Mechatronics. 58 : 70-79 (2019) https://doi.org/10.1016/j.mechatronics.2019.02.002

Inclusive and seamless control framework for safe robot-mediated therapy for upper limbs rehabilitation

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Abstract

Robot-based rehabilitation requires not only the use of a suitable robot, but also an optimal strategy to guarantee that the interaction forces with the patient fit his or her impairment level. In this work, an inclusive and seamless control framework for upper limb rehabilitation robots is presented and validated. The proposed control framework involves 1) a complete set of training modes (assistive, corrective and resistive) that can be adapted to the needs of the different states of the patient's recovery, and 2) three different advanced controllers (position, force, impedance) to track safely the force and motion references defined by the aforementioned training modes. In addition, the proposed framework allows one to tune the parameters critical to the safety of the user, such as the maximum interaction forces or the maximum speed of the robot movement. In order to validate the proposed control framework, a set of experiments have been carried out in the Universal Haptic Pantograph (UHP) upper-limb rehabilitation robot. Results show that the proposed control framework for robot-mediated therapy works properly in terms of adaptability, robustness, and safety, which are crucial factors for use with patients.

Keywords: Adaptive training modes, Inclusive robotic rehabilitation,

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Seamless control, Upper-limb rehabilitation.

1. Introduction

In recent years, stroke has become one of the most common diseases. Every year, more than 15 million attacks are diagnosed [1]. Due to global aging, the number of attacks is expected to increase significantly in the coming years, reaching an estimated 23 million in 2030 [2]. In addition, new medical and therapeutic protocols have increased the survival rate of these patients [3]. Nowadays, an estimated 33 million people have survived to stroke, and have to live with one of its most common sequel: motor deficit. This way, due to the direct impact on the autonomy of the patients, stroke has become the primary cause of physical disability in industrialized countries in the last decades [4].

In absence of surgical or pharmacological treatments, rehabilitation has become essential to improve the quality of life for stroke patients. Rehabilitation programs help to recover lost functionalities and contribute to the recovery of self-esteem, reducing the risk of falling into a state of depression. However, rehabilitation of the lost functionalities is a long process that requires the therapist to both diagnose and treat the patient continuously [5]. As financial and staff limitations exist, traditional rehabilitation programs are usually constrained by time, making it difficult for the patient to achieve full recovery [6]. As a direct consequence, in patients with hemiplegia, recovery of lower extremities is prioritized over upper extremities to maximize the patient's autonomy. However, upper limbs are essential to the performance of daily tasks, and their restoration is critical to improve the quality of life of patients.

In this context, robot-mediated rehabilitation has been proposed in recent decades. Robots can execute the programmed tasks efficiently, with high intensity and precision, and can help to overcome the staff limitations of traditional programs. In fact, several studies have demonstrated that the performance of robot-mediated rehabilitation can be equivalent to the results obtained with traditional therapies [7, 8]. Based on these facts, several robotic devices have been proposed for the rehabilitation of the upper limbs over the last years [9].

However, for rehabilitation robots to be effective, it is important to design not only appropriate mechatronic hardware but also a suitable set of training exercises that can be adapted to the impairment level of the patient. Generally these are designed to be similar to those performed by a physiotherapist in a conventional rehabilitation process. Thus, the exercises are usually based on the guided manipulation of the affected limb, while trying to mimic daily tasks (picking and placing small elements, pushing light elements, opening drawers, etc).

Up until now, robot-mediated rehabilitation exercises have been classified into three main groups: Assistive, Corrective and Opposition training modes [10, 11]. In Assistive Training (which can be subdivided into passive, assistive and active), the robot applies forces in the direction of the motion to be performed, helping the patient to accomplish the exercise. In Corrective Training Modes, the robot helps the patient to move within a predefined region, forcing the patient back into this region if the motion exerted by the user falls outside it. Finally, in Opposition Training Modes the robot hampers the movement of the patient in order to improve his/her movement accuracy and coordination capability. It is important to note that although Corrective and Opposition training modes are regarded as the modes that have more impact in the recovery of the motor function of the patient (especially in the last phases of the recovery), these have rarely been implemented due to their complexity, instability issues and issues of applicability [12, 13].

In order to implement the aforementioned Training Modes in rehabilitation robots, an adequate control strategy is required. In the literature, position control, torque/force control and admittance or impedance control have been used for this purpose. For instance, the MIT-Manus [14, 15], the first rehabilitation robot on the market, uses an impedance controller to drive the robot. Another early robot, MIME (Mirror Image Movement Enabler) [16], and the ARM Guide rehabilitation robot [17] implement a position controller in combination with a torque controller. The ARMin exoskeleton [18], on the other hand, uses admittance and impedance control approaches. The choice of control strategy depends on the particular specification of both the mechanical structure used and the Training Modes to be implemented.

To implement all training modes (Assistive, Corrective and Opposition), a combination of position, torque/force and impedance control algorithms is usually required. For instance, if a high impedance is required for a Training Mode, the controller will be best implemented by a position controller, while if a very low impedance is required, a force controller will be more suitable. For example: the Assistive training mode encompasses three sub-modes that are passive, assistive, and active. In each sub-mode, the robot plays a different role in rehabilitating the limb. The passive mode, for instance, is used in the acute phase for stroke patients, and the robot's role is to move the patient's limb. For this purpose a pure position controller is required. However, in assistive mode, the role of the robot is to help the patient move the limb. Hence, an impedance controller is more appropriate.

A robot-mediated rehabilitation exercise may not be only defined by its training mode. In fact, switching between different modes during a rehabilitation exercise has been demonstrated as an effective approach to maximize patient's involvement as well as training outcomes [5]. This requires an appropriate strategy to switch smoothly between the different low-level controllers, such as the hybrid impedance control proposed in [9]. This technique includes both force-based and position-based impedance control, and the controller selection is carried out by a switching matrix. Using this framework, most of the aforementioned Training Modes can be implemented. For instance, the passive training mode can be implemented using a position-based impedance control, while active mode can be implemented using force-based impedance control. However, the framework proposed by [9] is not appropriate for robots with low mechanical impedance, as the position-based impedance controller can decrease the accuracy of movement in passive modes. For these robots, the best alternative is to combine impedance controllers with pure position and force controllers, as proposed in this work.

