CHAPTER NINE

Upper Extremity Rehabilitation Robots: A Survey

Borna Ghannadi, Reza Sharif Razavian, John McPhee
Systems Design Engineering, University of Waterloo, Waterloo, ON, Canada

Contents

1 INTRODUCTION

Upper extremity movement defects are caused by different sources such as upper limb component injuries and surgeries, overuse (Skirven et al., 2011), stroke, traumatic brain injury, spinal cord injury, motoneuron defects, and neurological diseases such as cerebral palsy and Parkinson's disease (Maciejasz et al., 2014). Most of these defects need sessions of physical therapy to improve joint range of motion (ROM), strengthen muscles (Skirven et al., 2011), restore functional capabilities, and resolve impairments (Maciejasz et al., 2014).

Stroke causes longstanding impairments, and it has a noticeable risk factor in older adults. One-sixth of people worldwide will experience stroke in

Handbook of Biomechatronics
https://doi.org/10.1016/B978-0-12-812539-7.00012-X

their lifetime; 15 million people are suffering from stroke every year. Following these trends, it is estimated that 23 million stroke cases will happen in 2030 (Mendis, 2013). Thus, procedures to rehabilitate this long-term disability are essential (Broeren et al., 2004; Oujamaa et al., 2009; Turolla et al., 2013; Hatem et al., 2016). Studies have reported that following a stroke upper extremity motor defects have the highest prevalence among movement disorders (Bansil et al., 2012; Mehrholz et al., 2012). Therefore, rehabilitation approaches for upper extremity motor control and function recovery are of importance. Consequently, this chapter will focus on upper extremity movement disorders in poststroke patients.

Neurological complications of stroke are various (Fulk et al., 2014) and need to be considered in rehabilitation therapy. Some of these complications are:

1. *Hemispheric behavioral differences*: Stroke patients may show different behaviors in doing a task. Those with right hemiplegia have difficulty accomplishing consecutive tasks; these patients may need some assistance in their therapy. On the other hand, patients with left hemiplegia have task perception problems, and they overestimate their abilities. Fluctuations in doing a task are common among them. To address the wrong perception, safety issues should be considered carefully.
2. *Perceptual dysfunction*: It is common among left hemiplegia patients, and can be revealed as one of these symptoms: body scheme, spatial relation, and agnosia. The body scheme is the difficulty in realizing the relationship between body parts. The spatial relation is having trouble in perceiving the relationship between body and other objects. The agnosia is the problem in distinguishing incoming information, which can be visual, auditory, or tactile.
3. *Osteoporosis and fracture risk*: Because of the lack of physical activity, these patients may get osteoporosis. Osteoporosis is a bone disease for which the mass of bone will decrease and cause fractures.

There are two main types of training for stroke rehabilitation: *unilateral* and *bilateral* (Wu et al., 2013). Unilateral training is a therapy for the single impaired limb. *Constraint-induced therapy*, which is an intensive use of the impaired limb while constraining the unaffected limb, is a kind of unilateral training therapy. Taking into account bimanual daily activities like hand washing, the idea of getting more help from undamaged neural pathways, and case-dependent use of unilateral training, has led to bilateral training theory. Bilateral training is used for symmetric, asymmetric, and complementary movements of both impaired and unimpaired limbs

(Stoykov and Corcos, 2009). In symmetric movements of the upper extremity, arms are moved in the same way. In asymmetric movements, arm movements are opposing. In complementary movements, both arms are performing a combinatory task.

Although unilateral and bilateral training approaches are different, they are pursuing the same goal. Recent studies (Wu et al., 2013; van Delden et al., 2013) have stated that there are no significant outcomes that can make one method of training superior to the other. The procedures of these training methods are developed by motor learning theories. These theories are sometimes contradicting and are not fully determined; some of the available ones are (Brewer et al., 2007; Muratori et al., 2013; Hatem et al., 2016):

- *Implicit or explicit learning*: Implicit learning is unconscious during indirect task execution, while explicit learning is directed. *Bobath concept training* can be defined as an implicit learning exercise; it facilitates voluntary movement by handling specific points of the patient's body.
- *Massed or variable practice*: Massed practice (*repetitive task training*) is repetitive single task accomplishment, while variable practices (*task-oriented training* and *goal-directed training*) are for training multiple tasks. In the task-oriented (*task-specific*) training, a real-life practice is provided to reacquire a specific skill. The goal-directed (*client-centered*) training is a type of task-specific training in which the practice is defined based on the directed goals of the patient and therapist.
- *Feedback distortion or assistance*: Feedback distortion is magnifying movement errors instead of assisting the patient to reduce the errors.
- *Real-world practice*: This can be done by virtual reality methods that are enhanced by visual, auditory, or tactile feedback.

Although it has been found that therapy is effective in the treatment of movement disorders, therapy hours per patient have decreased because of economic burdens (Reinkensmeyer et al., 2002). Studies have shown that comprehensive and optimal stroke care can decrease the associated costs significantly (Krueger et al., 2012; Blacquiere et al., 2017). This optimal care can be achieved by implementing new technologies. That is why the design and development of biomechatronic devices (i.e., rehabilitation robots) have gained more importance.

To show the need for rehabilitation robots, we should survey the goals of therapy (Reinkensmeyer, 2009; Richards and Malouin, 2015; Hatem et al., 2016):

- *Increase activity*: It is done by the use of Thera-bands, pegboards, and blocks in conventional therapy.

- *Provide intense repetitive and engaging exercises*: This is the best practice guideline for therapy (Richards and Malouin, 2015). Conventionally, a therapist's labor and enthusiasm plays an important role in providing these exercises. However, there is a high interest in applying less therapist labor-intensive modes, and this is in contrast to conventional therapy approach for providing intense repetitive exercises.
- *Provide assistance*: Conventionally is accomplished with the help of therapists, splints, and arm-supports.
- *Improve assessment*: Traditionally is achieved by force gauges, goniometers, and timers.
- *Provide feedback*: This can be visual, auditory, or tactile.

Considering these goals and their effectiveness, increasing physically impaired patient population (Maciejasz et al., 2014), the limited number of therapists and decreased therapy hours because of economic issues (Reinkensmeyer et al., 2002), and versatile features offered by robotic devices justify the employment of rehabilitation robots in therapy sessions. These features include automation and versatility in procedures and assessments while applying intense repetitive and engaging exercises (Reinkensmeyer, 2009).

There are various reviews of upper extremity rehabilitation robots (devices) in the literature (Hesse et al., 2003a; Brewer et al., 2007; Brochard et al., 2010; Lo and Xie, 2012; Maciejasz et al., 2014; Babaiasl et al., 2016; Proietti et al., 2016; Brackenridge et al., 2016; Gopura et al., 2016; Huang et al., 2017), and there are different classifications for these robots. However, there is a lack of comprehensive classification of these robots. In this study, we thoroughly categorize these robots for different contexts. Here we use upper extremity rehabilitation robots and upper extremity rehabilitation devices interchangeably. It is worth noting that upper extremity rehabilitation devices include passive and active robots. Mechanical, and visual and auditory feedback devices are part of passive robots.

In the next sections, classification of these robots based on different approaches is discussed. Next, a proper planning for rehabilitation is presented. Finally, recent developments and research opportunities in the field of upper extremity rehabilitation robots are reviewed and conclusions are made.

2 CLASSIFICATION BY MECHANICAL DESIGN

The mechanical design of upper extremity rehabilitation robotic systems can be classified as *manipulanda* or *exoskeletons* (Maciejasz et al., 2014).

Manipulanda are end-effector-based robots that have a simple structure and control algorithms. Thus, it is hard to perform special movements of a distinct joint using these robots. Another design issue in these robots is that the end-effector at most can provide 6 degree-of-freedom (DOF). Hence, the number of anatomical movements should not exceed 6; otherwise, it will cause redundancy, which may be unsafe.

These devices can be composed of multiple robots (*multirobot manipulandum* in Fig. 1) such as "iPAM" (Jackson et al., 2007, 2013) and "REHAROB" (Fazekas et al., 2006), which are dual-robot manipulanda. However, generally, these devices are a single robot (*single-robot manipulandum* in Fig. 1). The "InMotion Arm" (which is the commercial version of "MIT-MANUS" (Krebs et al., 1998)), "HapticMaster" (Van der Linde and Lammertse, 2003), and "ReoGo" (from Motorika Medical Inc.) are some examples of single-robot manipulanda.

It is worth noting that some of these devices are connected to the body segments by cables (*cable-based devices*), and in some references, cable-based

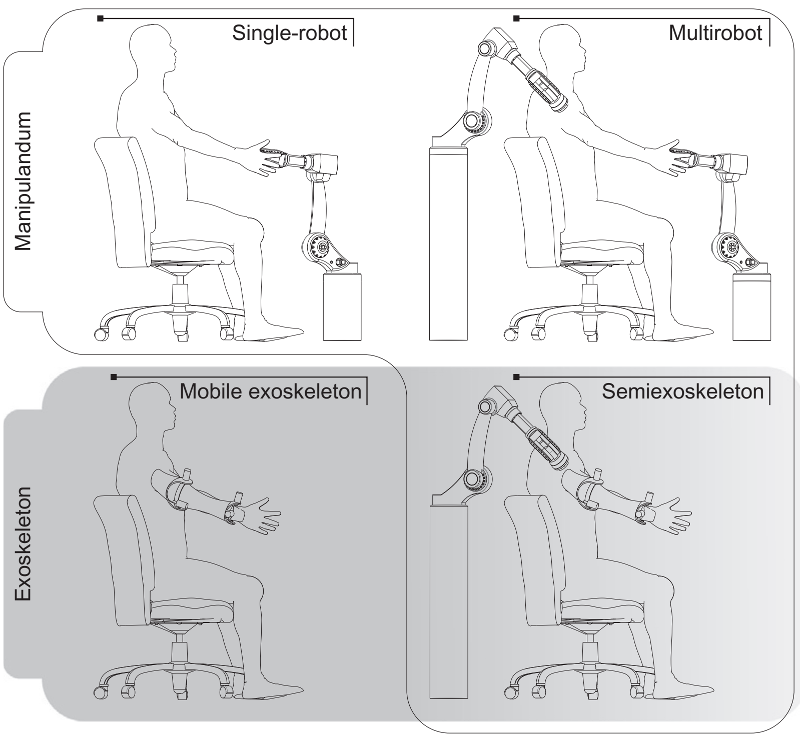

Fig. 1 Mechanical classification of upper extremity rehabilitation robots.

devices are categorized separately. Nonetheless, we have considered them as a type of manipulanda (*cable-based manipulanda*). Cable-based manipulanda can also be categorized as single-robot and multirobot. "DIEGO" (from Tyromotion GmbH) and "MariBot" (Rosati et al., 2005) are examples of cable-based single-robot manipulanda. "GENTLE/S" (Loureiro et al., 2003), which is an integrated "HapticMaster" with a cable-based mechanism, is a type of cable-based multirobot manipulanda.

Exoskeletons can provide movements to particular joints (see Fig. 1), and the number of anatomical movements can exceed 6. Nonetheless, increasing the number of moving parts increases the number of device modules, so the system setup becomes difficult. Moreover, since the shoulder has a variable joint center, the mechanical design and control algorithms become more complicated. Mostly these robots are combined with weight supporting devices or manipulanda (*semiexoskeleton* in Fig. 1). "ArmeoPower" (which is based on "ARMin III" (Nef et al., 2009)) and "ArmeoSpring" (which is based on "T-WREX" (Sanchez et al., 2004)) are commercial semiexoskeletons (Proietti et al., 2016; Maciejasz et al., 2014). If exoskeletons are not connected to any external mechanism, they will be mobile (*mobile exoskeleton* in Fig. 1). "CyberGrasp" (Adamovich et al., 2009) and "RUPERT" (Balasubramanian et al., 2008) are examples of these devices.

Manipulanda are most often used for training nonmobile gross movements (e.g., reaching task); on the other hand, exoskeletons are perfect for training mobile or joint-specific movements (i.e., perform specific movements of distinct body joints, e.g., grasping task). Manipulanda usually enjoy lower cost margins than exoskeletons as well as less complicated setups and shorter patient-preparation time for therapy. The selection of one of these two different devices highly depends on the level of the patient's disability; for example, in early stages of stroke when the patient is more vulnerable and unstable, manipulandum training seems to be a safer choice.

Mechanical design of these devices can be improved by considering the patient's ergonomics and removing higher transformation ratios using efficient direct-drive motors. Furthermore, exoskeletons benefit from the use of lighter parts with a high mechanical strength to be attached to the patient's body. However, these advancements are limited by the production cost; finding the best price-quality trade-off requires proper design methodology, such as model-based system engineering (MBSE). MBSE is a designated modeling application that supports system requirements, design, analysis, verification, and validation of conceptual designs throughout the development and lifecycle phases.

3 CLASSIFICATION BY TRAINING

Based on Brewer et al. (2007), these robotic systems can be categorized by training approaches. Accordingly, these robots are classified as either unilateral or bilateral trainers. Unilateral trainers compromise repetitive practice of a single arm, while bilateral trainers perform bimanual therapy. Compared with unilateral trainers, there are a limited number of bilateral devices available in the literature (Sheng et al., 2016). Both the classes of trainers can provide gross and/or fine motor movements.

In gross motor movements, massed practice with explicit learning is accomplished. Gross motor movement is an established method of therapy used in various rehabilitation robots. Unilateral trainers, such as "MIT-MANUS" (Krebs et al., 1998), "GENTLE/S" (Loureiro et al., 2003), "MariBot" (Rosati et al., 2005), "ARM Guide" (Kahn et al., 2006), and "ARMin" (Nef et al., 2007), and bilateral trainer "MIME" (Burgar et al., 2000) are used for gross motor movements.

