Z	0.513	129	Pres 25P	0.283
12	Accel IR Z	1.527	71	Magne Variance X	0.508	130	Gyro 50P X	0.276
13	Accel 25P Y	1.507	72	Baro 25P WF	0.504	131	Antero 50P	0.271
14	Magne 50P X	1.503	73	Magne 25P Z	0.504	132	Pres Variance	0.268
15	Magne 25P X	1.402	74	Baro AUtC WOutF	0.502	133	75P Roll	0.267
16	Antero SD	1.213	75	Gyro SD Z	0.501	134	Pres 50P	0.261
17	Antero Variance	1.178	76	Kur Pitch	0.491	135	Antero AUtC	0.258
18	Accel 25P Z	1.159	77	Baro 75P WOutF	0.484	136	25P Roll	0.258
19	Gyro IR Y	1.131	78	Baro Mean WOutF	0.481	137	Accel AUtC Y	0.256
20	SD Pitch	1.126	79	Latero 50P	0.467	138	Magne Kur Z	0.230
21	Accel SD Z	1.103	80	Magne Corr. Coef. XY	0.461	139	Accel Corr. Coef. XY	0.210
22	Variance Pitch	1.087	81	SD Yaw	0.457	140	Gyro AUtC X	0.205
23	Accel Variance Z	1.078	82	Antero 75P	0.457	141	Gyro 75P Z	0.201
24	Gyro 75P X	1.063	83	Accel Corr. Coef. YZ	0.455	142	Magne Corr. Coef. YZ	0.200
25	Accel IR Y	1.060	84	Accel Variance Y	0.447	143	Pres AUtC	0.199
26	Accel AUtC Z	1.022	85	Baro 75P WF	0.444	144	Pres SD	0.195
27	Accel 50P X	1.021	86	Baro Mean WF	0.439	145	Mean Roll	0.193
28	Accel Mean X	1.003	87	Kur Yaw	0.437	146	50P Yaw	0.188
29	Gyro 50P Y	0.966	88	Magne Mean Z	0.433	147	Mean Yaw	0.186
30	Accel 75P X	0.942	89	Accel Mean Y	0.433	148	Magne Variance Y	0.179
31	Antero Ini Contact	0.939	90	Accel Kur Y	0.430	149	Baro IR WOutF	0.172
32	Accel IR X	0.916	91	Magne SD Z	0.429	150	Variance Roll	0.172
33	Gyro SD Y	0.910	92	Latero 75P	0.428	151	Latero IR	0.157
34	Stance Ph. %	0.900	93	Baro 25P WOutF	0.422	152	Latero Amplitude	0.152
35	Gyro IR X	0.886	94	Baro 50P WOutF	0.418	153	Pres IR	0.147
36	Gyro Variance Y	0.881	95	Antero Stance End Value	0.416	154	Latero SD	0.146
37	Accel Kur X	0.880	96	Antero Mean	0.414	155	Latero Variance	0.145
38	Accel 75P Z	0.849	97	Baro AUtC WF	0.412	156	Gyro Mean Y	0.136
39	Accel Kur Z	0.796	98	Accel 50P Z	0.404	157	Pres 75P	0.131
40	Gyro Corr. Coef. XZ	0.779	99	Gyro 75P Y	0.403	158	Magne SD Y	0.129
41	Corr. Coef. RollPitch	0.753	100	Magne Variance Z	0.395	159	Gyro 50P Z	0.129
42	Antero Amplitude	0.742	101	IR Yaw	0.388	160	Pres Kur	0.124
43	Antero Value at Max. Force	0.732	102	Baro 50P WF	0.381	161	Magne Kur Y	0.124
44	Gyro Variance X	0.719	103	Mean Pitch	0.381	162	Magne IR Y	0.123
45	Accel 25P X	0.695	104	50P Pitch	0.375	163	Magne IR Z	0.111
46	Gyro Corr. Coef. YZ	0.682	105	75P Yaw	0.370	164	Gyro AUtC Y	0.106
47	Gyro 25P X	0.670	106	Pres Mean	0.366	165	IR Roll	0.092
48	Gyro SD X	0.652	107	Variance Yaw	0.360	166	SD Roll	0.089
49	Gyro IR Z	0.640	108	Latero Stance End Value	0.360	167	Latero Kur	0.082
50	Gyro Kur Y	0.638	109	Magne 75P Z	0.359	168	Gyro Kur Z	0.079
51	Latero Ini Contact	0.617	110	Gyro Corr. Coef. XY	0.355	169	Gyro Mean Z	0.071
52	Accel AUtC X	0.604	111	25P Yaw	0.341	170	Baro Kur WOutF	0.071
53	Magne Corr. Coef. XZ	0.593	112	75P Pitch	0.341	171	Kur Roll	0.067
54	Magne Mean Y	0.569	113	Latero AUtC	0.340	172	Baro SD WF	0.067
55	Antero 25P	0.557	114	Accel Corr. Coef. XZ	0.339	173	Baro IR WF	0.048
56	Corr. Coef. PitchYaw	0.557	115	Magne 50P Z	0.337	174	Baro Variance WF	0.005
57	Magne 25P Y	0.551	116	Gyro 25P Z	0.319	175	Gyro AUtC Z	-0.022
58	Magne IR X	0.548	117	Baro SD WOutF	0.316	176	Baro Kur WF	-0.063
59	Magne 75P Y	0.544	118	AUtC Pitch	0.313			

hyperparameters for each ML-based classifier is to be calculated. For that purpose a K-fold cross-validation approach is proposed with $K = 5$ [52]. This approach allows to effectively evaluate different ML-based models. Note that for this purpose only the data from the *Training Set* defined in Section III. is used. Once the best hyperparameters have been chosen, these are used to train the ML-approach using supervised methods and the *Training Set* data.

It is to be noted that in the case of the SVM and K-NN, Matlab's Statistic and Machine Learning Toolbox integrates the aforementioned steps, optimizing the related hyperparameters (Kernel functions, number of neighbours,...) [51]. For the case of the ANN, the authors have ad hoc programmed the hyperparameter selection. In this latter case, a single hidden layer Multi Layer Perceptron (MLP) ANN has been selected, with 5 output neurons (one for each PA), a number of inputs equal to the n feature set to be processed and m hidden layer neurons with hyperbolic tangent sigmoid activation function. The number of hidden layer neurons m has been considered as the hyperparameter to be tuned using the aforementioned procedure, with m ranging from 1 to 10 neurons, since experimental tests have determined that ANN with 10 or lower neurons provide good results. Once the best (higher success rate) value for m has been selected, a Bayesian regularization-based training algorithm is used to train the ANN.

V. COMPARATIVE ANALYSIS

In this section, a comparative analysis is carried out considering the features selected in Section IV-B. The aim is to: 1) analyze the best approach for the proposed PA classificator application; and 2) analyze the validity of the feature selection approach in different ML-based classification approaches.

Note that all the ML-based classifiers analyzed in this section have been trained following the methodology proposed in the previous section.

A. ANALYSIS OF THE EFFECT OF THE NUMBER OF FEATURES CONSIDERED FOR CLASSIFICATION

In order to analyze the effect of the number of features considered, a comparative analysis is carried out considering the features defined in Table 3. This way, each ML-based classification approach proposed previously is trained with 176 different feature sets following the procedure detailed in Section IV-C. These feature sets are defined incrementally considering the n most relevant features. This is: in the first set, only the most relevant feature is considered; in the second one, the two most relevant features are considered; while in the last one, all 176 potential features are considered.

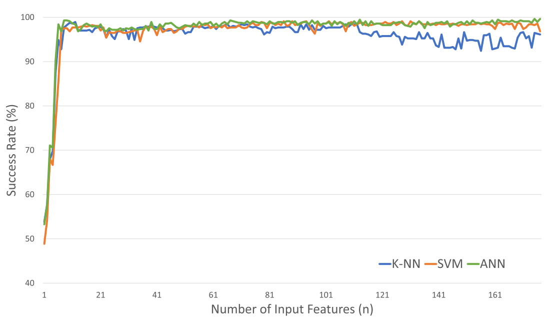


FIGURE 5. Success rate of the classifiers based on K-NN, SVM and ANN, with respect to the number of the *n* most relevant features ordered according to the RF.

Figure 5 shows the total classification success rate percentage for the proposed approaches with respect to the number n of the most relevant features according to the RF approach. This success rate is defined as the percentage of PA samples of the *Test Set* whose type the classifier identifies correctly with respect to the total number of PA samples in the set. Note that the samples in this latter set have not been considered in the training procedure, so that the results can be used to analyze also the generalization capability of the approaches.

As it can be seen, if the seven most significant features are considered, a success rate percentage of over 90% can be achieved in all cases (92.8% for the K-NN, 97% for the SVM and 96.8% for the ANN). This value increases up to 97% if the nine most relevant features are selected for all approaches.

The general tendency is that a higher number of features considered allows better classification. A maximum success rate of 98.4% (66 features) for the K-NN, 99.1% (87 features) for the SVM and 99.6% (174 features) for the ANN is obtained. Note that the small oscillations are due to the randomized nature of the ML approaches training, with a success rate variation in the range from 7 to 176 most relevant features of 2.8% in the case of the ANN and 4.6% for the SVM.

There is an exception in the case of the K-NN approach, as the percentage of success decreases slightly when the number of features is higher than 119, reaching a value lower than 96% (92.8% with 147 and 160 most relevant features).

The results confirm that if a proper feature selection is carried out, a small set of features can be used to design the ML-based PA classificator, as the effect of increasing the number of features is small in the total success rate of the classifier. Moreover, this has an impact on computational cost. As previously stated, a K-Fold cross-validation procedure has been used to calculate the best configuration of hyperparameters for each feature set. For instance, in the particular case of the ANN the obtained optimal number of hidden layer neurons is summarized in Figure 6 for each feature set. It can be seen that although a lower number of neurons (5-6) is required for small values of n, the number of neurons stabilizes with a mean of 9 neurons. Hence, selecting a moderate number of features (for example the 7 most relevant ones) also leads to smaller ANN and lower computational cost.

Finally, in order to illustrate the classification capabilities of the ML-based PA classifiers, a particular example of the classifiers performance is shown in Table 4, where the Confusion Matrices for all classifiers when all features are considered are shown. In this particular case, the overall performance of the K-NN is 96.1%, SVM performance is 96.8% and in ANN 99.6%. However, it can be seen that the K-NN has a problem classifying *Walking Normal* case, as up to 20 samples are identified erroneously as *Walking Fast* and *Going Up Stairs*. The same effect is seen in the SVM's Confusion Matrix. The ANN outperforms the previous approaches, obtaining better results.

B. ANALYSIS OF THE EFFECT OF FEATURE SELECTION

In order to emphasize the importance of the feature selection procedure, the procedure defined in the previous section has

TABLE 4. Confusion matrix of K-NN, SVM and ANN with all features.

			Predicted				
			Walk Normal	Walk Fast	Going Up Stairs	Going Down Stairs	Standing Still
K-NN	Real	Walk Normal	103	11	9	0	0
		Walk Fast	2	116	0	0	0
		Going Up Stairs	0	0	109	0	0
		Going Down Stairs	0	0	0	106	0
		Standing Still	0	0	0	0	111
SVM	Real	Walk Normal	111	10	0	2	0
		Walk Fast	1	117	0	0	0
		Going Up Stairs	0	2	106	1	0
		Going Down Stairs	2	0	0	104	0
		Standing Still	0	0	0	0	111
ANN	Real	Walk Normal	122	0	0	1	0
		Walk Fast	1	117	0	0	0
		Going Up Stairs	0	0	109	0	0
		Going Down Stairs	0	0	0	106	0
		Standing Still	0	0	0	0	111

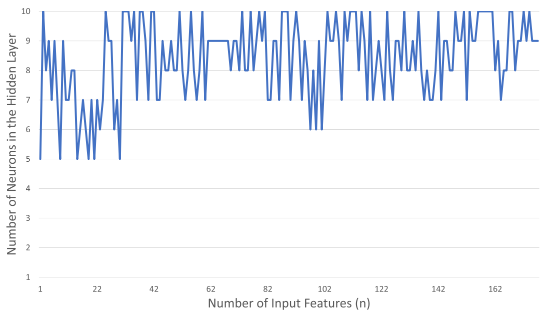


FIGURE 6. Optimal number of neurons in the hidden layer of the ANN with respect to the number of the *n* most relevant features ordered according to the RF.