Safety is also a critical point when designing low-level controllers, as in most cases the robots are physically attached to patients and operate closely with them in the same workspace. Moreover, rehabilitation robots usually have heavy, high power actuators and stiff joints in order to interact with the patient. This implies that there is risk of serious injury to the patient if the robot does not operate properly [19]. Robot safety can be implemented by imposing constraints to the motion, speed and robot-user interaction forces [20, 21]. Specifically, the motions performed by the robot have to be within the range of motion of the user; the robot must not execute sudden movements but make gentle and robust motions; and the interaction force between the user and the robot should not be greater than the maximum force that the patient can handle, nor should it vary abruptly.

Taking into account this context, this work presents two main contributions to the field of robotic rehabilitation of the upper limbs:

- A comprehensive control framework that involves a complete set of training modes (Assistive, Corrective and Opposition) that can be adapted to the needs of robot-mediated rehabilitation therapies in accordance with any recovery state of patient. To the best of our knowledge, the proposed strategy is the first approach that deals with all three training modes.
- An implementation strategy based on smooth and safe switching between three low-level controllers (position, force, impedance) during training.

The proposed control framework is validated in a specific upper limb rehabilitation robot, the Universal Haptic Pantograph (UHP). This robot is used for the training of the shoulder, elbow and wrist in people who suffer motor deficit after a stroke [22, 23].

The rest of the article is organized as follows. In Section II, the overall structure of the proposed control framework is presented. In Section III, the three low level controllers (position, force, impedance) and the seamless switching strategy are described. In Section IV, several experimental studies with the

UHP robot and a healthy subject are presented, in order to demonstrate the performance of the proposed control framework. Finally, the most important ideas and future works are summarized in Section V.

2. Inclusive control framework for robot-mediated therapy

As stated in the introduction, rehabilitation training exercises should be adapted to the recovery state of the patient, from acute to chronic phases. In this section, an inclusive control framework that involves a complete set of training modes for robot-mediated upper limb rehabilitation is described in detail.

Fig. 1 presents the proposed inclusive control framework. In this framework, the therapist plays an important role in determining the training task (e.g. the game) as well as the training mode. Note that the therapist is aware not only of the patient's current abilities, but also the evolution of his or her state over time. This way, from the user interface, the therapist can select the training level, which groups such parameters as the training time (t_m) or the maximum interaction force ($\mathbf{F_{Max}}$).

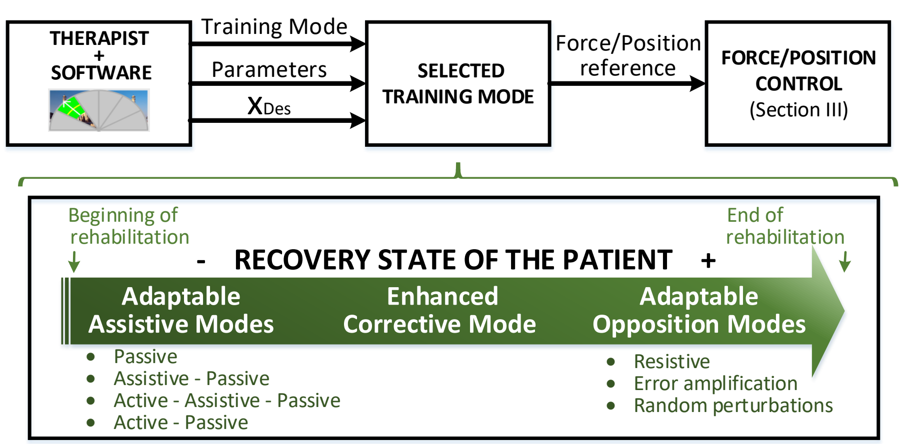


Figure 1: Inclusive Control Framework.

The framework also includes an option to automatically perform flexion motions of the upper limb by the robot. This functionality is designed to allow the patient to focus on the extension motion of the limb. Note that impaired limbs after a stroke tend to contract, making the extension of the limb difficult.

Using the configuration data and the training mode selected by the therapist, proper force ($\mathbf{F_{Ref}}$) and/or position ($\mathbf{x_{Ref}}$) references are generated. These references are followed by the robot using low-level position/force/impedance control strategies, which will be detailed in Section 3.

In the next section we describe in detail the proposed Training Modes for robot-mediated upper limb rehabilitation.

2.1. Adaptable Assistive Training Modes

Assistive Training Mode has been widely studied in the literature. This mode is appropriate for the initial (acute) stages of the rehabilitation process. In this stage, the patient does not have the ability to generate movement, and consequently the robot moves the impaired limb [11]. Hence, the goal of this training mode is to help the patient to move the affected limb and execute the desired movement.

Assistive Training Mode is commonly divided into three sub-modes depending on the level of assistance provided: passive, assistive and active. In the *passive mode*, the robot performs the desired motion ($\mathbf{x_{Ref}}$) without considering user activity [10]. In the *assistive mode* the patient attempts to execute the task and the robot helps by applying an assistive force ($\mathbf{F_{Ref}}$) that depends on the error between the real motion ($\mathbf{x_{Cn}}$) and the desired one ($\mathbf{x_{Ref}}$) [24]. Finally, in the *active mode*, the user is supposed to perform the desired task, and the robot only constraints the range of motion and compensates the gravitational force (weight support) and/or robot inertia ($\mathbf{F_{Ref}} = 0$) [11].

Although each sub-mode has its own role when training is considered, properly combining these modes can maximize training outcome and patient involvement. For example, even if the patient is not fully able to complete the desired motion in the early stages of rehabilitation, encouraging the patient to complete the exercise one way or another would increase his/her motivation and involvement. To this end, appropriate combinations of assistive, active and passive modes is strongly recommended.

In order to adapt the Assistive Training mode to the the recovery state of the patient, an Adaptable Assistive Training methodology is proposed in this work. In this methodology, each Adaptable Assistive Training Mode is defined considering three stages, each of which with a configurable time window ($t_0 \rightarrow t_1$, $t_1 \rightarrow t_2$ and $t_2 \rightarrow t_3$). For each stage, a different sub-mode (passive, assistive or active) is implemented, so that different combinations can be defined, as summarized in Table 1.

