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Review

A Review on Upper Limb Rehabilitation Robots

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Abstract: Rehabilitation is the process of treating post-stroke consequences. Impaired limbs are considered the common outcomes of stroke, which require a professional therapist to rehabilitate the impaired limbs and restore fully or partially its function. Due to the shortage in the number of therapists and other considerations, researchers have been working on developing robots that have the ability to perform the rehabilitation process. During the last two decades, different robots were invented to help in rehabilitation procedures. This paper explains the types of rehabilitation treatments and robot classifications. In addition, a few examples of well-known rehabilitation robots will be explained in terms of their efficiency and controlling mechanisms.

Keywords: exoskeleton; electromyograph; rehabilitation robots; stroke

1. Introduction

Stroke is considered one of the leading causes of death; it comes in the third place after heart disease and cancer [1]. The World health organization (WHO) has defined stroke as a dysfunction of the brain that continues for more than one day. It has been reported that up to 30% of stroke patients suffer from permanent disabilities and up to 20% require intensive rehabilitation programs [2]. Stroke patients go through three stages starting directly after the stroke: firstly, the acute stage that extends for one week; secondly, the subacute stage, which lasts for six months, followed by the third stage, which is the chronic stage [2]. Impairment of the arm and the wrist forms the main consequence resulted from stroke [3].

Stroke consequences can be treated or reduced by rehabilitation [4]. Rehabilitation requires a professional therapist to perform repetitive movements of the impaired limb [2]. However, the availability of therapists, the duration of the therapeutic session and the cost of rehabilitation tools are all considered as factors that affect both the therapist and the patients [5]. Furthermore, rehabilitation programs require one-on-one interactions between the therapist and the patient. Nevertheless, interactive rehabilitation is a time-consuming and labor-intensive for both the therapist and the patient [2]. These facts pushed researchers to invent rehabilitation robots that can be used as assistive devices for therapists. Rehabilitation robots provide intensive, accurate, quantitative and safe rehabilitation in addition to their ability to provide repeated motions for a patient's limb [6,7].

This paper focuses on after-stroke rehabilitation and upper limb rehabilitation robots. The next section lists the types of rehabilitation treatments and their differences. Section 3 defines the term of rehabilitation robot and how it is classified. A few examples of rehabilitation robots and their clinical results will be explained in Section 4. Section 5 explains the electromyogram (EMG)-driven exoskeleton robots, and a comparison is given. A discussion and a conclusion are given in Sections 6 and 7, respectively.

2. Rehabilitation Treatments

Once a limb's motor control is compromised, a therapist has to look for the optimum procedure to treat the impaired limb. Choosing the right treatment procedure is a crucial decision, which ultimately affects the efficiency of the treatment [8]. Robot therapy has been intensively introduced to rehabilitation. Robots have the ability to provide repetitive movements for impaired limbs [3]. There are three types of robot therapies, as follows [9,10].

2.1. Passive Therapy

Passive therapy requires no effort from the patient and is usually applied at the early stages of post-stroke symptoms, specifically when there is no response from the impaired limb [9]. Passive therapy is usually prescribed for hemiplegia patients that are suffering from one-side paralysis [11]. It involves moving the impaired limb in a specific trajectory for a number of times during the session, which is usually performed by a rehabilitation robot (Figure 1) [12]. The trajectory of the movement is preplanned carefully to avoid any harm that could affect the patient [13].

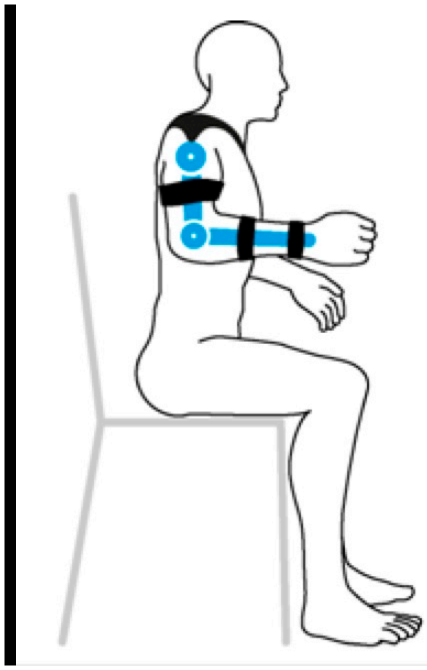

Figure 1. Shows an example of passive therapy, where the impaired limb is moved according to the planned movement (flexion/extension of the upper limb at the elbow joint) by the rehabilitation robot. Source: [10].

This kind of treatment focuses on stretching and contracting the impaired upper limb [12]. It is also used to assess the range of motion of the limb [14]. Exoskeleton robots are used in this treatment to provide repetitive motions according to the range of motion [3]. A clinical study was carried out on passive therapy; three subjects were involved in the study and obtained a training session for 40 min. Passive therapy showed an effectiveness in reducing the spasms and the stiffness of the impaired limbs [15].