Fine motor movements are mostly related to hand and wrist rehabilitation. This method can be used for increasing ROM or regulation of motor tasks like independent movements of fingers. Unilateral trainers, such as "Hand Mentor" (Koeneman et al., 2004), "HEXORR" (Schabowsky et al., 2010), "HandTutor" (Carmeli et al., 2011), "Amadeo" (Sale et al., 2012), and "VAEDA glove" (Thielbar et al., 2017), and bilateral trainer "Bi-Manu-Track" (Hesse et al., 2003b) provide fine motor movements.

Some rehabilitation robots can be used for both gross and fine motor movements. "RUPERT" (Sugar et al., 2007), the single arm "CADEN-7" (also known as "EXO-UL7") (Perry et al., 2007; Simkins et al., 2013), "ARMin III" (Nef et al., 2009), and "Universal Haptic Drive" (Oblak et al., 2010) are unilateral trainers of this type. The double arm "EXO-UL7" (Rosen and Perry, 2007; Simkins et al., 2013) is a bilateral trainer that provides both gross and fine motor movements.

Together with the above tasks, some robots have additional features such as real-world practice (Patton et al., 2004), functional electrical stimulation (FES) (Hu and Tong, 2014), electromyography (EMG) (Rahman et al., 2015), electroencephalogram (EEG) (Fok et al., 2011), gravity compensation (Stienen et al., 2007; Moubarak et al., 2010), feedback distortion (Brewer et al., 2008), telerehabilitation (Ivanova et al., 2015), and progress assessment (e.g., "KINARM" is used for motor function assessments (Coderre et al., 2010; Mostafavi et al., 2015)).

As discussed in Section 1, there is no significant advantage that can make one method of training superior to the other. Both unilateral and bilateral trainers are pursuing the same goal, and their selection depends on the patient's condition and his/her level of disability. Hence, plotting a general guideline for the selection of a suitable trainer is a complicated and cumbersome procedure, and it is case-dependent. For example, in early stages of stroke, a unilateral trainer who provides gross movements is a generally preferable choice. In the next stages, this training can be combined with real-world practice. For fine movements, if exoskeletons are not affordable, FES can be used instead. Finally, to quantify functional activities of the subject, bio-feedback features (EMG and EEG) can be used.

4 CLASSIFICATION BY FORM OF REHABILITATION

Upper extremity rehabilitation robots can support daily activities and are designed for home or clinical use (Maciejasz et al., 2014). The target population for most of these robotic systems is poststroke patients, for whom these robots can be active, passive, haptic, or coaching devices.

Active devices provide active/passive assistance therapy. In passive mode, the robot moves the patient's limb without any muscular activity of the passive patient, while in active mode the patient is active during training. Most upper extremity rehabilitation robots are active devices (Maciejasz et al., 2014). In contrast to active devices, *passive devices* perform passive resistance therapy. These devices are used to provide different types of muscle strengthening exercises including isometric, isotonic, isokinetic, and iso-contractile. "Biodex System 4 Pro" is used for isokinetic exercises (Cvjetkovic et al., 2015), "MEM-MRB" is an isokinetic and iso-contractile exercise machine (Oda et al., 2009), and "PLEMO" (Kikuchi et al., 2007) and "WOTAS" (Rocon et al., 2007) are other examples of passive devices.

In addition to active and passive devices, there are some devices that do not explicitly assist or resist the patient's movement; instead they are used for real-world practice. *Haptic devices* transfer tactile sensing to the patient. They do not assist or resist movement, but they provide real-world practice by incorporating haptic feedback while a patient is manipulating virtual objects in the simulated environment (i.e., virtual reality). There are various examples of virtual reality in rehabilitation research in which actuated feedback is implemented (Todorov et al., 1997; Prisco et al., 1998; Jack et al., 2001; Sveistrup, 2004). In Johnson et al. (2004) and Wamsley et al. (2017), gaming steering wheels are used to generate force feedback for poststroke upper extremity rehabilitation. "Handreha" is a hand-wrist haptic device that is used for hemiplegic children rehabilitation (Bouri et al., 2013). *Coaching devices* coach the individual by providing real-world practice via visual or auditory feedback. For example, "T-WREX" monitors functional arm movements during a home-therapy (Sanchez et al., 2004), and "DIEGO" (from Tyromotion GmbH) with active gravity compensation and "Microsoft Kinect" are used in virtual rehabilitation (Tseng et al., 2014).

Once again, selection of a suitable form of rehabilitation depends on the patient's condition and his/her level of disability. Recommending a general guideline for this selection requires significant years of experience with movement disorder therapy. Studies have shown that assisted therapy with active devices is prevalant for most rehabilitation procedures, and other forms of rehabilitation can be achieved by means of these active devices if needed (Maciejasz et al., 2014).

5 CLASSIFICATION BY CONTROL SCENARIOS

Human arm motions are controlled by the biological feed-forward and feedback control commands of the central nervous system (CNS) (Mehrabi et al., 2017). The feed-forward commands are predicted using an internal model of the arm. Feedback commands are corrective commands generated by the assessment of movements by sensory organs. Any electronic controller that can maintain these characteristics might be advantageous in rehabilitation robotics.

For exerting therapy approaches by upper extremity rehabilitation robots, different control algorithms are utilized. The control inputs are dynamic measurements such as force and torque signals, kinematic displacement and velocity signals, and triggers such as switches and EMG signals. Their feedbacks to the user are tactile, visual, auditory, or electrical (FES). The control strategies for these robots are categorized as (Maciejasz et al., 2014; Proietti et al., 2016) high- and low-level control scenarios. High-level control scenarios help to stimulate motor plasticity, and low-level control scenarios are used to implement high-level scenarios. These control scenarios with their subcategories are summarized in Fig. 2.

5.1 High-Level Control Scenarios

As shown in Fig. 2, there are three high-level control scenarios (Marchal-Crespo and Reinkensmeyer, 2009; Maciejasz et al., 2014; Proietti et al., 2016), which are assistive, resistive, and corrective control.

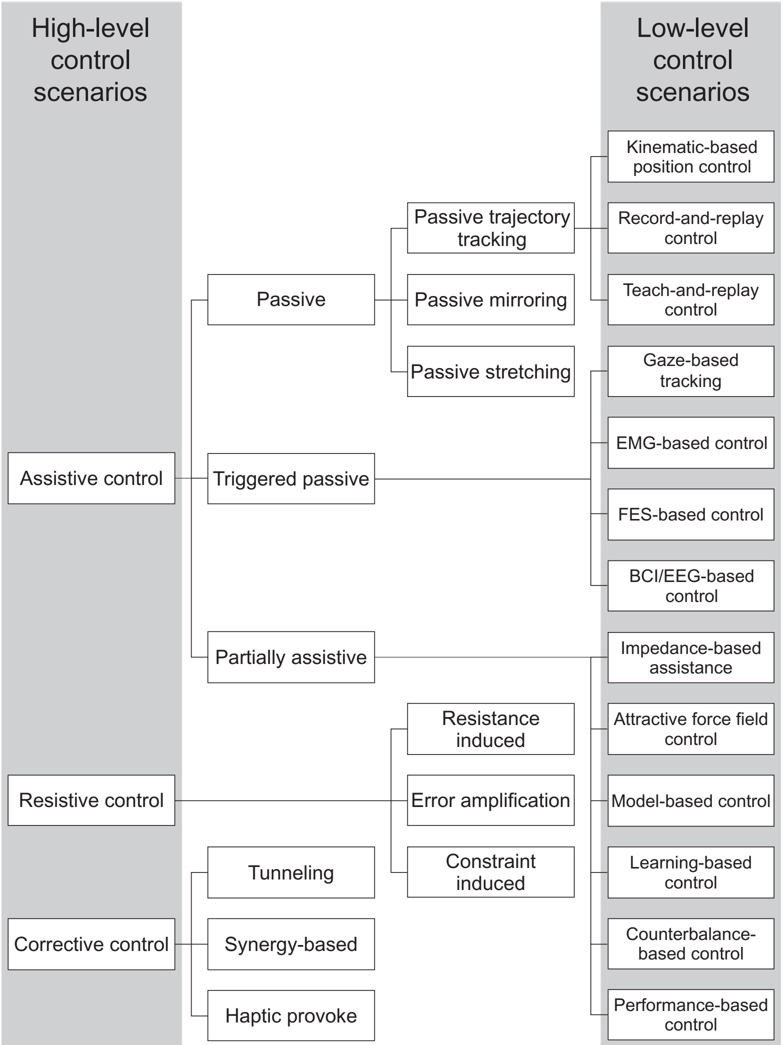

Fig. 2 Different control scenarios in rehabilitation robotics.

In assistive control, the robot helps the patient's movements using passive, triggered passive, or partially assistive control.

In passive control, the device tries to constrain the patient's hand to the desired track. This track can be defined in different ways. If it is a reference tracking control, then it is called *passive trajectory tracking*. This trajectory can be achieved by *kinematic-based position control*, where the tracking is done on a smooth trajectory (Krebs et al., 2003; Johnson et al., 2006; Brewer et al., 2006; Amirabdollahian et al., 2007; Wolbrecht et al., 2007; Rosati et al., 2007; Loureiro and Harwin, 2007; Montagner et al., 2007; Erol and Sarkar, 2007) that is determined by the "minimum-jerk" hypothesis (Flash and Hogan, 1985). The reference trajectory can be obtained from unimpaired volunteers in the so-called "record-and-replay" method (Kousidou et al., 2007; Staubli et al., 2009), or it can be generated by the therapist guidance, which is called "teach-and-replay" (Pignolo et al., 2012). If the desired trajectory is a path followed by the unimpaired limb, it is called *passive mirroring*, which is based on bilateral training (Pignolo et al., 2012; Guo et al., 2013). Finally, in the *passive stretching*, the limbs are coordinated by measuring the angle-resistance torque relation (Ren et al., 2013).

In triggered passive control, the device uses biosignals as control inputs, but this triggering may cause slacking in which the patient does not show any effort and waits for the robot assistance. These controllers are gaze-based tracking (Loconsole et al., 2011; Novak and Riener, 2013), EMG-based (Crow et al., 1989; Dipietro et al., 2005; Stein et al., 2007; Choi and Kim, 2007; Duc et al., 2008; Cesqui et al., 2013; Loconsole et al., 2014; Rahman et al., 2015; Leonardis et al., 2015; Elbagoury and Vladareanu, 2016), FES-based (Hu and Tong, 2014; Kapadia et al., 2014), and brain-computer interface (BCI)-based (which also includes EEG-based controllers) (Fok et al., 2011; Frisoli et al., 2012; Sakurada et al., 2013; Venkatakrishnan et al., 2014; Dremstrup et al., 2014; Brauchle et al., 2015; Barsotti et al., 2015).

Partially assistive control is implemented by various methods (see Fig. 2). In *impedance-based assistance*, different variations of impedance and admittance controls are used to control the rehabilitation robot (Reinkensmeyer et al., 2000; Colombo et al., 2005; Kahn et al., 2006; Gupta and O'Malley, 2006; Carignan et al., 2009; Culmer et al., 2010; Tsai et al., 2010; Miller and Rosen, 2010; Yu et al., 2011). In *attractive force field control*, some types of manipulability ellipsoid are used to apply force in specific directions (Kim et al., 2013; Yamashita, 2014). If a musculoskeletal upper extremity model is used to implement a model-based assistive control in an exoskeleton, it is a *model-based assistance* (Ding et al., 2008, 2010). If the adaption to the performance index is done from trial to trial, it is called *learning-based control*. Offline adaptive (Balasubramanian et al., 2008; Wolbrecht et al., 2008; Pérez-Rodríguez et al., 2014; Proietti et al., 2015) and artificial intelligence (AI) (Hernández Arieta et al., 2007) controls are among this type of control structure. In *counterbalance-based control*, the device applies active/passive counterbalance to the patient limb for gravity compensation (Sanchez et al., 2006; Sukal et al., 2006; Stienen et al., 2007; Montagner et al., 2007; Jackson et al., 2007; Mihelj et al., 2007). Lastly, if the robotic system tracks the performance of the patient using an error-based strategy and adapts some features for assistance, this is *performance-based adaptive control* (Kahn et al., 2004; Krebs et al., 2003; Riener et al., 2005).

As in Fig. 2, there are different methods to implement resistive (challenge-based) control. In *resistance induced* therapy, the robot resists patient's movements (Morris et al., 2004; Patten et al., 2006). In *error amplification* (feedback distortion) therapy, the robot amplifies kinematic (Patton et al., 2006a,b), visual (Wei et al., 2005; Brewer et al., 2006; Patton et al., 2006b), or tactile errors (Liu et al., 2017). Finally, sometimes constraint-induced therapy is used in resistive robotic control (Johnson et al., 2003; Shaw et al., 2005).

Corrective control is a kind of time-independent assistive control, in which the assistance is done when there are large tracking, coordination, or skill errors. This can be achieved by *tunneling*, in which an impedance-based control is applied at the boundaries of a wider trajectory (Guidali et al., 2011; Klamroth-Marganska et al., 2014; Mao et al., 2015). *Coordination* (synergy-based) control prevents large coordination errors between joints during a rehabilitation task (Guidali et al., 2009; Brokaw et al., 2011; Crocher et al., 2012). Finally, *haptic provoke* is used for providing real-world experience based on gaming control schemes (Burdea, 2003; Patton et al., 2004; Broeren et al., 2006; Yeh et al., 2013).

