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Control Mechanisms and Strategies of Upper-Limb Exoskeleton Rehabilitation Robots

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Abstract:
Diseases such as stroke are a leading cause of long-term chronic disability around the world and affect people in their most productive years, frequently posing disabling motor impairments that limit dependency and a person's quality of life. Traditional rehabilitation processes have made significant advances, yet continue to be limited due to physical intensity, consistency and scalability. Exoskeleton rehabilitation robots have emerged as a possible solution to address these issues by providing repetitive, controlled, and adaptive treatment. This dissertation reviewed some of the recent advances made in the control mechanisms to develop upper-limb exoskeleton rehabilitation robots. The focus was on passive and active control methods. Passive control methods provide safety and mechanical consistency, particularly beneficial to patients in the early phase of recovery, while active control methods, such as those using electromyography (EMG) and electroencephalography (EEG), allow patient participation in the rehabilitation process by decoding the patient's motor intent. Those findings demonstrated that neither passive nor active approaches are mutually exclusive, but rather exist on a spectrum of control methods, and a combination of both may offer the best opportunities for rehabilitation care.

Keywords: Electromyography (EMG); Electroencephalography (EEG); Lower-limb exoskeleton; Rehabilitation robots.

1. Introduction

As the world's population becomes progressively older, diseases such as stroke have become one of the leading causes of long-term disability. The World Health Organization estimates that there are approximately 15 million stroke patients per year, and around 5 million become permanently disabled from their stroke [1]. Patients after stroke can have severe motor impairments and disabilities such as hemiplegia (paralysis of one side of the body), muscle weakness, and gait instability, which stop them from completing the activities in daily life and limit their independence. These disabilities not only affect their quality of life, but also have a considerable cost for their families or themselves [2]. The ultimate objective to consider with stroke patients is the timely and effective rehabilitation to regain their motor functions.

Traditional rehabilitation methods such as physiotherapy and occupational therapy are vitally important for stroke recovery, but are often limited by factors such as therapist fatigue, inconsistency in patient engagement, etc. Robotic-assisted rehabilitation is designed to overcome these obstacles in rehabilitation. Among all robotic rehabilitation technologies, exoskeleton rehabilitation robots draw attention because they can provide consistent, repetitive and intensive movement training for patients experiencing motor dysfunction. In the case of post-stroke rehabilitation, for example, exoskeleton rehabilitation robots can be used for assisted limb movements in rehabilitation programming, restoring walking function and promoting neural plasticity, a fundamental need for motor relearning after stroke.

However, it should be noted that simply having the right mechanical design or drive system does not dictate the effectiveness of robotic rehabilitation therapy, as other factors will influence patient return rehabilitation outcomes. Arguably, the most significant factor is the control mechanism of the rehabilitation device, or the mechanism of how the robot takes the user‘s environmental input and values, assists the user depending on their level of effort, and accepts and carries out appropriate and safe movements. The control mechanism, as the robots' "brain", has a key role to play in rehabilitation by providing real-time performance responses. Intelligent and responsive control mechanisms could enhance the assistance provided by machines to society.

There have been numerous types of control mechanisms for rehabilitation purposes for exoskeleton rehabilitation robotics researchers in recent years [3]. For example, a passive mode of control, where the machine controls the limb and no initiation from the user is expected. Active control, where the user actively participates in the limb movement. Bio-inspired controls, where movement can be considered mimicked natural movement. Intention-detection controls, where physiological signals are used to instruct the robot on the user‘s intention instead of controlling the limb, or a combination of all methods [4].

Therefore, the aim of this paper is to systematize the forms of control in exoskeleton rehabilitation robots and pay particular attention to the classification of control mechanisms; the basic working principles of the control mechanisms; the representative applications of each control method; and future trends and directions. This review paper aims to offer technical insights for researchers and developers in the field, and for clinicians to consider options designed to enhance stroke recovery and rehabilitation therapy for patients receiving post-stroke care.

2. Control Mechanism of the Upper Limb Exoskeleton Rehabilitation Robot

2.1 Passive Control and Force Control for Upper-Limb Robots

Passive control is a basic model of control used in robotic rehabilitation, especially for stroke patients who struggle to move their arms. In passive control, the robot moves the patient‘s arm over a programmed route or trajectory with zero or minimal help from the patient. This situation allows stroke patients to practice arm movements within ‚safe limits‘ of robotic support, even when they are too weak to move their arms voluntarily [4].