	Adaptable Assistive Training Modes			
	High $\leftarrow$ Intensity of the robot assistance $\rightarrow$ *Low*			
Stage 1 ($t_0 \rightarrow t_1$)	Passive	Assistive	Active	Active
Stage 2 ($t_1 \rightarrow t_2$)	Passive	Assistive	Assistive	Active
Stage 3 ($t_2 \rightarrow t_3$)	Passive	Passive	Passive	Passive

Table 1: Adaptable Assistive Training Modes according to the intensity of the robot assistance.

Based on this idea, four Adaptable Assistive Training Modes are proposed (Table 1), which consider all possible states of the patient: from the case in which the patient can barely make voluntary movement (Column 1, *Passive-Passive-Passive Mode*) to the case in which the patient is able to perform some motions (Column 4, *Active-Active-Passive Mode*). Note, however, that both the proper combination of Adaptable Assistive Training Modes, and the the length of each time window ($t_0 \rightarrow t_1$, $t_1 \rightarrow t_2$ and $t_2 \rightarrow t_3$) are to be determined by the therapist based in the recovery state of the patient.

In order to explain the basic idea of the Adaptable Assistive Training methodology, the *Active-Assistive-Passive* adaptable assistive mode (Table 1-Column 3) is considered. When this adaptable assistive mode is activated, in a first stage the robot uses the active mode, providing zero resistance to the motion and allowing voluntary movement of the patient during a first time window ($t_0 \rightarrow t_1$). However, if the patient is not able to initiate the movement during this first time window, the adaptable assistive approach triggers the second stage in which the assistive sub-mode is activated and the robot partially assists limb movement. Finally, if a second time window ($t_1 \rightarrow t_2$) expires and the patient has still not finished the exercise, the adaptive approach triggers a final stage in which the passive mode is activated and the robot drives the limb and finishes the exercise.

The proposed Adaptable Assistive Training Modes allow not only greater adaptability of the robot-mediated therapy but also greater involvement of the patient to finish the rehabilitation task. To operate correctly, however, appropriate control of the reference force ($\mathbf{F_{Ref}}$) and motion ($\mathbf{x_{Ref}}$) and swift and gentle mode changes are required.

2.2. Enhanced Corrective Training Mode

Using the aforementioned Adaptable Assistive Training modes, patients can achieve voluntary movement generation. Hence, the next step in the rehabilitation process is to improve movement coordination. For that purpose, studies reported in the literature point to Corrective Training Modes as being most effective.

The main aim of these modes is to train the patient to correctly track a desired trajectory, rather than simply reaching the final desired point. For that purpose, Corrective Training Modes are based on letting the patient drive the robot (active mode) through a defined region surrounding the desired path, but correcting movements using an orthogonal assistive force when the patient leaves this region. Therefore, in these modes the patient has to be able to execute the exercise without external assistance and the robot's task is to prevent the patient from deviating from a predefined region of the workspace.

The most common corrective training mode is based on tunneling. As detailed before, in this strategy the robot only applies assistance (usually a constant force) if the user leaves a predefined region [10]. For optimal training, however, in this work a progressive assistive force to drive the patient back into the desired region has been implemented. Thus, when the user begins to move away from the desired path, even within the predefined region, a small assistive force is applied to correct the motion error. If this force is not enough and the patient leaves the region, greater force is applied to force the patient into the predefined region. This approach has been named the 'Enhanced Corrective Training Mode'.

Fig. 2 illustrates how the proposed Enhanced Corrective Training Mode works. During training, three cases have been identified depending on the position of the limbs ($\mathbf{x_{Cn}}$) that are being trained by the robot: **A-** $\mathbf{x_{Cn}}$ stays on the desired path ($\mathbf{x_{Ref}}$), **B-** $\mathbf{x_{Cn}}$ is within the desired region, but not on the desired path, and **C-** $\mathbf{x_{Cn}}$ is outside the desired region.

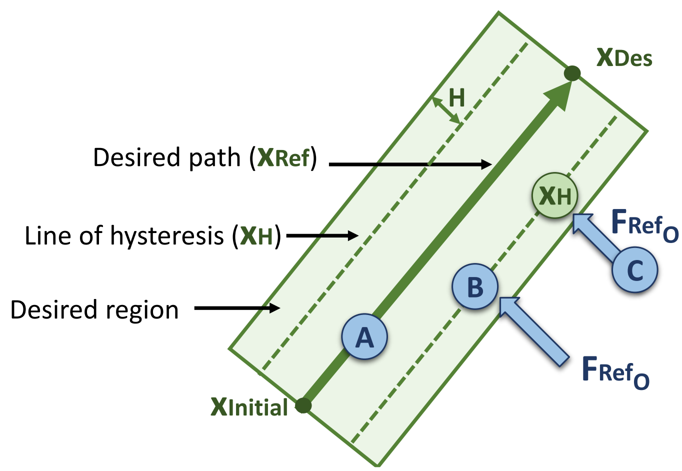


Figure 2: Proposed Enhanced Corrective Training Mode.

In case **A**, which is an ideal case, the patients motion ($\mathbf{x_{Cn}}$) is aligned with the desired path ($\mathbf{x_{Ref}}$) so the orthogonal force ($\mathbf{F_{Ref_O}}$) is zero. If $\mathbf{x_{Cn}}$ starts deviating from $\mathbf{x_{Ref}}$ (case **B**), an assistive force $\mathbf{F_{Ref_O}}$ proportional to the orthogonal error ($\mathbf{x_{Ref}} - \mathbf{x_{Cn}}$) is applied to correct the movement direction. If this force is not enough and the patient continues to deviate (case **C**), $\mathbf{x_{Cn}}$ falls out of the desired region. In this case, the robot must force the limb back into desired region. Note that, for safety reasons, the robot will move the limb not to the boundary of the desired region, but to an inner point within the line of hysteresis ($\mathbf{x_H}$). This avoids possible chattering issues in the boundary line area, as the user has an H margin to react, minimizing the possibility of leaving the region again.

The proposed Enhanced Corrective Training Mode can help to improve the patient's mobility, and more specifically, their ability to perform coordinated movements. However, as mentioned above, it requires switching between force and position control depending on the current position of the limb (cases A, B, C). Hence, a safe and seamless switching technique is crucial to prevent any sudden and undesired behavior of the robot during the transition between controllers within this mode.