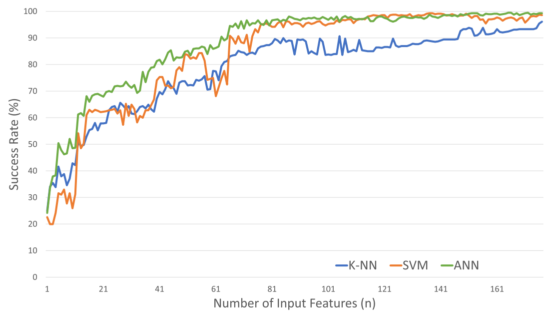


FIGURE 7. Success rate of the K-NN, SVM and ANN based classifiers, with respect to the number of the *n* less relevant features ordered according to the RF approach.

been repeated from the less significant feature to the most significant one. This is, 176 sets of features have been analyzed: the first set has considered only the less significant feature; the second, the two less significant features; and so on. As previously detailed, for each set of features, the optimum hyperparameters have been tuned, by the use of a K-fold procedure. For the particular case of the ANN, an average of 7.99 neurons with a standard deviation of 1.75 neurons have been obtained.

Results are summarized in Figure 7 for all proposed approaches. As it can be seen, the success rates evolution presents an increasing tendency. This is, as more significant features are added, the classifier quality increases. Hence, the success rate increases when adding more and more features, from approximately 22% to 99%.

Note that this is a very different evolution compared with the one analyzed in the previous section (Fig. 5). In the previous case, with few of the most significant, success rates up to 95% could be achieved, while in this latter case, a greater number of features are required to achieve the same performance: 86 for SVM, 68 for ANN, and almost all features for K-NN. This emphasizes the need of correctly selecting the features for designing PA classifiers.

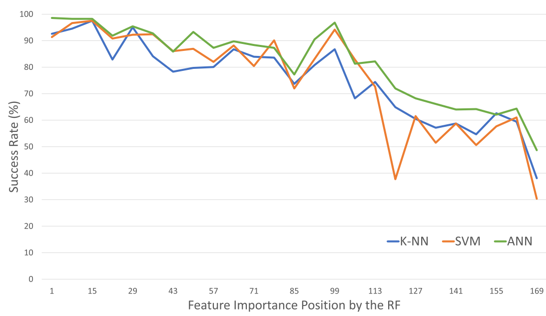


FIGURE 8. Success rate of the K-NN, SVM and ANN based classifiers, with 7 indicators as input selected according to the relative significance provided by the RF approach.

The relevance of correctly selecting the features is also demonstrated in Figure 8. As analyzed in the previous subsection, the seven most significant features provide acceptable success rates for the classifier (over 92%). Hence, all proposed approaches have been evaluated by considering sets of 7 features. This is, the first 7 features have been evaluated first, then the next 7 and so on, ordered from the most significant ones to the less ones. As previously detailed, for each set of features, the optimum hyperparameters for the three ML have been obtained in a first step (for the particular case of the ANN, an average of 9.28 neurons with a standard deviation of 1.24 neurons have been obtained). After training, the resulting classifiers show that a variation of more than 50% on the performance of the classifier can exist depending on the set of features considered.

In summary, the aforementioned results demonstrate that: 1) a proper feature selection is mandatory when designing PA classification; 2) The proposed RF-based feature selection is an appropriate approach to optimize the number of features; 3) the ANN and SVM-based approach is the most stable classifier, although the K-NN approach can provide good results for the same number of features, however the best results are obtained from the ANN-based classifier; and 4) The inclusion of more and more features does not always imply an increase of the success rate, as proper hyperparameter selection is needed to handle all the input information.

VI. CONCLUSION

An individualization of rehabilitation therapies of people suffering from lower-limb impairment is essential during the whole rehabilitation process, specially those that require Assistive Devices for Walking (ADW). Recently, monitoring the types of Physical Activity (PA) carried out by the patients in their daily life has become an important source of information for this purpose.

In order to develop PA identification and monitoring, proper sensorized devices and processing algorithms are required. Typically wearable sensors have been proposed for this purpose, although they present limitations for people that require ADW. Moreover, in order to process PA data related to gait, a set of gait-based features is traditionally proposed, and brute-force approaches are followed to design the monitoring algorithms.

Different from other works, in this paper a novel approach for the development of PA classifiers is proposed. The approach makes use of a Sensorized Tip that can be fitted into the personal ADW of the patient. The 17 sources of data available are processed to define a set of 176 features that can be used to classify five relevant PAs (Standing Still, Walking Fast, Walking at a Normal pace, Going Up and Going Down Stairs).

In order to optimize the PA classificator, a Machine Learning approach, the Random Forest approach, is used to perform a feature selection. This allows to classify the features depending on their relative significance for the PA classification.

The approach is validated by implementing three different Machine Learning-based classifiers for PA: SVM, K-NN and ANN. Results demonstrate: 1) the validity of the proposed approach for gait monitoring; 2) the importance of feature selection when designing PA classifiers; 3) the validity of the feature selection approach, as with the identified seven most relevant features a success rate of 92-97% can be obtained, which is higher than the results offered by other related works (91%).

However, it should be noted that the development presented has been carried out with healthy people and in a laboratory-based testing. For this reason, future work will focus on studying classifier's performance in specific populations of people that require ADW, in order to analyze possible drawbacks of the proposed methodology in these cases. Moreover, more types of PA, such as going up and down slopes, different speeds, etc will be analyzed.

REFERENCES

[1] P. Flachenecker, "Clinical implications of neuroplasticity—The role of rehabilitation in multiple sclerosis," *Frontiers Neurol.*, vol. 6, p. 36, Mar. 2015.

[2] A. E. Latimer-Cheung, L. A. Pilutti, A. L. Hicks, K. A. M. Ginis, A. M. Fenuta, K. A. MacKibbon, and R. W. Motl, "Effects of exercise training on fitness, mobility, fatigue, and health-related quality of life among adults with multiple sclerosis: A systematic review to inform guideline development," *Arch. Phys. Med. Rehabil.*, vol. 94, no. 9, pp. 1800–1828, Sep. 2013.

[3] F. Tokucoglu, "Monitoring physical activity with wearable technologies," *Arch. Neuropsychiatry*, vol. 55, p. S63, Oct. 2018.

[4] M. Brandes, R. Schomaker, G. Möllenhoff, and D. Rosenbaum, "Quantity versus quality of gait and quality of life in patients with osteoarthritis," *Gait Posture*, vol. 28, no. 1, pp. 74–79, Jul. 2008.

[5] A. Rajavenkatanarayanan, V. Kanal, K. Tsiakas, D. Calderon, M. Papakostas, M. Abujelala, M. Galib, J. Ford, G. Wylie, and F. Makedon, "A survey of assistive technologies for assessment and rehabilitation of motor impairments in multiple sclerosis," *Multimodal Technol. Interact.*, vol. 3, no. 1, p. 6, Feb. 2019.

[6] M. Weikert, Y. Suh, A. Lane, B. Sandroff, D. Dlugonski, B. Fernhall, and R. W. Motl, "Accelerometry is associated with walking mobility, not physical activity, in persons with multiple sclerosis," *Med. Eng. Phys.*, vol. 34, no. 5, pp. 590–597, Jun. 2012.

[7] J. Gong, M. D. Goldman, and J. Lach, "Deepmotion: A deep convolutional neural network on inertial body sensors for gait assessment in multiple sclerosis," in *Proc. IEEE Wireless Health (WH)*. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Oct. 2016, pp. 164–171.

[8] M. Awais, L. Chiari, E. A. F. Ihlen, J. L. Helbostad, and L. Palmerini, "Physical activity classification for elderly people in free-living conditions," *IEEE J. Biomed. Health Informat.*, vol. 23, no. 1, pp. 197–207, Jan. 2019.

[9] H. L. Bartlett and M. Goldfarb, "A phase variable approach for IMU-based locomotion activity recognition," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 6, pp. 1330–1338, Jun. 2018.

[10] B. Sheng, O. M. Moosman, B. Del Pozo-Cruz, J. Del Pozo-Cruz, R. M. Alfonso-Rosa, and Y. Zhang, "A comparison of different machine learning algorithms, types and placements of activity monitors for physical activity classification," *Measurement*, vol. 154, Mar. 2020, Art. no. 107480.

[11] N. Nazmi, M. A. Abdul Rahman, S.-I. Yamamoto, and S. A. Ahmad, "Walking gait event detection based on electromyography signals using artificial neural network," *Biomed. Signal Process. Control*, vol. 47, pp. 334–343, Jan. 2019.

[12] J. Triloka, S. M. N. A. Senanayake, and D. Lai, "Neural computing for walking gait pattern identification based on multi-sensor data fusion of lower limb muscles," *Neural Comput. Appl.*, vol. 28, no. S1, pp. 65–77, Dec. 2017.

[13] R. I. Spain, R. J. St. George, A. Salarian, M. Mancini, J. M. Wagner, F. B. Horak, and D. Bourdette, "Body-worn motion sensors detect balance and gait deficits in people with multiple sclerosis who have normal walking speed," *Gait Posture*, vol. 35, no. 4, pp. 573–578, Apr. 2012.

[14] R. Sun, Y. Moon, R. S. McGinnis, K. Seagers, R. W. Motl, N. Sheth, J. A. Wright, R. Ghaffari, S. Patel, and J. J. Sosnoff, "Assessment of postural sway in individuals with multiple sclerosis using a novel wearable inertial sensor," *Digit. Biomarkers*, vol. 2, no. 1, pp. 1–10, Jan. 2018.

[15] I. C. Gyllensten and A. G. Bonomi, "Identifying types of physical activity with a single accelerometer: Evaluating laboratory-trained algorithms in daily life," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 9, pp. 2656–2663, Sep. 2011.

[16] A. Muro-de-la-Herran, B. Garcia-Zapirain, and A. Mendez-Zorrilla, "Gait analysis methods: An overview of wearable and non-wearable systems, highlighting clinical applications," *Sensors*, vol. 14, no. 2, pp. 3362–3394, Feb. 2014.

[17] B. Aguiar, J. Silva, T. Rocha, S. Carneiro, and I. Sousa, "Monitoring physical activity and energy expenditure with smartphones," in *Proc. IEEE-EMBS Int. Conf. Biomed. Health Informat. (BHI)*, Jun. 2014, pp. 664–667.

[18] M. Lv, W. Xu, and T. Chen, "A hybrid deep convolutional and recurrent neural network for complex activity recognition using multimodal sensors," *Neurocomputing*, vol. 362, pp. 33–40, Oct. 2019.

[19] P. Li, Y. Wang, Y. Tian, T.-S. Zhou, and J.-S. Li, "An automatic user-adapted physical activity classification method using smartphones," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 3, pp. 706–714, Mar. 2017.

[20] A. Jain and V. Kanhangad, "Human activity classification in smartphones using accelerometer and gyroscope sensors," *IEEE Sensors J.*, vol. 18, no. 3, pp. 1169–1177, Feb. 2018.

[21] L. Bao and S. Stephen Intille, "Activity recognition from user-annotated acceleration data," in *Pervasive Computing* (Lecture Notes in Computer Science: Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 3001. 2004, pp. 1–17.

[22] W. Zijlstra, "Assessment of spatio-temporal parameters during unconstrained walking," *Eur. J. Appl. Physiol.*, vol. 92, nos. 1–2, pp. 39–44, Jun. 2004.

[23] K. Aminian, P. Robert, E. Jequier, and Y. Schutz, "Estimation of speed and incline of walking using neural network," in *Proc. Conf. 10th Anniversary IMTC Adv. Technol. IEEE Instrum. Meas. Technolgy Conf.* Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, 1994, pp. 160–162.

[24] J. Stephen Preece, Y. John Goulermas, P. J. Laurence Kenney, D. Howard, K. Meijer, and R. Crompton, "Activity identification using body-mounted sensors—A review of classification techniques," vol. 30, no. 4, p. R1, 2009.

[25] A. Godfrey, R. Conway, D. Meagher, and G. ÓLaighin, "Direct measurement of human movement by accelerometry," *Med. Eng. Phys.*, vol. 30, no. 10, pp. 1364–1386, Dec. 2008.

[26] W. Zeng and C. Wang, "Classification of neurodegenerative diseases using gait dynamics via deterministic learning," *Inf. Sci.*, vol. 317, pp. 246–258, Oct. 2015.

[27] G. Sprint, J. Diane Cook, and L. Douglas Weeks, "Quantitative assessment of lower limb and cane movement with wearable inertial sensors," in *Proc. 3rd IEEE EMBS Int. Conf. Biomed. Health Informat. (BHI)*. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Apr. 2016, pp. 418–421.