2.2. Active Therapy

This kind of treatment is prescribed for patients who are able to move their impaired limb to some limit. The active term refers to the ability of moving the impaired limb but not efficiently [11]. Active therapy can be classified as active-assistive therapy or active-resistive therapy. Active-assistive therapy involves applying an external force by a therapist or robot to help the patient fulfil the appointed task [16]. It is also used to improve the range of motion [17]. Active-assistive therapy was applied to a patient with an impaired shoulder and elbow, where the patient was asked to reach a specific target, and the attached robot helped the patient complete the task (Figure 2) [18]. The attached robot intervened once the patient was not able to perform the full task correctly and efficiently [3]. Active-assistive therapy was performed on eight subjects to evaluate its efficiency; the evaluation involved eighteen treatment sessions for six weeks and one hour for each session. The impaired limb movement was significantly improved [9].

Active-resistive treatment, however, involves applying an opposing force on the impaired limbs. The opposing force can be applied by a therapist or robot (Figure 2) [15]. Studies showed that the performances of patients become better gradually where the opposing force can be increased gradually [7,19]. The opposing force is determined by an algorithm according to the ability of the patient [19].

Eight subjects obtained active-resistive therapy in 18 1-h sessions for six weeks [19]. This treatment is dedicated to improving the long-term strength of the arm [3].

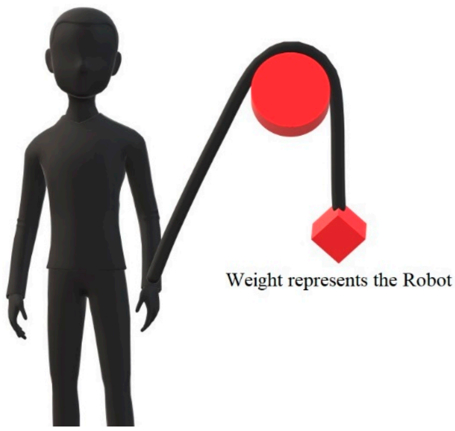

Figure 2. Represents patient trying to perform the abduction and the adduction of the upper limb. The weight helps the patient to perform the abduction which represents the Active-Assistive therapy. Also, the weight prevents the patient performing the adduction which represents Active-Resistive therapy.

2.3. Bilateral Therapy

Bilateral therapy refers to the mirroring principle in performing rehabilitation [4]. Where the impaired limb copies the movement of the functional limb (Figure 3), this gives the user whole control of the affected limb [20,21].

Mirror image movement enabler (MIME) and a few other exoskeletons employ bilateral therapy [22]. A clinical study on the bilateral therapy mode was performed by [23]; fourteen subjects were involved in the study and obtained professional training of the therapy. The study consisted of thirty-one sessions distributed over two months; nevertheless, the study was performed in the first six months after a stroke. The results showed a significant improvement in the impaired hemisphere and motor functions [9].

It was noticed that each therapy is dedicated to specific conditions and mainly depends on the patient's ability. Table 1 summarizes the therapy types in terms of targeted patients, therapy procedure and limitations. In addition, Table 2 was added to summarize the therapy types in terms of clinical results.

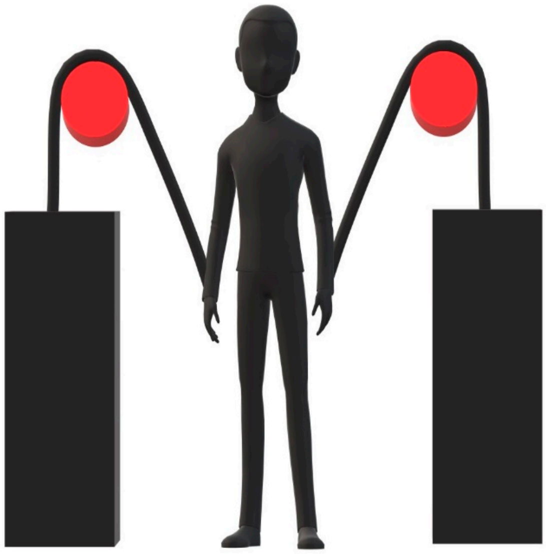

Figure 3. Shows an example of bilateral therapy, where one of the limbs is functional, and the other is impaired. The patient has the ability to freely move the functional limb, and the impaired one follows this movement.

Table 1. Summary of the therapy types in terms of targeted patient, therapy procedure and limitations.

Characteristics / Type of Treatment	Targeted Patient	Therapy Procedure	Limitations
Passive Therapy	hemiplegia patient	Flexing and extending the impaired limb	Beneficial for upper limb extremities
Active-assistive Therapy	Patient with some degree of moving ability	A force is provided to help the patient complete a task	Beneficial for shoulder and elbow exercises
Active-resistive Therapy		A force is applied against the desired movement	Beneficial for treating impaired arms
Bilateral Therapy	Patient has one functional limb	Impaired limb copies the trajectory of the functional limb	Beneficial for upper limb extremities

Table 2. Summary of the therapy types in terms of the clinical results.