2.3. Adaptable Opposition Training Modes

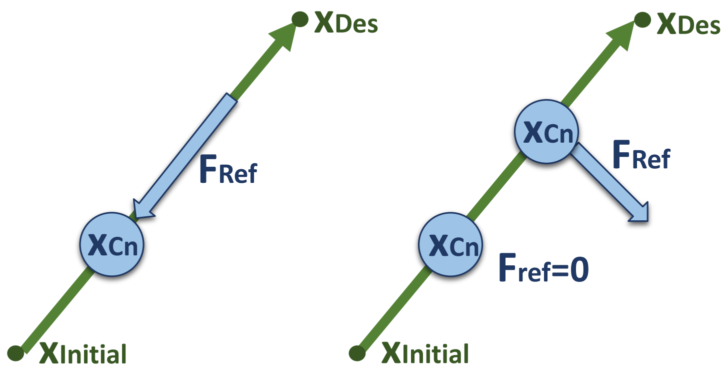
The aforementioned proposed Assistive and Corrective Training modes are designed so that the patient can recover the main functionality of the impaired limb and coordinate its motion. However, in the last stages of the rehabilitation program, and in order to fully recover, it is important to improve the strength and dexterity of the limb. For this purpose, Opposition Training Modes are considered to be the best alternative [13]. In these training modes, the robot exerts opposition forces to user motion, increasing the difficulty of the task.

In this work, three Adaptable Opposition Training Modes are proposed: resistive, error amplification and random disturbances. Each mode is described briefly below:

1. *Resistive mode*: in this mode, the robot applies a force in the opposite direction of the desired trajectory, simulating the compression of a spring (Fig 3.a).

   The exerted resistive force ($\mathbf{F_{Ref}}$) is inversely proportional to the difference between the limb position ($\mathbf{x_{Cn}}$) and the desired ($\mathbf{x_{Des}}$) one. In this way, the opposite force increases as the limb position ($\mathbf{x_{Cn}}$) approaches the desired one ($\mathbf{x_{Des}}$). This helps the patient to modulate the force of the impaired limb.

   Note that the maximum resistive force ($\mathbf{F_{Max}}$) to be exerted by the robot is configurable, giving the therapist the possibility to adapt the exercise to the patient's current state of recovery. This maximum force value is always applied in the desired (final) position, which means that $\mathbf{F_{Ref}} = \mathbf{F_{Max}}$ when $\mathbf{x_{Cn}} = \mathbf{x_{Des}}$, while the force at the beginning of the exercise (the initial position) is zero ($\mathbf{F_{Ref}} = 0N$) when $\mathbf{x_{Cn}} = \mathbf{x_{Initial}}$.



(a) Resistive (b) Error amplication

Figure 3: Opposition training modes: (a) Resistive and (b) Error amplification. Note that the circles represent the current position of the robot ($\mathbf{x_{Cn}}$).

2. *Error amplification mode*: this mode has been proposed based on the notion that kinematic errors generated during the movement provide fundamental neuronal signals that enhance the learning process of the patients motor system [24, 25].
   Based on this idea, in this mode, the rehabilitation robot increases the error caused by the user by applying an additional disturbance force in the orthogonal direction to the trajectory (Fig 3.b). This disturbance force ($\mathbf{F_{Ref}}$) varies with the motion error: when the error is small (the patient is following the desired path) the force is zero, but when the patient moves his/her limb away from the desired path, additional disturbance forces are applied. Note that, as in the resistive mode, the exerted disturbance force ($\mathbf{F_{Ref}}$) is limited by a maximum force value ($\mathbf{F_{Max}}$) selected by the therapist, which will depend on the state of the patient.
3. *Random disturbances mode*: this mode focuses on the training of the neural responses in the case of unexpected situations. While it is known

that humans have the ability to adapt to their environment by learning to overcome external disturbances or unexpected forces, humans tend to make erroneous moves in the opposite direction to the force when the disturbance forces are unexpectedly removed [13]. By this process, humans learn how to deal with such cases, resulting in the improvement of neural responses.

The aim of this mode is to train these neural responses. For that purpose, the robot applies different disturbance forces during the exercise that vary randomly, so that the patient has to overcome their effect while trying to reach the desired position. As in other modes, the applied force ($\mathbf{F_{Ref}}$) is limited by the maximum force ($\mathbf{F_{Max}}$) selected by the therapist.

In summary, the proposed Adaptable Opposition Training Modes allow to improve the dexterity of upper limbs in terms of force and motion. However, as in the previous cases, it is necessary to control both contact force and motion between the user and the robot in all possible directions of the motion range, which means that safe and seamless switching techniques between force and position controls is also required.

3. Control architecture for safe and seamless force/impedance/position control

As stated in the previous section, proper control approaches are required to implement the proposed Training Modes (Fig. 1). Moreover, their requirements are different in terms of force and motion, requiring a set of controllers to fulfill all the needs. In this work, a set of three control algorithms (force, position and impedance) are proposed to implement the proposed Training Modes (Fig. 4):

1. *Impedance Controller*: The impedance controller is suitable for most of the proposed training modes (For instance for Assistive, Corrective, Resistive and Error Amplification Modes). The role of this controller is to track a

reference impedance,

$$\mathbf{Z_{Des}}(s) = \frac{\mathbf{F_{Ref_I}}(s)}{\mathbf{x_{Ref}}(s) - \mathbf{x_{Cn}}(s)} = \mathbf{K} + \mathbf{B}\ s + \mathbf{M}\ s^2 \quad (1)$$

where $\mathbf{x_{Ref}}$ and $\mathbf{x_{Cn}}$ are the reference and current positions of the robot, $\mathbf{F_{Ref_I}}$ is the force reference generated by the impedance controller, $\mathbf{K}$ the stiffness matrix, $\mathbf{B}$ the damping matrix, $\mathbf{M}$ the inertia matrix and $\mathbf{Z_{Des}}$ the desired mechanical impedance of the robot [26].

In order to comply with safety requirements, the desired impedance ($\mathbf{Z_{Des}}$) is selected such that the force reference generated by the impedance controller ($\mathbf{F_{Ref_I}}$) is always less than the maximum force ($\mathbf{F_{Max}}$) defined by the therapist. Moreover, to prevent sudden changes in the force generated by the robot that may harm the patient, a limit to the the first time-derivative of the force ($\mathbf{F_{Ref_I}}$) is included.