[28] A. Moncada-Torres, K. Leuenberger, R. Gonzenbach, A. Luft, and R. Gassert, "Activity classification based on inertial and barometric pressure sensors at different anatomical locations," *Physiol. Meas.*, vol. 35, no. 7, pp. 1245–1263, Jul. 2014.

[29] A. Fleury, M. Vacher, and N. Noury, "SVM-based multimodal classification of activities of daily living in health smart homes: Sensors, algorithms, and first experimental results," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 274–283, Mar. 2010.

[30] D. Rodríguez-Martín, A. Samà, C. Pérez-López, J. Cabestany, A. Català, and A. Rodríguez-Molinero, "Posture transition identification on PD patients through a SVM-based technique and a single waist-worn accelerometer," *Neurocomputing*, vol. 164, pp. 144–153, Sep. 2015.

[31] W.-Y. Lin, C.-H. Chen, Y.-J. Tseng, Y.-T. Tsai, C.-Y. Chang, H.-Y. Wang, and C.-K. Chen, "Predicting post-stroke activities of daily living through a machine learning-based approach on initiating rehabilitation," *Int. J. Med. Informat.*, vol. 111, pp. 159–164, Mar. 2018.

[32] L. Lei, Y. Peng, L. Zuojun, G. Yanli, and Z. Jun, "Leg amputees motion pattern recognition based on principal component analysis and BP network," in *Proc. 25th Chin. Control Decis. Conf. (CCDC)*, May 2013, pp. 3802–3804.

[33] I. M. Pires, N. M. Garcia, N. Pombo, F. Flórez-Revuelta, S. Spinsante, and M. C. Teixeira, "Identification of activities of daily living through data fusion on motion and magnetic sensors embedded on mobile devices," *Pervas. Mobile Comput.*, vol. 47, pp. 78–93, Jul. 2018.

[34] P. Compagnon, G. Lefebvre, S. Duffner, and C. Garcia, "Learning personalized ADL recognition models from few raw data," *Artif. Intell. Med.*, vol. 107, Jul. 2020, Art. no. 101916.

[35] A. M. Khan, Y. K. Lee, and T. S. Kim, "Accelerometer signal-based human activity recognition using augmented autoregressive model coefficients and artificial neural nets," in *Proc. Conf. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., IEEE Eng. Med. Biol. Soc. Annu. Conf.*, Aug. 2008, pp. 5–5172.

[36] F. Rasouli and K. B. Reed, "Walking assistance using crutches: A state of the art review," *J. Biomech.*, vol. 98, Jan. 2020, Art. no. 109489.

[37] G. Chamorro-Moriana, J. Sevillano, and C. Ridao-Fernández, "A compact forearm crutch based on force sensors for aided gait: Reliability and validity," *Sensors*, vol. 16, no. 6, p. 925, Jun. 2016.

[38] E. Sardini, M. Serpelloni, and M. Lancini, "Wireless instrumented crutches for force and movement measurements for gait monitoring," *IEEE Trans. Instrum. Meas.*, vol. 64, no. 12, pp. 3369–3379, Dec. 2015.

[39] J. W. Wade, R. Boyles, P. Flemming, A. Sarkar, M. de Riesthal, T. J. Withrow, and N. Sarkar, "Feasibility of automated mobility assessment of older adults via an instrumented cane," *IEEE J. Biomed. Health Informat.*, vol. 23, no. 4, pp. 1631–1638, Jul. 2019.

[40] Y. F. Chen, D. Napoli, S. K. Agrawal, and D. Zanotto, "Smart crutches: Towards instrumented crutches for rehabilitation and exoskeletons-assisted walking," in *Proc. 7th IEEE Int. Conf. Biomed. Robot. Biomechatronics (Biorob)*, Aug. 2018, pp. 193–198.

[41] A. Brull, A. Zubizarreta, I. Cabanes, and A. Rodriguez-Larrad, "Sensorized tip for monitoring people with multiple sclerosis that require assistive devices for walking," *Sensors*, vol. 20, no. 15, p. 4329, Aug. 2020.

[42] C. Pradhan, M. Wuehr, F. Akrami, M. Neuhaeusser, S. Huth, T. Brandt, K. Jahn, and R. Schniepp, "Automated classification of neurological disorders of gait using spatio-temporal gait parameters," *J. Electromyogr. Kinesiol.*, vol. 25, no. 2, pp. 413–422, Apr. 2015.

[43] M. Kubat, *An Introduction to Machine Learning*. Cham, Switzerland: Springer, Sep. 2017.

[44] H. Salehinejad, S. Valaee, T. Dowdell, E. Colak, and J. Barfett, "Generalization of deep neural networks for chest pathology classification in X-Rays using generative adversarial networks," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Apr. 2018, pp. 990–994.

[45] G. Douzas and F. Bacao, "Effective data generation for imbalanced learning using conditional generative adversarial networks," *Expert Syst. Appl.*, vol. 91, pp. 464–471, Jan. 2018.

[46] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, Oct. 2001.

[47] G. Gazzola and M. K. Jeong, "Dependence-biased clustering for variable selection with random forests," *Pattern Recognit.*, vol. 96, Dec. 2019, Art. no. 106980.

[48] C. Aldrich and L. Auret, "Fault detection and diagnosis with random forest feature extraction and variable importance methods," in *Proc. IFAC (IFAC–PapersOnline)*, vol. 43, Jan. 2010, pp. 79–86.

[49] H. Chen, X. Liu, Z. Jia, Z. Liu, K. Shi, and K. Cai, "A combination strategy of random forest and back propagation network for variable selection in spectral calibration," *Chemometric Intell. Lab. Syst.*, vol. 182, pp. 101–108, Nov. 2018.

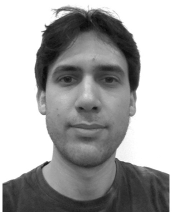
[50] L. Toloşi and T. Lengauer, "Classification with correlated features: Unreliability of feature ranking and solutions," *Bioinformatics*, vol. 27, no. 14, pp. 1986–1994, Jul. 2011.

[51] P. Kim, *MATLAB Deep Learning*. New York, NY, USA: Apress, 2017.

[52] E. Alpaydin, *Introduction to Machine Learning*, 2nd ed. Cambridge, MA, USA: MIT Press, 2010.

ASIER BRULL MESANZA received the master's degree in automation, control and robotics from the University of the Basque Country (UPV/EHU), in 2017. He is currently pursuing the Ph.D. degree. Since July 2015, he has been a Control Engineer with the UPV/EHU.His research interests include intelligent diagnostic systems, artificial neural networks, and the detection of gait patterns.

SERGIO LUCAS is currently pursuing the master's degree in industrial engineering specialized in automation and control. Since September 2018, he has been an Industrial Engineer with the University of the Basque Country (UPV/EHU).

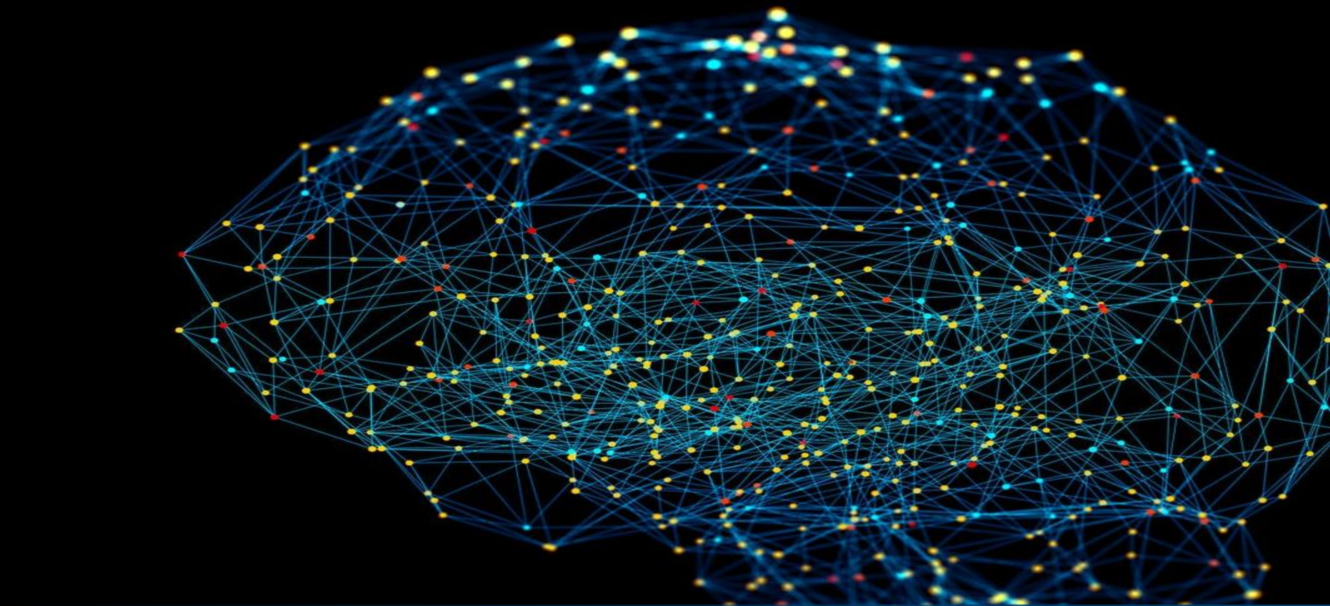


ASIER ZUBIZARRETA is graduated in automation and electronics engineering from the University of the Basque Country (UPV/EHU), in 2006, where he received the Ph.D. degree in robotics and automatic control systems, in 2010. He is currently an Assistant Professor with the Department of Automatic Control and System Engineering, Faculty of Engineering of Bilbao, UPV/EHU. His research interests include mechatronics, model-based advanced control, and bioengineering.

ITZIAR CABANES received the Ph.D. degree in engineering from the University of the Basque Country (UPV/EHU), Spain, in 2001, where she is currently an Assistant Professor with the Department of Automatic Control and Systems Engineering, Faculty of Engineering of Bilbao. She is also the Head of the Master Control Engineering, Automation, and Robotics, UPV/EHU. Her research interests include industrial robotics, bioengineering, and the optimization of manufacturing processes. She was a recipient of the Outstanding Doctoral Thesis Award from UPV/EHU, in 2002. Also, she has seven awards at conferences.

EVA PORTILLO received the Ph.D. degree in engineering from the University of the Basque Country, in 2007, where she is currently an Associate Professor with the Department of Automatic and Control Systems. In 2016, she was a Visiting Professor with the Knowledge Engineering and Discovery Research Institute (KEDRI) (Auckland University of Technology, Auckland, New Zealand). From 2017 to 2019, she was the Deputy Head of the Master and Doctoral School, University of the Basque Country. She is also an Academic Secretary with the Doctoral School, University of the Basque Country. She was a recipient of the Outstanding Doctoral Thesis Award from the University of the Basque Country, in 2010. Also, she has several awards at national conferences.

ANA RODRIGUEZ-LARRAD received the Ph.D. degree in public health from the University of the Basque Country (UPV/EHU), in 2015. She is currently a Physiotherapist with more than 15 years of clinical experience in neurology. She is also an Associate Professor with the Department of Physiology, Faculty of Medicine and Nursing, UPV/EHU. Her research interests include design and validation of tools and interventions directed to neurorehabilitation diseases and ageing related dysfunction.



Appendix 3
3. eranskina

Asier Brull Mesanza, Ilaria D'Ascanio, Asier Zubizarreta, Luca Palmerini, Lorenzo Chiari, and Itziar Cabanes. Machine Learning based Fall Detector with a Sensorized Tip. *IEEE Access*, pages 1–1, dec 2021. *doi: https://doi.org/10.1109/ACCESS.2021.3132656*
JCR2020: 3.367 (Q2)

IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received November 15, 2021, accepted December 1, 2021, date of publication December 3, 2021, date of current version December 20, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3132656

Machine Learning Based Fall Detector With a Sensorized Tip

ASIER BRULL MESANZA [1], ILARIA D'ASCANIO [2], ASIER ZUBIZARRETA [1], LUCA PALMERINI [2], LORENZO CHIARI [2], AND ITZIAR CABANES [1]

[1] Department of Automatic Control and Systems Engineering, Faculty of Engineering of Bilbao, University of the Basque Country (UPV/EHU), 48013 Bilbao, Spain

[2] Department of Electrical, Electronic, and Information Engineering "Guglielmo Marconi," University of Bologna, 40126 Bologna, Italy

Corresponding author: Asier Brull Mesanza (asier.brull@ehu.eus)

This work was supported in part by the University of the Basque Country (UPV/EHU) under Grant PIF18/067, Project GIU19/045, Project DPI 2007-82694-R, and Project PID2020-112667RB-I00 funded by MCIN/AEI/10.13039/501100011033.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Alma Mater Studiorum Università di Bologna Ethics Committee under Approval No. 149960.