Source	Therapy Type	Post-Stroke Time	No. of Subjects	No. of Sessions	Improvements
[15]	Passive	<6 months	3	1 session 40 min	Reducing the spasm and the stiffness of the impaired limb
[9]	Active-Assistive	>6 months	8	18 sessions 6 weeks 1 h/workday	Results showed an improvement in the impaired joints
[19]	Active-Resistive	>6 months	8	18 sessions 6 weeks 1 h/workday	Results showed an improvement in the long-term strength
[23]	Bilateral	<6 months	14	31 sessions 8 weeks 1 h/workday	Results showed an improvement of the impaired hemisphere and motor functions

3. Rehabilitation Robots and Their Classifications

The World Health Organization reported that around 15 million people suffer from stroke yearly; around six million of them become disabled. The disabilities vary form fully paralyzed limbs to weakness [2,24].

Scientists have found that particular activities of the brain can be transferred to a different location in the brain, and this is known as neuroplasticity [25]. Studies showed that repetitive motions for the impaired limbs allow the brain to develop new neural pathways and, ultimately, restore full or partial control of motor functions [24].

Impaired functions can be fully or partially restored by investigating neuroplasticity [18]. Using a rehabilitation robot could trigger neuroplasticity by providing a repetitive exercise for the impaired functions. In this respect, rehabilitation robots are defined as an operated machine that is designed to perform specific movements [24].

The importance of using a rehabilitation robot comes from its ability to provide quantitative and continuous monitoring for patient performances during the training, which allows us to understand the recovery mechanism during the repeated tasks [7].

Rehabilitation robots are classified either by their treatment approaches or by their structures [8]. Each type is further classified into two types, as follows:

3.1. According to Robot Treatment Approaches

Rehabilitation robots can be classified into two types, according to their treatment approaches. The first approach is continuous passive movement (CPM). CPM requires no volunteer effort performed by the patient where the limb is controlled and moved by the robot [26]. CPM treatment reduces muscle tone, which eventually improves the mobility of muscles, joints and tendons [7]. Furthermore, CPM activates the cortical area that has the corresponding sensorimotor and leads to an action similar to normal movement [7]. The second approach is active-assisted movement, where the robot requires a signal from the patient to perform the movement. This signal could be an electromyogram (EMG) and follows the patient's intention to move the limb [27]. Rehabilitation robots with active-assisted movement require voluntary effort from the patient and, consequently, provide significant motor improvement when they are compared to CPM rehabilitation [7]. Therefore, most of the current researchers focus on active-assisted rehabilitation using robots [7].

The EMG-driven robots use an EMG signal an as "on-off" controller, which means that, once the patient voluntarily initiates the robot, the robot will repeat its action for a period of time. Then, the patient will be allowed another voluntary signal [28].

3.2. According to the Robot Structures

Rehabilitation robots are also classified as end-effectors and exoskeleton robots [29]. End-effectors are simple robots that have a distal movable handle, and the patient attaches his/her hand to this handle and follows a specific trajectory [30]. This kind of robot is characterized by its ability to adapt to different sizes and shapes of movements, as the rehabilitation process requires [31]. End-effector robots have the disadvantage of not providing a rotation movement, which makes it not suitable for pronation and supination movements [24]. End-effectors have been developed recently to provide bilateral rehabilitation training, where the impaired limb copies the movement of the unimpaired limb in a synchronized behavior [22]. Some researchers have reported that bilateral rehabilitation has the feature of activating the impaired hemisphere by making the left side and the right side of the body follow the same trajectory [21].

Exoskeleton robots are characterized by encapsulating the limb with a splint or bionic structure [32]. Exoskeleton robots calculate the required torque for each joint and control the limb movements [13]. In comparison with end-effector robots, exoskeletons require a smaller working environment. Exoskeleton robots, however, comprise the limb joint axes as they provide a very specific movement [24].

In addition, exoskeleton robots are not feasible for bilateral rehabilitation, as the right limb exoskeleton cannot be used for the left limb, and eventually, it is expensive to design right and left exoskeleton robots to perform bilateral rehabilitation training [22].

4. Examples of Rehabilitation Robots

Designing a rehabilitation robot faces a few challenges that have to be considered first [33]. Electromechanical implementation is one of these challenges, which refers to that the robot has to be light, durable, flexible and have the mechanism to perform a normal muscle motion [20]. The interpretation of user intent is another challenge, where the human–robot interaction plays an important role in the rehabilitation process [33]. A neural muscle signal is one of the tools that is used to extract the user's intent [3]. In addition, a robot's degrees of freedom (DOF) and the safety precautions should be taken into account in designing the rehabilitation robot; otherwise, the safety and the efficiency of the robot will be compromised [3,34]. The following are some examples of well-known rehabilitation robots [35]. Table 3 summarizes the characteristics of the rehabilitation robots.

Table 3. Characteristics of the rehabilitation robots. DOF: degrees of freedom, MIME: mirror image movement enabler, ARM: Assisted Rehabilitation and Measurement, CADEN-7: cable actuated dexterous exoskeleton for neuro-rehabilitation with seven degrees of freedom, T-Wrex: therapy Wilmington exoskeleton and BONES: Biomimetic Orthosis for Neurorehabilitation.