2. *Force Controller*: The force controller is used to follow either a force reference generated by the impedance controller ($\mathbf{F_{Ref_I}}$) or a pure force reference ($\mathbf{F_{Ref}}$). This latter case is used, in Active Mode, where $\mathbf{F_{Ref}} = 0N$, and Random Disturbances Mode where $\mathbf{F_{Ref}}$ vary randomly.

   The force controller is implemented using a PID control that compares the reference force ($\mathbf{F_{Ref}}$) and the current patient/robot interaction force ($\mathbf{F_{Cn}}$). Note that the controller output needs to be projected to the input of the actuator system control loop ($\tau_{\mathbf{m_F}}$), which will depend on the particular structure of the rehabilitation robot. Similarly, the measurement of the patient/robot interaction force ($\mathbf{F_{Cn}}$) can be carried out using a proper force sensor, or using force estimators.

   In the particular study case analyzed in Section IV, the Universal Haptic Pantograph rehabilitation robot, the dynamic model of the robot is used to estimate the interaction force ($\mathbf{F_{Cn}}$) as detailed in [27]. And the force controller is used to generate a reference ($\tau_{\mathbf{m_F}}$) to the low-level PID controller that controls the Serial Elastic Actuator system of the robot.

3. *Position Controller*: The position controller is mainly applied in cases where the user is not able to complete the exercise, or the positioning ac-

curacy of the impedance/force controller is not enough to guarantee proper task execution due to the maximum impedance limit of the rehabilitation robot. This controller is mainly used in Passive Mode, where the position controller tracks the desired position reference ($\mathbf{x_{Ref}}$) regardless of the interaction between the user and robot. For safety reasons, the motion speed is limited, being possible to select a different value according to the status of the patient. In addition, a fifth-order trajectory generator is used to generate smooth and robust position reference trajectories.

The position controller is a PID controller which, based on the error between the position reference ($\mathbf{x_{Ref}}$) and the current robot position ($\mathbf{x_{Cn}}$), computes the torque/force command ($\tau_{\mathbf{m_P}}$) for the actuation system of the robot. Note that the current robot position ($\mathbf{x_{Cn}}$) is usually estimated using the kinematic model of the robot [22].

As in the force controller, the particular parameters of the controller depends on the specific structure and actuation system of the rehabilitation robot. In the particular study case analyzed in Section IV, the Universal Haptic Pantograph rehabilitation robot, a classical servocontrol scheme with nonlinear compensation has been implemented as defined in [28].

The implementation of the Training Modes proposed in Section II requires the implementation of all aforementioned controllers. Moreover, in several of these modes, multiple controllers need to be combined, which requires switching between them. This is critical, for instance, in Adaptable Training Modes. However, suddenly switching from one controller to another can lead to instabilities and force/motion oscillations in the transition, which may harm the patient. Hence, a proper switching strategy is needed to prevent those undesired situations.

In this work a state-machine-based approach has been implemented to safely manage controller switching, as depicted in Fig. 4. This state machine generates two Boolean signals (I_C and F_C), which are used to: a) determine the controller corresponding to the selected training mode; and b) control the inputs of all engaged and unengaged controllers in order to prevent sudden motions of the robot.

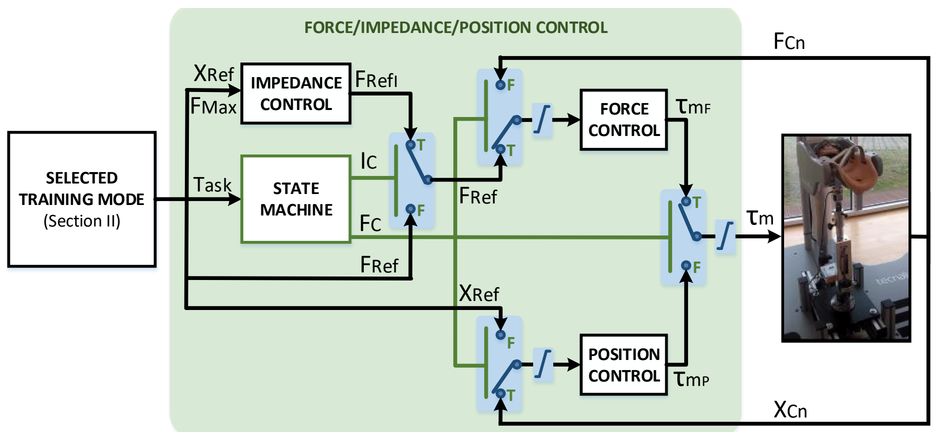


Figure 4: Control architecture and safe and smooth control switching approach.

Table 2 shows how both controller and controller inputs are determined by the Boolean signals. For instance, when both I_C and F_C are true (T) the impedance controller is engaged ($\tau_{\mathbf{m}} = \tau_{\mathbf{m_F}}$); when F_C is true (T) but I_C is false (F), the force controller is engaged ($\tau_{\mathbf{m}} = \tau_{\mathbf{m_F}}$); and the position controller is engaged ($\tau_{\mathbf{m}} = \tau_{\mathbf{m_P}}$) when both signals are false (F). Note that when a controller is not engaged, its input is connected to the current value of the corresponding variable ($\mathbf{x_{Cn}}$ for position and $\mathbf{F_{Cn}}$ for force) so that when the controller is engaged, the control can start smoothly from its current value, resulting in stable operation of the robot.

Table 2: Determination of the control mode and controller inputs by the state machine.

Boolean signals		**Control**	**Controller input**		**Actuator input**
$\mathbf{I_C}$	$\mathbf{F_C}$	**mode**	***Force***	***Position***	$\tau_{\mathbf{m}}$
T	T	Impedance	$\mathbf{F_{Ref_I}}$	$\mathbf{x_{Cn}}$	$\tau_{\mathbf{m_F}}$
F	T	Force	$\mathbf{F_{Ref}}$	$\mathbf{x_{Cn}}$	$\tau_{\mathbf{m_F}}$
F	F	Position	$\mathbf{F_{Cn}}$	$\mathbf{x_{Ref}}$	$\tau_{\mathbf{m_P}}$

In addition, a rate limiter has been introduced in the input of both force and position controllers, and the input of the actuator control system (Fig. 4). This allows a progressive setpoint change, eliminating sudden actuator torque changes.

