CHAPTER

5

Assistive controllers and modalities for robot-aided neurorehabilitation

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INTRODUCTION

Therapy robots have been specifically designed to deliver and/or support rehabilitation exercises for neurological patients, in particular stroke survivors. The existing robot therapy devices differ widely in terms of their mechanical design, number of degrees of freedom, and control architectures [1]. One feature common to all is that they incorporate sensors of different types, including movement sensors. Hence, both therapeutic and measurement functions are integrated into the same device. As therapeutic devices, robots can be programmed to implement a variety of highly reproducible, repetitive exercise protocols and/or interaction modalities. As measuring devices, they are capable of detecting and quantifying many aspects of both the movement and the physical interaction with the user (movements, forces, and possibly also physiological signals).

Therapy robots are conceived and designed to promote neural plasticity processes through motor learning/relearning; such learning is considered a key element for successful neurorehabilitation. This is based on recent findings showing that it is not the movement per se (such as obtained through passive mobilization) that is effective in promoting plasticity but rather movement associated to *volitional effort*, that is, involving purposeful actions and tasks [2,3]. There are two different ways to enhance the voluntary control during neuromotor rehabilitation of an impaired limb: (1) by providing (electric) assistance through functional electric stimulation or (2) by using robots to facilitate goal-oriented exercise. The two methods of assistance (electric and haptic) are complementary, and the literature provides some examples showing increased beneficial effects when the two modes are used in combination [4,5]; see also Chapter 20 for details. In the following sections, we discuss the different types of haptic assistance that a therapy robot can provide to the patient during training.

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THERAPEUTIC EXERCISES

Different approaches have been proposed for the use of robots to promote neuromotor recovery. Early approaches were mostly heuristic and limited by the available hardware that had been designed for industrial applications. More recent applications are based on an improved understanding of the physiology of the nervous system reorganization after a lesion. Following the taxonomy proposed by Marchal-Crespo et al. [6], existing approaches to robot-assisted exercise can be summarized into three broad scenarios: haptic simulation, challenge-based, and assistive.

HAPTIC SIMULATION

Robots are used for haptic rendering in virtual environments—in the virtual environment, the subject can exercise with a variety of interaction tasks, generally inspired by activities of daily living (ADLs). Robots in combination with visual displays allow the joint visual and haptic interaction with virtual objects. The advantages of a virtual environment over practice in a real-life context include greater safety and flexibility, better adaptation to the individual subject ability, and the possibility to quantify performance.

CHALLENGE-BASED

The robot provides disturbances and/or perturbations to make a task more difficult or challenging with respect to performance without the robot. Several approaches have been proposed. During exercise, the robot can generate perturbations that oppose the subject's movement or compel the subject to provide a greater force. The robot may also be programmed to generate dynamic environments that have a destabilizing effect, for example, negative viscous forces [7]. Another possibility is to visually amplify motor errors. The rationale underlying challenge-based scenarios is that making the task more difficult during training will later result to an improved performance in unassisted or unperturbed exercises.

A number of studies have pointed out that training within negative viscous fields, that is, destabilizing forces that are proportional to movement velocity and equal direction, has a facilitatory effect on sensorimotor adaptation [8]. It has been suggested that the greater variability induced by negative viscosity leads to a greater amount of exploration and therefore a faster and more accurate adaptation to unfamiliar dynamics [9,10]. Training within negative viscosity was also found to facilitate neuromotor recovery from stroke [11].

ASSISTIVE

The robot provides forces that facilitate task performance or task completion. The goal is to help the subject move the impaired limb in specific goal-oriented tasks such as grasping, reaching, and walking.

These categories are not mutually exclusive, in the sense that they can be combined in a given application. In addition, there is no immediate association between one or other approach and specific robots. Rather, all robots can be programmed to work according to each of the above scenarios. For a comprehensive review of robot therapy scenarios, the reader is referred to [6].

ASSISTIVE SCENARIOS

Assistive scenarios are widely used in rehabilitation because they are flexible enough to fit a wide range of impairments. In assistive scenarios, robot devices have been frequently used to enforce passive movements. Repetitive passive training may improve recovery, at least in specific clinical conditions, as it counteracts the deterioration of the mechanical properties of tendon and muscle tissues that are an indirect consequence of the reduced mobility associated with limb paresis. However, better results are obtained when exercise takes into account the adaptive nature of the nervous system and forces the patient to execute voluntary movements.