An excellent example is the MIT-Manus robot (see Fig. 1), which was designed for upper-limb rehabilitation to allow stroke patients to practice very simple reaching movements over and over again. The robot moved the patient‘s arm along a defined path, which allows the stroke survivors‘ brain to learn how to control the arm again [5].

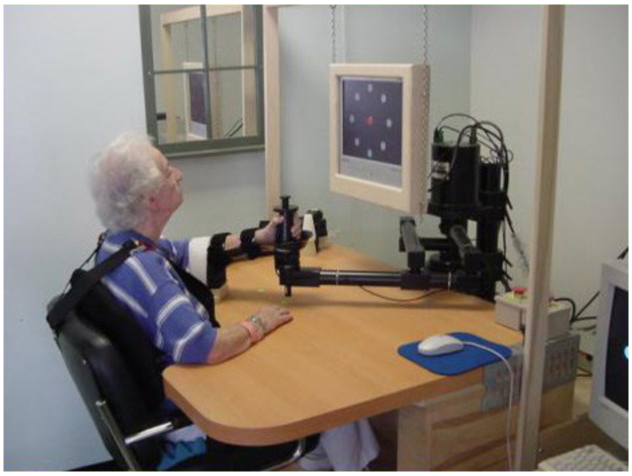

Fig. 1. An example of MIT-Manus robot [6]

Most passive robots use what‘s called position control. Position control means that the robot is programmed to move the patient‘s arm along an exact route. If the arm strays off the defined route, the robot simply corrects the patient‘s arm.

The intuition driving position control can be understood by a simple equation:

$$u(t) = K_p e(t) + K_d \frac{de(t)}{dt} \tag{1}$$

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$u(t)$ describes how much force the robot applies to move the arm. $e(t)$ indicates the error (difference between the actual position of the arm and the planned position). K_p and K_d are the constants that control how quickly and smoothly the robot corrects the arm's position. The derivative $\frac{de(t)}{dt}$ is the rate of change of that error (how fast it is drifting off course).

Sometimes, being moved by the robot along the fixed path could be discomforting or unsafe, especially given that perhaps the patient has stiff or sensitive muscles. To address these safety concerns, the robot could also utilize force control, which is when the robot employs either impedance controllers or admittance controllers. The basic idea behind force control is to allow the robot to behave efficiently like a soft spring or cushion; when the patient's arm starts resisting or feels pain, the robot will allow an increase in compliance [4].

An example of how an impedance-controlled robot works is given below:

$$F = M\ddot{x} + B\dot{x} + Kx \tag{2}$$

F is the amount of force between the robot and the patient's arm. M, B, K are constants for virtual mass, damping, and stiffness. $\ddot{x}$ and $\dot{x}$ are derivatives of displacement x which stands for acceleration and velocity of the arm.

An example of a robot using this kind of control is the ArmeoPower robot for upper-limb rehabilitation. The robot measures the force being applied by the patient and changes its trajectory according to the force applied by the patient. This allows for safe robot therapy and encourages the patient to move more independently as permitted [7]. Fig. 2 shows an ArmeoPower's product displayed on the official webpage.