It was mentioned in Section 1 that optimal care is of great importance for rehabilitation robotics. This optimal care can be achieved only if the robot has an understanding of the coupled human-robot rehabilitation system. Thus, one major stream of recent studies is dedicated to the improvement of triggered passive control methods, which will be discussed in Section 7: Recent developments and research opportunities. Patient preparation is the downside for the direct use of biosignals (triggered passive control); however, partially assistive controllers use internal bio-inspired models of the patients to make decisions. Consequently, another major stream of recent research is focused on partially assistive control methods since these devices can assist the patients using some helpful bio-inspired information. Later in Section 7, recent developments and research opportunities, some of these developments, will be discussed.

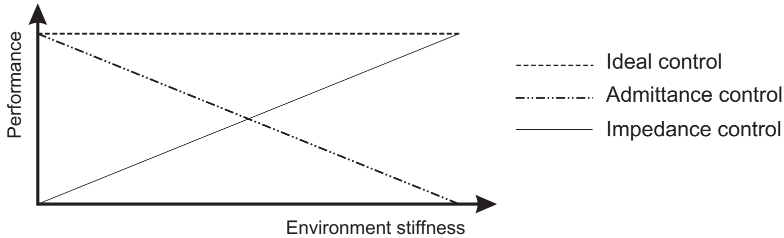

Fig. 3 Qualitative performance of impedance and admittance controllers in different environments.

5.2 Low-Level Control Scenarios

In robotic rehabilitation, since the human body is interacting with the mechatronic device, safety issues in the design of appropriate control strategies are very important. Conventional position or force control approaches (because of poor dynamic interaction modeling) are not safe enough to be implemented in these devices (Hogan, 1985). Therefore, modified control approaches like impedance and admittance control are used. In impedance control, the position of the impaired limb is measured, and appropriate force is applied (i.e., it is a force control with a position feedback), while in admittance control the applied force by the impaired limb is measured and the corresponding movement is imposed (i.e., it is a position control with a force feedback). Use of these methods is design and task specific. Impedance control has a poor accuracy; however, it becomes more stable by increasing the environment stiffness (see Fig. 3, which is adopted from Ott et al., 2010). On the other hand, as in Fig. 3, admittance control in stiff environments is not stable, while it has a good accuracy in less stiff environments. Implementing admittance control needs high transmission ratios to be considered in the mechanical design, while impedance control works well with direct drives (i.e., it is efficient for a light-weight back-drivable robot) (Ott et al., 2010; Proietti et al., 2016).

6 REHABILITATION PLANNING

Since rehabilitation robots are in contact with the human body, proper planning for rehabilitation needs design and decisions that consider the patient. The goal of the human-robot interaction (HRI) field is the design, development, and assessment of *human-centered* products (Goodrich and Schultz, 2007; Louie et al., 2017). HRI research in upper extremity robotic rehabilitation dates back to the 1990s (Van der Loos et al., 1999).

The interaction term in HRI for rehabilitation robots can be categorized into two levels: physical and social. Mechanical upper extremity devices have physical interactions, while noncontact upper extremity devices such as "Microsoft Kinect" are considered to have social interaction. Most active rehabilitation robots that provide different types of visual and auditory feedback have physical-social interaction.

To study HRI in rehabilitation robotics, one should consider HRI parameters: interaction arrangement, user interface, ability level, learning and adaption, exterior design, and therapy time (Louie et al., 2017). In robotic rehabilitation, *interaction arrangement* includes single-robot and single-user, single-robot and multiple-user, and multiple-robot and single-user; this arrangement can help to find the required mechanical design. Robot *user interface* can be auditory, tactile, or visual; the type of training can be distinguished by the user interface. *Ability level* indicates the robot's ability to perform a task, and this factor can have 10 levels varying from no-assistance to independent control modes; these levels indicate the form of rehabilitation. Regarding *learning and adaption*, both robot and user should learn and adapt to each other's performances, and this can motivate the type of control scenario. *Therapy time* is each rehabilitation session's duration, and it is important to consider patient fatigue in control scenario selection.

In addition to the HRI parameters, HRI metrics including user acceptance, user participation, user accompaniment, and user safety should be considered. These metrics are used for postprocessing the results of a rehabilitation task with a robot. User acceptance indicates how much the user is satisfied with the robot, user participation shows how long the user is engaged in the robotic rehabilitation task, user accompaniment evaluates how often the user is accompanying the robotic task (learning and adaption), and the robot's reliability is assessed by user safety (which is ensured by limiting the robot's ROM, kinetic variables, and motor torques).

To have a systematic and human-centered approach for optimal mechanical design, these HRI metrics and parameters should be included in the system requirements of the MBSE design process.

7 RECENT DEVELOPMENTS AND RESEARCH OPPORTUNITIES

In previous sections, we categorized upper extremity rehabilitation robots by mechanical design, type of training, form of rehabilitation, and control scenarios. In this section, we focus on recent advancements in the control strategies for upper extremity rehabilitation robots with different mechanical designs, including single- and multirobot manipulanda, mobile exoskeletons, and semiexoskeletons.

7.1 BCI-Based Strategies for Control and Rehabilitation

Methods for recording electrical (e.g., EEG) or magnetic fields (e.g., functional magnetic resonance imaging (fMRI) and functional near-infrared spectroscopy (fNIRS)) are used to monitor brain activities. Studies have shown that the intention to perform a specific physical activity generates consistent EEG patterns in BCI (Liu et al., 2012; Xu et al., 2014). BCI may recover brain plasticity and motor function by means of focused attention on and guidance of activation patterns of brain signals (Daly and Huggins, 2015; Yao et al., 2017). This feature motivates the application of BCI in rehabilitation robotics. Recent advancements in real-time signal processing, identification of new brain signal patterns, widespread acceptance of BCI, and less-satisfactory intense rehabilitation methods have increased the interest in BCI deployment.

BCI-based rehabilitation studies (Ang and Guan, 2015, 2017; Ang et al., 2015) at the Nanyang Technological University (Singapore) have led to well-established results in the use of BCI for rehabilitation robots. In Ang et al. (2015), they used the “MIT-MANUS” (single-robot manipulandum) with their proposed EEG-based motor imagery BCI (BCI-MANUS therapy) and compared the rehabilitation results with MANUS therapy.

In the MANUS therapy, poststroke subjects performed self-paced voluntary reaching movements. The robot assisted the subject if there were no detectable movements from them after a 2-second interval. Prior to the BCI-MANUS therapy, the robot was calibrated based on the recorded EEG signals when the subject was asked to imagine a voluntary reaching movement while the robot’s end-effector was locked in its position. Then, in the BCI-MANUS therapy, the subject was asked to imagine voluntary reaching movements with minimal voluntary movements. Based on the trained subject-specific motor imagery results, the robot manipulated the subject’s arm toward the target.

Results of the study showed that the BCI-MANUS therapy is more effective than the MANUS therapy. Furthermore, despite the reduced number of repetitions (i.e., less intensity) in the BCI-MANUS, it results in motor gains similar to more intense robotic therapy. Although BCI-based rehabilitation has been successful in laboratory-based studies, it needs more clinical trials. Currently, available BCIs can improve motor function, if they are applied in a larger number of therapy sessions (Mrachacz-Kersting et al., 2016). Further developments of this system depend on our knowledge of motor recovery and skill learning, involved motor centers, and intervention mechanisms. Discoveries in these areas will lead to more reliable clinical BCI-based therapy (Daly and Huggins, 2015).

7.2 FES-Based Strategies for Control and Rehabilitation

With FES, a series of electrical pulses are applied to the skeletal muscles of the affected limb to compensate for the loss of voluntary neural commands. It is possible to modulate the amount of force produced in the muscles by controlling either the electrical current or pulse-width of the stimulation (Sharif Razavian et al., 2018). FES has been shown to be an effective therapy program in restoring hand function in severe chronic stroke patients (Kapadia et al., 2014; Thrasher et al., 2008). Due to the complexity of the FES control, the combination of robotic and FES therapy paradigms has been proposed (Hu and Tong, 2014; Kapadia et al., 2014). In such setups, the robot is usually used to resist the motion while "guiding" the patient's limb, while FES is the main driver of the affected limb. Therefore, a robotic controller is needed to allow for such interactive movement.

Combination of FES with an upper extremity stroke rehabilitation robot is an ongoing research, which is mostly focused on its possibility (Hu and Tong, 2014; Kapadia et al., 2014). Recently, at the University of Leeds (United Kingdom), a proof of concept study on the feasibility of this combination has been performed (O'Connor et al., 2015). In this study, "iPAM" (double-robot manipulandum) was used to assist active reaching of a subject, and "Odstock Pace" (neuromuscular electrical stimulator) was assisting and restoring grasp in the subject. In a big picture view, if "Odstock Pace" is viewed as an exoskeleton, this system can be considered as a semiexoskeleton (see Fig. 1), which is used for *reach-and-grasp* arm movement.

The objective of this study was to enable natural prehension (reach-and-grasp) instead of over-imposed therapy, which is achieved by separate reaching and grasping exercises. "iPAM" provides arm reaching (shoulder and elbow motion) from a target to another target; once the hand is close to the reaching target, "Odstock Pace" is triggered by "iPAM" and it stimulates forearm muscles to open the patient's hand. The results of this study proved the possibility of combining FES with an upper extremity rehabilitation robot.

The effectiveness of the FES therapy seems to be tied to the simultaneous activation of sensory and motor pathways in the nervous system, which coupled with the associated mental effort may increase the neuroplasticity (Daly and Wolpaw, 2008). Therefore, the use of EEG in the detection of motor imagery and proper timing of FES signals is proposed as a possible solution to further improve the therapy outcome (Marquez-Chin et al., 2016).

7.3 EMG-Based Strategies for Control and Rehabilitation

EMG signals are used to evaluate the amount of muscle activity during a specific task. If upper extremity rehabilitation robots target deficits in muscle activations, their therapy will be more beneficial. The best way to capture muscle activation patterns is to use bio-feedback (i.e., EMG) signals. In a study by the Rehabilitation Institute of Chicago (RIC, United States), a special voice and EMG-driven mobile exoskeleton (called "VAEDA glove") for hand rehabilitation has been developed (Thielbar et al., 2017). Compared to other hand rehabilitation robots, the "VAEDA glove" is advantageous since it allows for practice of functional task.

Poststroke patients were divided into two groups: (1) with rehabilitation robot therapy (VAEDA) and (2) traditional fine-motor rehabilitation therapy (No-VAEDA). The therapy was focused on *grasp-and-release* tasks. In VAEDA therapy, the voice commands triggered the movement and the EMG command drove the actuators. Results of this study showed that the patients with VAEDA therapy could achieve better performances in physiotherapy assessments.

Despite the satisfactory outcomes of EMG-based rehabilitation, it is not suitable for performing complex movements. The success of EMG-based methods highly depends on how well muscle synergies and activation patterns are identified. The learning algorithm which is used to relate muscle activations to physical activities plays an important role in the establishment of better EMG-based rehabilitation. Advancements in deep learning will provide a platform for EMG-based therapy in complex activities.

7.4 Model-Based Strategies for Control and Rehabilitation

Best design practices demand a proper understanding of the whole system, which for this case consists of a human body interacting with a rehabilitation robot. This interaction will affect rehabilitation procedures; however, there is a lack of studies considering human body interaction with the rehabilitation robot. In Ding et al. (2010), a musculoskeletal upper extremity model (without including muscle dynamics) was used to implement a model-based assistive controller for a full-body rehabilitation exoskeleton.

At the University of Zurich (Switzerland), model-based arm weight compensation is used inside the controller for "ARMin V" (semiexoskeleton). The results of this study showed that with active model-based gravity compensation, the patient's effort will drop significantly.

The biological control structure of the CNS can be represented by an nonlinear model predictive control (NMPC) with receding horizon. In the NMPC, a forward dynamics model is used to generate gross optimal movements, and feedback information is used for fine-tuning. NMPC is used in a variety of applications in biomechanics (Mehrabi et al., 2017) and automotive control (Maitland and McPhee, 2018). Recent progress in the development of NMPC motivated researchers at the University of Waterloo (Ontario, Canada) to control a rehabilitation robot using NMPC with a nonlinear dynamic HRI model (Ghannadi et al., 2017). In this research, the HRI model was confined within an NMPC of the single-robot manipulandum (which is designed and developed by the Toronto Rehabilitation Institute (TRI) and Quanser Consulting Inc.). The proposed controller used a musculoskeletal model of the upper extremity to predict human movements and muscle activations (Mehrabi et al., 2017), thereby providing optimal assistance to the patient. In this study, the controller successfully predicts the muscular activations in model-in-the-loop simulations.

Model-based strategies for rehabilitation are more appealing than the triggered-passive methods since they do not require patient preparation for sensor attachment. However, the models should be identified within an acceptable accuracy to ascertain the validity of bio-inspired information. This accuracy should be achieved with a proper parameter identification procedure that is done with the use of bio-sensors in pretests with the robot. Thus, having a systematic approach for pretests and developing powerful tools for parameter identification is a key element in the success of these methods.

8 CONCLUSION

In this chapter, a review of upper extremity rehabilitation robots was presented, considering their mechanical design, type of training, form of rehabilitation, and control scenarios. Then, recent enhancements in the field of rehabilitation robotics were introduced.