4. Experimental Validation

The main goal of this section is to demonstrate the adaptability, robustness and safety of the proposed control framework for rehabilitation purposes. For that purpose, an experimental validation of the framework is presented, based on several tests carried out with the help of a healthy subject.

4.1. Universal Haptic Pantograph

The Universal Haptic Pantograph (UHP) (Fig. 5) is a rehabilitation robot developed for upper limb training of people who suffer motor deficit after a stroke. The robot is an enhanced version of the previously designed Universal Haptic Drive (UHD), which was described in detail in [29]. While the UHP uses the same elastic component-based drive system as that used in the UHD, in the new version the interaction of the patient with the robot is carried out using an innovative pantograph-shaped mechanism [22].

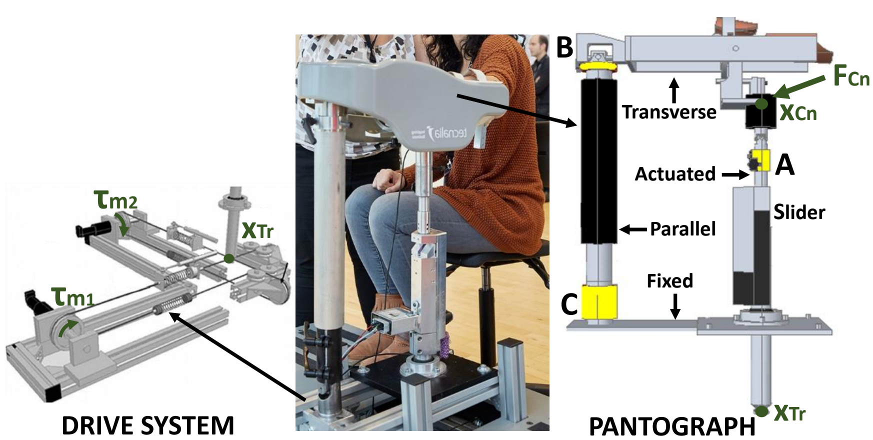


Figure 5: Universal Haptic Pantograph (UHP) rehabilitation robot.

As shown in Fig. 5, the pantograph structure is a four-bar structure composed of three movable bars (actuated, transverse and parallel) and a fixed bar. The actuated bar is connected to the elastic drive system at the transmission point $\mathbf{x_{Tr}}$, while the contact point with the patient is $\mathbf{x_{Cn}}$. The transverse bar is used as a support for the hand and forearm of the patient. Finally, the parallel and fixed bars are used to support the rest of the structure, giving robustness to the robot.

One of the main advantages of the UHP is the possibility of varying its mechanical structure through three lockable/unlockable joints located in the pantograph joints **A**, **B** and **C** and a slider placed in the actuated bar (Fig. 5). Thanks to this reconfigurable structure, the UHP allows eight mechanical configurations or rehabilitation modes which can be easily modified by the therapist with minimal effort [30]. This way, all the joints of the upper limb (wrist, elbow, shoulder) can be rehabilitated with a single device.

This work focuses on one of the most complete modes: the ARM operation mode. This mode allows rehabilitation exercises associated with the three shoulder movements (rotation, flexion/extension and abduction/adduction) and flexion/extension movement of the elbow. Note that in ARM mode, due to its mechanical configuration, the robot workspace is a partial spherical surface, allowing the user to perform quasi-planar reaching movements.

4.2. Experimental setup

The proposed control framework (Figs. 1 and 4) was implemented on a National Instruments CompactRIO platform using Labview Real-Time programming software. Communication between the robot and the CompactRIO platform is achieved using analog and digital data acquisition cards, while UDP (User Datagram Protocol) is used to communicate with a graphical user interface (GUI).

This GUI provides the functionalities required for user interaction, and is based on the Telereha rehabilitation software [31]. The software provides different sets of games for the patient, including one to train reaching movements

(Fig. 6). This game defines 6 reaching points on a half-circle of radius $0.14m$ in the xy plane which is mapped into the range of motion of the UHP robot in ARM mode. The training modes and controllers detailed in Sections II and III have been implemented in this framework and connected with this game.

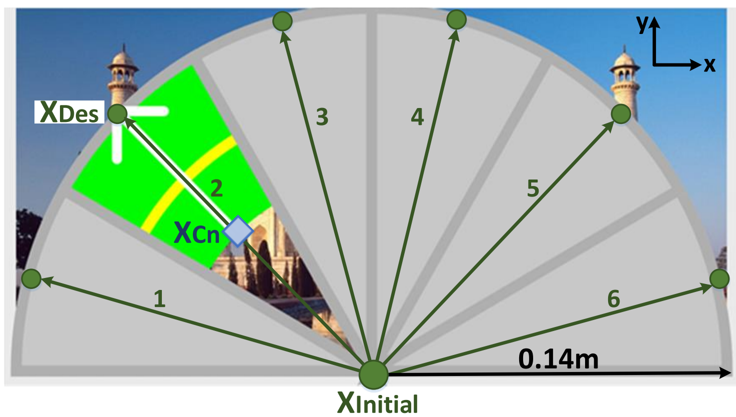


Figure 6: Desired points (green circles) and path (green lines) for the reaching exercise in the game from Telereha rehabilitation software.

As the objective of the experiments is to validate the proposed control framework in terms of applicability, adaptability, robustness and safety, a healthy subject was selected to perform the tests. From the proposed set of Training Modes, Assistive (active-assistive-passive), Corrective and Opposition (resistive) modes were tested. Table 3 shows the parameters used in the experiments.

4.3. Results and discussions

In this subsection the most important results are evaluated and conclusions are drawn for each tested training mode.