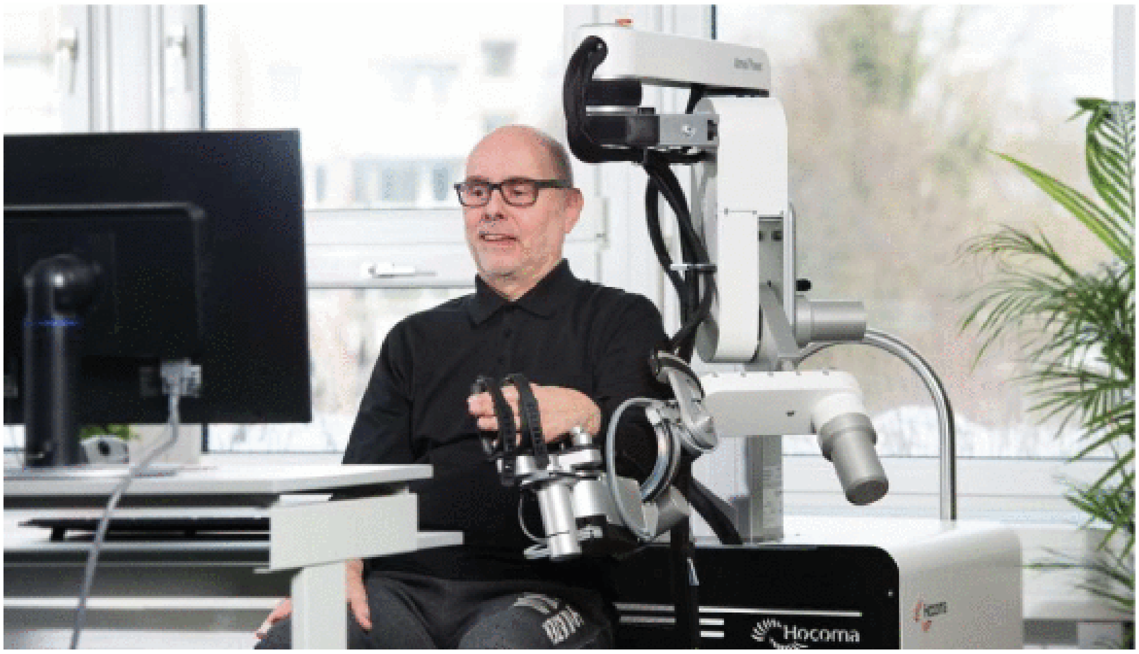

Fig. 2. ArmeoPower's product displayed on the official webpage [8]

Passive control robots can be described as beneficial because they model safe and repeatable movements that are important to early recovery. However, passive movement is no longer useful when it encourages the patient to learn how to move independently. Therefore, the robotic rehabilitation process usually begins with passive training and shifts to one that incorporates other possibilities as the patient progresses or gets better [4].

2.2 Active Control and Motor Intention Recognition

Motor Intention Recognition is a core form of active control in exoskeleton robots, where physiological sensor signals are interpreted to decode human movement intentions. The two most commonly used sources of intention information include the measurement of electromyography (EMG) and electroencephalography (EEG) data. EMG reflects motor commands from the muscular level and EEG represents motor commands at the central neural level.

2.2.1 Electromyography (EMG)-Driven control

EMG signals are basically bio-electrical activities when muscle activities occur, and they are a direct measure of the motor command given by the central nervous system. Once the brain gives a command to perform a set of work, motor commands, or neural impulses, are transmitted through the peripheral nerves to the specific muscle(s). This effect causes changes in the potential of cell membranes, which by definition are the EMG signals [9]. EMG signals are an accurate representation of strength, speed, and duration of contraction and can be mapped directly to motor intentions. For example, a change in the amplitude of the EMG signals from the flexor hallucis brevis and flexor digitorum profundus muscles can signal to the control system how much grip force and speed of finger flexion is intended.

EMG signals are gathered using electrodes. When electrodes are not implanted or intramuscular, which refer to it as surface electrodes (sEMG). sEMG signals are non-invasive, easy to set up and collect data with, and are appropriate for the majority of rehabilitation scenarios, just like finding maximum contractions with an athlete‘s biceps and triceps to control an upper-limb exoskeleton for rehabilitation purposes [10]. When impulse potentials are so low related to the bio-electrical activity causing muscle contraction, and they are not sEMG, take more localized muscle movement and direct longer noise-free signal captures relative to organism variability and environmental noise cases, they are usually found in academic institutions doing relevant research, or in practice during tasks requiring precise behavior such as actions using fingers. Once data is collected, the raw EMG signals need to be filtered, amplified, and features extracted from them (root mean square and integrated EMG, for example) and further translated to commands to control the exoskeleton. For example, if the raw EMG signal exceeds a threshold you can determine „grasp,“ and depending on the amplitude the grab signal will control grip strength.

As a fast-responding physiological signal (milliseconds), with a well-established link to movement intention and as a portable device, EMG controlled exoskeletons have been extensively used in clinical rehabilitation. In stroke patients with upper extremity spasticity, EMG signals from the muscles of the hand and forearm can drive the exoskeleton to provide assistance to open and close the hand, wrist rotation and flexion-extension of their elbow, and help restore proprioception and motor control ability. Similarly, in patients with spinal cord injury, EMG signals can produce shoulder and elbow impulses to help drive the exoskeleton for lifting and carrying behaviors, which may lead to increased levels of independence.

2.2.2 Electroencephalography (EEG)-Driven control

EEG signals arise from neuronal activity in the cortex; introduced behavioral state strategies are reflexive of brain states associated with motor function. In the preparing phase related to movement execution, the brain prompts ‘readiness potentials’ in the motor cortex where execution of movement actually generates shifting rhythms (for instance, μ- and β-desynchronization) which function as a coding model that reflects direction and amplitude [11]. Hence, the decoding of the neural dynamics indicates that they may also act as motor intentions at the central processing level.