In the human body, the arm motion is controlled by the CNS, so controllers that have any characteristics of the CNS might be advantageous for rehabilitation robotics. Since triggered passive controllers are dealing with biosignals, they can provide powerful tools for rehabilitation by inclusion of biological feedback. Thus, recent developments in rehabilitation robotics are mostly focused on leveraging these type of controllers to improve the quality of *biologically plausible* therapy. Furthermore, model-based controllers (e.g., NMPC) can also provide *biomechanically plausible* tools for rehabilitation; consequently, some studies in recent years have been focused on this idea.

Traditional physical therapies suffer from various inadequacies (Jorgensen et al., 1995; Ifejika-Jones and Barrett, 2011) and may result in significant financial burdens from costly therapy sessions (Dong et al., 2006; Krebs and Hogan, 2012). It is important to continue advancing rehabilitation robots, supported by innovative motor learning scenarios (Brewer et al., 2007; Cano-de-la Cuerda et al., 2015) and the optimization of mechatronic design and control algorithms, since they can result in effective in-home rehabilitation and patient care (Dong et al., 2006; Poli et al., 2013). Furthermore, these interactive and friendly robots can provide variations in delivering therapy (building on new achievements in motor learning studies) (Brewer et al., 2007; Reinkensmeyer, 2009), and meaningful restoration of functional activities (Krebs and Volpe, 2013). In conclusion, we fully expect that more progress will be made in the near future to improve the design and control of rehabilitation robots for providing biologically plausible *autonomous* therapy.

GLOSSARY

AI Artificial intelligence
BCI Brain-computer interface
CNS Central nervous system
DOF Degree-of-freedom
EEG Electroencephalogram
EMG Electromyography
FES Functional electrical stimulation
fMRI Functional magnetic resonance imaging
fNIRS Functional near-infrared spectroscopy
HRI Human-robot interaction
MBSE Model-based system engineering
NMPC Nonlinear model predictive control
ROM Range of motion
TRI Toronto Rehabilitation Institute

REFERENCES

Adamovich, S.V., Fluet, G.G., Mathai, A., Qiu, Q., Lewis, J., Merians, A.S., 2009. Design of a complex virtual reality simulation to train finger motion for persons with hemiparesis: a proof of concept study. J. Neuroeng. Rehabil. 1743-00036 (1), 28. https://doi.org/10.1186/1743-0003-6-28. Available from: http://jneuroengrehab.biomedcentral.com/articles/10.1186/1743-0003-6-28.

Amirabdollahian, F., Loureiro, R., Gradwell, E., Collin, C., Harwin, W., Johnson, G., 2007. Multivariate analysis of the Fugl-Meyer outcome measures assessing the effectiveness of GENTLE/S robot-mediated stroke therapy. J. Neuroeng. Rehabil. 1743-00034 (1), 4. https://doi.org/10.1186/1743-0003-4-4. Available from: http://www.springerlink.com/index/10.3758/BF03203630.

Ang, K.K., Guan, C., 2015. Brain-computer interface for neurorehabilitation of upper limb after stroke. Proc. IEEE 103 (6), 944–953. https://doi.org/10.1109/JPROC.2015.2415800. Available from: http://ieeexplore.ieee.org/document/7105815/.

Ang, K.K., Guan, C., 2017. EEG-based strategies to detect motor imagery for control and rehabilitation. IEEE Trans. Neural Syst. Rehabil. Eng. 25 (4), 392–401. https://doi.org/10.1109/TNSRE.2016.2646763. Available from: http://ieeexplore.ieee.org/document/7802578/.

Ang, K.K., Chua, K.S.G., Phua, K.S., Wang, C., Chin, Z.Y., Kuah, C.W.K., Low, W., Guan, C., 2015. A randomized controlled trial of EEG-based motor imagery brain-computer interface robotic rehabilitation for stroke. Clin. EEG Neurosci. 46 (4), 310–320. https://doi.org/10.1177/1550059414522229. Available from: http://journals.sagepub.com/doi/10.1177/1550059414522229.

Babaiasl, M., Mahdioun, S.H., Jaryani, P., Yazdani, M., 2016. A review of technological and clinical aspects of robot-aided rehabilitation of upper-extremity after stroke. Disabil. Rehabil. Assist. Technol. 1748-310711 (4), 263–280. https://doi.org/10.3109/17483107.2014.1002539. Available from: http://www.tandfonline.com/doi/full/10.3109/17483107.2014.1002539.

Balasubramanian, S., Wei, R., Perez, M., Shepard, B., Koeneman, E., Koeneman, J., He, J., 2008. RUPERT: an exoskeleton robot for assisting rehabilitation of arm functions. In: 2008 International Conference on Virtual Rehabilitation (ICVR). IEEE, pp. 163–167. Available from: http://ieeexplore.ieee.org/document/4625154/.

Bansil, S., Prakash, N., Kaye, J., Wrigley, S., Manata, C., Stevens-Haas, C., Kurlan, R., 2012. Movement disorders after stroke in adults: a review. Tremor Other Hyperkinet. Mov. 2160-82882, 1–7. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3570045&tool=pmcentrez&rendertype=abstract.

Barsotti, M., Leonardis, D., Loconsole, C., Solazzi, M., Sotgiu, E., Procopio, C., Chisari, C., Bergamasco, M., Frisoli, A., 2015. A full upper limb robotic exoskeleton for reaching and grasping rehabilitation triggered by MI-BCI. In: 2015 IEEE International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 49–54. Available from: http://ieeexplore.ieee.org/document/7281174/.

Blacquiere, D., Lindsay, M.P., Foley, N., Taralson, C., Alcock, S., Balg, C., Bhogal, S., Cole, J., Eustace, M., Gallagher, P., Ghanem, A., Hoechsmann, A., Hunter, G., Khan, K., Marrero, A., Moses, B., Rayner, K., Samis, A., Smitko, E., Vibe, M., Gubitz, G., Dowlatshahi, D., Phillips, S., Silver, F.L., 2017. Canadian stroke best practice recommendations: telestroke best practice guidelines update 2017. Int. J. Stroke 1747-493012 (8), 886–895. https://doi.org/10.1177/1747493017706239. Available from: http://journals.sagepub.com/doi/10.1177/1747493017706239.

Bouri, M., Baur, C., Clavel, R., Zedka, M., Newman, C.J., 2013. "Handreha": a new hand and wrist haptic device for hemiplegic children. In: The Sixth International Conference on Advances in Computer-Human Interactions (ACHI)pp. 286–292. Available from: https://www.thinkmind.org/index.php?view=article&articleid=achi_2013_11_20_20392.

Brackenridge, J., Bradnam, L.V., Lennon, S., Costi, J.J., Hobbs, D.A., 2016. A review of rehabilitation devices to promote upper limb function following stroke. Neurosci. Biomed. Eng. 221338524 (1), 25–42. https://doi.org/10.2174/2213385204666160303220102. Available from: http://www.eurekaselect.com/openurl/content.php?genre=article&issn=2213-3852&volume=4&issue=1&spage=25http://www.ingentaconnect.com/content/ben/nbe/2016/00000004/00000001/art00006.

Brauchle, D., Vukelić, M., Bauer, R., Gharabaghi, A., 2015. Brain state-dependent robotic reaching movement with a multi-joint arm exoskeleton: combining brain-machine interfacing and robotic rehabilitation. Front. Hum. Neurosci. 1662-51619, 564. https://doi.org/10.3389/fnhum.2015.00564. Available from: http://journal.frontiersin.org/Article/10.3389/fnhum.2015.00564/abstracthttp://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC4607784http://www.ncbi.nlm.nih.gov/pubmed/26528168.

Brewer, B.R., Klatzky, R., Matsuoka, Y., 2006. Initial therapeutic results of visual feedback manipulation in robotic rehabilitation. In: 2006 International Workshop on Virtual RehabilitationIEEE, pp. 160–166. Available from: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1707546http://ieeexplore.ieee.org/document/1707546/.

Brewer, B.R., McDowell, S.K., Worthen-Chaudhari, L.C., 2007. Poststroke upper extremity rehabilitation: a review of robotic systems and clinical results. Top. Stroke Rehabil. 1074-935714 (6), 22–44. https://doi.org/10.1310/tsr1406-22. Available from: http://www.ncbi.nlm.nih.gov/pubmed/18174114.

Brewer, B.R., Klatzky, R., Matsuoka, Y., 2008. Visual feedback distortion in a robotic environment for hand rehabilitation. Brain Res. Bull. 0361923075 (6), 804–813. https://doi.org/10.1016/j.brainresbull.2008.01.006. Available from: http://linkinghub.elsevier.com/retrieve/pii/S0361923008000099. http://www.ncbi.nlm.nih.gov/pubmed/18394527.

Brochard, S., Robertson, J., Médée, B., Rémy-Néris, O., 2010. What's new in new technologies for upper extremity rehabilitation? Curr. Opin. Neurol. 1350-754023, 683–687. https://doi.org/10.1097/WCO.0b013e32833f61ce.

Broeren, J., Rydmark, M., Sunnerhagen, K.S., 2004. Virtual reality and haptics as a training device for movement rehabilitation after stroke: a single-case study. Arch. Phys. Med. Rehabil. 0003999385, 1247–1250. https://doi.org/10.1016/j.apmr.2003.09.020.

Broeren, J., Dixon, M., Sunnerhagen, K.S., Rydmark, M., 2006. Rehabilitation after stroke using virtual reality, haptics (force feedback) and telemedicine. Stud. Health Technol. Inform. 0926-9630124, 51–56. Available from: http://www.ncbi.nlm.nih.gov/pubmed/17108503.

Brokaw, E.B., Murray, T., Nef, T., Lum, P.S., 2011. Retraining of interjoint arm coordination after stroke using robot-assisted time-independent functional training. J. Rehabil. Res. Dev. 1938-135248 (4), 299–316. Available from: http://www.ncbi.nlm.nih.gov/pubmed/21674385.

Burdea, G.C., 2003. Virtual rehabilitation-benefits and challenges. Methods Inf. Med. 0026-127042 (5), 519–523. https://doi.org/10.1267/METH03050519. Available from: http://www.ncbi.nlm.nih.gov/pubmed/14654886.

Burgar, C.G., Lum, P.S., Shor, P.C., Machiel Van der Loos, H.F., 2000. Development of robots for rehabilitation therapy: the Palo Alto VA/Stanford experience. J. Rehabil. Res. Dev. 37 (6), 663–673. Available from: http://www.ncbi.nlm.nih.gov/pubmed/11321002.

Cano-de-la Cuerda, R., Molero-Sánchez, A., Carratalá-Tejada, M., Alguacil-Diego, I.M., Molina-Rueda, F., Miangolarra-Page, J.C., Torricelli, D., 2015. Theories and control models and motor learning: clinical applications in neurorehabilitation. Neurología (English Edition) 2173580830 (1), 32–41. https://doi.org/10.1016/j.nrleng.2011.12.012. Available from: http://linkinghub.elsevier.com/retrieve/pii/S2173580814001424. http://www.sciencedirect.com/science/article/pii/S2173580814001424.

Carignan, C., Tang, J., Roderick, S., 2009. Development of an exoskeleton haptic interface for virtual task training. In: 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, pp. 3697–3702. Available from: http://ieeexplore.ieee.org/document/5354834/.

Carmeli, E., Peleg, S., Bartur, G., Elbo, E., Vatine, J.-J., 2011. HandTutor enhanced hand rehabilitation after stroke—a pilot study. Physiother. Res. Int. 16 (4), 191–200. https://doi.org/10.1002/pri.485. Available from: http://www.ncbi.nlm.nih.gov/pubmed/20740477.

Cesqui, B., Tropea, P., Micera, S., Krebs, H., 2013. EMG-based pattern recognition approach in post stroke robot-aided rehabilitation: a feasibility study. J. Neuroeng. Rehabil. 1743-000310 (1), 75. https://doi.org/10.1186/1743-0003-10-75. Available from: http://jneuroengrehab.biomedcentral.com/articles/10.1186/1743-0003-10-75.

Choi, C., Kim, J., 2007. A real-time EMG-based assistive computer interface for the upper limb disabled. In: 2007 IEEE 10th International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 459–462. Available from: http://ieeexplore.ieee.org/document/4428465/.

Coderre, A.M., Amr Abou Zeid, A.A., Dukelow, S.P., Demmer, M.J., Moore, K.D., Demers, M.J., Bretzke, H., Herter, T.M., Glasgow, J.I., Norman, K.E., Bagg, S.D., Scott, S.H., 2010. Assessment of upper-limb sensorimotor function of subacute stroke patients using visually guided reaching. Neurorehabil. Neural Repair 24 (6), 528–541. https://doi.org/10.1177/1545968309356091. Available from: http://www.ncbi.nlm.nih.gov/pubmed/20233965.

Colombo, R., Pisano, F., Micera, S., Mazzone, A., Delconte, C., Carrozza, M.C., Dario, P., Minuco, G., 2005. Robotic techniques for upper limb evaluation and rehabilitation of stroke patients. IEEE Trans. Neural Syst. Rehabil. Eng. 1534-432013 (3), 311–324. https://doi.org/10.1109/TNSRE.2005.848352. Available from: http://www.ncbi.nlm.nih.gov/pubmed/16200755.

Crocher, V., Sahbani, A., Robertson, J., Roby-Brami, A., Morel, G., 2012. Constraining upper limb synergies of hemiparetic patients using a robotic exoskeleton in the perspective of neuro-rehabilitation. IEEE Trans. Neural Syst. Rehabil. Eng. 1534-432020 (3), 247–257. https://doi.org/10.1109/TNSRE.2012.2190522. Available from: http://ieeexplore.ieee.org/document/6177268/. http://www.ncbi.nlm.nih.gov/pubmed/22481836.