The notion of "assistance," whether electric or haptic, is closely related to the patient's intention to move. Intention to move can be assessed either directly or indirectly. Direct approaches rely on recording the brain or muscle activity (EEG or EMG), and motor intention can be inferred even from extremely reduced mobility patterns [12,13]. In some devices, the recorded signal is used as an indicator of effort generation to trigger assistance [14]. Other devices generate assistive forces proportional to the amplitude of the processed EMG so providing a sort of "proportional myoelectric control" for the arm [15].

Indirect approaches rely on the notion that robot action must be controlled/modulated in such a way to avoid the phenomenon of "slacking" (see below for details), that is, a reduction of the subject's voluntary control as a consequence of the minimization of effort in assisted movement or passive mobilizations [16,17]. Irrespective of the detection method adopted, when the subject's intention to move is recognized, it triggers the robot controller to provide and/or modulate the proper form of assistance through specific modalities.

ASSISTIVE CONTROLLERS

Like haptic rendering, assistance (or resistance) is obtained through the use of controllers in which the robot guides the movement along a desired path. For an end-effector robot for upper-limb rehabilitation, for example, assistance is described by the following linear proportional-derivative controller:

$$F(t) = K_P \cdot \left[x_d(t) - x_H(t)\right] + K_D \cdot \left[\dot{x}_d(t) - \dot{x}_H(t)\right] \tag{1}$$

where $x_d(t)$ is the desired trajectory, $x_H(t)$ is the trajectory of the hand, and K_P and K_D are the proportional and derivative constants of the controller. More often, the controller does not specify the desired trajectory, but simply constrains movements to be directed toward a target, x_T:

$$F(t) = K_P \cdot \left[x_T - x_H(t)\right] - K_D \cdot \dot{x}_H(t) \tag{2}$$

where K_P and K_D are, respectively, the position and velocity gains (i.e., the controller's apparent stiffness and viscosity).

One problem with the above controller is that it does not limit the force magnitude. For safety reasons, a constant-magnitude assistive force is often preferred:

$$F(t) = F_A \cdot \frac{x_T - x_H(t)}{\left|x_T - x_H(t)\right|} \tag{3}$$

In this way, the force is always directed toward the target but has a constant magnitude, F_A.

One special case of assistive controller is the situation in which the robot simply counteracts the effects of body dynamics, either partly or totally. The T-WREX device, commercialized as ARMEO (Hocoma, Switzerland), is a passive orthosis that uses springs to counteract the effect of gravity in three-dimensional arm movements [18]. In a similar way, all gait robots are equipped with weight support devices that compensate for body weight during robot-assisted gait movements. These weight compensation devices represent a form of assistance. Using the ACT^{3D} device, Ellis et al. [19] imposed forces on the arm to either increase or decrease the amount of limb support required to the subject and measured the workspace explored during planar free reaching movement as a function of active limb support. They concluded that progressive shoulder abduction loading can be utilized to ameliorate the reaching range of motion against gravity. Based on the above taxonomy of robot assistance scenarios, the provided force/torque can be used either to assist (constant assistance) or to disturb (challenge-based assistance) the patient during motor task execution.

ASSISTANCE MODALITIES

Assistive modalities also differ in terms of when and how the assistive force is provided.

The different types of assistance can be summarized as follows:

Continuous assistance

An assistive force is continuously provided starting from the target onset [20]. The assistive force comes into play gradually, in a ramp-like mode of duration T:

$$A(t) = F(t) \cdot R(t;T) \tag{4}$$

where $R(t; T)$ is a ramp-and-hold function (t is the rise time) that enables a gradual onset of force within the time interval T.The magnitude of the assistive force (expressed as stiffness or maximum force) must be carefully set at the minimum magnitude enabling the patient to initiate the movement. In this assistance modality, there are no explicit constraints on the maximum duration of the movement. This assistive modality is the simplest form of assistance and is suitable for subjects who are initially unable to autonomously initiate movements. It is applied in the most severe patients when no "intention to move" detection strategies are included in the robot device. The disadvantage is that in order to keep the task challenging, the magnitude of the assistive force needs to be continuously regulated by the therapist and adapted in step with the patient's improvement on a session-by-session basis.

Time-triggered assistance

At the beginning of the trial, the patient is free to move the arm within the workspace. After a predefined time, t_0 (e.g., 2 s) from target onset, the assistive force gradually comes into play in a ramp-like mode, up to a predefined value (soft application of assistance). The force is then maintained at that magnitude for a time T so as to guide the patient's arm to the target:

$$A(t) = F(t) \cdot R(t - t_0; T) \tag{5}$$

In this way, the patient is challenged to autonomously initiate the movement. Assistance only comes into play after a delay to help the patient complete the movement, thus motivating the patient to be actively engaged in the exercise [21] but, at the same time, enabling a minimum dose of exercise within the duration of the training session. As before, time-triggered assistance is typically used with the more impaired patients.

