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Machine Learning Based Fall Detector With a Sensorized Tip

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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].

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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.

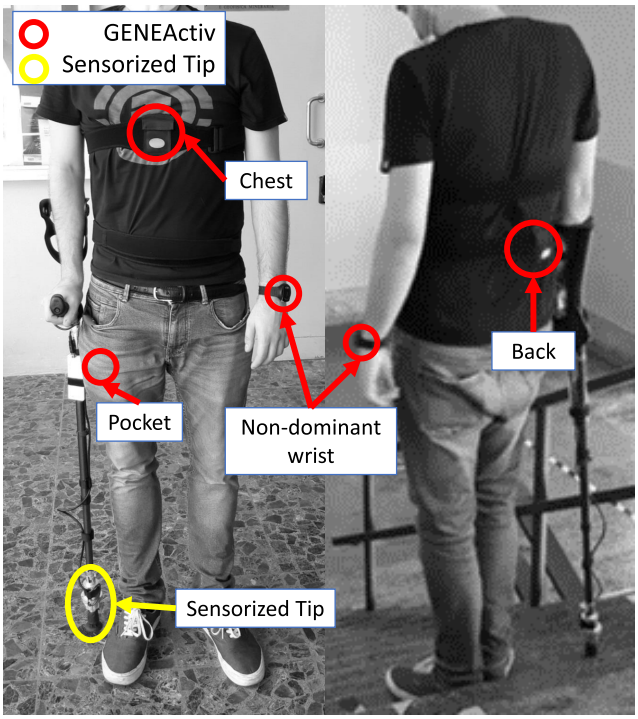

FIGURE 2. GENEActiv accelerometer sensors positions in the body.

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,

$$\alpha = \pi/2 - acos(proj_{\mathbf{Z}}\mathbf{z}/|proj_{\mathbf{Z}}\mathbf{z}|) \quad (1)$$

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 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

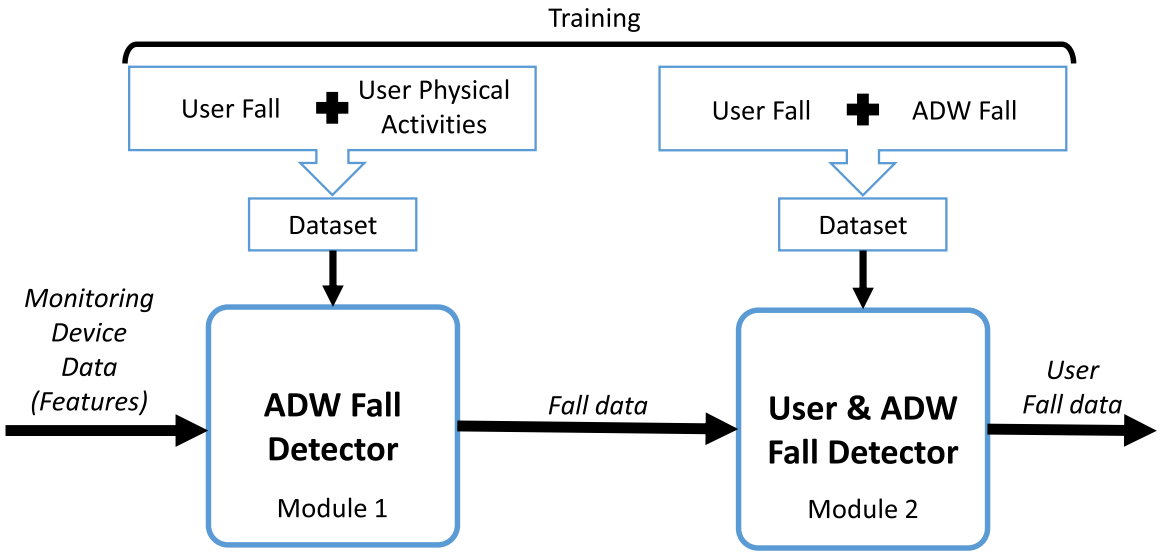

FIGURE 3. Two-module methodology followed for falls detection.

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.