ABSTRACT Fall detection has become an area of interest in recent years, as quick response to these events is critical to reduce the morbidity and mortality rate. In order to ensure proper fall detection, several technologies have been developed, including vision system, environmental detection systems, and wearable sensor based systems. However, in elderly or impaired people, it has been shown that the implementation of sensors in Assistive Devices for Walking, such as crutches or canes, can also be a promising alternative. In this work, a Support Vector Machine (SVM) based Fall Detection system is proposed, which uses the data provided by a Sensorized Tip which can be attached to different Assistive Devices for Walking (ADW). Unlike other approaches, the developed one is able to differentiate the fall of the ADW from the fall of the user. For that purpose, the developed Fall Detector uses two modules connected in series. The first one detects all falls, while the second differentiates between user and ADW falls. The proposed approach is validated in a set of experimental tests carried out by healthy volunteers that have simulated different falls. In addition, a comparative analysis is carried out by comparing the performance of the Sensorized Tip based Fall Detector and a state-of-the-art commercial accelerometer system. Results demonstrate that the proposed approach provides high Fall Detection Ratios (over 90%), similar or higher to wearable-sensor based approaches.

INDEX TERMS Machine learning, support vector machine, random forest, fall detection, wearable sensors, instrumented crutch, monitoring.

I. INTRODUCTION

Recent studies, including relevant ones from the World Health Organization (WHO) [1], [2], state that more than 28% of the population over 64 years suffers at least one fall per year. In elderly or physically impaired people falls can have a great impact on their health and daily life [3], [4]. In fact, falls cause physical injuries in 6% of the cases [5], [6], from which 14% can be serious injuries [7]. Moreover, the fear to falls in elderly people has an important impact in their social life, as 15% reduce their social activity outside their home [6].

Studies have emphasised that quick action in the event of a fall is critical, especially in people who live alone, since the longer it takes to react to the event, the higher the morbidity or mortality rate is [8], [9]. Hence, the development of novel approaches to detect falls and reduce the reaction time is critical to minimize the impact of these situations.

In the literature, three main sensing systems have been proposed to detect falls, which are differentiated considering the nature of the captured signals [10]–[12]: 1) vision systems; 2) environmental detection systems; and 3) wearable sensor-based systems.

Vision systems [13]–[21], process images of one or several cameras to detect falls. An advantage of these systems is that they can also provide an image of the fallen person, which helps evaluating the severity of the fall. However, as the system is designed to be static, they present limited range of capture, typically constrained to a specific room, being unable to detect falls outside this area. Moreover, having a constantly active home vision-based system can cause privacy problems [15].

The associate editor coordinating the review of this manuscript and approving it for publication was Khin Wee Lai.

Environmental detection systems are based on the detection of the variation of environmental signals such as radio signals [22]–[24], sound signals [25], [26] or ground vibrations [27] to detect falls. These approaches present less privacy concerns, but their applicability is also limited to a specific capture range. In addition, in home environments, different activities can cause interference with the monitoring systems.

Wearable sensors are small sensors that can be placed almost anywhere in the body. Thanks to their small size and weight, they can be carried out by the person to be monitored, increasing their capture range significantly. Most of the approaches to detect falls based on wearable sensors are based on the use of inertial sensors. Among these, multiple solutions can be found using accelerometers in the literature [19], [28]–[39]. Some works also propose the use of IMUs (Inertial Measurement Unit) which combine the former with gyroscopes and magnetometers and allow to estimate the 3D orientation of the device in a global reference system [40]–[43]. A particular subset of these approaches use the internal IMUs of current smartphones [44]–[47]. Other approaches propose the use of barometers [48] or even the microphone of smartphones [25].

In recent years, wearable sensors have become one of the main approaches for Fall Detection. However, it is to be noted that their placement with respect to the body is a critical issue when processing the captured data, as the received signals will vary depending on this relative position. Most of the works propose to place the sensors on the waist [29], [31], [34], [35], [48]. Nevertheless, others propose their use on the wrist [19], [28], [33], the foot [32] or the back [41]. Defining the optimal placement of sensors has been the focus of different studies [30], [42], evaluating their placement in the ankles, chest and waist [30], and adding to these the head, wrists and thigh [42]. The aforementioned studies conclude that the best position to perform Fall Detection is at the waist, although optimal results are also achieved with the sensor element located on the chest [30], [38].

Although in the last years the size of wearable sensors has reduced, in elderly or impaired people, the attachment of the sensor to the body can cause rejection by the user. In these cases, several works have proposed to introduce sensors into Assistive Devices for Walking (ADW) such as crutches [49] or canes [50]–[52] in order to detect falls. The proposed devices use inertial sensors [52] which can be combined with force sensors [49], [50], or GPS and heart rate sensors [51]. These devices allow minimal discomfort of the user, but also require a proper algorithm to detect the fall.

Fall Detection is carried out by interpreting the data provided by the sensors integrated in the aforementioned devices. Two main approaches exist for this purpose. The first processes directly the raw data of the sensors [28], [33], requiring algorithms that typically imply higher computational cost. The second considers a pre-processing step, in which a set of features are extracted from the raw data, reducing the dimensionality of the problem [32], [34], [37], [42], [46], [53], [54].

The implementation of the Fall Detection algorithm is typically addressed by the design of a machine learning technique based classifier [55]. Among the different approaches, Artificial Neural Networks (ANN) based on MLP (Multi-Layer Perceptron) [31], [33], [34], [41], [42], [53], Convolutional Neural Networks (CNN) [17], [19], [24], or Deep Learning approaches [22], [28], [35], [46] can be found. Other classification approaches based on SVM (Support Vector Machine) [26], [30], [32], [36], [37], [41], [42], [46]–[48], or K-NN (K-Nearest Neighbor) [14], [15], [37] have been also proposed. The aforementioned solutions provide a high rate of Fall detection when applied to different devices. However, in the case of Fall Detectors developed for ADW, the proposed approaches have not been designed to differentiate between the user falling with the ADW, and the ADW falling without the user.

In summary, it can be concluded that due to the importance of quick action in the event of falls, their detection using monitoring devices has raised as a relevant research line in recent years. In the case of impaired or elderly people the use of sensorized ADW has been proposed as an appropriate approach. However, most works proposed in this area do not consider these devices. Moreover, the proposed ADW-based Fall Detectors are prone to false positives, as they are not able to discern when he ADW has fallen with the user or without it.

Hence, in this work, a novel Fall Detection approach is proposed for people that require ADW. The proposed approach is based on a Sensorized Tip which can be attached to a standard crutch or cane, and aims to give some insight into the previously cited issues, with four relevant contributions: 1) The approach is focused on people that require ADW; 2) A comprehensive set of features to detect falls is proposed and optimized using a Feature Selection methodology; 3) Falls of the ADW without the user (false positives) are considered; 4) A comparative analysis is carried out considering four different scenarios: using only data from the Sensorized Tip, from the wearable sensors, from all accelerometer data; or using all data.

The rest of the work is structured as follows. Section II details both the developed Sensorized Tip and the wearable sensors used for the development of the Fall Detectors. Section III presents an overview of the proposed two-step Machine Learning-based Fall Detection approach. Section IV details the experiments executed to generate the datasets to develop the Fall Detector. Section V explains the methodology used to define the fall Detection algorithms. Section VI shows the results of the comparative analysis carried out to evaluate the approach. Finally, the most important ideas are summarized in Section VII.

II. FALL MONITORING SYSTEMS

In this work, the use of the Sensorized Tip developed in [56] is proposed to monitor the user that requires an Assistive

FIGURE 1. Sensorized Tip used for fall detection (on a crutch and off) and local axes of the Sensorized Tip.

Device for Walking. As it can be seen in Figure 1, the Sensorized Tip can be easily attached to a crutch or cane, providing data of both the user's motion and the force exerted.

The Sensorized Tip is made of a lightweight aluminum structure, which contains a set of sensors: an Inertial Measurement Unit with 9 degrees of freedom MTi-3 from XSens, which provides information on the 3D motion of the Sensorized Tip (linear acceleration, angular velocity and magnetic field in the local xyz axes); a BMP280 barometer from Bosch that can provide estimation on the relative height of the Sensorized Tip; and a C9C force sensor from HBM that provides the axial force applied on the ADW. In addition, the MTi-3 provides an estimation of the global orientation of the device on a global XYZ coordinate system, which allows to estimate its angle of inclination (α) with respect to the ground by,

$$\alpha = \pi/2 - acos(proj_{\mathbf{Z}}\mathbf{z}/|proj_{\mathbf{Z}}\mathbf{z}|) \tag{1}$$

where $proj_{\mathbf{Z}}\mathbf{z}$ is the projection of the local z axis (Figure 1) in the global Z axis (normal to the ground) and $|proj_{\mathbf{Z}}\mathbf{z}|$ is its module.

It is to be noted that the data from the magnetometer and the BMP280 barometer will not be used in this work.

In order to evaluate the aforementioned device as a fall monitoring system, in this work, the Fall Detectors will be also be developed for a wearable sensor system. The

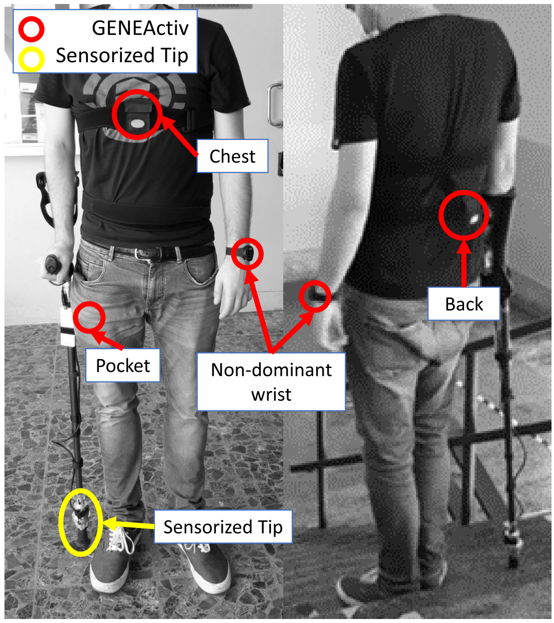


FIGURE 2. GENEActiv accelerometer sensors positions in the body.

GENEActiv commercial 3-axis accelerometers, manufactured by Activinsights, have been selected for this purpose. In particular the GENEActiv devices were located on the non-dominant wrist, on the chest, on the lower back, and in the pocket corresponding to the dominant side (see Figure 2). The GENEActiv wearable sensors on the wrist and in the pocket are used to simulate a smartwatch and a smartphone respectively. This way, the different sensor data provided by the Sensorized Tip and the Wearable system can be evaluated to analyze their effectiveness to detect falls.

III. OVERVIEW

This paper presents a novel Fall Detector approach based on the data provided by a Sensorized Tip attached to an Assistive Device for Walking (ADW). The proposed approach is composed by two modules connected in series, as detailed in Figure 3. The first module (*ADW Fall Detector*) is focused on detecting the fall of the ADW; while the second (*User & ADW Fall Detector*) uses the fall data to evaluate if the user has fallen with the ADW, or only the ADW has fallen. This latter module is designed to avoid false positives due to ADW accidental falls.