Crow, J.L., Lincoln, N.B., Nouri, F.M., Weerdt, W.D., 1989. The effectiveness of EMG biofeedback in the treatment of arm function after stroke. Int. Disabil. Stud. 0259-914711 (4), 155–160. https://doi.org/10.3109/03790798909166667. Available from: http://www.tandfonline.com/doi/full/10.3109/03790798909166667.

Culmer, P.R., Jackson, A.E., Makower, S., Richardson, R., Cozens, J.A., Levesley, M.C., Bhakta, B.B., 2010. A control strategy for upper limb robotic rehabilitation with a dual robot system. IEEE/ASME Trans. Mechatron. 1083-443515 (4), 575–585. https://doi.org/10.1109/TMECH.2009.2030796. Available from: http://ieeexplore.ieee.org/document/5263023/.

Cvjetkovic, D.D., Bijeljac, S., Palija, S., Talic, G., Radulovic, T.N., Kosanovic, M.G., Manojlovic, S., 2015. Isokinetic testing in evaluation rehabilitation outcome after ACL reconstruction. Med. Arch. (Sarajevo, Bosnia and Herzegovina) 69 (1), 21–23. https://doi.org/10.5455/medarh.2015.69.21-23. Available from: http://www.ncbi.nlm.nih.gov/pubmed/25870471.

Daly, J.J., Huggins, J.E., 2015. Brain-computer interface: current and emerging rehabilitation applications. Arch. Phys. Med. Rehabil. 0003999396 (3), S1–S7. https://doi.org/10.1016/j.apmr.2015.01.007. Available from: http://linkinghub.elsevier.com/retrieve/pii/S0003999315000209. http://www.ncbi.nlm.nih.gov/pubmed/25721542.

Daly, J.J., Wolpaw, J.R., 2008. Brain-computer interfaces in neurological rehabilitation. Lancet Neurol. 147444227 (11), 1032–1043. https://doi.org/10.1016/S1474-4422(08)70223-0. Available from: http://www.sciencedirect.com/science/article/pii/S1474442208702230?via%3Dihub.

Ding, M., Ueda, J., Ogasawara, T., 2008. Pinpointed muscle force control using a power-assisting device: system configuration and experiment. In: Proceedings of the 2nd Biennial IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechatronics, BioRob 2008. IEEE, pp. 181–186. Available from: http://ieeexplore.ieee.org/document/4762829/.

Ding, M., Hirasawa, K., Kurita, Y., Takemura, H., Takamatsu, J., Mizoguchi, H., Ogasawara, T., 2010. Pinpointed muscle force control in consideration of human motion and external force. In: 2010 IEEE International Conference on Robotics and Biomimetics (ROBIO). IEEE, pp. 739–744. Available from: http://ieeexplore.ieee.org/document/5723418/.

Dipietro, L., Ferraro, M., Palazzolo, J.J., Krebs, H.I., Volpe, B.T., Hogan, N., 2005. Customized interactive robotic treatment for stroke: EMG-triggered therapy. IEEE Trans. Neural Syst. Rehabil. Eng. 1534-432013 (3), 325–334. https://doi.org/10.1109/TNSRE.2005.850423. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC2752646. http://www.ncbi.nlm.nih.gov/pubmed/16200756.

Dong, S., Lu, K.-Q., Sun, J.Q., Rudolph, K., 2006. Smart rehabilitation devices: part II—adaptive motion control. J. Intell. Mater. Syst. Struct. 1045-389X17 (7), 555–561. https://doi.org/10.1177/1045389X06059076. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=2424262&tool=pmcentrez&rendertype=abstract.

Dremstrup, K., Niazi, I.K., Jochumsen, M., Jiang, N., Mrachacz-Kersting, N., Farina, D., 2014. Rehabilitation using a brain computer interface based on movement related cortical potentials—a review. In: Roa Romero, L.M. (Ed.), XIII Mediterranean Conference on Medical and Biological Engineering and Computing 2013. Springer International Publishing, Cham, pp. 1659–1662.

Duc, D.M., Kazuhiko, T., Takanori, M., 2008. EMG-moment model of human arm for rehabilitation robot system. In: 2008 10th International Conference on Control, Automation, Robotics and Vision. IEEE, pp. 190–195. Available from: http://ieeexplore.ieee.org/document/4795515/.

Elbagoury, B.M., Vladareanu, L., 2016. A hybrid real-time EMG intelligent rehabilitation robot motions control based on Kalman filter, support vector machines and particle swarm optimization. In: 2016 10th International Conference on Software, Knowledge, Information Management & Applications (SKIMA). IEEE, pp. 439–444. Available from: http://ieeexplore.ieee.org/document/7916262/.

Erol, D., Sarkar, N., 2007. Intelligent control for robotic rehabilitation after stroke. J. Intell. Robot. Syst. 0921-029650 (4), 341–360. https://doi.org/10.1007/s10846-007-9169-2. Available from: http://link.springer.com/10.1007/s10846-007-9169-2.

Fazekas, G., Horvath, M., Toth, A., 2006. A novel robot training system designed to supplement upper limb physiotherapy of patients with spastic hemiparesis. Int. J. Rehabil. Res. 29 (29) Available from: https://insights.ovid.com/pubmed?pmid=16900048.

Flash, T., Hogan, N., 1985. The coordination of arm movements: an experimentally confirmed mathematical model. J. Neurosci. 0270-64745 (7), 1688–1703. Available from: https://doi.org/4020415. http://www.ncbi.nlm.nih.gov/pubmed/4020415. http://www.jneurosci.org/cgi/content/abstract/5/7/1688.

Fok, S., Schwartz, R., Wronkiewicz, M., Holmes, C., Zhang, J., Somers, T., Bundy, D., Leuthardt, E., 2011. An EEG-based brain computer interface for rehabilitation and restoration of hand control following stroke using ipsilateral cortical physiology. In: 2011

Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, pp. 6277–6280. Available from: http://ieeexplore.ieee.org/document/6091549/.
Frisoli, A., Loconsole, C., Leonardis, D., Banno, F., Barsotti, M., Chisari, C., Bergamasco, M., 2012. A new gaze-BCI-driven control of an upper limb exoskeleton for rehabilitation in real-world tasks. IEEE Trans. Syst. Man Cybern. Part C Appl. Rev. 1094-697742 (6), 1169–1179. https://doi.org/10.1109/TSMCC.2012.2226444. Available from: http://ieeexplore.ieee.org/document/6392463/.
Fulk, G., O'sullivan, S.B., Schmitz, T.J., 2014. Physical Rehabilitation, sixth ed. F.A. Davis Company. ISBN 978-0-8036-2579-2.
Ghannadi, B., Mehrabi, N., Sharif Razavian, R., McPhee, J., 2017. Nonlinear model predictive control of an upper extremity rehabilitation robot using a two-dimensional human-robot interaction model. In: IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, Vancouver, British Columbia, Canada, pp. 502–507. Available from: http://ieeexplore.ieee.org/document/8202200/.
Goodrich, M.A., Schultz, A.C., 2007. Human-robot interaction: a survey. Found. Trends Hum. Comput. Interact. 1551-39551 (3), 203–275. https://doi.org/10.1561/1100000005. Available from: http://www.nowpublishers.com/article/Details/HCI-005.
Gopura, R.A.R.C., Bandara, D.S.V., Kiguchi, K., Mann, G.K.I., 2016. Developments in hardware systems of active upper-limb exoskeleton robots: a review. Robot. Auton. Syst. 0921889075, 203–220. https://doi.org/10.1016/j.robot.2015.10.001. Available from: http://www.sciencedirect.com/science/article/pii/S0921889015002274.
Guidali, M., Schmiedeskamp, M., Klamroth, V., Riener, R., 2009. Assessment and training of synergies with an arm rehabilitation robot. In: 2009 IEEE International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 772–776. Available from: http://ieeexplore.ieee.org/document/5209516/.
Guidali, M., Duschau-Wicke, A., Broggi, S., Klamroth-Marganska, V., Nef, T., Riener, R., 2011. A robotic system to train activities of daily living in a virtual environment. Med. Biol. Eng. Comput. 0140-011849 (10), 1213–1223. https://doi.org/10.1007/s11517-011-0809-0. Available from: http://link.springer.com/10.1007/s11517-011-0809-0. http://www.ncbi.nlm.nih.gov/pubmed/21796422.
Guo, S., Zhang, W., Wei, W., Guo, J., Ji, Y., Wang, Y., 2013. A kinematic model of an upper limb rehabilitation robot system. In: 2013 IEEE International Conference on Mechatronics and Automation. IEEE, pp. 968–973. Available from: http://ieeexplore.ieee.org/document/6618046/.
Gupta, A., O'Malley, M.K., 2006. Design of a haptic arm exoskeleton for training and rehabilitation. IEEE/ASME Trans. Mechatron. 1083-443511 (3), 280–289. https://doi.org/10.1109/TMECH.2006.875558. Available from: http://ieeexplore.ieee.org/document/1642690/.
Hatem, S.M., Saussez, G., della Faille, M., Prist, V., Zhang, X., Dispa, D., Bleyenheuft, Y., 2016. Rehabilitation of motor function after stroke: a multiple systematic review focused on techniques to stimulate upper extremity recovery. Front. Hum. Neurosci. 1662-516110, 442. https://doi.org/10.3389/fnhum.2016.00442. Available from: http://journal.frontiersin.org/Article/10.3389/fnhum.2016.00442/abstract. http://www.ncbi.nlm.nih.gov/pubmed/27679565.
Hernández Arieta, A., Kato, R., Yu, W., Yokoi, H., 2007. The man-machine interaction: the influence of artificial intelligence on rehabilitation robotics. In: 50 Years of Artificial IntelligenceSpringer, Berlin, Heidelberg, pp. 221–231. Available from: http://link.springer.com/10.1007/978-3-540-77296-5_21.
Hesse, S., Schmidt, H., Werner, C., Bardeleben, A., 2003. Upper and lower extremity robotic devices for rehabilitation and for studying motor control. Curr. Opin. Neurol. 1350-754016, 705–710. https://doi.org/10.1097/00019052-200312000-00010.

Hesse, S., Schulte-Tigges, G., Konrad, M., Bardeleben, A., Werner, C., 2003. Robot-assisted arm trainer for the passive and active practice of bilateral forearm and wrist movements in hemiparetic subjects. Arch. Phys. Med. Rehabil. 0003999384 (6), 915–920. https://doi.org/10.1016/S0003-9993(02)04954-7. Available from: http://www.sciencedirect.com/science/article/pii/S0003999302049547?via%3Dihub.

Hogan, N., 1985. Impedance control: an approach to manipulation: part I—theory. J. Dyn. Syst. Meas. Control. 00220434107 (1), 1. https://doi.org/10.1115/1.3140702. Available from: http://dynamicsystems.asmedigitalcollection.asme.org/article.aspx?articleid=1403621.

Hu, X., Tong, R.K.Y., 2014. FES in rehabilitation robotics. In: 2014 IEEE 19th International Functional Electrical Stimulation Society Annual Conference (IFESS). IEEE, pp. 1–3. Available from: http://ieeexplore.ieee.org/document/7036730/.

Huang, X., Naghdy, F., Naghdy, G., Du, H., Todd, C., 2017. Robot-assisted post-stroke motion rehabilitation in upper extremities: a survey. Int. J. Disabil. Hum. Dev. 16 (3), 233–247. https://doi.org/10.1515/ijdhd-2016-0035. Available from: http://www.degruyter.com/view/j/ijdhd.2017.16.issue-3/ijdhd-2016-0035/ijdhd-2016-0035.xml.

Ifejika-Jones, N.L., Barrett, A.M., 2011. Rehabilitation-emerging technologies, innovative therapies, and future objectives. Neurotherapeutics 193372138 (3), 452–462. https://doi.org/10.1007/s13311-011-0057-x. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3148149. http://www.ncbi.nlm.nih.gov/pubmed/21706265.

Ivanova, E., Kruger, J., Steingraber, R., Schmid, S., Schmidt, H., Hesse, S., 2015. Design and concept of a haptic robotic telerehabilitation system for upper limb movement training after stroke. In: IEEE 14th International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 666–671. Available from: http://ieeexplore.ieee.org/document/7281277/.

Jack, D., Boian, R., Merians, A.S., Tremaine, M., Burdea, G.C., Adamovich, S.V., Recce, M., Poizner, H., 2001. Virtual reality-enhanced stroke rehabilitation. IEEE Trans. Neural Syst. Rehabil. Eng. 153443209 (3), 308–318. https://doi.org/10.1109/7333.948460. Available from: http://ieeexplore.ieee.org/document/948460/.

Jackson, A.E., Culmer, P.R., Makower, S.G., Levesley, M.C., Richardson, R.C., Cozens, J.A., Williams, M.M., Bhakta, B.B., 2007. Initial patient testing of iPAM—a robotic system for Stroke rehabilitation. In: IEEE 10th International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 250–256. Available from: http://ieeexplore.ieee.org/document/4428435/.

Jackson, A.E., Levesley, M.C., Makower, S.G., Cozens, J.A., Bhakta, B.B., 2013. Development of the iPAM MkII system and description of a randomized control trial with acute stroke patients. In: IEEE 13th International Conference on Rehabilitation Robotics (ICORR), vol. 2013. IEEE, pp. 1–6. Available from: http://www.ncbi.nlm.nih.gov/pubmed/24187226.