Characteristics / Type of Robot	Targeted Impaired Functions	Number of DOF Provided	Therapy Classification	Security Precautions
MIT-MANUS	Upper limb rehabilitation	Five DOF	Passive	• Therapy session has to be monitored by a therapist. • Magnet safety lock is equipped to provide further safety. • MANUS provides a low torque to avoid limb fatigue.
MIME	Upper limb rehabilitation (Shoulder and Elbow)	Six DOF	Passive Active Bilateral	• The affected limb is strapped by a splint. • The performance is guided by a PUMA robot.
ARM Guide	Upper limb function	One DOF	Passive Active	One DOF that provides linear constraints.
ARMin	Upper limb rehabilitation	Seven DOF	Passive	• Robot has no sharp edges. • Robot has several positions sensors. • Unique software to monitor the performance.
CADEN-7	Upper limb rehabilitation	Seven DOF	Passive Active	Three levels of safety: mechanical, electrical and software.
L-EXOS	Upper limb rehabilitation	Five DOF	Active	• Maximum velocity is 10 rpm. • Maximum torque is 120 Nm.
T-Wrex	Upper limb rehabilitation	Five DOF	Active	Positions sensors and custom grip sensors
REHAROB	Upper limb rehabilitation (Shoulder and Elbow)	Three DOF	Passive	Sensors to control and monitor the generated forces.
BONES	Upper limb rehabilitation	Four DOF	Active	One extra actuator is added for safety issues.

4.1. MIT-MANUS

MIT-MANUS is a CPM robotic workstation developed by the Massachusetts Institute of Technology that is used to rehabilitate upper limbs post-stroke [36]. MIT-MANUS is an interactive workstation where the patient has to visually interact with a PC game to follow specific movements [20]. The MANUS workstation provides five degrees of freedom, two translation degrees of freedom for the elbow and the forearm, represented by flexion/extension and pronation/supination, respectively. In addition, three degrees of freedom for the wrist, represented by flexion/extension, pronation/supination and abduction/adduction [36]. A magnet safety lock is used to attach the patient's hand to the device; this technique provides an easy procedure to free the patient from the device [36]. Furthermore, the MANUS workstation provides low torques [36]. Therapy sessions, however, have to be monitored by a therapist to ensure the patient's safety [3]. The MANUS workstation is characterized by its impedance control, which provides a specific movement to the limbs [36]. The MANUS workstation records the patient's performance (specifically, the force, velocity and the position); then, the performance data are sent to the control computer to adapt the robot according to the patient's requirements [37]. The MANUS workstation has been experimentally proven to provide therapeutic effects for upper limb impairment [28].

4.2. MIME

Mirror image movement enabler (MIME) is a CPM robotic system that consists of a wheelchair and height-adjustable table [38], where the patient sits on the wheelchair and puts his/her affected limb on the adjustable table. The affected limb is strapped into the forearm splint that restricts the movements of the wrist and the hand [38]. A Puma 560 (Programmable Universal Machine for Assembly) robot was used as the manipulator, where the robot attached to the splint and applied force to the affected limb during its movements [39]. The Puma 560 robot provided six degrees of freedom, which provided a large range of movement positions in a 3D space [40]. MIME, provides the three treatments modes that are the passive, active-assistive/active-resistive and bilateral modes [20]. In addition, MIME is commonly used in the passive and active-resistive modes [22]. In the passive mode, the robot moves the limb in a specific trajectory towards the target. The active-resistive mode involves prohibiting the limb's movements in the identified trajectory by providing a viscous resistance, and the patient has to provide maximal effort to reach the target [4]. MIME is used to strengthen the muscles and improve the limb's motions [28].

4.3. Assisted Rehabilitation and Measurement (ARM) Guide

The Assisted Rehabilitation and Measurement guide (ARM guide) is also an example of a CPM rehabilitation robot and is used for the training and evaluating of upper limb functions [41]. The ARM guide, shown in Figure 4, uses the reaching principle as a therapy technique, where the patient's arm is attached to a splint, and the patient is advised to reach for things [20]. The ARM guide provides one degree of freedom on a linear constraint rather than multiple active degrees of freedom. Therefore, the ARM guide is considered as an inexpensive and a simple rehabilitation robot [41]. The orientation of the ARM guide can be changed vertically or horizontally [41].

Figure 4. Assisted Rehabilitation and Measurement (ARM) guide robotic system. Source: [41].

4.4. *ARMin*

ARMin is an upper limb rehabilitation robot and is characterized by providing seven degrees of freedom (DOF), allowing shoulder rotations in three dimensions, flexion/extension of the elbow, supination/ pronation of the forearm and flexion/ extension of the wrist, in addition to supporting the closing and opening of the hand [42]. ARMin consists of a chair and robotic arm, where the seated patient attaches his/her hand to the robotic arm and adjusts its length to its optimum, as shown in Figure 5 [43,44]. ARMin has three levels of safety, where the device is equipped by many sensors that work as a system to detect any malfunction that could arise. Secondly, the ARMin has no sharp edges, and no joint will move out of the range of a human limb [42]. Thirdly, a unique algorithm was developed to monitor the repeated motions, and immediate shutdown happens in case of malware being found [39].