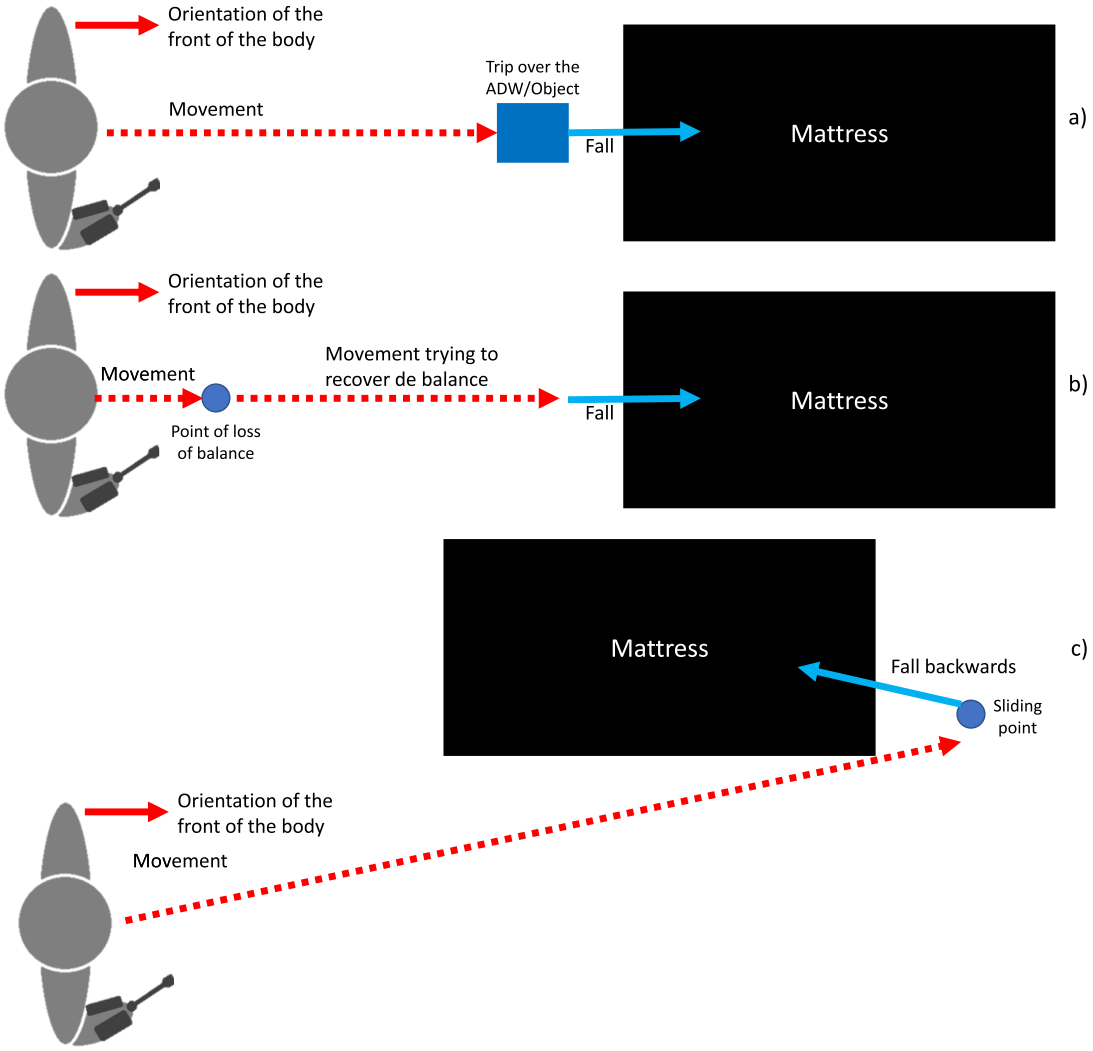

FIGURE 4. Graphical representation of some of the simulated falls during the walking: a) Cases 9, 10, 11, 12 and 13. b) Cases 14, 15. c) Case 16.

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.