For the development of the *ADW Fall Detector* module, two experimentally obtained datasets will be used to generate the training set: a dataset composed by user falls and a dataset that includes different physical activities carried out by the user. For the *User & ADW Fall Detector* module, where the goal is to determine if the user has fallen with the ADW, the user fall dataset will be combined with a set of experiments in which only the ADW has fallen to

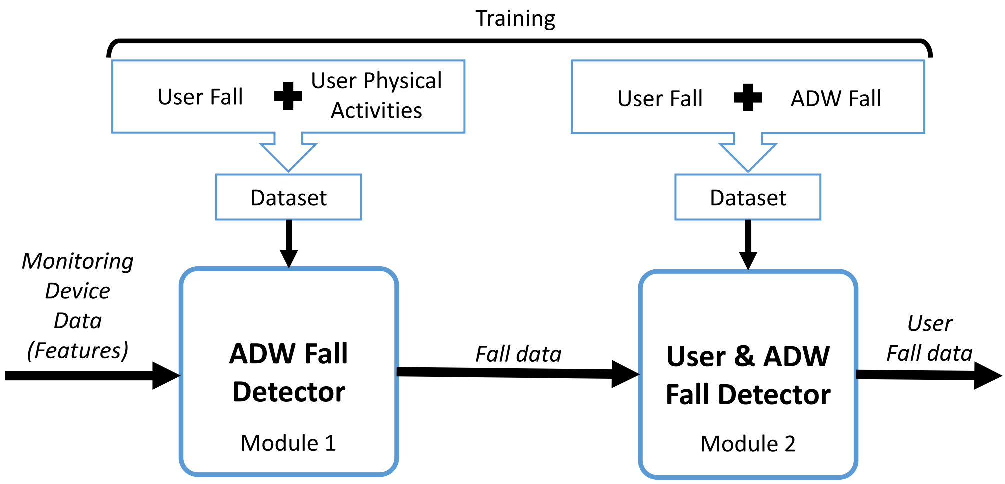


FIGURE 3. Two-module methodology followed for falls detection.

generate the training set. The protocol that was defined to obtain the different datasets will be detailed in Section IV. This two-module approach has been designed in order to develop two different Machine-Learning based detectors. The presented two-module approach has also a reduced computational cost. In fact, if a fall of the ADW is not detected by the first module, the second module is not applied.

The training datasets are processed to generate a set of features to characterize each fall, and a feature evaluation procedure is implemented to detect the most relevant ones to design each Machine Learning-based module. In particular a Support Vector Machine (SVM) approach will be used to implement the algorithm of each module. The procedure will be detailed in Section V.

Finally, in order to evaluate the proposed approach, this will be compared with the performance of a Fall Detector that uses different sets of sensor data: with GENEActiv wearable sensor data, all possible accelerometers (Sensorized Tip internal accelerometer and four GENEActiv accelerometers) and all data sensors. It is to be noted that for these particular cases, only the first module (see Figure 3) will be implemented, as the sensors are placed also in the user. Results will be analyzed in Section VI.

IV. EXPERIMENTAL PROTOCOL AND DATASET GENERATION

In order to develop a Machine Learning-based algorithm, a proper database is to be generated. This requires the definition and execution of a protocol containing a set of falls and physical activities while using an ADW. In this section, the definition of the experiments is detailed.

The simulations were carried out by 12 healthy volunteers (4 women and 8 men, ranging between 25-40 years, 3 left-handed and the rest right-handed) in a controlled environment. In order to perform the falling simulations, a mattress was used, to avoid possible injuries to the volunteers. The volunteers wore the GENEActiv accelerometers during the experiments, and the Sensorized Tip was attached to the crutch (Figure 2). The protocol was approved by the Ethics Committee at University of Bologna and all participants provided informed written consent.

Three datasets have been created in order to generate the training set of each module (*ADW Fall Detector* and *User & ADW Fall Detector*): a) User Fall dataset, which included data from people falling while using a crutch; b) User Physical Activities dataset, which included data from people performing different physical activities using the crutch; c) ADW Fall dataset, in which the crutch was left standing still at different positions, and then forced to fall without the user. As previously detailed, datasets 1 and 2 will be used to train the *ADW Fall Detector* module, while datasets 1 and 3 are used to train the User & ADW Fall Detection module. Next, the experiments included in each dataset are detailed:

A. USER FALL DATASET

In order to simulate as close as possible real falls, videos associated to falls of people falling while using ADW from the *Databrary* database [57], [58] were analyzed. From this analysis, 16 scenarios were considered, in particular the protocol defined includes 8 static falls from an upright position (1-8) and 8 dynamic falls from walking (9-16):

1) While standing still, try to take a step and trip over the ADW and fall forwards.
2) Fall forwards.
3) Fall backwards simulating a faint.
4) Fall backwards.

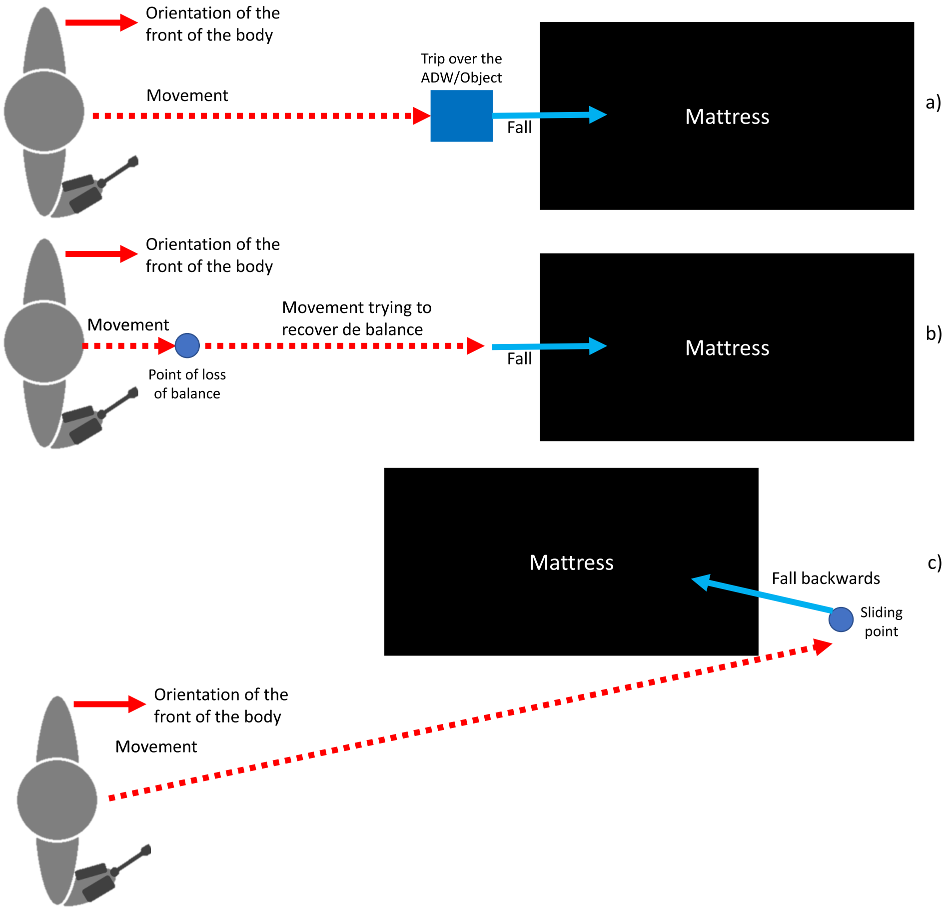


FIGURE 4. Graphical representation of some of the simulated falls during the walking: a) Cases 9, 10, 11, 12 and 13. b) Cases 14, 15. c) Case 16.

5) Rotate 90° to the right and fall on the right side.
6) Fall on the right side.
7) Rotate 90° to the left and fall on the left side.
8) Fall on the left side.
9) Walk towards the mattress, trip over the ADW and fall forwards (see Figure 4a).
10) Walk towards the mattress, simulate a trip over an object and fall forwards (see Figure 4a).
11) Walk towards the mattress, simulate a trip over an object and fall on the left side (see Figure 4a).
12) Walk towards the mattress, simulate a trip over an object and fall on the right side (see Figure 4a).
13) Walk towards the mattress, simulate a trip over an object and fall backwards (see Figure 4a).
14) Loss of balance, try to recover it by walking a few meters and fall forwards (see Figure 4b).
15) Loss of balance, try to recover it by walking a few meters and fall backwards (see Figure 4b).
16) Walk and slide to end up falling backwards (see Figure 4c).

B. USER PHYSICAL ACTIVITY DATASET

In order to complete the database with no-fall activities, a total of 7 different physical activities using ADW have been simulated:

1) Walking at a normal pace: a circuit (see Figure 5) has been defined in which the volunteer has to walk straight in several directions and make turns.
2) Walking quickly: the same circuit (see Figure 5) performed previously is repeated, but in this case walking approximately 30% faster.
3) Standing still: stay still in place for 30 seconds.
4) Going up and down stairs: going up and down stairs repeatedly.
5) Get up and sit in a chair: get up and sit down repeatedly for 30 seconds.

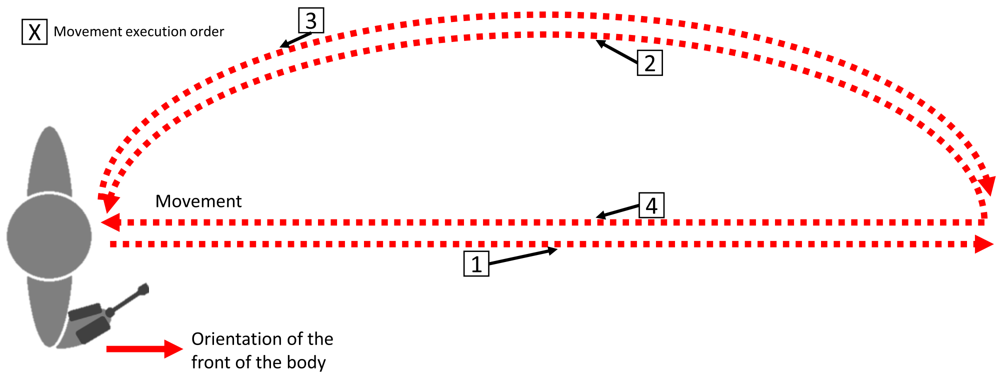


FIGURE 5. Graphical representation of some of the physical activities walking circuit.

6) Pick up an object from the floor and stand up repeatedly for 30 seconds.
7) Loss of balance without falling (near fall), repeated 4 times.

C. ADW FALL DATASET

Finally, a series of tests has been carried out in which the ADW falls without the user:

1) Crutch placed in different static positions on the floor or while leaning on a site.
2) Dropping the crutch while standing still, or while walking. 80 crutch falls will be performed.

The dataset consists of 192 user falls (using ADW), 108 minutes of physical activities (using ADW), 5 minutes of different static ADW positions and 80 ADW falls.

V. DESIGN METHODOLOGY

Once the datasets have been generated, the two algorithms proposed in Figure 3 will be designed. The first will be a *ADW Fall Detection* module, which will be designed to detect a fall; while the second will determine if the user is involved in the fall (or only the ADW). As the system is designed so that the first module output is used in the second one, each algorithm will require different input data, as it will be explained next.

A. ADW FALL DETECTOR DESIGN

The purpose of the *ADW Fall Detection* module is to detect when a fall happens while using the ADW. In this section, the methodology used to design the Machine Learning-based detector will be detailed (see Figure 7). This methodology is based on well-established methodologies ones in the literature [39].

1) DATA SEGMENTATION AND SET GENERATION FOR TRAINING

The data used to design the *ADW Fall Detector* module is extracted from the User Fall dataset and the User Physical Activity dataset previously detailed. The time sequences captured in these datasets are first processed using a segmentation process, allowing to extract a set of features from each segment or window.

For this purpose, the data is divided into fixed-size sliding windows. The window size has been set to 100 samples (2 seconds), as in the experiments this value allows to capture the fall (see Figure 6a). In addition, the beginning of each window will be shifted by 20 samples (0.4 seconds) from the beginning of the previous one (see Figure 6b) to limit the computational cost.

Once segmentation has been carried out, each window will be considered a sample for the design of the *ADW Fall Detector*. For this purpose, each window is labelled to define if it corresponds to a fall or not. The event of a fall will be considered if a window contains more than 50% of its data samples associated to a fall (see Figure 6a). Note that the physical activity related samples are not tagged as falls.

In order to develop the Machine Learning-based *ADW Fall Detector*, the aforementioned set is divided into two: a training dataset, which will be used to develop the *ADW Fall Detector*, and a test dataset, which will be used to validate its generalization capabilities. The training dataset is composed the simulations carried out by 8 subjects, while the remaining data (4 subjects) are used for testing. In addition, in order to balance the number of fall/not falls samples, an adjusted set is generated, as detailed in Table 1. This adjustment has been made, in the case of falls, by eliminating those windows that do not have 50% of the window in the fall period. In the case of physical activities, this adjustment has been made trying to maintain a similar number of samples with respect to the falls.

As defined in Section II, each set associated to the *ADW Fall Detector* will contain the segmented windows related to the data captured from the Sensorized Tip: 3-axis accelerometer, 3-axis gyroscope, force sensor and estimated inclination (α) with respect to the ground (see Table 2).