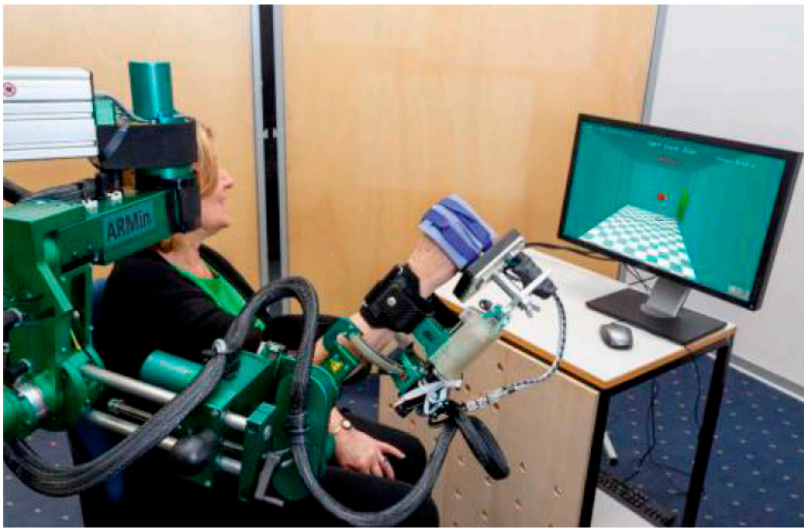

Figure 5. ARMin rehabilitation robot. Source: [44].

The results showed an improvement in the limb's motion, where the user was able to extend his/her limb to further distances. In addition, the strength of the support was decreased gradually as the patient recovered their motor sensory [3,44].

4.5. Cable Actuated Dexterous Exoskeleton for Neuro-Rehabilitation with Seven Degrees of Freedom (CADEN-7)

Cable actuated dexterous exoskeleton for neuro-rehabilitation (CADEN-7) provides seven degrees of freedom [45]. CADEN-7 is considered an active-assisted robot that uses surface electromyography to control the upper limb [46]. CADEN-7 is also equipped with three levels of safety, taking into consideration the electrical aspects, mechanical aspects and software aspects [45]. The unique design of CADEN-7 makes it suitable to avoid hyperextension and erratic motions. CADEN-7, however, has to be fixed on external forms and cannot be portable due its size and weight [3].

4.6. L-EXOS

The Light Exoskeleton (L-EXOS) system focuses on providing repetitive movements and gives a simultaneous measurement for the therapeutic progress [47]. L-EXOS, incorporates visual reality to guide the patient to a specific trajectory [48]. In terms of safety concerns, L-EXOS provides a velocity equal to 10 rpm, and the maximum torque cannot exceed 120 Nm. In addition, L-EXOS provides five degrees of freedom, and each movement is equipped by a sensor [3].

4.7. Therapy Wilmington Exoskeleton (T-Wrex)

The therapy Wilmington exoskeleton (T-Wrex) is an active upper limb rehabilitation robot with five degrees of freedom [49,50]. It is dedicated for individuals with significant arm weakness by providing intensive training. The T-Wrex uses the feature of gravity compensation or antigravity for the entire arm, where the patient experiences the sense of a floating arm in space [50]. In addition, the T-Wrex is characterized by providing a large 3D movement that naturalizes the upper limb movements [49]. The T-Wrex consists of two links attached to the forearm and upper arm. In terms of safety, position sensors and custom grip sensors are integrated to the robot, which provide movement measurements for the upper limb [49].

4.8. REHAROB

The Rehabilitation Robot (REHAROB) therapeutic system is a passive rehabilitation robot with three degrees of freedom dedicated for the shoulder and the elbow [50]. The movement trajectory is preprogrammed by the therapist and followed by repetitive movement for the impaired limb. The exercises performed by REHAROB are different than those performed by MIT-MANUS and MIME by providing slow repetitive movements with a constant velocity [51]. These kinds of exercises are efficient in reducing spasticity and increasing the range of mobility for the shoulder and elbow joints [51]. The patient's upper arm and forearm are attached to the robot's arm [52]. The REHAROB is equipped by sensors to control and monitor the generated forces [51].

4.9. Exoskeleton Biomimetic Orthosis for Neurorehabilitation (BONES)

The Biomimetic Orthosis for Neurorehabilitation (BONES) is an active rehabilitation robot with four degrees of freedom [50]. The BONES is characterized by its ability to provide arm internal/external rotations without the need to bring or use any bearing element. The unique design was inspired by human biomechanics. In addition, the BONES occupies five actuators to provide a wide range of motion for the upper limb and further measurements for safety issues [53].