Activity-triggered assistance

The objective of this type of assistance is to stimulate and enhance the patient's voluntary motor activity. In active-triggered techniques, the robot provides assistance only if the subject is unable to complete the task by herself/himself.

The patient is required to move the arm from the starting point to the target, the only restriction being the working plane supporting the arm for an exercise carried out in two dimensions. If the patient cannot complete the task autonomously, the robot evaluates the current position of the arm/end effector depending on the type of robot and, after a predefined period of time in which there is no movement, guides the patient's arm to the target position [21,22]. The scheme can be represented by the following function:

$$A(t) = F(t) \cdot k(v_H, t) \cdot R(t - t_0; T) \tag{6}$$

where $F(t)$ is the assistive force, $R(t-t_0; T)$ is a ramp-and-hold function, and $k(v_H, t)$ is the output of a finite-state machine that outputs one when hand-speed v_H remains below a threshold value for a predefined interval (e.g., 3 s) and zero otherwise.

Pulsed assistance

The aim of this type of assistance is to provide an assistive force that is pulsed in time, with a predefined repetition frequency (e.g., 2 Hz) that is compatible with recent theories on intermittent control [23]. The assistive force consists of a constant component plus a periodic sequence of force pulses. It can be assimilated to a force field that is turned on smoothly (by gating the field generator with a ramp-and-hold function) and is turned off suddenly as soon as the target is reached. In this case, the force field can be represented by the following function:

$$A(t) = \left[k + (1-k) \cdot \sum_{n=1}^{N} \varphi_{\Delta t}\left(t - nT_p\right) \right] \cdot F(t) \cdot R(t) \tag{7}$$

where $F(t)$ is the assistive force (see Eq. 3) and $R(t)$ is a ramp-and-hold function and $\varphi_{\Delta t}(t)$ is a smooth peak function (pulse) with unit amplitude ($\varphi_{\Delta t}(0)=1$) and duration Δt. The pulse train has N pulses and period T_p, both adjustable in accordance with the distance from the target; k is a weighting factor ranging from 0 to 1, which selects between a pure pulsed field ($k=0$), a mixed continuous and pulsed field ($0<k<1$) and a continuous field ($k=1$). Preliminary findings suggested that pulsed assistance allows subjects to reach a similar performance level to that obtained with continuous assistance after a single training session [24].

Negative assistance

In this type of assistance, the patient is required to execute the reaching task while working against a negative force of constant or variable magnitude. This can take the form of the robot resisting the desired movement or creating an unfamiliar dynamic environment that the subject has to adapt to. This type of assistance may be implemented by using a continuous or pulsed paradigm, but the force magnitude F_A or the position gain K_P are negative. This modality is intended for less compromised patients or for those who have already made a significant motor recovery and need mainly to improve the quality of their motor control.

Fig. 1 shows a graphic representation of the different types of assistance as a function of time. The fact that robots can provide different types of assistance should increase the number of patients who can benefit from robotic treatment.

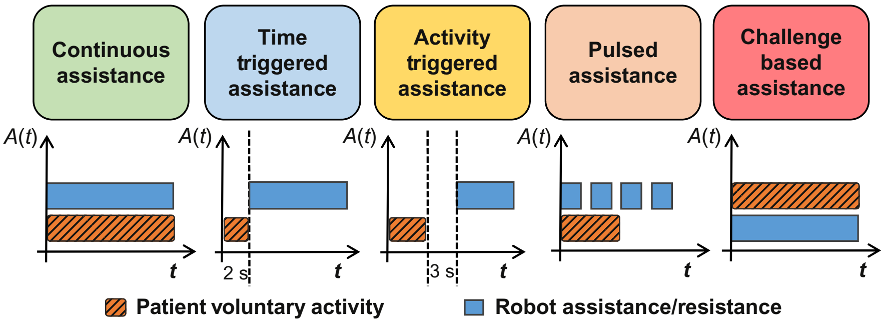

FIG. 1

Types of assistance as a function of time. The figure reports, for each type of assistance, the time of activation of the assistive force and its relationship to the patient's voluntary activity. Note that in the challenge-based assistance case, in contrast to the other cases, the patient needs to exert a force (voluntary activity) that is generally higher in magnitude than that exerted by the robot.

REGULATION OF ASSISTANCE

In the foregoing section, we have shown that the different forms of assistance provided by the robot can be broadly categorized into discrete and continuous regulation of assistance depending on their modality of activation. Of course, this is only a broad categorization, because often the same device can implement different forms of assistance depending on the type of exercise required during training.