4.3.1. Adaptable Assistive Training Mode

Fig. 7 shows the performance of the robot in the case of 'active-assistive-passive' training mode, which is one of the Adaptable Assistive Training Modes proposed (Table 1). In the first plot, the directions (θ) of the desired reaching points in the xy plane are shown, while the second presents the desired setpoint

<table>
<thead>
<tr><th>Desired positions</th><th>Total time $\mathbf{t_m}$</th><th>Training modes</th><th>Max. force $\mathbf{F_{Max}}$</th><th>Max. force change</th></tr>
</thead>
<tbody>
<tr><td rowspan="3">Randomly selected from the 6 points (Fig. 6).
- Distance from $\mathbf{x_{Initial}}$ to all $\mathbf{x_{Des}}$ is $0.14m$
- $\mathbf{x_{Des}}$ is detected by the direction (angle, θ)
- Automatic flexion movement with $3s$ (0.47m/s)</td><td rowspan="3">$120s$</td><td>Assistive
(active-assistive)
-passive)
$t_0 \rightarrow t_1 = 7s$,
$t_1 \rightarrow t_2 = 4s$,
$t_2 \rightarrow t_3 = 3s$</td><td>$25N$</td><td rowspan="3">$8.33N/s$</td></tr>
<tr><td>Corrective
(Fig.2)</td><td>$20N$</td></tr>
<tr><td>Opposition
(resistive, Fig.3)</td><td>$30N$</td></tr>
</tbody>
</table>

Table 3: Parameters used in the validation experiments.

($\mathbf{x_{Des}}$) and the current motion ($\mathbf{x_{Cn}}$) of the robot in the direction of the trajectory. In the third plot, the current ($\mathbf{F_{Cn}}$) and reference ($\mathbf{F_{Ref}}$) user/robot interaction forces in the direction of the trajectory are shown. The blue, orange and green regions correspond to the active, assistive and passive modes respectively. Automatic flexion movement (return) is performed in the white region using a position controller. Note that in the experiment, reaching and return motions were executed for randomly selected desired points. Numbers 1, 2, ... 6 in the upper part of the first plot indicate the region of the game where the user has performed the exercise (see Fig. 6).

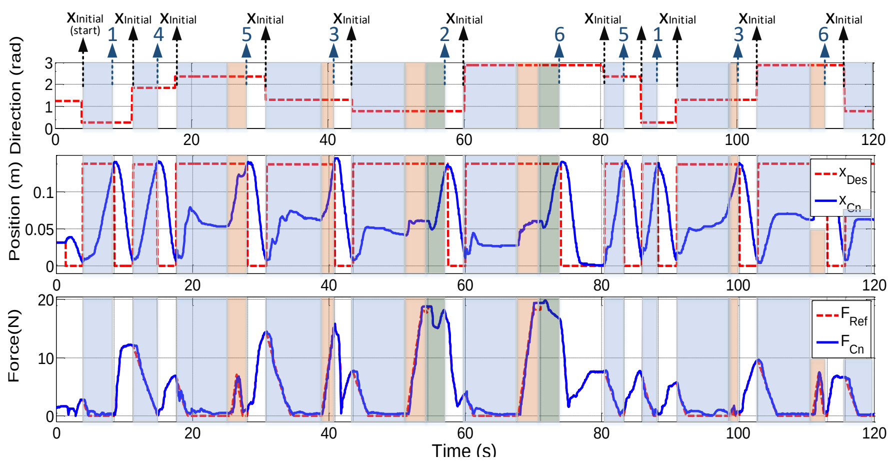


Figure 7: Performance in the active-assistive-passive Adaptable Assistive Training sub-mode.

As can be seen in the data, the subject adopted several different behaviors to emulate a real patient. In the first iteration, after starting the training, the active mode was activated and the subject voluntarily moved to the robot in order to reach desired point (blue region), while force control was applied to provide a zero interaction force effect for the user ($\mathbf{F_{Ref}} = \mathbf{F_{Cn}} = 0$).

In the third iteration ($18s - 25s$, desired point 5), the subject intentionally stopped the motion in the middle of the exercise. In order to finish the exercise, after 7 seconds, in stage 2, the assistive mode that uses impedance control was activated to help the subject complete the reaching motion (first orange region). Note that in this region, the assistive force was proportional to the position error.

In the fifth iteration ($51s-55s$, desired point 2), the subject also intentionally stopped the motion in the middle of the exercise, and in addition, resisted the assistive force by maintaining the position of the robot constant. It can be seen that the robot engaged the assistive mode (orange region) and larger assistive forces than in the previous case (around $20N$) were generated to try to move the robot to the desired point. Finally, as the robot detected that the subject was unable to reach the desired point ($\mathbf{x_{Des}}$), the passive mode is engaged as the third and final stage (green region). In this mode, a position controller was activated and the robot finished the task.

4.3.2. Enhanced Corrective Training Mode

Fig. 8 shows the performance of the proposed control framework in the Corrective Mode. In the first plot, Direction represents the angle (θ) associated to the region of each desired point $\mathbf{x_{Des}}$. The region number is indicated in the top of the plot (see Fig. 6). The second plot represents the absolute error of the motion ($\mathbf{e} = |\mathbf{x_{Des}} - \mathbf{x_{Cn}}|$) in the orthogonal direction of the desired trajectory. In the third plot, the current ($\mathbf{F_{Cn}}$) and desired ($\mathbf{F_{Ref}}$) user/robot interaction forces in the orthogonal direction of the desired trajectory are illustrated.

The blue areas in the plot indicate that the subject is within the desired region. In these areas, the impedance control is engaged, and it applies a corrective force proportional to the trajectory tracking error. The orange areas highlight when the user has left the desired region, and the position control is engaged to force the user to return to the safe area. The automatic flexion movement is indicated in white, as in the previous section.

From the shown data, the performance of the Enhanced Corrective Training Mode can be evaluated. Note that in the two first iterations of the exercise, the subject tried to follow the desired trajectory as close as possible, making the tracking error almost zero. In this ideal case, no corrective force is applied.

However, in the third iteration ($18s$, desired point 1), the subject intentionally started moving away from the desired trajectory to test the corrective mode.

As it can be seen, error increases from $t = 22$ seconds on, and the impedance controller applies a proportional corrective force to assist the subject, helping him/her back to the desired trajectory.

Finally, in the fifth iteration ($48s$, desired point 5), the user intentionally deviates from the desired trajectory and leaves the desired region at $t = 56s$. When the region boundary is traversed, the UHP robot engages the position control to force the user back to this region (orange zone). Note that the force increased and the position error was reduced to a safe (albeit nonzero) value inside the desired region ($t = 56 - 58s$), after which the impedance controller was engaged again. It is important to point out that the controller transition was smooth from the force and position point of view.