5. EMG-Driven Exoskeleton Robots

An electromyograph (EMG) signal should be efficiently extracted in order to use it in rehabilitation robots [32]. There are two ways to extract the EMG signal: invasive, which results in an intramuscular electromyograph (iEMG), and noninvasive, which results in a surface electromyograph (sEMG) [18]. The invasive technique involves placing the electrodes on the motor units of the muscle, while the electrodes of the noninvasive technique are placed on the belly area of the muscle that provides maximum contraction [54]. Despite the fact that iEMGs provide accurate EMG signals, sEMGs are commonly used due to their acceptability by the patient, and they do not require any invasive procedure [55]. Using the EMG signal as a control input for robots goes through several steps, starting by choosing the right muscle to obtain the EMG, then amplifying the extracted EMG to be, finally, processed and classified by a PC, as shown in Figure 6 [54,56].

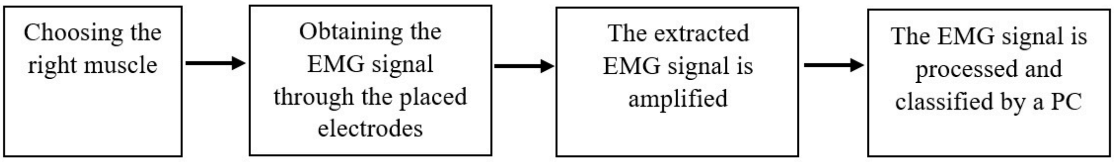

Figure 6. Block diagram of extracting and processing the surface electromyograph (sEMG) signal.

The EMG signal can be either processed in a time domain or frequency domain. Most of the current research focused on time domain processing, as it does not require further transformation and, eventually, provides low complex computations [57]. The root mean square (RMS), mean absolute value (MAV), summation of the absolute value (IAV), zero-crossing (ZC), slope sign changes (SSC) and waveform length are all features that can be extracted from the EMG in the time domain. Feature extraction in the time domain are evaluated based on its amplitude versus time and, therefore, its preferable in pattern recognition [57].

Processing the EMG in the frequency domain, however, requires more computing time when compared to time domain processing. Consequently, processing the EMG in the frequency domain is usually used to assess muscle fatigue over time. The mean frequency (MNF), median frequency (MDF) and mean power frequency are features that can be extracted from the EMG in the frequency domain [58].

The raw EMG data should be amplified, filtered and segmented before extracting its features. In addition, the length of the segment was proven to have an effect on the accuracy of the EMG classification. It was shown that increasing the segment length from 125 ms to 500 ms provided better accuracy. The response time for a prosthetic limb should not be more than 300 ms in order to be considered a real-time response [55,57].

This paper explains a few examples on how the EMG signal is used as a control input for rehabilitation robots. EMG-based control methods are categorized into two terms: pattern recognition-based and non-pattern recognition-based [54]. Both methods share the acquisitioning and the segmenting of the obtained signal [54]. The pattern recognition-based method, however, requires further processing to obtain an accurate EMG signal, where the acquired signal goes through three further stages, which are data segmenting, feature extraction and classification. Consequently, many assistive robots use the pattern recognition-based method, as it provides accurate information [55,59].

A few examples of EMG-driven upper limb robots and their control methods will be explained in the following subsections. A robot comparison based on the input signal, features used and mechanism of the controller will be also explained. Table 4 summarizes the EMG-driven rehabilitation robots and their control methods.

Table 4. Summary of electromyogram (EMG)-driven robots and their control methods.

Source	Type of Exoskeleton	Input Parameters	Controlling Technique	Characteristics
[60,61]	Hand Exoskeleton	EMG signal	Blind source separation	Adding further degrees of freedom requires adding more sensors
[62,63]	Hand Exoskeleton	EMG signal	• binary controlling algorithm • Variable controlling algorithm	• It is characterized by its low weight. • More robust controlling algorithm is required to obtain accurate movements.
[64]	Upper limb Exoskeleton	EMG signal and force signal	Neuro-fuzzy controlling	Mean absolute value (MAV) is used as a controlling feature.
[65]	SUEFUL-7 exoskeleton	Combination of EMG signal and force signal.	Muscle model oriented based on neuro-fuzzy	Impedance control is modified in real time according to the extracted EMG signal and limb posture.
[66]	NEUROExos	EMG signal	proportional control method	Two EMG signals are extracted from the biceps and triceps to provide better control.
[55]	Elbow exoskeleton	EMG signal	Artificial Neural Network (ANN)	Seven EMG signals are extracted from seven muscles.
[67]	Upper limb Exoskeleton	EMG signal	Genetic algorithm (GA)	• RMS is used as a controlling feature. • Shoulder, upper arm, lower arm muscles and joints are involved.

5.1. Hand Exoskeleton

A hand exoskeleton was developed by researchers from the University of Berlin, Germany to increase hand mobility [60]. This type of exoskeleton uses the principal of blind source separation as a controlling algorithm, which provides an accurate motion for the finger joints [55]. Blind source separation has its own limitations, where adding additional degrees of freedom requires additional sensors, which ultimately increases the complexity of placing the electrodes [60,61].