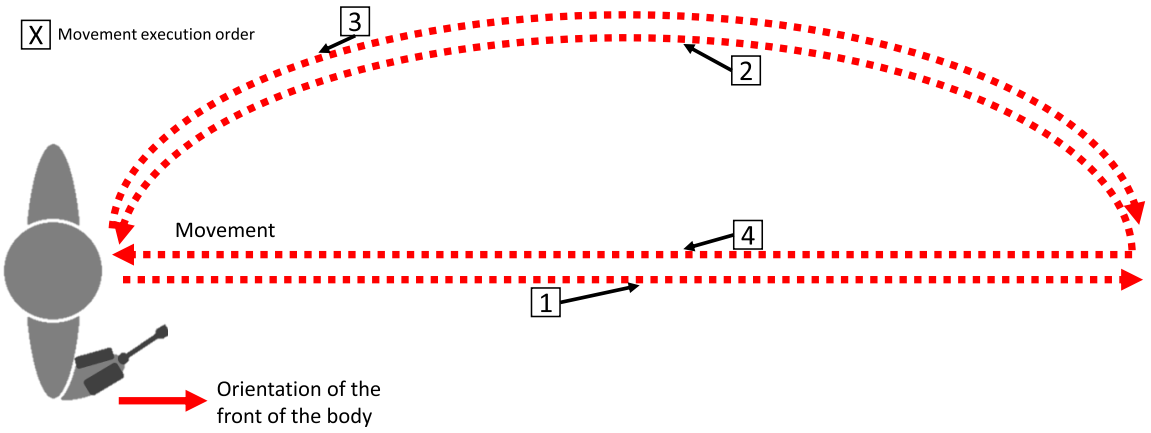

FIGURE 5. Graphical representation of some of the physical activities walking circuit.

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).

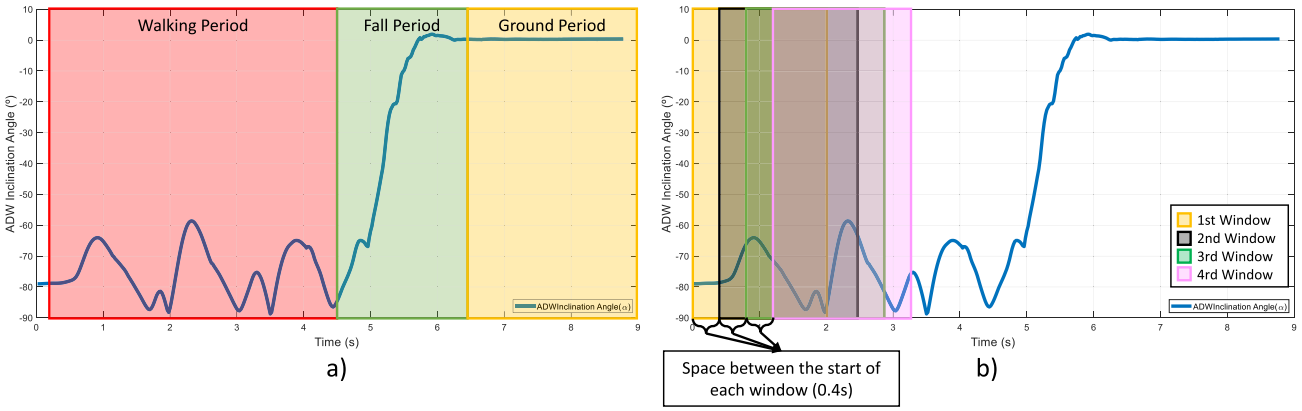

FIGURE 6. Graph of the ADW inclination angle: a) ADW fall time and states. b) Fixed-size window division with space between window starts.

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.

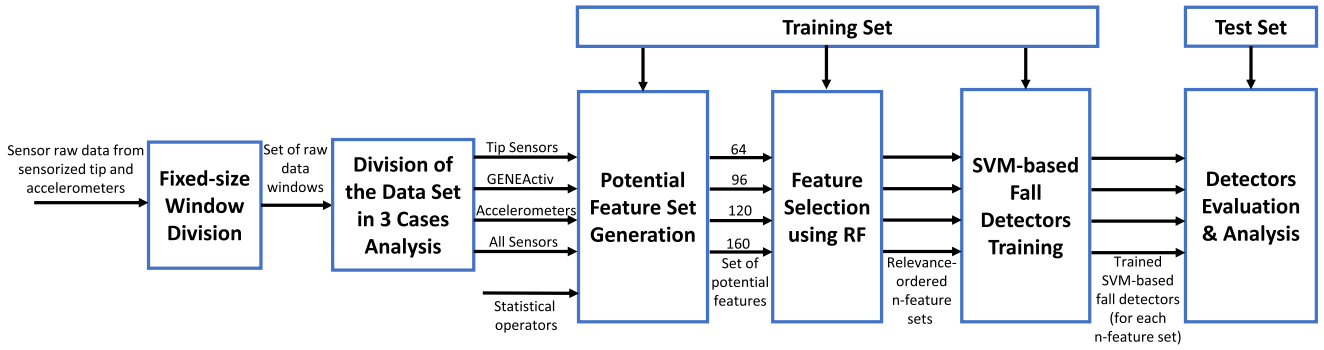

FIGURE 7. Methodology followed for the design of the Fall Detector modules based on Machine Learning.

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.

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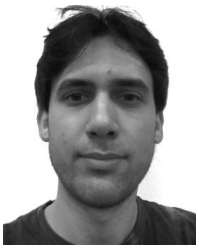

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