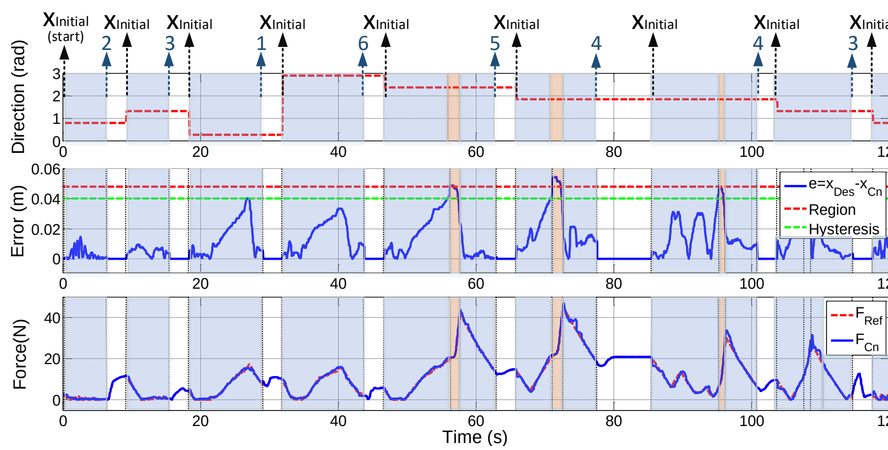


Figure 8: Performance in the Enhanced Corrective Training Mode.

4.3.3. Adaptable Opposition training mode

Fig. 9 shows the performance of the robot in the case of resistive training, which is one of the Adaptable Opposition Training Modes described in Fig. 3. As in the previous cases, the first plot represents the region of the game where the exercise was performed, the second plot represents the desired and current robot position and the third plot, the user/robot interaction force. In addition, the blue regions correspond to limb extension movements with resistive forces, while the white regions represent the automatic flexion movement performed by the position controller.

In this training exercise, the user tried to reach the desired points while the UHP applied resistive forces in the opposite direction of the desired trajectory using an impedance controller. In the different iterations it can be seen that the resistive forces were inversely proportional to the position error. In this way, zero resistive force was applied in the initial point $\mathbf{x_{Cn}} = \mathbf{x_{Initial}}$, and maximum in the desired point $\mathbf{x_{Cn}} = \mathbf{x_{Des}} = 0.14m$. The data confirms that the designed training mode works properly and the controllers are switched safely as well as seamlessly.

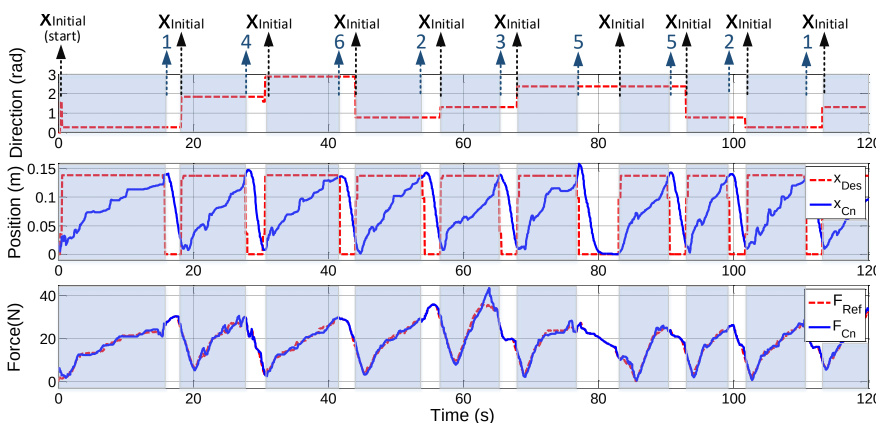


Figure 9: Performance in the resistive training mode.

Summing up, the results obtained experimentally with the UHP rehabilitation robot show that the proposed control framework can be applied to any recovery phase of the rehabilitation procedures for patients with neuromuscular diseases. In the framework, the therapist plays an important role in determining not only the right training mode but also safety parameters such as maximum interaction force and velocity. Although this study was focused on a specific rehabilitation robot with only one training game for a reaching exercise, the framework can be extended in a straightforward manner to other types of upper limb rehabilitation robots and training games for different types of exercises.

5. Conclusion

In this work an inclusive and seamless control framework for upper limb rehabilitation robots was presented. The proposed control framework can be adapted to different stages of the rehabilitation process and can be configured to fit the needs of each patient considering his/her recovery state.

The control framework contains a complete set of training modes: Assistive, Corrective and Opposition training modes. Assistive modes are appropriate for patients in acute phase where active help from the robot is required to properly perform the rehabilitation exercise. Corrective modes are used to improve the impaired limb motion coordination once the patient has gained the ability to move. Finally, Opposition training modes focus on the improvement of dexterity by applying disturbance forces during the exercises and are used in the last phase of the rehabilitation process.

To effectively implement the proposed training modes three controllers have been implemented: impedance, force and position. These are combined in each training mode, requiring switching from one to the other in the middle of the exercise. For that purpose, a state machine-based approach has been implemented, which ensures safe and smooth transitions from one controller to another.

Validation of the proposed control framework was conducted in a specific upper limb rehabilitation robot, the Universal Haptic Pantograph (UHP). To validate the approach, a training game for emulating reaching exercises was used while a healthy subject emulated different patient behaviors. Results show that all training modes and controllers worked properly in terms of adaptability, robustness, and safety. In addition, the extension of the proposed framework to other upper-limb rehabilitation robots is straightforward.

On the basis of the performance that we have achieved, we intend in the future to apply the proposed framework to rehabilitation processes covering a wide span of motor impairments caused by neuromuscular diseases.

Acknowledgment

This work was supported in part by the Basque Country Governments (GV/EJ) under grant PRE-2014-1-152, UPV/EHU's PPG17/56 project, Basque Country Governments IT914-16 project, Spanish Ministry of Economy and Competitiveness' MINECO & FEDER inside DPI2017-82694-R project, Euskampus, FIK and Spanish Ministry of Science and Innovation PDI-020100-2009-21 project.

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