EEG can be recorded noninvasively through scalp electrodes (for instance, 10–20 system) representing a safe, less intrusive, and patient-contentious method of measurement, however, noninvasiveness does entail a level signal degradation and signal-to-noise ratio, meaning that commands are ultimately limited to basic command levels such as ‘move left/right arm’ or ‘stop’. Invasive methods of EEG provide a better electrical signal if the measurements are taken from the surface of the cortex, where the ‘electrocorticography’ (ECoG) obtains maximum performance realities, or senses taken from a microelectrode array (MEA) application to neurons also, are suggesting the greatest electrical performance signal, along with other neural performance as well. An example would be from Stanford using monkeys, where decoding of cortical activity obtained through MEAs can control robotic arms within a millimeter range, using 3D object grasping tasks.

Applications toward a clinical implementation in neurological stroke rehabilitation are yet to be accomplished, however future patient performance collectives. Noninvasively, EEG decoding borders on a level of robustness and is characteristically limited-using invasive methods by design characteristics to include acute safety and long-term issues to include as inflammation and signal loss. Another meta-analysis point is depending on the level of motor impairment and rehabilitation strategy, which can involve different cortical locations of the brain and methods used requires patient-individualized models. Yet, the post-rehabilitation studies show how EEG controlled robotic devices could work for high-level paralytic patients, while EEG controlled even an exoskeleton could be operated directly from thinking about moving themselves.

3. Comparison Between Passive and Active Control

The primary advantage of passive control lies in providing a safe and organized environment for training, making it appropriate for early intervention patients who are very

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impaired in their ability to move. This is particularly useful when guiding movement of a limb through specific trajectories, since it would also assist in limiting joint stiffness and muscle atrophy [12]. However, overreliance on passive control may disengage the patient when active control and rehabilitation are encouraged, thus potentially delaying long term recovery. The use of active control reinforces that an intention to interact occurs, by utilizing physiological signals like EMG or EEG. This form of rehabilitation is more appropriate during middle to late-stage rehabilitation, as the level of participation is much higher compared to being less engaged with passive control, thus allowing some early stages of neuroplasticity to occur, especially if fine motor function is starting to recover [13, 14].

From an engineering perspective, passive control designs may be better established since the safety limits are known whereas active control systems have discrete signal processing requirements for signal acquisition, signal processing algorithms, and compliant actuation. The introduction of series elastic actuators (SEAs), which incorporate a spring between the motor and the load, improved stability of force control and compliance by design, offering a better opportunity to implement active control that is safer and inherently easier [15, 16, 17].

Evidence from clinical trials suggests that robot-assisted rehabilitation presents a greater, but not always significant, advantage over standard care, and may be more important than the robotic device itself, to provide an appropriate goal-matched dosage of practice. Furthermore, early data indicates concurrent paired brain-computer interfaces and upper-limb exoskeletons were effective and safe for patients with severe hemiplegia [3, 13].

To sum up, passive control and active control are not opposing categories, but rather they work together complementarily. Passive control is valuable in early rehabilitation in order to maintain safety and dosage objectives while active control can be introduced in the later stages of rehabilitation to increase patient engagement and functional recovery. By employing combinations of passive and active control, depending on the stage of rehabilitation, exoskeleton systems can provide the most therapeutic effect to promote progressive motor recovery.

4. Conclusion

This dissertation has described features of the control systems of upper-limb exoskeleton rehabilitation robots with a focus on their critical role of recovery. While the mechanical configuration and ergonomics may be seen as the basis for building effective exoskeletons, the control strategy to run the motion system would determine how well their active and passive capabilities could custom configure for patients, provide safety, and promote resilient functional motor recovery.

To summarize, these developments in upper-limb exoskeleton rehabilitation robots will fundamentally become very intelligent adaptive ethically conscious devices combining a surgeon‘s intelligence and a machine artisan‘s ingenuity into clinically realizable, possible success. The rendering if upper-limb exoskeletons combine passive and active paradigms that move from a passive mode into acting as a closed loop adaptive and deliberatively adaptive, forward thinking, sustained safety and patient agency move from device testing, experimentation, technology research into radical repositioning of upper-limb exoskeletons as integral mechanisms of post-stroke rehabilitation care become real. Either way, or both ways, upper-limb exoskeleton rehabilitation robots stand a chance of recovering not just independent motor function but also independently at the human level to improve independence and quality of life for millions of stroke survivors in the world.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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