An orthotic hand exoskeleton that was developed by a researcher from Carnegie Mellon University, Pittsburgh, Pennsylvania, USA is characterized by its low weight [55]. Two controlling algorithms were used in the orthotic exoskeleton [62]. Firstly, a binary controlling algorithm, which provides two states: either "on" or "off", which turn on and off the actuators [28]. This type of controlling algorithm cannot predict the intermediate state between the on and off states [55]. Secondly, a variable controlling algorithm that provides the information of the intermediate state in addition to the "on" and "off" states [55]. A variable controlling algorithm is beneficial for patients with one impaired limb and the other limb is functional. It was concluded that the controlling algorithm has to meet the requirements needed by the patient to say it is efficient [55,63].

5.2. Exoskeleton Based on the Neuro-Fuzzy Control Method

EMG controlling based on the neuro-fuzzy method is characterized by providing a real-time controlling and was efficiently used to control exoskeletons [64]. The physical condition and the nonlinear behavior of the muscle contractions are factors that affect the strength of the EMG, which can be eliminated by using the neuro-fuzzy controlling method. In addition, the EMG quality could be compromised due to shifting of the sEMG electrodes from their positions during limb movements, and ultimately, the neuro-fuzzy method can be used to reduce this shifting effect [64]. The mean absolute value (MAV) feature is used as a control feature in the neuro-fuzzy control method. The MAV feature was chosen due to its efficiency in comparison to other features, such as the slope sign changes, slope mean absolute value, zero-crossing or wave form length [68]. The neuro-fuzzy control method is characterized by its ability to adapt to any physical condition for different patients; training, however, is required for an efficient adaption [55]. The neuro-fuzzy method is commonly used in robots that are dedicated for improving the life quality of elderly and disabled people [69,70].

Reference [69] designed a one degree of freedom exoskeleton robot that is used at the elbow complex. The proposed exoskeleton robot depends on the extracted EMG signal to perform the limb's motions. The fuzzy neural network controller was embedded into the controller [64]. The proposed exoskeleton rehabilitates the impaired limb by providing different angular velocities in addition to variations in impedance. The EMG signal extracted from the biceps and the wrist force were used as inputs for the exoskeleton robot [62]. The study involved recruiting three subjects; the subjects were asked to perform flexion/extension at the elbow joint with no weight at first; then, a weight of seven kilograms was used. The system showed effectiveness in supporting the lower limb movements. The proposed system, however, has its own limitations, such as its size and weight, in addition to its poor attachment [69].

5.3. SUEFUL-7 Exoskeleton Based on the Muscle-Model-Oriented Control Method

SUEFUL-7 is an upper limb exoskeleton that is used to help patients with weak motions [27]. SUEFUL-7 uses a unique controlling method named muscle-model-oriented that also depends on the fuzzy principal, where a high number of degrees of freedom require a high number of fuzzy mathematical models [71]. SUEFUL-7 employs impedance control in combination with the muscle-model-oriented method, and the parameters of the impedance are modified in real time, according to the extracted EMG signal and limb posture [27]. The root mean square (RMS) is the feature that is extracted from the EMG signal to control the SUEFUL-7 [55]. SUEFUL-7 is characterized by a hybrid controlling nature, where other variables such as forearm force, forearm torque and hand force are used as input signals in addition to the EMG signal [55]. The controller depends mainly on the EMG signal when it is high and the RMS is accurate; otherwise, the controller uses all other aforementioned variables [71].

5.4. NEUROExos Based on the Proportional Control Method

NEUROBOTICS Elbow Exoskeleton (NEUROExos) is also an EMG-driven rehabilitation robot that uses the principal of proportional control method as a mechanism of control [14], where the linear envelope (LE) is extracted from the processed EMG by means of a full wave rectifier and low pass filtering, specifically the Butterworth filter [66]. The LE represents the waveforms of the muscle tension during the force dynamic change [72].

NEUROExos uses two EMG signals extracted from the biceps and triceps; both signals are amplified gradually until the user feels comfortable with the provided support [66]. NEUROExos employs the neuro-fuzzy modifier to help the user obtain the required motion in the minimum time [65].

5.5. Exoskeleton Robots Based on the Artificial Neural Network Control Method

The artificial neural network (ANN) is mainly used to interpret the flexion/extension of the elbow and the supination/pronation of the forearm [55]. EMG signals are amplified after being extracted from seven muscles that are the brachialis, biceps, triceps, posterior deltoid, anterior deltoid, clavicular and pectoralis major [55]. The mean absolute value, number of zero-crossing and waveform length are features used in the ANN controlling algorithm. EMG signals are, firstly, filtered and windowed; then, the features are extracted [73,74].

5.6. Arm Exoskeleton Employs a Genetic Algorithm as a Control Method

Reference [67] used the genetic algorithm (GA) to control an ARM exoskeleton. An EMG signal was used as an input signal, and an optimization was performed using a GA [13]. A GA is characterized by its ability in eliminating the local optimum solutions [67]. The GA algorithm also uses the RMS as a controlling feature, where the best output solution "which is usually named as a chromosome" is the output that minimizes the RMS between the torque estimated by the EMG signal and the torque estimated by the model [67]. The muscles of the shoulder, upper arm, lower arm and the joints are involved to provide an accurate output solution [13].