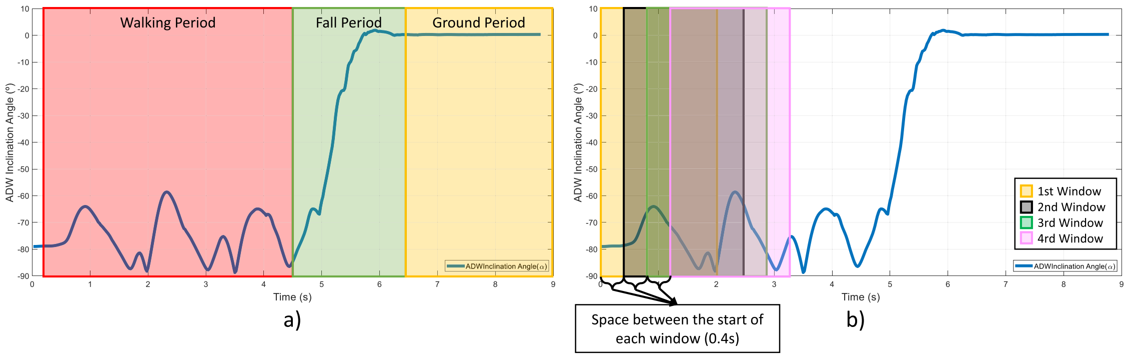


FIGURE 6. Graph of the ADW inclination angle: a) ADW fall time and states. b) Fixed-size window division with space between window starts.

TABLE 1. Distribution of the dataset and adjustment of the number of data.

			Windows		
			Train	Test	Total
Participants			8	4	12
Fall Detector Set	Non Adjusted	Falls	2770	1216	3986
		Not Falls	5805	2600	8405
	Adjusted	Falls	759	382	1141
		Not Falls	866	433	1299
User Fall Detector Set		User Falls	128	64	192
		ADW Falls	50	30	80

2) POTENTIAL FEATURES SET GENERATION

The use of segmentation allows to obtain a dataset composed by discrete data units, one for each window, from which a set of features can be easily extracted. These features (such as mean, variance, ...) allow to reduce the dimensionality of the data, generating numeric values that can be easily processed by Machine Learning-based approaches. In this section, a methodology to select the most appropriate features to design a Machine Learning (ML)-based Fall Detector is detailed (see Figure 7).

In the literature, there are different approaches to define the set of potential features. A typical approach is to use statistical operators to characterize the data from the window. In this work, the following statistical features will be extracted:

- Mean (MEAN).
- Standard Deviation (STD).
- Variance (VAR).
- Kurtosis (KUR).
- Intercuartile Range (IR).
- Area Under the Signal (AUS).
- Maximum value of the window (MAX).
- Minimum value of the window (MIN).

These statistical operators are applied to the previously defined training dataset, composed by the segmented windows or samples related to each of the signals provided by the monitoring device (Sensorized Tip's force sensor, Sensorized Tip's gyroscope (x, y, z), Sensorized Tip's accelerometer (x, y, z) and Sensorized Tip's inclination angle (α)). The combination of these operators on each sensor signal device generates a feature. In the case of the Sensorized Tip, a total of 64 features can be defined per each sample.

3) ADW FALL DETECTOR TRAINING

Although all possible features can be used to train the ML-based Fall Detector, due to the high dimension of the input data, it is advisable to perform an analysis to detect the most relevant features. This will allow to reduce the computational cost of the approach, if implemented in real-time.

In the literature, different approaches are proposed to determine the relative importance of a feature for a classification problem, such as Random Forest (RF) [59] and Relief [60]. In this work, the Random Forest approach has been selected, as it provided better results. This approach consists of the generation of a large set of decision trees for classification purposes, also known as a forest. The trees are generated by using a random set of samples and features, so that in the training process different features can be tested and their relative importance evaluated.

Hence, once the training dataset is processed by the Random Forest and the features have been ordered considering their relative importance to the Fall Detection process, a set of Support Vector Machines (SVMs) will be trained, considering different subsets of features. The goal is to determine the minimum number of features to achieve an appropriate Fall Detection performance.

To achieve this goal, first the most relevant features will be used to train the Fall Detector SVM, then the number of features will be gradually increased. Each SVM is trained using Matlab's Statistic and Machine Learning toolbox, where the SVM hyperparameters are optimized by the use of a K-Fold cross validation approach with $K = 10$. Once trained, the test set is used to evaluate the Fall Detection performance of each SVM. Results will be detailed in Section VI.

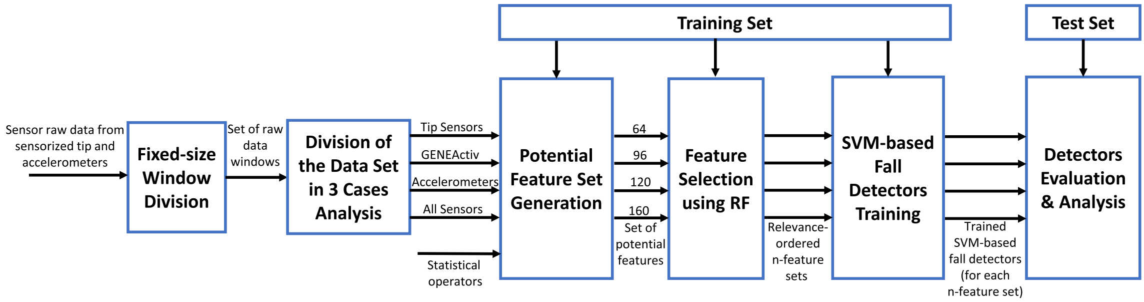


FIGURE 7. Methodology followed for the design of the Fall Detector modules based on Machine Learning.

B. USER AND ADW FALL DETECTOR

This algorithm is executed only when the *ADW Fall Detector* module has detected a fall. In this scenario, *User & ADW Fall Detector* module analyzes the fall data in order to determine if the user has fallen with the ADW, or only the ADW has fallen. This is one of the novel contributions of the present work.

The methodology used for the development of this module is similar to the previous one (see Figure 7). However, the input datasets differ, as data from the ADW Fall and User Fall datasets are used to train and test this algorithm.

1) DATA SEGMENTATION AND SET GENERATION FOR TRAINING

This module uses the data provided by the ADW Fall Detection module. Hence, the sample detected as a fall by the latter *ADW Fall Detector* will be processed in this algorithm. Based on this premise, a set of fall samples is generated from the User Fall dataset, in which the detected central fall window is only considered for this module. In addition, the falls associated to ADW fall dataset will also be included, tagged as negative user falls. A set composed by a total of 192 user falls and 80 ADW falls (without the user) is generated, from which 128 user falls and 50 ADW falls are used for training (Table 1).

2) USER AND ADW FALL DETECTOR TRAINING

Once the datasets are generated, the statistical operators previously detailed are applied on the sensor signals of the Sensorized Tip to extract the 64 features associated to each sample. These are then processed through a Random-Forest approach, obtaining the relative importance of each feature. A set of SVMs is trained using the same approach as the *ADW Fall Detector* module.

VI. RESULTS AND COMPARATIVE ANALYSIS

This section focuses on evaluating the proposed two-module Fall Detection approach using the data provided by the Sensorized Tip. For that purpose, a comparative analysis is carried out by considering also the data provided by the wearable sensor GENEActiv detailed in Section II.

In the analysis four cases are compared: 1) The proposed approach based on the Sensorized Tip Data; 2) The use of the GENEActive wearable sensor data; 3) The use of all possible accelerometers (Sensorized Tip internal accelerometer and four GENEActiv accelerometers); 4) The use of all data sensors (Table 2).

In order to perform the comparison, the procedure to design the *ADW Fall Detector* module has been applied to all aforementioned cases: feature generation, Random Forest-based relative importance detection and SVM training. Note that the User & ADW Fall Detection module has been only used for the Sensorized Tip case, as no sensor is placed on the user. Hence, this case will be analyzed in a separate subsection.

A. ADW FALL DETECTOR MODULE EVALUATION

1) FEATURE RELEVANCE ANALYSIS

Following the feature extraction procedure, a set of 64 features per sample are generated for the dataset based on the Sensorized Tip's sensor data; 96 for the case of the GENEActiv wearable sensors; 120 if all accelerometer data is considered; and 160 if all sensor data is considered.

As the number of features is important, in order to reduce the dimensionality of the problem, a Random-Forest approach is used for each case to detect the most relevant features, detailed in Section VI. These are detailed in the *Fall Detector* columns of Table 3.

As it can be seen, when the angle of inclination of the ADW is considered in the set of data, the features extracted from this signal are among the most relevant, the maximum angle being the most important, as it reflects large variations due to falls.

In the case of GENEActiv sensors, the 3 most important features are derived from the sensor on the lower back of the user (in particular its X axis, vertical), which is the one which suffers the most variation when the user falls. Note that features from sensors located on the chest are also among the 10 most relevant features.

If only accelerometer data is used from both the Sensorized Tip and the GENEActiv sensors, the most relevant

TABLE 2. Analyzed Cases considering sensor input.

Device	Sensors	Different analysis forms			
		Sensorized Tip	GENEActiv Sensors	*Accelerometer Sensors*	*All Sensors*
Sensorized Tip	Angle of inclination (α)	X			X
	3 axis Gyroscope	X			X
	Force Sensor	X			X
	3 axis Accelerometer	X		X	X
4x GENEActiv Accelerometers	3 axis Accelerometer		X	X	X

TABLE 3. Weight of the features provided by the RF in the different case studies. (α = ADW inclination angle, accel = accelerometer, gyro = gyroscope), for the ***ADW Fall Detector*** and the ***User & ADW Fall Detector***.

Evaluated Fall Detector approaches									
Fall Detector								User & ADW Fall Detector	
Sensorized Tip		GENEActiv		Accelerometers		All Sensors			
Feature	Weight	Feature	Weight	Feature	Weight	Feature	Weight	Feature	Weight
α MAX	3.587	Back accel MEAN X axis	2.619	Tip accel MEAN Z axis	2.293	α MAX	1.773	Tip force STD	4.988
Tip gyro MIN Z axis	2.803	Back accel MIN X axis	2.514	Tip accel AUS Z axis	2.127	Back accel MIN X axis	1.767	Tip force VAR	4.708
Tip gyro KUR X axis	2.788	Back accel AUS X axis	2.250	Back accel MEAN X axis	2.125	Back accel MEAN X axis	1.715	Tip force AUS	4.236
α MEAN	2.630	Chest accel MEAN X axis	2.147	Back accel MIN X axis	2.091	α MEAN	1.460	Tip force MEAN	4.232
Tip gyro MIN X axis	2.545	Chest accel AUS X axis	2.096	Back accel AUS X axis	1.889	Back accel AUS X axis	1.454	Tip gyro STD Z axis	4.100
α STD	2.485	Chest accel MIN Z axis	1.943	Chest accel AUS X axis	1.851	Tip accel MEAN Z axis	1.433	Tip gyro VAR Z axis	3.894
Tip gyro KUR Y axis	2.394	Wrist accel KUR X axis	1.625	Chest accel MEAN X axis	1.845	Chest accel AUS X axis	1.433	Tip force MAX	3.778
α VAR	2.379	Back accel KUR Y axis	1.535	Tip accel MAX Z axis	1.626	α AUS	1.418	Tip accel MIN Z axis	3.648
α AUS	2.348	Back accel KUR X axis	1.521	Chest accel MIN X axis	1.473	Chest accel MEAN X axis	1.361	Tip force KUR	2.765
Tip accel MEAN Z axis	2.341	Back accel MAX X axis	1.519	Tip accel MIN Z axis	1.315	Tip accel AUS Z axis	1.341	Tip gyro KUR Y axis	2.730
Tip gyro MIN Y axis	2.167	Chest accel KUR Y axis	1.505	Tip accel STD Y axis	1.246	Tip gyro KUR X axis	1.213	Tip gyro IR Z axis	2.727
Tip accel AUS Z axis	2.165	Wrist accel MIN Z axis	1.459	Tip accel VAR Y axis	1.231	Chest accel MIN X Axis	1.192	Tip force IR	2.621
Tip accel MAX Z axis	2.095	Pocket accel KUR Z axis	1.441	Wrist accel KUR Z axis	1.227	Tip gyro KUR Y axis	1.091	Tip gyro MAX X axis	2.555
Tip accel KUR Z axis	1.947	Back accel AUS Z axis	1.434	Pocket accel MEAN Y axis	1.191	Tip gyro MIN Z axis	1.088	α IR	2.345
Tip force MEAN	1.915	Pocket accel MIN Z axis	1.411	Back accel MAX X axis	1.186	Tip accel MAX Z axis	1.077	Tip gyro KUR X axis	2.331

features include both the Sensorized Tip's accelerometer and the GENEActiv sensor on the lower back, as in the previous case.