Johnson, M.J., Van der Loos, H.F.M., Burgar, C.G., Shor, P., Leifer, L.J., 2003. Design and evaluation of Driver's SEAT: a car steering simulation environment for upper limb stroke therapy. Robotica 0263-574721 (1), 13–23. https://doi.org/10.1017/S0263574702004599. Available from: http://www.journals.cambridge.org/abstract_S0263574702004599.

Johnson, M.J., Trickey, M., Brauer, E., Feng, X., 2004. TheraDrive: a new stroke therapy concept for home-based, computer-assisted motivating rehabilitation. In: The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS), vol. 4. IEEE, pp. 4844–4847. Available from: http://ieeexplore.ieee.org/document/1404340/.

Johnson, M.J., Wisneski, K.J., Anderson, J., Nathan, D., Smith, R.O., 2006. Development of ADLER: the activities of daily living exercise robot. In: Proceedings of the First IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechatronics, 2006, BioRob 2006, vol. 2006. IEEE, pp. 881–886. Available from: http://ieeexplore.ieee.org/document/1639202/.

Jorgensen, H.S., Nakayama, H., Raaschou, H.O., Vive-Larsen, J., Stoier, M., Olsen, T.S., 1995. Outcome and time course of recovery in stroke. Part II: time course of recovery. The Copenhagen Stroke Study. Arch. Phys. Med. Rehabil. 0003999376, 406–412. https://doi.org/10.1016/S0003-9993(95)80568-0.

Kahn, L.E., Rymer, W.Z., Reinkensmeyer, D.J., 2004. Adaptive assistance for guided force training in chronic stroke. In: The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, vol. 3. IEEE, pp. 2722–2725. Available from: http://ieeexplore.ieee.org/document/1403780/.

Kahn, L.E., Zygman, M.L., Rymer, W.Z., Reinkensmeyer, D.J., 2006. Robot-assisted reaching exercise promotes arm movement recovery in chronic hemiparetic stroke: a randomized controlled pilot study. J. Neuroeng. Rehabil. 1743-00033, 12. https://doi.org/10.1186/1743-0003-3-12. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC1550245. http://www.ncbi.nlm.nih.gov/pubmed/16790067.

Kapadia, N.M., Nagai, M.K., Zivanovic, V., Bernstein, J., Woodhouse, J., Rumney, P., Popovic, M.R., 2014. Functional electrical stimulation therapy for recovery of reaching and grasping in severe chronic pediatric stroke patients. J. Child Neurol. 0883-073829 (4), 493–499. https://doi.org/10.1177/0883073813484088. Available from: http://journals.sagepub.com/doi/10.1177/0883073813484088. http://www.ncbi.nlm.nih.gov/pubmed/23584687.

Kikuchi, T., Xinghao, H., Fukushima, K., Oda, K., Furusho, J., Inoue, A., 2007. Quasi-3-DOF rehabilitation system for upper limbs: its force-feedback mechanism and software for rehabilitation. In: IEEE 10th International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 24–27. Available from: http://ieeexplore.ieee.org/document/4428401/.

Kim, H., Miller, L.M., Fedulow, I., Simkins, M., Abrams, G.M., Byl, N., Rosen, J., 2013. Kinematic data analysis for post-stroke patients following bilateral versus unilateral rehabilitation with an upper limb wearable robotic system. IEEE Trans. Neural Syst. Rehabil. Eng. 1534432021 (2), 153–164. https://doi.org/10.1109/TNSRE.2012.2207462. Available from: http://ieeexplore.ieee.org/document/6252060/.

Klamroth-Marganska, V., Blanco, J., Campen, K., Curt, A., Dietz, V., Ettlin, T., Felder, M., Fellinghauer, B., Guidali, M., Kollmar, A., Luft, A., Nef, T., Schuster-Amft, C., Stahel, W., Riener, R., 2014. Three-dimensional, task-specific robot therapy of the arm after stroke: a multicentre, parallel-group randomised trial. Lancet Neurol. 1474442213 (2), 159–166. https://doi.org/10.1016/S1474-4422(13)70305-3. Available from: http://linkinghub.elsevier.com/retrieve/pii/S1474442213703053. http://www.ncbi.nlm.nih.gov/pubmed/24382580.

Koeneman, E.J., Schultz, R.S., Wolf, S.L., Herring, D.E., Koeneman, J.B., 2004. A pneumatic muscle hand therapy device. In: Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS), vol. 4. IEEE, pp. 2711–2713. Available from: http://ieeexplore.ieee.org/document/1403777/.

Kousidou, S., Tsagarakis, N.G., Smith, C., Caldwell, D.G., 2007. Task-orientated biofeedback system for the rehabilitation of the upper limb. In: 2007 IEEE 10th International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 376–384. Available from: http://ieeexplore.ieee.org/document/4428453/.

Krebs, H.I., Hogan, N., 2012. Robotic therapy: the tipping point. Am. J. Phys. Med. Rehabil. 1537-738591, S290–S297. https://doi.org/10.1097/PHM.0b013e31826bcd80. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3480667. http://www.ncbi.nlm.nih.gov/pubmed/23080044.

Krebs, H.I., Volpe, B.T., 2013. Rehabilitation robotics. Handb. Clin. Neurol. 00729752110, 283–294. https://doi.org/10.1016/B978-0-444-52901-5.00023-X. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC4688009. http://www.ncbi.nlm.nih.gov/pubmed/23312648.

Krebs, H.I., Hogan, N., Aisen, M.L., Volpe, B.T., 1998. Robot-aided neurorehabilitation. IEEE Trans. Rehabil. Eng. 6 (1), 75–87. Available from: http://www.ncbi.nlm.nih.gov/pubmed/9535526.

Krebs, H.I., Palazzolo, J.J., Dipietro, L., Ferraro, M., Krol, J., Rannekleiv, K., Volpe, B.T., Hogan, N., 2003. Rehabilitation robotics: performance-based progressive robot-assisted therapy. Auton. Robot. 0929559315 (1), 7–20. https://doi.org/10.1023/A:1024494031121. Available from: http://link.springer.com/10.1023/A:1024494031121.

Krueger, H., Lindsay, P., Cote, R., Kapral, M.K., Kaczorowski, J., Hill, M.D., 2012. Cost avoidance associated with optimal stroke care in Canada. Stroke 0039249943 (8), 2198–2206. https://doi.org/10.1161/STROKEAHA.111.646091. Available from: http://stroke.ahajournals.org/content/early/2012/05/24/STROKEAHA.111.646091.

Leonardis, D., Barsotti, M., Loconsole, C., Solazzi, M., Troncossi, M., Mazzotti, C., Castelli, V.P., Procopio, C., Lamola, G., Chisari, C., Bergamasco, M., Frisoli, A., 2015. An EMG-controlled robotic hand exoskeleton for bilateral rehabilitation. IEEE Trans. Haptics 1939-14128 (2), 140–151. https://doi.org/10.1109/TOH.2015.2417570. Available from: http://ieeexplore.ieee.org/document/7072553/.

Liu, C., Wang, H., Pu, H., Zhang, Y., Zou, L., 2012. EEG feature extraction and pattern recognition during right and left hands motor imagery in brain-computer interface. In: 5th International Conference on BioMedical Engineering and Informatics. IEEE, pp. 506–510. Available from: http://ieeexplore.ieee.org/document/6513023/.

Liu, Y., Li, C., Ji, L., Bi, S., Zhang, X., Huo, J., Ji, R., 2017. Development and implementation of an end-effector upper limb rehabilitation robot for hemiplegic patients with line and circle tracking training. J. Healthcare Eng. 2040-22952017, 1–11. https://doi.org/10.1155/2017/4931217. Available from: https://www.hindawi.com/journals/jhe/2017/4931217/.

Lo, H.S., Xie, S.Q., 2012. Exoskeleton robots for upper-limb rehabilitation: state of the art and future prospects. Med. Eng. Phys. 1350453334 (3), 261–268. https://doi.org/10.1016/j.medengphy.2011.10.004. Available from: http://www.sciencedirect.com/science/article/pii/S1350453311002694#fig0015.

Loconsole, C., Bartalucci, R., Frisoli, A., Bergamasco, M., 2011. A new gaze-tracking guidance mode for upper limb robot-aided neurorehabilitation. In: 2011 IEEE World Haptics Conference. IEEE, pp. 185–190. Available from: http://ieeexplore.ieee.org/document/5945483/.

Loconsole, C., Dettori, S., Frisoli, A., Avizzano, C.A., Bergamasco, M., 2014. An EMG-based approach for on-line predicted torque control in robotic-assisted rehabilitation. In: 2014 IEEE Haptics Symposium (HAPTICS)IEEE, pp. 181–186. Available from: http://ieeexplore.ieee.org/document/6775452/.

Louie, W.-Y.G., Mohamed, S., Nejat, G., 2017. Human-robot interaction for rehabilitation robots. In: Encarnação, P., Cook, A.M. (Eds.), Robotic Assistive Technologies: Principles and Practice. Taylor & Francis Group, CRC Press, pp. 25–70. Available from: http://www.crcnetbase.com/doi/10.1201/9781315368788-3.

Loureiro, R.C.V., Harwin, W.S., 2007. Reach & grasp therapy: design and control of a 9-DOF robotic neuro-rehabilitation system. In: 2007 IEEE 10th International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 757–763. Available from: http://ieeexplore.ieee.org/document/4428510/.

Loureiro, R., Amirabdollahian, F., Topping, M., Driessen, B., Harwin, W., 2003. Upper limb robot mediated stroke therapy—GENTLE/s approach. Auton. Robot.

0929559315 (1), 35–51. https://doi.org/10.1023/A:1024436732030. Available from: http://link.springer.com/10.1023/A:1024436732030. http://link.springer.com/article/10.1023/A%3A1024436732030.

Maciejasz, P., Eschweiler, J., Gerlach-Hahn, K., Jansen-Troy, A., Leonhardt, S., 2014. A survey on robotic devices for upper limb rehabilitation. J. Neuroeng. Rehabil. 1743-000311(1), 3. https://doi.org/10.1186/1743-0003-11-3. Available from: http://www.jneuroengrehab.com/content/11/1/3.

Maitland, A., McPhee, J., 2018. Fast NMPC with mixed-integer controls using quasi-translations. In: 6th IFAC Conference on Nonlinear Model Predictive Control. Madison, Wisconsin, USA.

Mao, Y., Jin, X., Gera Dutta, G., Scholz, J.P., Agrawal, S.K., 2015. Human movement training with a cable driven arm exoskeleton (CAREX). IEEE Trans. Neural Syst. Rehabil. Eng. 1534-432023 (1), 84–92. https://doi.org/10.1109/TNSRE.2014.2329018. Available from: http://ieeexplore.ieee.org/document/6826540/. http://www.ncbi.nlm.nih.gov/pubmed/24919202.

Marchal-Crespo, L., Reinkensmeyer, D.J., 2009. Review of control strategies for robotic movement training after neurologic injury. J. Neuroeng. Rehabil. 1743-00036 (1), 20. https://doi.org/10.1186/1743-0003-6-20. Available from: http://www.jneuroengrehab.com/content/6/1/20.

Marquez-Chin, C., Marquis, A., Popovic, M.R., 2016. EEG-triggered functional electrical stimulation therapy for restoring upper limb function in chronic stroke with severe hemiplegia. Case Rep. Neurol. Med. 2016, 1–11. https://doi.org/10.1155/2016/9146213. Available from: https://www.hindawi.com/journals/crinm/2016/9146213/.

Mehrabi, N., Sharif Razavian, R., Ghannadi, B., McPhee, J., 2017. Predictive simulation of reaching moving targets using nonlinear model predictive control. Front. Comput. Neurosci. 1662-518810, 143. https://doi.org/10.3389/fncom.2016.00143. Available from: http://journal.frontiersin.org/article/10.3389/fncom.2016.00143/full.

Mehrholz, J., Hädrich, A., Platz, T., Kugler, J., Pohl, M., 2012. Electromechanical and robot-assisted arm training for improving generic activities of daily living, arm function, and arm muscle strength after stroke. In: Jan, M. (Ed.), Cochrane Database of Systematic Reviews. In: vol. 6. John Wiley & Sons, Ltd, Chichester, p. CD006876. Available from: http://doi.wiley.com/10.1002/14651858.CD006876.pub3. http://onlinelibrary.wiley.com/doi/10.1002/14651858.CD006876.pub3/pdf/standard. http://www.ncbi.nlm.nih.gov/pubmed/22696362.

Mendis, S., 2013. Stroke disability and rehabilitation of stroke: World Health Organization perspective. Int. J. Stroke 8 (1), 3–4. https://doi.org/10.1111/j.1747-4949.2012.00969.x. Available from:. http://www.ncbi.nlm.nih.gov/pubmed/23280261.

Mihelj, M., Nef, T., Riener, R., 2007. A novel paradigm for patient-cooperative control of upper-limb rehabilitation robots. Adv. Robot. 0169-186421 (8), 843–867. https://doi.org/10.1163/156855307780851975. Available from: http://www.tandfonline.com/doi/abs/10.1163/156855307780851975.

Miller, L.M., Rosen, J., 2010. Comparison of multi-sensor admittance control in joint space and task space for a seven degree of freedom upper limb exoskeleton. In: 2010 3rd IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob). IEEE, pp. 70–75. Available from: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5628069.

Montagner, A., Frisoli, A., Borelli, L., Procopio, C., Bergamasco, M., Carboncini, M.C., Rossi, B., 2007. A pilot clinical study on robotic assisted rehabilitation in VR with an arm exoskeleton device. In: 2007 International Conference on Virtual Rehabilitation (ICVR). IEEE, pp. 57–64. Available from: http://ieeexplore.ieee.org/document/4362131/.