6. Results and Discussion

It was clearly explained in previous sections that the rehabilitation robots are different in terms of shape, structure, controlling mechanism and even in their specific dedicated treatments. Clinical studies were performed on the rehabilitation robots to evaluate their efficacy. Table 5 summarizes the rehabilitation robots and their clinical studies.

Table 5. Clinical results of the rehabilitation robots.

Source	Robot	Therapy Type	Post-Stroke Time	No. of Subjects	No. of Sessions	Improvements
[20]	MIT-MANUS	Assistive	<6 months	96	25 sessions 5 weeks 1 h/workday	motor power of the shoulder and the elbow was significantly improved
[38]	MIME	Assistive	>6 months	27	24 sessions 8 weeks 1 h/workday	the reach ability and the proximal arm strength were largely improved
[41]	ARM Guide	Assistive	>6 months	3	24 sessions 8 weeks 1 h/workday	motion velocity and range of motion were greatly improved
[29]	ARMin	Passive	>6 months	3	40 sessions 8 weeks 1 h/workday	significant improvement in muscle strength, arm motion and other functional tasks
[40]	CADEN-7	Passive-Assistive	-	-	-	Unverified No clinical study was carried out on CADEN-7
[48]	L-EXOS	Passive-Assistive	>6 months	9	18 sessions 6 weeks 1 h/workday	Results showed a relative improvement in three tasks: reaching task, motion task and object manipulating

Estimating the accurate torque that is required to perform the limb movements should be taken into account in designing the exoskeleton. Identifying the accurate torque required by each specific movement is considered one of the drawbacks of exoskeleton robots [66]. In addition, the user's reaction to the extra torque has to be figured out by an accurate algorithm during the manufacturing of the exoskeleton [66].

In order to have an accurate estimation of the torque, many parameters should be examined intensively, which include joint positions, velocity and acceleration, as well as the dynamic model of the impaired limb [12]. Furthermore, the interaction with the external environment, such as the exoskeleton itself, should be calculated by force sensors [16,75]. All the aforementioned requirements have to be satisfied to obtain the optimum torque, which makes this approach hard to obtain [12].

The importance of the EMG comes from its ability to estimate the required torque for each specific movement [76]. An electromyograph (EMG) signal extracted from the muscles fibers is used to estimate the required torque for each specific movement [77]. Using an EMG signal exhibits many advantages. Firstly, there is no need to have a dynamic model for the impaired limb, and the user can interact freely with the external environment. Secondly, the EMG signal is generated prior to a muscle contraction by 20-30ms; this delay is very beneficial in compensating the limited bandwidth of the actuator [66]. Finally, having the EMG signal prior to the muscle contraction is considered a very important feature that provides the time required for calculating the accurate torque before performing the movement. Consequently, the user will be assisted even if he/she is not able to initiate the movement autonomously [66].

The relationship between the EMG signal and the torque has been studied and explained by many researchers. Reference [73] used a recurrent artificial neural network (RANN) to investigate the relationship between the EMG signal and the required torque at the elbow joint under volunteer efforts. The EMG signal and the kinematic data—specifically, the angle and angular velocity—were used as inputs to expect the required torque. The role of the kinematic data was investigated to check its effect on the predicted torque [78]. The EMG signal with kinematic joint inputs was firstly used to predict the torque; then, only the EMG signal was used to predict the torque, and the comparison between the two approaches was investigated. The study involved recruiting six healthy subjects with three different loads (0 kg, 1 kg and 2 kg) held by the hand at two different positions: elbow flexion (90°) and full elbow extension (0°). The approach was performed at two different angular velocities (60°/s and 90°/s) [79]. The subjects were trained to perform the aforementioned procedure, and the root mean square error (RMSE) was calculated between the expected and the predicted torques for each procedure. The results showed that the RMSE when using the EMG signal and the kinematic data was 0.17 ± 0.03 Nm for the training dataset and 0.35 ± 0.06 Nm for the test dataset. Furthermore, the RMSE when using the EMG alone was 0.57 ± 0.07 Nm for the training dataset and 0.73 ± 0.11 Nm for the test dataset [73]. Therefore, using the EMG and the kinematic data as inputs for estimating the torque showed better performance [79]. To conclude, EMG-driven robots are considered the better choice to rehabilitate impaired limbs when compared to normal robots [8].

7. Conclusions

The clinical results showed that rehabilitation robots play a crucial role in fully or partially restoring motor functions. Using rehabilitation robots allows us to efficiently plan the rehabilitation process in terms of cost, the duration of sessions, the required tools and the availability of a therapist. Furthermore, EMG-driven rehabilitation robots showed better performances when compared to passive rehabilitation robots. This paper explained the most common rehabilitation robots and their efficacy depending on the available clinical studies. Further clinical studies on rehabilitation robots based on their control mechanisms are required to accurately prove their efficiency.

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