These trends seem to be confirmed if all sensors are used, being the Tip inclination angle, the acceleration of the back sensor and tip sensor among the most relevant ones.

2) PERFORMANCE ANALYSIS

As defined in Section V, once the relative importance of features has been determined, a set of SVMs is trained with an increasing number of features, taking into account the most relevant features.

Table 4 shows the performance results for the Fall Detector associated to each number of the first n most relevant features (first column). In general, all the analyzed cases provide F-score over 0.96, which validate the use of the Sensorized Tip. In addition, it can be seen that the number of features used is not especially relevant, since very good results are achieved for all scenarios. However, there are slight differences between the approaches that can be analyzed.

Using only the sensors included in the Sensorized Tip, results for this case are good for any number of features. Considering the 2 most relevant features (α maximum and Tip gyroscope minimum in Z axis, Table 3) provide the best results: a precision of 0.986, a specificity of 0.988,

TABLE 4. Results of the different cases to be analyzed of the SVM-based Fall Detectors (P=Precision, Sp=Specificity, Se=Sensitivity, F=F-score).

	Sensorized Tip				GENEActiv				Accelerometers				All Sensors			
No. In	P	SP	Se	F	P	SP	Se	F	P	SP	Se	F	P	SP	Se	F
1	0.982	0.984	1.000	0.991	0.941	0.945	0.984	0.962	0.979	0.982	0.979	0.979	0.970	0.972	1.000	0.985
2	0.986	0.988	1.000	0.993	0.956	0.960	1.000	0.978	0.979	0.982	0.981	0.980	0.986	0.988	1.000	0.993
3	0.980	0.982	1.000	0.990	0.957	0.960	1.000	0.978	0.982	0.984	0.989	0.985	0.986	0.988	1.000	0.993
4	0.982	0.984	1.000	0.991	0.957	0.961	1.000	0.978	0.984	0.985	1.000	0.992	0.982	0.984	1.000	0.991
5	0.983	0.985	1.000	0.991	0.953	0.957	0.999	0.976	0.980	0.982	1.000	0.990	1.000	1.000	1.000	1.000
6	0.983	0.984	1.000	0.991	0.969	0.972	1.000	0.984	0.990	0.991	1.000	0.995	1.000	1.000	1.000	1.000
7	0.987	0.988	1.000	0.993	0.978	0.980	1.000	0.989	0.997	0.998	1.000	0.999	1.000	1.000	1.000	1.000
8	0.982	0.983	1.000	0.991	0.971	0.973	1.000	0.985	0.981	0.983	1.000	0.991	1.000	1.000	1.000	1.000
9	0.982	0.984	1.000	0.991	0.970	0.973	0.999	0.985	0.984	0.986	1.000	0.992	0.992	0.993	1.000	0.996
10	0.982	0.984	1.000	0.991	0.974	0.977	0.997	0.986	0.982	0.983	1.000	0.991	0.989	0.991	1.000	0.995
11	0.982	0.984	1.000	0.991	0.969	0.972	0.992	0.980	0.977	0.979	1.000	0.988	0.993	0.994	1.000	0.996
12	0.983	0.985	1.000	0.991	0.969	0.972	0.999	0.984	0.980	0.982	1.000	0.990	0.997	0.998	1.000	0.999
13	0.982	0.984	1.000	0.991	0.968	0.971	0.999	0.983	0.979	0.981	0.999	0.989	0.998	0.998	1.000	0.999
14	0.982	0.984	1.000	0.991	0.974	0.977	1.000	0.987	0.976	0.979	0.998	0.987	0.987	0.988	1.000	0.993
15	0.984	0.985	1.000	0.992	0.976	0.979	1.000	0.988	0.979	0.981	0.999	0.989	1.000	1.000	1.000	1.000

a sensitivity of 1 and an F-score of 0.993 is achieved. Moreover, using the maximum inclination angle (α) can also provide very good results.

The GENEActiv wearable devices, provide the lower performance of all analyzed cases. A maximum F-score of 0.989, with a precision of 0.978, specificity of 0.980 and sensibility of 1, can be achieved using the 7 most relevant features. On the other hand, the accelerometer only approach can provide near 0.999 F-score, precision of 0.997, specificity of 0.998 and sensibility of 1, with the same 7 features. If all data is considered, 5 features are required to obtain a precision, specificity, sensibility and F-score of 1 with the proposed test dataset.

B. USER AND ADW FALL DETECTOR

1) FEATURE RELEVANCE ANALYSIS

The *User & ADW Fall Detector* is only used if the Sensorized Tip data is used. This algorithm is used to determine if a fall detected by the ADW Fall Detection module is a user fall or an ADW fall without the user.

In order to develop the detector, a Random-Forest analysis is performed over the 64 features defined for the sensor data. Results are summarized in Table 3, where the 10 most relevant features are shown. As it can be seen, the four most relevant features are associated to the Tip Force, which measures the load the user applies on the ADW. The relative importance of these features is derived from the fact that when a person falls with an ADW, he/she tries to recover balance by leaning on the ADW. This, however does not happen when the ADW falls without the user.

2) PERFORMANCE ANALYSIS

Table 5 summarizes the results obtained for each SVM trained with the n most relevant features detailed in Table 3. The precision, specificity, sensitivity and F-score data are shown for each case.

Results show that the best results are achieved using at least the most relevant 6 features, with a F-score of 0.963, precision of 0.943, specificity of 0.873 and sensitivity of 0.984. These can be considered good results, and demonstrate that the proposed approach can also be an effective one to detect falls.

TABLE 5. Results of the *ADW Fall Detector* with and without user (P=Precision, Sp=Specificity, Se=Sensitivity, F=F-score).

Number Input Features	P	Sp	Se	F
1	0.876	0.717	0.936	0.905
2	0.880	0.733	0.917	0.898
3	0.888	0.757	0.906	0.897
4	0.880	0.737	0.906	0.893
5	0.940	0.867	0.984	0.962
6	0.943	0.873	0.984	0.963
7	0.940	0.867	0.984	0.962
8	0.930	0.843	0.969	0.949
9	0.926	0.833	0.967	0.946
10	0.943	0.873	0.981	0.962
11	0.942	0.870	0.983	0.962
12	0.946	0.880	0.978	0.962
13	0.925	0.830	0.977	0.950
14	0.928	0.837	0.981	0.954
15	0.912	0.797	0.983	0.946

VII. CONCLUSION

Early detection of falls is critical, especially in those people that require the use of ADW. Current Fall Detection approaches do not traditionally consider people with ADW, which has opened a new research area focused on developing sensorized ADW for monitoring purposes.

This work presents a novel Fall Detector based on the data provided by a Sensorized Tip that can be attached to different ADW such as crutches or canes. The approach has four relevant contributions: 1) The approach is focused on people that require ADW; 2) A methodology is proposed to present and evaluate a set of features to develop the Fall Detector; 3) Falls without the user are considered as false positives; 4) A comparative analysis is carried out to evaluate the approach.

In order to validate the innovative Fall Detector system, a set of experiments has been designed, including simulated falls and regular activities (walking, walking faster, go up/down stairs, sit, bend down to pick something...), carried out by 12 volunteers. The experiments have been used to train a set of Machine Learning-based approaches to detect falls. The results of the proposed approach demonstrate that it can provide high Fall Detection ratios using the Sensorized Tip, similar or higher than state-of-the-art devices.