Morris, S.L., Dodd, K.J., Morris, M.E., 2004. Outcomes of progressive resistance strength training following stroke: a systematic review. Clin. Rehabil. 0269-215518 (1), 27–39. https://doi.org/10.1191/0269215504cr699oa. Available from: http://journals.sagepub.com/doi/10.1191/0269215504cr699oa.

Mostafavi, S.M., Mousavi, P., Dukelow, S.P., Scott, S.H., 2015. Robot-based assessment of motor and proprioceptive function identifies biomarkers for prediction of functional independence measures. J. Neuroeng. Rehabil. 1743-000312 (1), 105. https://doi.org/10.1186/s12984-015-0104-7. Available from: http://www.jneuroengrehab.com/content/12/1/105. http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC4661950. http://www.ncbi.nlm.nih.gov/pubmed/26611144.

Moubarak, S., Pham, M.T., Moreau, R., Redarce, T., 2010. Gravity compensation of an upper extremity exoskeleton. In: 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology, vol. 2010. IEEE, pp. 4489–4493. Available from: http://ieeexplore.ieee.org/document/5626036/. http://www.ncbi.nlm.nih.gov/pubmed/21095778.

Mrachacz-Kersting, N., Jiang, N., Stevenson, A.J.T., Niazi, I.K., Kostic, V., Pavlovic, A., Radovanovic, S., Djuric-Jovicic, M., Agosta, F., Dremstrup, K., Farina, D., 2016. Efficient neuroplasticity induction in chronic stroke patients by an associative brain-computer interface. J. Neurophysiol. 0022-3077115 (3), 1410–1421. https://doi.org/10.1152/jn.00918.2015. Available from: http://www.physiology.org/doi/10.1152/jn.00918.2015.

Muratori, L.M., Lamberg, E.M., Quinn, L., Duff, S.V., 2013. Applying principles of motor learning and control to upper extremity rehabilitation. J. Hand Ther. 0894113026, 94–103. https://doi.org/10.1016/j.jht.2012.12.007.

Nef, T., Mihelj, M., Riener, R., 2007. ARMin: a robot for patient-cooperative arm therapy. Med. Biol. Eng. Comput. 0140-011845 (9), 887–900. https://doi.org/10.1007/s11517-007-0226-6. Available from: http://link.springer.com/10.1007/s11517-007-0226-6.

Nef, T., Guidali, M., Riener, R., 2009. ARMin III—arm therapy exoskeleton with an ergonomic shoulder actuation. Appl. Bionics Biomech. 6 (2), 127–142. https://doi.org/10.1080/11762320902840179. Available from: http://content.iospress.com/doi/10.1080/11762320902840179.

Novak, D., Riener, R., 2013. Enhancing patient freedom in rehabilitation robotics using gaze-based intention detection. In: 2013 IEEE 13th International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 1–6. Available from: http://ieeexplore.ieee.org/document/6650507/.

Oblak, J., Cikajlo, I., Matjacic, Z., 2010. Universal haptic drive: a robot for arm and wrist rehabilitation. IEEE Trans. Neural Syst. Rehabil. Eng. 18 (3), 293–302. https://doi.org/10.1109/TNSRE.2009.2034162. Available from: http://ieeexplore.ieee.org/document/5290020/.

O'Connor, R.J., Jackson, A., Makower, S.G., Cozens, A., Levesley, M., 2015. A proof of concept study investigating the feasibility of combining iPAM robot assisted rehabilitation with functional electrical stimulation to deliver whole arm exercise in stroke survivors. J. Med. Eng. Technol. 0309-190239 (7), 411–418. https://doi.org/10.3109/03091902.2015.1088094. Available from: http://www.tandfonline.com/doi/full/10.3109/03091902.2015.1088094. http://www.ncbi.nlm.nih.gov/pubmed/26414146.

Oda, K., Isozumi, S., Ohyama, Y., Tamida, K., Kikuchi, T., Furusho, J., 2009. Development of isokinetic and iso-contractile exercise machine "MEM-MRB" using MR brake. In: IEEE 11th International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 6–11. Available from: http://ieeexplore.ieee.org/document/5209510/.

Ott, C., Mukherjee, R., Nakamura, Y., 2010. Unified impedance and admittance control. In: 2010 IEEE International Conference on Robotics and Automation (ICRA) pp. 554–561. https://doi.org/10.1109/ROBOT.2010.5509861. Available from: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5509861.

Oujamaa, L., Relave, I., Froger, J., Mottet, D., Pelissier, J.Y., 2009. Rehabilitation of arm function after stroke. Literature review. Ann. Phys. Rehabil. Med. 1877065752, 269–293. https://doi.org/10.1016/j.rehab.2008.10.003.

Patten, C., Dozono, J., Schmidt, S., Jue, M., Lum, P., 2006. Combined functional task practice and dynamic high intensity resistance training promotes recovery of upper-extremity motor function in post-stroke hemiparesis: a case study. J. Neurol. Phys. Ther. 1557-057630 (3), 99–115. Available from: http://www.ncbi.nlm.nih.gov/pubmed/17029654.

Patton, J.L., Dawe, G., Scharver, C., Mussa-Ivaldi, F.A., Kenyon, R., 2004. Robotics and virtual reality: the development of a life-sized 3-D system for the rehabilitation of motor function. In: The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, vol. 4. IEEE, pp. 4840–4843. Available from: http://ieeexplore.ieee.org/document/1404339/.

Patton, J.L., Kovic, M., Mussa-Ivaldi, F.A., 2006. Custom-designed haptic training for restoring reaching ability to individuals with poststroke hemiparesis. J. Rehabil. Res. Dev. 1938-135243 (5), 643–656. Available from: http://www.ncbi.nlm.nih.gov/pubmed/17123205.

Patton, J.L., Stoykov, M.E., Kovic, M., Mussa-Ivaldi, F.A., 2006. Evaluation of robotic training forces that either enhance or reduce error in chronic hemiparetic stroke survivors. Exp. Brain Res. 0014-4819168 (3), 368–383. https://doi.org/10.1007/s00221-005-0097-8. Available from: http://link.springer.com/10.1007/s00221-005-0097-8. http://www.ncbi.nlm.nih.gov/pubmed/16249912.

Pérez-Rodríguez, R., Rodríguez, C., Costa, Ú., Cáceres, C., Tormos, J.M., Medina, J., Gómez, E.J., 2014. Anticipatory assistance-as-needed control algorithm for a multijoint upper limb robotic orthosis in physical neurorehabilitation. Expert Syst. Appl. 0957417441 (8), 3922–3934. https://doi.org/10.1016/j.eswa.2013.11.047. Available from: http://linkinghub.elsevier.com/retrieve/pii/S0957417413009895.

Perry, J.C., Rosen, J., Burns, S., 2007. Upper-limb powered exoskeleton design. IEEE/ASME Trans. Mechatron. 12 (4), 408–417. https://doi.org/10.1109/TMECH.2007.901934. Available from: http://ieeexplore.ieee.org/document/4291584/.

Pignolo, L., Dolce, G., Basta, G., Lucca, L.F., Serra, S., Sannita, W.G., 2012. Upper limb rehabilitation after stroke: ARAMIS a "robo-mechatronic" innovative approach and prototype. In: 2012 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob). IEEE, pp. 1410–1414. Available from: http://ieeexplore.ieee.org/document/6290868/.

Poli, P., Morone, G., Rosati, G., Masiero, S., 2013. Robotic technologies and rehabilitation: new tools for stroke patients' therapy. Biomed. Res. Int. 23146-1332013, 153872. https://doi.org/10.1155/2013/153872. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3852950. http://www.ncbi.nlm.nih.gov/pubmed/24350244.

Prisco, G.M., Avizzano, C.A., Calcara, M., Ciancio, S., Pinna, S., Bergamasco, M., 1998. A virtual environment with haptic feedback for the treatment of motor dexterity disabilities. In: Proceedings. 1998 IEEE International Conference on Robotics and Automation (Cat. No. 98CH36146), vol. 4. IEEE, pp. 3721–3726. Available from: http://ieeexplore.ieee.org/document/681418/.

Proietti, T., Jarrasse, N., Roby-Brami, A., Morel, G., 2015. Adaptive control of a robotic exoskeleton for neurorehabilitation. In: 2015 7th International IEEE/EMBS Conference on Neural Engineering (NER). IEEE, pp. 803–806. Available from: http://ieeexplore.ieee.org/document/7146745/.

Proietti, T., Crocher, V., Roby-Brami, A., Jarrasse, N., 2016. Upper-limb robotic exoskeletons for neurorehabilitation: a review on control strategies. IEEE Rev. Biomed. Eng.

1937-33339, 4–14. https://doi.org/10.1109/RBME.2016.2552201. Available from: http://www.ncbi.nlm.nih.gov/pubmed/27071194. http://ieeexplore.ieee.org/document/7450169/.

Rahman, M.H., Ochoa-Luna, C., Saad, M., 2015. EMG based control of a robotic exoskeleton for shoulder and elbow motion assist. J. Autom. Control Eng. 230137023 (4), 270–276. https://doi.org/10.12720/joace.3.4.270-276. Available from: http://www.joace.org/index.php?m=content&c=index&a=show&catid=44&id=242.

Reinkensmeyer, D.J., 2009. Robotic assistance for upper extremity training after stroke. In: Studies in Health Technology and Informatics, vol. 145. pp. 25–39.

Reinkensmeyer, D.J., Kahn, L.E., Averbuch, M., McKenna-Cole, A., Schmit, B.D., Rymer, W.Z., 2000. Understanding and treating arm movement impairment after chronic brain injury: progress with the ARM guide. J. Rehabil. Res. Dev. 0748-771137 (6), 653–662. Available from: http://www.ncbi.nlm.nih.gov/pubmed/11321001.

Reinkensmeyer, D.J., Lum, P., Winters, J.M., 2002. Emerging technologies for improving access to movement therapy following neurologic injury. In: Winters, J., Robinson, C., Simpson, R., Vanderheiden, G. (Eds.), Emerging and Accessible Telecommunications, Information and Healthcare Technologies—Engineering Challenges in Enabling Universal Access. IEEE Press Available from: http://www.eng.uci.edu/dreinken/publications/djrresnachapter.pdf.

Ren, Y., Hoon Kang, S., Park, H.-S., Wu, Y.-N., Zhang, L.-Q., 2013. Developing a multi-joint upper limb exoskeleton robot for diagnosis, therapy, and outcome evaluation in neurorehabilitation. IEEE Trans. Neural Syst. Rehabil. Eng. 1534-432021 (3), 490–499. https://doi.org/10.1109/TNSRE.2012.2225073. Available from: http://ieeexplore.ieee.org/document/6335485/.

Richards, C.L., Malouin, F., 2015. Stroke rehabilitation: clinical picture, assessment, and therapeutic challenge. Prog. Brain Res. 00796123218, 253–280. https://doi.org/10.1016/bs.pbr.2015.01.003.

Riener, R., Lunenburger, L., Jezernik, S., Anderschitz, M., Colombo, G., Dietz, V., 2005. Patient-cooperative strategies for robot-aided treadmill training: first experimental results. IEEE Trans. Neural Syst. Rehabil. Eng. 1534-432013 (3), 380–394. https://doi.org/10.1109/TNSRE.2005.848628. Available from: http://ieeexplore.ieee.org/document/1506824/. http://www.ncbi.nlm.nih.gov/pubmed/16200761.

Rocon, E., Belda-Lois, J.M., Ruiz, A.F., Manto, M., Moreno, J.C., Pons, J.L., 2007. Design and validation of a rehabilitation robotic exoskeleton for tremor assessment and suppression. IEEE Trans. Neural Syst. Rehabil. Eng. 15 (3), 367–378. https://doi.org/10.1109/TNSRE.2007.903917. Available from: http://ieeexplore.ieee.org/document/4303108/.

Rosati, G., Gallina, P., Masiero, S., Rossi, A., 2005. Design of a new 5 D.O.F. wire-based robot for rehabilitation. In: 9th International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 430–433. Available from: http://ieeexplore.ieee.org/document/1501135/.

Rosati, G., Volpe, G., Biondi, A., 2007. Trajectory planning of a two-link rehabilitation robot arm. In: Proceedings of the 12th IFToMM World Congress, Besancon, France. Available from: http://www.iftomm.org/iftomm/proceedings/proceedings_WorldCongress/WorldCongress07/articles/sessions/papers/A884.pdf.

Rosen, J., Perry, J.C., 2007. Upper-limb powered exoskeleton. Int. J. Humanoid Robot. 4 (3), 529–548. https://doi.org/10.1142/S021984360700114X. Available from: http://www.worldscientific.com/doi/abs/10.1142/S021984360700114X.

Sakurada, T., Kawase, T., Takano, K., Komatsu, T., Kansaku, K., 2013. A BMI-based occupational therapy assist suit: asynchronous control by SSVEP. Front. Neurosci. 1662-453X7, 172. https://doi.org/10.3389/fnins.2013.00172. Available from: http://journal.frontiersin.org/article/10.3389/fnins.2013.00172/abstract. http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3779864. http://www.ncbi.nlm.nih.gov/pubmed/24068982.

Sale, P., Lombardi, V., Franceschini, M., 2012. Hand robotics rehabilitation: feasibility and preliminary results of a robotic treatment in patients with hemiparesis. Stroke Res. Treat. 2090-81052012, 1–5. https://doi.org/10.1155/2012/820931. Available from: http://www.hindawi.com/journals/srt/2012/820931/. http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3540892. http://www.ncbi.nlm.nih.gov/pubmed/23320252.