A recent study on locomotion [25] suggested that the motor system acts like a "greedy" optimizer, quickly incorporating the assistive forces generated by the robot into the motor plan in order to reduce the degree of voluntary control (and therefore muscle activation) while keeping the position error small. This phenomenon is known as "slacking" and is likely to occur during active-assisted exercises (and, even more, during passive training) when assistive forces are set independently from the subject intervention. A continuous assistive force, if not properly regulated, can induce a reduction of voluntary control that could have adverse effects on recovery. To prevent slacking, assistance should only be provided "as needed", that is, the subject should perform the task with only the minimal amount of robot assistance necessary for task completion. As patients improve their performance, the amount of assistance needs to be adjusted accordingly.

Several robot control strategies have been designed to satisfy this requirement, for both upper limb and gait training [6]. They usually imply the presence in the robot of a controller that provides an appropriate regulation of the assistive force, either continuously or on a trial-by-trial basis.

Hogan et al. [26] found that a treatment protocol that continuously adapts to the subject's motor ability achieves a better recovery than a training protocol in which assistive forces are not adapted. In Casadio et al. [20], the therapist manually selected the assistance level in order to keep it to the minimum level required to evoke the functional response needed to accomplish the task. In Vergaro et al. [27], a linear controller continuously and automatically regulated the assistive force provided by the robot, based on the online performance measures. Similar mechanisms have been proposed for both the upper limb (i.e., the performance-based progressive robot-assisted therapy used by the MIT-Manus robot [28]) and the lower limb (i.e., the patient-cooperative training modality used by the Lokomat system [29]).

Squeri et al. [30] designed an adaptive Bayesian regulator that adjusts the magnitude of the assistive force (or other task parameters) to keep the average performance around a target magnitude (performance clamp). In this way, as performance improves, the controller automatically reduces the amount of assistance.

Another determinant of neuromotor recovery is the regulation of task difficulty or equivalently the "desired" or target performance. This can be implemented by regulating assistance, providing different forms of assistance or changing the properties of the assigned motor task [21]. To this end, regulation requires a proper estimation of patient performance through measurement of movement kinematics and kinetics. The idea behind this concept is to control the motor recovery processes through the performance-based regulation of the training parameters. We can represent the whole system through a control loop in which the motor control system of the patient influences the performance of the motor task using voluntary activity (voluntary control). The resulting performance influences both the motor control system through the sensory system and the robot, which in turn can modify the amount of assistance provided and the properties of the motor task. Fig. 2 shows a schematic representation of the control loop.

Computational models of motor learning further suggest that large initial errors may prevent learning [31]. The challenge point theory states that "optimal" learning is achieved when the difficulty of the task is matched to the subject's level of expertise (i.e., learning is optimal when the individual's challenge point is reached) [32]. This would imply that giving a difficult task to a less skilled person would result in less learning after a similar amount of practice, as compared with training when the task difficulty is adjusted to the skill level. This theory is supported by a recent study that demonstrated that a force field that guided subjects through a desired movement was more beneficial for less skilled participants [33]. Similar effects have been observed in the neurorehabilitation field.

Overall, these considerations suggest that a controller that (i) maximally promotes the subject's involvement, (ii) provides enough assistance so that the subject completes the desired movements, and (iii) is adapted to the subject's skill level and to his/her improvements will maximize motor skill learning and neuromotor recovery.

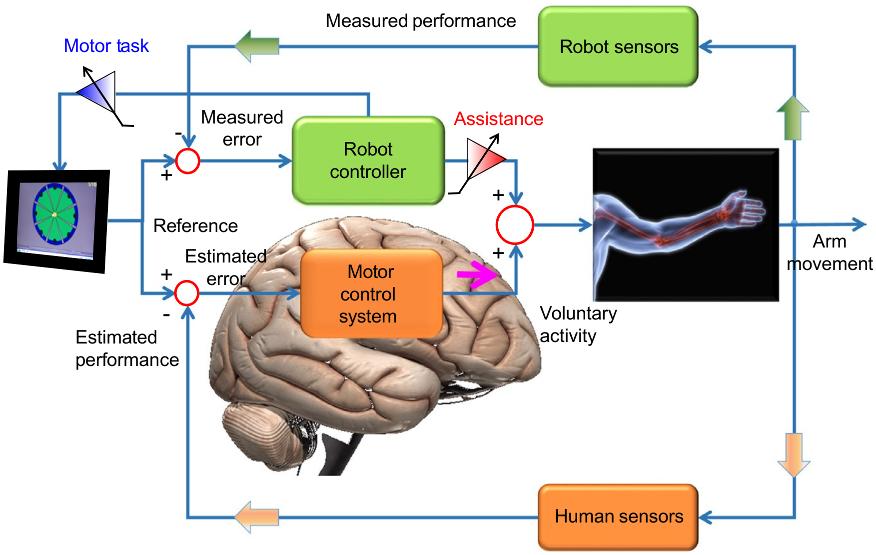

FIG. 2

Control loop for task difficulty regulation. The motor control system of the patient influences the execution of the motor task by voluntary activity (voluntary control). The resulting performance influences both the motor control system through the sensory system and the robot that can modify the amount of assistance and the type of motor task.