REFERENCES

[1] S. Yoshida, *A Global Report on Falls Prevention: Epidemiology of Falls*, World Health Organization, Geneva, Switzerland, 2007.
[2] N. K. Sekaran, H. Choi, R. A. Hayward, and K. M. Langa, "Fall-associated difficulty with activities of daily living in functionally independent individuals aged 65 to 69 in the United States: A cohort study," *J. Amer. Geriatrics Soc.*, vol. 61, no. 1, pp. 96–100, Jan. 2013.
[3] P. Pasquetti, "Pathogenesis and treatment of falls in elderly," *Clin. Cases Mineral Bone Metabolism*, vol. 11, no. 3, pp. 222–225, 2014.
[4] C. Griffiths, C. Rooney, and A. Brock, "Leading causes of death in England and Wales–how should we group causes," *Health Statist. Quart.*, vol. 28, no. 9, pp. 6–17, 2005.
[5] A. M. Tromp, J. H. Smit, D. J. H. Deeg, L. M. Bouter, and P. Lips, "Predictors for falls and fractures in the longitudinal aging study Amsterdam," *J. Bone Mineral Res.*, vol. 13, no. 12, pp. 1932–1939, Dec. 1998.
[6] V. S. Stel, J. H. Smit, S. M. F. Pluijm, and P. Lips, "Consequences of falling in older men and women and risk factors for health service use and functional decline," *Age Ageing*, vol. 33, no. 1, pp. 58–65, Jan. 2004.
[7] M. E. Tinetti, J. Doucette, E. Claus, and R. Marottoli, "Risk factors for serious injury during falls by older persons in the community," *J. Amer. Geriatrics Soc.*, vol. 43, no. 11, pp. 1214–1221, Nov. 1995.
[8] R. J. Gurley, N. Lum, M. Sande, B. Lo, and M. H. Katz, "Persons found in their Homes helpless or dead," *New England J. Med.*, vol. 334, no. 26, pp. 1710–1716, Jun. 1996.
[9] D. Wild, U. S. Nayak, and B. Isaacs, "How dangerous are falls in old people at home?" *Brit. Med. J.*, vol. 282, no. 6260, pp. 266–268, Jan. 1981.
[10] R. Y. W. Lee and A. J. Carlisle, "Detection of falls using accelerometers and mobile phone technology," *Age Ageing*, vol. 40, no. 6, pp. 690–696, 2011.
[11] M. Patel, A. Pavic, and V. A. Goodwin, "Wearable inertial sensors to measure gait and posture characteristic differences in older adult fallers and non-fallers: A scoping review," *Gait Posture*, vol. 76, pp. 110–121, Feb. 2020.
[12] M. Mubashir, L. Shao, and L. Seed, "A survey on fall detection: Principles and approaches," *Neurocomputing*, vol. 100, pp. 144–152, Jan. 2013.
[13] M. Belshaw, B. Taati, J. Snoek, and A. Mihailidis, "Towards a single sensor passive solution for automated fall detection," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2011, pp. 1773–1776.
[14] K. de Miguel, A. Brunete, M. Hernando, and E. Gambao, "Home camera-based fall detection system for the elderly," *Sensors*, vol. 17, no. 12, p. 2864, Dec. 2017.
[15] C.-L. Liu, C.-H. Lee, and P.-M. Lin, "A fall detection system using K-nearest neighbor classifier," *Expert Syst. Appl.*, vol. 37, no. 10, pp. 7174–7181, Oct. 2010.
[16] X. Luo, T. Liu, J. Liu, X. Guo, and G. Wang, "Design and implementation of a distributed fall detection system based on wireless sensor networks," *EURASIP J. Wireless Commun. Netw.*, vol. 2012, no. 1, pp. 1–13, 2012.
[17] A. Núñez-Marcos, G. Azkune, and I. Arganda-Carreras, "Vision-based fall detection with convolutional neural networks," *Wireless Commun. Mobile Comput.*, vol. 2017, Dec. 2017, Art. no. 9474806.
[18] H. Rimminen, J. Lindström, M. Linnavuo, and R. Sepponen, "Detection of falls among the elderly by a floor sensor using the electric near field," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 6, pp. 1475–1476, Nov. 2010.
[19] Y. M. Galvão, J. Ferreira, V. A. Albuquerque, P. Barros, and B. J. T. Fernandes, "A multimodal approach using deep learning for fall detection," *Expert Syst. Appl.*, vol. 168, Apr. 2021, Art. no. 114226.
[20] F. Shu and J. Shu, "An eight-camera fall detection system using human fall pattern recognition via machine learning by a low-cost Android box," *Sci. Rep.*, vol. 11, no. 1, pp. 1–17, Jan. 2021.
[21] J. Gutiérrez, V. Rodríguez, and S. Martin, "Comprehensive review of vision-based fall detection systems," *Sensors*, vol. 21, no. 3, p. 947, Feb. 2021.
[22] B. Jokanović and M. Amin, "Fall detection using deep learning in range-Doppler radars," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 54, no. 1, pp. 180–189, Feb. 2018.
[23] Y. Wang, K. Wu, and L. M. Ni, "WiFall: Device-free fall detection by wireless networks," *IEEE Trans. Mobile Comput.*, vol. 16, no. 2, pp. 581–594, Feb. 2017.
[24] H. Sadreazami, M. Bolic, and S. Rajan, "Contactless fall detection using time-frequency analysis and convolutional neural networks," *IEEE Trans. Ind. Informat.*, vol. 17, no. 10, pp. 6842–6851, Oct. 2021.
[25] M. Cheffena, "Fall detection using smartphone audio features," *IEEE J. Biomed. Health Inform.*, vol. 20, no. 4, pp. 1073–1080, Jul. 2016.
[26] X. Zhuang, J. Huang, G. Potamianos, and M. Hasegawa-Johnson, "Acoustic fall detection using Gaussian mixture models and GMM supervectors," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, Apr. 2009, pp. 69–72.
[27] M. Alwan, P. J. Rajendran, S. Kell, D. Mack, S. Dalal, M. Wolfe, and R. Felder, "A smart and passive floor-vibration based fall detector for elderly," in *Proc. 2nd Int. Conf. Inf. Commun. Technol.*, Apr. 2006, pp. 1003–1007.
[28] S. Yoo and D. Oh, "An artificial neural network–based fall detection," *Int. J. Eng. Bus. Manage.*, vol. 10, Jan. 2018, Art. no. 184797901878790.
[29] J. Chen, K. Kwong, D. Chang, J. Luk, and R. Bajcsy, "Wearable sensors for reliable fall detection," in *Proc. IEEE Eng. Med. Biol. 27th Annu. Conf.*, vol. 7, 2005, pp. 3551–3554.
[30] W.-C. Cheng and D.-M. Jhan, "Triaxial accelerometer-based fall detection method using a self-constructing cascade-adaboost-SVM classifier," *IEEE J. Biomed. Health Informat.*, vol. 17, no. 2, pp. 411–419, Mar. 2013.
[31] C. Dinh and M. Struck, "A new real-time fall detection approach using fuzzy logic and a neural network," in *Proc. 6th Int. Workshop Wearable, Micro, Nano Technol. Personalized Health*, Jun. 2009, pp. 57–60.
[32] C. Doukas, I. Maglogiannis, P. Tragas, D. Liapis, and G. Yovanof, "Patient fall detection using support vector machines," in *Proc. IFIP Int. Conf. Artif. Intell. Appl. Innov.* (IFIP The International Federation for Information Processing), vol. 247. Boston, MA, USA: Springer, 2007, pp. 147–156.
[33] J. A. U. Sanchez and D. M. Muñoz, "Fall detection using accelerometer on the user's wrist and artificial neural networks," in *Proc. XXVI Brazilian Congr. Biomed. Eng.* (IFMBE Proceedings), vol. 70. Singapore: Springer-Verlag, 2019, pp. 641–647.
[34] M. Vallejo, C. V. Isaza, and J. D. Lopez, "Artificial neural networks as an alternative to traditional fall detection methods," in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2013, pp. 1648–1651.
[35] F. Luna-Perejon, J. Civit-Masot, I. Amaya-Rodriguez, L. Duran-Lopez, J. P. Dominguez-Morales, A. Civit-Balcells, and A. Linares-Barranco, "An automated fall detection system using recurrent neural networks," in *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11526. Cham, Switzerland: Springer-Verlag, Jun. 2019, pp. 36–41.
[36] C.-F. Lai, S.-Y. Chang, H.-C. Chao, and Y.-M. Huang, "Detection of cognitive injured body region using multiple triaxial accelerometers for elderly falling," *IEEE Sensors J.*, vol. 11, no. 3, pp. 763–770, Mar. 2011.
[37] L. Palmerini, J. Klenk, C. Becker, and L. Chiari, "Accelerometer-based fall detection using machine learning: Training and testing on real-world falls," *Sensors*, vol. 20, no. 22, p. 6479, Nov. 2020.
[38] K. Aminian and B. Najafi, "Capturing human motion using body-fixed sensors: Outdoor measurement and clinical applications," *Comput. Animation Virtual Worlds*, vol. 15, no. 2, pp. 79–94, 2004.
[39] M. J. Al Nahian, T. Ghosh, M. H. A. Banna, M. A. Aseeri, M. N. Uddin, M. R. Ahmed, M. Mahmud, and M. S. Kaiser, "Towards an accelerometer-based elderly fall detection system using cross-disciplinary time series features," *IEEE Access*, vol. 9, pp. 39413–39431, 2021.
[40] A. Purushothaman, K. V. Vineetha, and D. G. Kurup, "Fall detection system using artificial neural network," in *Proc. 2nd Int. Conf. Inventive Commun. Comput. Technol. (ICICCT)*, Apr. 2018, pp. 1146–1149.
[41] B. T. Nukala, N. Shibuya, A. Rodriguez, J. Tsay, J. Lopez, T. Nguyen, S. Zupancic, and D. Y.-C. Lie, "An efficient and robust fall detection system using wireless gait analysis sensor with artificial neural network (ANN) and support vector machine (SVM) algorithms," *Open J. Appl. Biosensor*, vol. 3, no. 4, pp. 29–39, 2014.
[42] A. T. Özdemir, "An analysis on sensor locations of the human body for wearable fall detection devices: Principles and practice," *Sensors*, vol. 16, no. 8, p. 1161, 2016.
[43] P. Compagnon, G. Lefebvre, S. Duffner, and C. Garcia, "Learning personalized ADL recognition models from few raw data," *Artif. Intell. Med.*, vol. 107, Jul. 2020, Art. no. 101916.

[44] B. Aguiar, T. Rocha, J. Silva, and I. Sousa, "Accelerometer-based fall detection for smartphones," in *Proc. IEEE Int. Symp. Med. Meas. Appl. (MeMeA)*, Jun. 2014, pp. 1–6.
[45] S. B. Khojasteh, J. R. Villar, C. Chira, V. M. González, and E. de la Cal, "Improving fall detection using an on-wrist wearable accelerometer," *Sensors*, vol. 18, no. 5, p. 1350, 2018.
[46] T. Mauldin, M. Canby, V. Metsis, A. Ngu, and C. Rivera, "SmartFall: A smartwatch-based fall detection system using deep learning," *Sensors*, vol. 18, no. 10, p. 3363, Oct. 2018.
[47] S. A. Mousavi, F. Heidari, E. Tahami, and M. Azarnoosh, "Fall detection system via smart phone and send people location," in *Proc. 28th Eur. Signal Process. Conf. (EUSIPCO)*, Jan. 2021, pp. 1605–1607.
[48] F. Bianchi, S. J. Redmond, M. R. Narayanan, S. Cerutti, and N. H. Lovell, "Barometric pressure and triaxial accelerometry-based falls event detection," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 6, pp. 619–627, Dec. 2010.
[49] L. Frizziero, G. Donnici, A. Liverani, G. Alessandri, G. C. Menozzi, and E. Varotti, "Developing innovative crutch using IDeS (Industrial design Structure) methodology," *Appl. Sci.*, vol. 9, no. 23, p. 5032, Nov. 2019.
[50] M. Lan, A. Nahapetian, A. Vahdatpour, L. Au, W. Kaiser, and M. Sarrafzadeh, "SmartFall: An automatic fall detection system based on subsequence matching for the SmartCane," in *Proc. 4th Int. ICST Conf. Body Area Netw.*, 2009, pp. 1–8.
[51] J. Yang, Y. Liu, Y. Chen, H. Nie, Z. Wang, X. Liu, M. A. Imran, and W. Ahmad, "Assistive and monitoring multifunctional smart crutch for elderly," in *Proc. IEEE Int. Conf. Dependable, Autonomic Secure Comput., Int. Conf. Pervasive Intell. Comput., Int. Conf. Cloud Big Data Comput., Int. Conf. Cyber Sci. Technol. Congr. (DASC/PiCom/CBDCom/CyberSciTech)*, Aug. 2019, pp. 397–401.
[52] H.-C. Chou and K.-Y. Han, "Developing a smart walking cane with remote electrocardiogram and fall detection," *J. Intell. Fuzzy Syst.*, vol. 40, no. 4, pp. 8073–8086, Apr. 2021.
[53] B. T. Nukala, N. Shibuya, A. I. Rodriguez, J. Tsay, T. Q. Nguyen, S. Zupancic, and D. Y. C. Lie, "A real-time robust fall detection system using a wireless gait analysis sensor and an artificial neural network," in *Proc. IEEE Healthcare Innov. Conf. (HIC)*, Oct. 2014, pp. 219–222.
[54] T. M. Le, L. V. Tran, and S. V. T. Dao, "A feature selection approach for fall detection using various machine learning classifiers," *IEEE Access*, vol. 9, pp. 115895–115908, 2021.
[55] N. Noury, A. Fleury, P. Rumeau, A. K. Bourke, G. O. Laighin, V. Rialle, and J. E. Lundy, "Fall detection–principles and methods," in *Proc. 29th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2007, pp. 1663–1666.
[56] A. Brull, A. Zubizarreta, I. Cabanes, and A. Rodriguez-Larrad, "Sensorized tip for monitoring people with multiple sclerosis that require assistive devices for walking," *Sensors*, vol. 20, no. 15, p. 4329, Aug. 2020.
[57] S. N. Robinovitch, F. Feldman, Y. Yang, R. Schonnop, P. M. Leung, T. Sarraf, J. Sims-Gould, and M. Loughi, "Video capture of the circumstances of falls in elderly people residing in long-term care: An observational study," *Lancet*, vol. 381, no. 9860, pp. 47–54, 2013.
[58] S. Robinovitch, "Falls experienced by older adult residents in long-term care Homes," *Databrary*, to be published, doi: 10.17910/b7.739.
[59] A. B. Mesanza, S. Lucas, A. Zubizarreta, I. Cabanes, E. Portillo, and A. Rodriguez-Larrad, "A machine learning approach to perform physical activity classification using a sensorized crutch tip," *IEEE Access*, vol. 8, pp. 210023–210034, 2020.
[60] M. Awais, L. Chiari, E. A. F. Ihlen, J. L. Helbostad, and L. Palmerini, "Physical activity classification for elderly people in free-living conditions," *IEEE J. Biomed. Health Informat.*, vol. 23, no. 1, pp. 197–207, Jan. 2019.

ASIER BRULL MESANZA received the master's degree in automation, control, and robotics, in 2017. He is currently pursuing the Ph.D. degree with research focus in the field of intelligent diagnostic systems, artificial neural networks, and the detection of gait patterns. He has been a Control Engineer with the University of the Basque Country (UPV/EHU), since July 2015.

ILARIA D'ASCANIO graduated from the University of Bologna. She is currently a Research Fellow with the Department of Electrical, Electronic, and Information Engineering "Guglielmo Marconi," University of Bologna. She is also an Electronic Engineer. Her research interests include fall detection and gait analysis using wearable sensors.

ASIER ZUBIZARRETA graduated in automation and electronics engineering in 2006, and received the Ph.D. degree in robotics and automatic control systems from the University of the Basque Country (UPV/EHU), in 2010. He is currently an Assistant Professor with the Department of Automatic Control and System Engineering, Faculty of Engineering of Bilbao, UPV/EHU. His research interests include mechatronics, model-based advanced control, and bioengineering.

LUCA PALMERINI received the Ph.D. degree in bioengineering in 2012. He is currently a Junior Assistant Professor with the Department of Electrical, Electronic, and Information Engineering "Guglielmo Marconi," University of Bologna. His main research interest includes the use of machine learning, wearable sensors, and statistics in movement analysis.

LORENZO CHIARI received the Ph.D. degree. He is currently a Professor of ageing and rehabilitation engineering with the University of Bologna, Italy. He conducts his research in the field of biomedical engineering. His research interests include active and healthy ageing, posture and movement analysis, physical activity monitoring, and fall risk assessment with wearable sensors, home-care and tele-rehabilitation, and digital biomarkers discovery.

ITZIAR CABANES received the Ph.D. degree in engineering from the University of the Basque Country (UPV/EHU), Spain, in 2001. She is currently an Assistant Professor with the Department of Automatic Control and Systems Engineering, Faculty of Engineering in Bilbao, UPV/EHU. She is currently the Head of the master Control Engineering, Automation, and Robotics, UPV/EHU. Her research interests include industrial robotics, bioengineering, and the optimization of manufacturing processes. She received the Prize for Outstanding Doctoral Thesis awarded by UPV/EHU, in 2002. She also has seven awards at conferences.