Sanchez, R., Reinkensmeyer, D., Shah, P., Liu, J., Rao, S., Smith, R., Cramer, S., Rahman, T., Bobrow, J., 2004. Monitoring functional arm movement for home-based therapy after stroke. In: The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, vol. 4. IEEE, pp. 4787–4790. Available from: http://www.ncbi.nlm.nih.gov/pubmed/17271381.

Sanchez, R.J., Jiayin Liu, J., Rao, S., Shah, P., Smith, R., Rahman, T., Cramer, S.C., Bobrow, J.E., Reinkensmeyer, D.J., 2006. Automating arm movement training following severe stroke: functional exercises with quantitative feedback in a gravity-reduced environment. IEEE Trans. Neural Syst. Rehabil. Eng. 1534-432014 (3), 378–389. https://doi.org/10.1109/TNSRE.2006.881553. Available from: http://ieeexplore.ieee.org/document/1703570/. http://www.ncbi.nlm.nih.gov/pubmed/17009498.

Schabowsky, C.N., Godfrey, S.B., Holley, R.J., Lum, P.S., 2010. Development and pilot testing of HEXORR: hand EXOskeleton rehabilitation robot. J. Neuroeng. Rehabil. 1743-00037, 36. https://doi.org/10.1186/1743-0003-7-36. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC2920290. http://www.ncbi.nlm.nih.gov/pubmed/20667083.

Sharif Razavian, R., Ghannadi, B., Mehrabi, N., Charlet, M., McPhee, J., 2018. Feedback control of functional electrical stimulation for 2D arm reaching movements. In: IEEE Trans. Neural Syst. Rehabil. Eng. https://doi.org/10.1109/TNSRE.2018.2853573. Available from: https://ieeexplore.ieee.org/document/8404077/.

Shaw, S.E., Morris, D.M., Uswatte, G., McKay, S., Meythaler, J.M., Taub, E., 2005. Constraint-induced movement therapy for recovery of upper-limb function following traumatic brain injury. J. Rehabil. Res. Dev. 0748771142 (6), 769–778. https://doi.org/10.1682/JRRD.2005.06.0094. Available from: http://www.ncbi.nlm.nih.gov/pubmed/16680614.

Sheng, B., Zhang, Y., Meng, W., Deng, C., Xie, S., 2016. Bilateral robots for upper-limb stroke rehabilitation: state of the art and future prospects. https://doi.org/10.1016/j.medengphy.2016.04.004. Available from: https://www.sciencedirect.com/science/article/pii/S1350453316300480.

Simkins, M., Hyuchul, K., Abrams, G., Byl, N., Rosen, J., 2013. Robotic unilateral and bilateral upper-limb movement training for stroke survivors afflicted by chronic hemiparesis. In: IEEE 13th International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 1–6. Available from: http://ieeexplore.ieee.org/document/6650506/.

Skirven, T., Osterman, A., Fedorczyk, J., Amadio, P., 2011. Rehabilitation of the Hand and Upper Extremity, sixth ed. Elsevier, Amsterdam. ISBN 978-0-323-05602-1.

Staubli, P., Nef, T., Klamroth-Marganska, V., Riener, R., 2009. Effects of intensive arm training with the rehabilitation robot ARMin II in chronic stroke patients: four single-cases. J. Neuroeng. Rehabil. 1743-00036 (1), 46. https://doi.org/10.1186/1743-0003-6-46. Available from: http://jneuroengrehab.biomedcentral.com/articles/10.1186/1743-0003-6-46.

Stein, J., Narendran, K., McBean, J., Krebs, K., Hughes, R., 2007. Electromyography-controlled exoskeletal upper-limb-powered orthosis for exercise training after stroke. Am. J. Phys. Med. Rehabil. 0894-911586 (4), 255–261. https://doi.org/10.1097/PHM.0b013e3180383cc5. Available from: http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00002060-200704000-00002.

Stienen, A.H.A., Hekman, E.E.G., Van der Helm, F.C.T., Prange, G.B., Jannink, M.J.A., Aalsma, A.M.M., Van der Kooij, H., 2007. Freebal: dedicated gravity compensation for the upper extremities. In: 2007 IEEE 10th International Conference on Rehabilitation Robotics (ICORR). IEEE, pp. 804–808. Available from: http://ieeexplore.ieee.org/document/4428517/.

Stoykov, M.E., Corcos, D.M., 2009. A review of bilateral training for upper extremity hemiparesis. Occup. Ther. Int. 0966790316 (3–4), 190–203. https://doi.org/10.1002/oti.277.

Sugar, T.G., He, J., Koeneman, E.J., Koeneman, J.B., Herman, R., Huang, H., Schultz, R.S., Herring, D.E., Wanberg, J., Balasubramanian, S., Swenson, P., Ward, J.A., 2007. Design and control of RUPERT: a device for robotic upper extremity repetitive therapy. IEEE Trans. Neural Syst. Rehabil. Eng. 15 (3), 336–346. https://doi.org/10.1109/TNSRE.2007.903903. Available from: http://ieeexplore.ieee.org/document/4303112/.

Sukal, T.M., Ellis, M.D., Dewald, J.P.A., 2006. Source of work area reduction following hemiparetic stroke and preliminary intervention using the ACT 3D system. In: 2006 International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, pp. 177–180. Available from: http://ieeexplore.ieee.org/document/4461714/.

Sveistrup, H., 2004. Motor rehabilitation using virtual reality. J. Neuroeng. Rehabil. 174300031 (1), 10. https://doi.org/10.1186/1743-0003-1-10. Available from: http://jneuroengrehab.biomedcentral.com/articles/10.1186/1743-0003-1-10.

Thielbar, K.O., Triandafilou, K.M., Fischer, H.C., O'Toole, J.M., Corrigan, M.L., Ochoa, J.M., Stoykov, M.E., Kamper, D.G., 2017. Benefits of using a voice and EMG-driven actuated glove to support occupational therapy for stroke survivors. IEEE Trans. Neural Syst. Rehabil. Eng. 25 (3), 297–305. https://doi.org/10.1109/TNSRE.2016.2569070. Available from: http://ieeexplore.ieee.org/document/7470432/.

Thrasher, T.A., Zivanovic, V., McIlroy, W., Popovic, M.R., 2008. Rehabilitation of reaching and grasping function in severe hemiplegic patients using functional electrical stimulation therapy. Neurorehabil. Neural Repair 22 (6), 706–714. https://doi.org/10.1177/1545968308317436. Available from: http://journals.sagepub.com/doi/10.1177/1545968308317436.

Todorov, E., Shadmehr, R., Bizzi, E., 1997. Augmented feedback presented in a virtual environment accelerates learning of a difficult motor task. J. Mot. Behav. 29 (2), 147–158. https://doi.org/10.1080/00222899709600829. Available from: https://www.tandfonline.com/doi/full/10.1080/00222899709600829.

Tsai, B.C., Wang, W.W., Hsu, L.C., Fu, L.C., Lai, J.S., 2010. An articulated rehabilitation robot for upper limb physiotherapy and training. In: IEEE/RSJ 2010 International Conference on Intelligent Robots and Systems, IROS 2010—Conference Proceedings. IEEE, pp. 1470–1475. Available from: http://ieeexplore.ieee.org/document/5649567/.

Tseng, C.M., Lai, C.L., Erdenetsogt, D., Chen, Y.F., 2014. A Microsoft Kinect based virtual rehabilitation system. In: 2014 International Symposium on Computer, Consumer and ControlIEEE, pp. 934–937. Available from: http://ieeexplore.ieee.org/document/6846037/.

Turolla, A., Dam, M., Ventura, L., Tonin, P., Agostini, M., Zucconi, C., Kiper, P., Cagnin, A., Piron, L., 2013. Virtual reality for the rehabilitation of the upper limb motor function after stroke: a prospective controlled trial. J. Neuroeng. Rehabil. 1743-000310 (1), 85. https://doi.org/10.1186/1743-0003-10-85. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3734026&tool=pmcentrez&rendertype=abstract.

van Delden, A.L.E.Q., Peper, C.L.E., Nienhuys, K.N., Zijp, N.I., Beek, P.J., Kwakkel, G., 2013. Unilateral versus bilateral upper limb training after stroke: the upper limb training after stroke clinical trial. Stroke 1524-462844 (9), 2613–2616. https://doi.org/10.1161/STROKEAHA.113.001969. Available from: http://www.ncbi.nlm.nih.gov/pubmed/23868279.

Van der Linde, R.Q., Lammertse, P., 2003. HapticMaster: a generic force controlled robot for human interaction. Ind. Robot. 30 (6), 515–524. https://doi.org/10.1108/01439910310506783. Available from: http://www.emeraldinsight.com/doi/10.1108/01439910310506783.

Van der Loos, H.F.M., Wagner, J.J., Smaby, N., Chang, K., Madrigal, O., Leifer, L.J., Khatib, O., 1999. ProVAR assistive robot system architecture. In: Proceedings 1999 IEEE International Conference on Robotics and Automation (Cat. No. 99CH36288C), vol. 1. IEEE, pp. 741–746. Available from: http://ieeexplore.ieee.org/document/770063/.

Venkatakrishnan, A., Francisco, G.E., Contreras-Vidal, J.L., 2014. Applications of brain-machine interface systems in stroke recovery and rehabilitation. Curr. Phys. Med. Rehabil. Rep. 2 (2), 93–105. https://doi.org/10.1007/s40141-014-0051-4. Available from: http://www.ncbi.nlm.nih.gov/pubmed/25110624.

Wamsley, C., Rai, R., Johnson, M., 2017. High-force haptic rehabilitation robot and motor outcomes in chronic stroke. Int. J. Clin. Case Stud. 3 (1) https://doi.org/10.15344/2455-2356/2017/115 Available from: https://www.graphyonline.com/archives/IJCCS/2017/IJCCS-115/.

Wei, Y., Bajaj, P., Scheldt, R., Patton, J., 2005. Visual error augmentation for enhancing motor learning and rehabilitative relearning. In: Proceedings of the 2005 IEEE 9th International Conference on Rehabilitation Robotics, vol. 2005. IEEE, pp. 505–510. Available from: http://ieeexplore.ieee.org/document/1501152/.

Wolbrecht, E.T., Chan, V., Le, V., Cramer, S.C., Reinkensmeyer, D.J., Bobrow, J.E., 2007. Real-time computer modeling of weakness following stroke optimizes robotic assistance for movement therapy. In: Proceedings of the 3rd International IEEE EMBS Conference on Neural Engineering. IEEE, pp. 152–158. Available from: http://ieeexplore.ieee.org/document/4227240/.

Wolbrecht, E.T., Chan, V., Reinkensmeyer, D.J., Bobrow, J.E., 2008. Optimizing compliant, model-based robotic assistance to promote neurorehabilitation. IEEE Trans. Neural Syst. Rehabil. Eng. 1534-432016 (3), 286–297. https://doi.org/10.1109/TNSRE.2008.918389. Available from: http://ieeexplore.ieee.org/document/4451797/.

Wu, C.-Y., Yang, C.-L., Chen, M.-D., Lin, K.-C., Wu, L.-L., 2013. Unilateral versus bilateral robot-assisted rehabilitation on arm-trunk control and functions post stroke: a randomized controlled trial. J. Neuroeng. Rehabil. 1743-000310, 35. https://doi.org/10.1186/1743-0003-10-35. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3640972&tool=pmcentrez&rendertype=abstract.

Xu, R., Jiang, N., Lin, C., Mrachacz-Kersting, N., Farina, K.D.D., 2014. Enhanced low-latency detection of motor intention from EEG for closed-loop brain-computer interface applications. IEEE Trans. Biomed. Eng. 61 (2), 288–296. https://doi.org/10.1109/TBME.2013.2294203. Available from: http://ieeexplore.ieee.org/document/6678728/.

Yamashita, M., 2014. Robotic rehabilitation system for human upper limbs using guide control and manipulability ellipsoid prediction. Proc. Technol. 2212017315, 559–565. https://doi.org/10.1016/j.protcy.2014.09.016. Available from: http://linkinghub.elsevier.com/retrieve/pii/S2212017314001315.

Yao, L., Sheng, X., Zhang, D., Jiang, N., Mrachacz-Kersting, N., Zhu, X., Farina, D., 2017. A stimulus-independent hybrid BCI based on motor imagery and somatosensory attentional orientation. IEEE Trans. Neural Syst. Rehabil. Eng. 25 (9), 1674–1682. https://doi.org/10.1109/TNSRE.2017.2684084. Available from: http://ieeexplore.ieee.org/document/7880549/.

Yeh, S.C., Lee, S.H., Wang, J.C., Chen, S., Chen, Y.T., Yang, Y.Y., Chen, H.R., Hung, Y.P., Rizzo, A., Tsai, T.L., 2013. Stroke rehabilitation via a haptics-enhanced virtual reality system. In: Advances in Intelligent Systems and Applications, vol. 2. Springer, Berlin, Heidelberg, pp. 439–453. Available from: http://link.springer.com/10.1007/978-3-642-35473-1_45.

Yu, W., Rosen, J., Li, X., 2011. PID admittance control for an upper limb exoskeleton. In: Proceedings of the 2011 American Control Conferencepp. 1124–1129. https://doi.org/10.1109/ACC.2011.5991147. ISSN 0743-1619 http://ieeexplore.ieee.org/document/5991147/.