However, translating this into actual mechanisms of regulation is far from easy. The problem of "optimally" regulating assistance is currently an open research area, and only heuristic, ad hoc solutions are currently available. The task of deriving an optimal (i.e., "assist-as-needed") controller would be relatively straightforward if the dynamics of the learning or recovery process were completely known. Although there have been attempts to model this process, these models are currently not accurate enough to allow the design of robust controllers [34].

The general goal of regulation of assistance is to decrease assistance as performance improves. This is often achieved through simple linear control models [28,29]. Controller parameters are usually set heuristically. However, stability of the closed-loop recovery process is critically dependent on these parameters, which may be a problem as very little prior information is available on the dynamics of the learning/relearning process. Moreover, the latter may be highly subject-dependent.

Model-based controllers rely on the exact knowledge of the parameters of the trainee learning model. These parameters can be obtained by observing how the dynamics of recovery is affected by varying amount of assistance. Moreover, the recovery process is nonlinear and inherently noisy (it includes a random component accounting for exploration of action space), which makes this approach quite problematic. Another possibility is to use adaptive controllers, which do not require a detailed knowledge of the learning process and automatically adapt to it.

OTHER TYPES OF ASSISTANCE

BILATERAL TRAINING

Bilateral trainers represent a special category of therapy robots. The focus of the first bilateral device was on shoulder and elbow movements [35]. Control was based on the mirror-image movement enabler (MIME) concept: a modified industrial robot applied forces to the impaired arm using position control, with the goal of replicating the movements of the other arm in a mirror-symmetrical way. Another device based on a similar bilateral approach is the Bi-Manu-Track, used for training of pronosupination of the forearm and flexion extension of the wrist [36]. The control of the impaired side can be either passive or active, and the movement may be in a mirrorlike or parallel fashion. Regarding the lower limb, the LOPES gait training robot uses a bilateral approach whereby the unimpaired leg determines the state of the other leg through a method called complementary limb motion estimation [37]. To date, in the majority of bimanual control schemes, the two sides are not required to cooperate, but rather interact in a master-slave fashion, with few exceptions [38].

SENSORY TRAINING

Finally, some experimental training protocols include sensory stimulation and training. For training of proprioception, for example, subjects are instructed to move their arm from the start to the end targets of the reaching path without assistance of vision.

Specifically, the subject's vision of the arm and robot handle is blocked through a specific opaque plane or by a special mask. In this case, the assistance may assume the form of a sensory feedback exploiting a different sensory channel. For example, the robot can provide vibratory feedback to the ipsilateral or contralateral arm to assist the patient in selecting the proper direction of movement (see Chapter 20 for more details).

CONCLUSIONS

We have shown that robot therapy is effective in promoting neuromotor recovery, but what about its mechanisms of action? Several studies have demonstrated that exercise facilitates the recovery of motor functions following stroke. Intensity and frequency of practice are major determinants of recovery. However, mere repetitive task training results in only modest increases in lower limb function and no improvement in the upper limb.

Robot-assistive therapy may be beneficial because (a) its assistive forces can help subjects to complete the motor task even in the early phases of the recovery process, which in turn may increase motivation; (b) it elicits the "right" afferent signals (proprioceptive and tactile), thus promoting the emergence of the appropriate associations in sensory and motor cortical areas; (c) it may induce a sensation of greater stability of the external environment, a necessary condition for long-term, more stable adaptation to occur; (d) it interleaves effort by the patient (essential to provoke motor plasticity) with stretching of muscles and connective tissue that is helpful to prevent stiffening of soft tissues; (e) it may help induce brain plasticity through moving the limb in a manner that self-generated effort cannot achieve; (f) it may help to perform more movements in a shorter amount of time, potentially allowing more intense practice; and (g) it allows subjects to practice a task more intensively by simply making it safer. All these factors may contribute to the recovery in robot-assisted exercise, but none of them has been tested empirically.

A better understanding of the way robot therapy works and, more generally, how physical assistance can facilitate motor skill learning and relearning may lead to novel, more innovative approaches and consequently to a wider range of applications and even more effective recovery.

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