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Review

Current State of Robotics in Hand Rehabilitation after Stroke: A Systematic Review

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Abstract: Among the methods of hand function rehabilitation after stroke, robot-assisted rehabilitation is widely used, and the use of hand rehabilitation robots can provide functional training of the hand or assist the paralyzed hand with activities of daily living. However, patients with hand disorders consistently report that the needs of some users are not being met. The purpose of this review is to understand the reasons why these user needs are not being adequately addressed, to explore research on hand rehabilitation robots, to review their current state of research in recent years, and to summarize future trends in the hope that it will be useful to researchers in this research area. This review summarizes the techniques in this paper in a systematic way. We first provide a comprehensive review of research institutions, commercial products, and literature. Thus, the state of the art and deficiencies of functional hand rehabilitation robots are sought and guide the development of subsequent hand rehabilitation robots. This review focuses specifically on the actuation and control of hand functional rehabilitation robots, as user needs are primarily focused on actuation and control strategies. We also review hand detection technologies and compare them with patient needs. The results show that the trends in recent years are more inclined to pursue new lightweight materials to improve hand adaptability, investigating intelligent control methods for human-robot interaction in hand functional rehabilitation robots to improve control robustness and accuracy, and VR virtual task positioning to improve the effectiveness of active rehabilitation training.

Keywords: rehabilitation medicine; rehabilitation engineering; hand rehabilitation robots

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1. Introduction

As China faces an aging population, younger stroke incidence and more frequent traffic accidents are occurring, stroke has become one of the major diseases that seriously endanger health and quality of life. Stroke is one of the major chronic non-communicable diseases that seriously endanger the health of Chinese people, and it is also the leading cause of death and disability among Chinese adults from 1990 to 2017 [1]. The most recent Global Burden of Disease (GBD) 2019 stroke burden estimates [2] showed that stroke remains the second leading cause of death and the third leading cause of death and disability combined (as expressed by disability-adjusted life-years lost—DALYs) in the world. The estimated global cost of stroke is over US $891 billion (1.12% of the global GDP) [3]. From 1990 to 2019, the burden (in terms of the absolute number of cases) increased substantially (70.0% increase in incident strokes, 43.0% deaths from stroke, 102.0% prevalent strokes, and 143.0% DALYs) [4]. According to statistics, China has 12.42 million stroke patients over the age of 40, and about 1.96 million patients died. As of today, 12.42 million people over the age of 40 suffer strokes in China, and about 1.96 million have died. About 75% of survivors are disabled (loss of body movement ability) [5].

According to incomplete statistics, nearly 80% of stroke patients develop hand dysfunction, one of the most common symptoms of stroke [5,6]. Hand function accounts for about 90% of upper limb function and plays an indispensable role in life. Hand dysfunction seriously affects the quality of daily life of patients and their families, and also has a negative impact on patients' psychology, so hand function rehabilitation has become one of the main tasks of stroke rehabilitation. Fortunately, the human motor system is able to restore the function of the injury through intensive and repetitive rehabilitation exercises [7,8]. In order for stroke patients to better return to society and family, systematic rehabilitation training is particularly important and will directly determine the possible degree of patient recovery. The hand dysfunction left by stroke seriously affects patients' ability to perform daily life activities and social abilities. Since hand function requires the participation of finger fine motor function and sensory function, and also requires the active participation of patients, its recovery is very slow and the rehabilitation efficacy is not significant [9]. In addition to the use of medications, appropriate rehabilitation exercises will have a greater impact on the rehabilitation of a patient's hand function.

The central nervous system is plastic, so repetitive rehabilitation will help the patient's limbs to establish new connections with the central nervous system, thus effectively treating stroke disease. In the treatment of stroke disease, effective rehabilitation is the key to treatment. Currently, rehabilitation exercises are used to help repair and rebuild tissues and nerves through repetitive rehabilitation. In addition to traditional rehabilitation methods, there is a need for a more rational and scientific approach to meet the rehabilitation needs of patients, which is why rehabilitation assisted robots have been developed [10–12].

The role of rehabilitation robots is to help patients perform effective rehabilitation exercises for damaged limb parts, thus promoting rapid recovery of damaged parts. Due to the drawbacks of traditional rehabilitation training methods, a variety of rehabilitation robots have been developed at home and abroad to assist patients to complete repetitive training through rehabilitation robots [13,14]. One of the important branches of medical robotics is rehabilitation robots [15,16]. In the United States and Europe and other countries due to the continuous development of rehabilitation medicine, the development of medical rehabilitation robotic market is rising year by year, more and more patients with hand dysfunction benefit from rehabilitation robotics. As shown in Figure 1, the annual trend of publications on topics related to hand rehabilitation robots in the web of science database has been in a growing phase, which indicates a very promising future for hand rehabilitation robots.

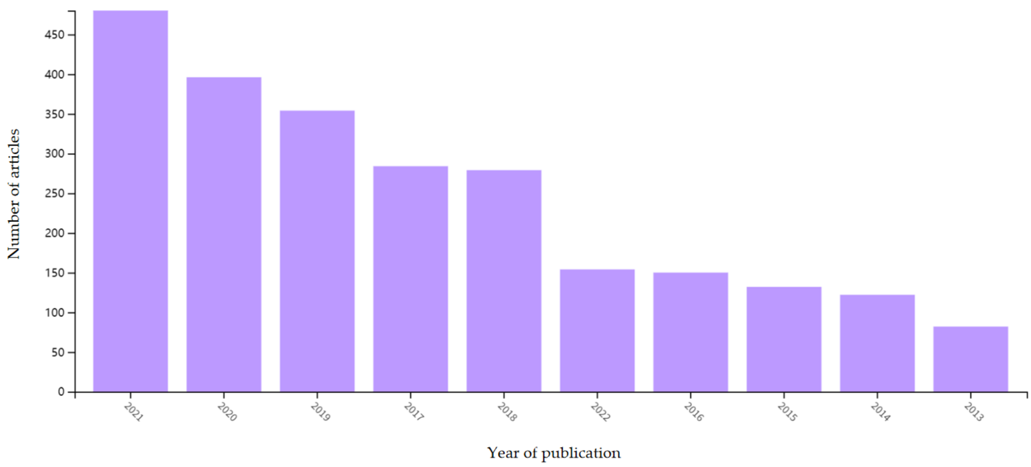


Figure 1. Frequency of publication per year.

Today, several review articles have been published on hand rehabilitation robots. However, few of them have described in detail the drive modes, control strategies, training modes, and hand state detection techniques of hand rehabilitation robots.

In this paper, we systematically review the current development of hand rehabilitation robots and provide an overview of the classification, comparison, and design of drive modes, control strategies, training modes, and hand state detection techniques. The basic outline of the content covered in this paper is shown in Figure 2. The rest of the paper is organized as follows: Section 2.1 describes the development of hand rehabilitation robots. Section 2.2 describes the drive modes of hand rehabilitation robots. Section 2.3 describes the control strategies, including force signal control and biomedical signal control. In Section 2.4, the training mode of the hand rehabilitation robot is presented. In Section 2.5, different hand state detection techniques are analyzed. In Section 3, the limitations of the study and future directions are discussed and summarized. In Section 4, the full text is summarized.

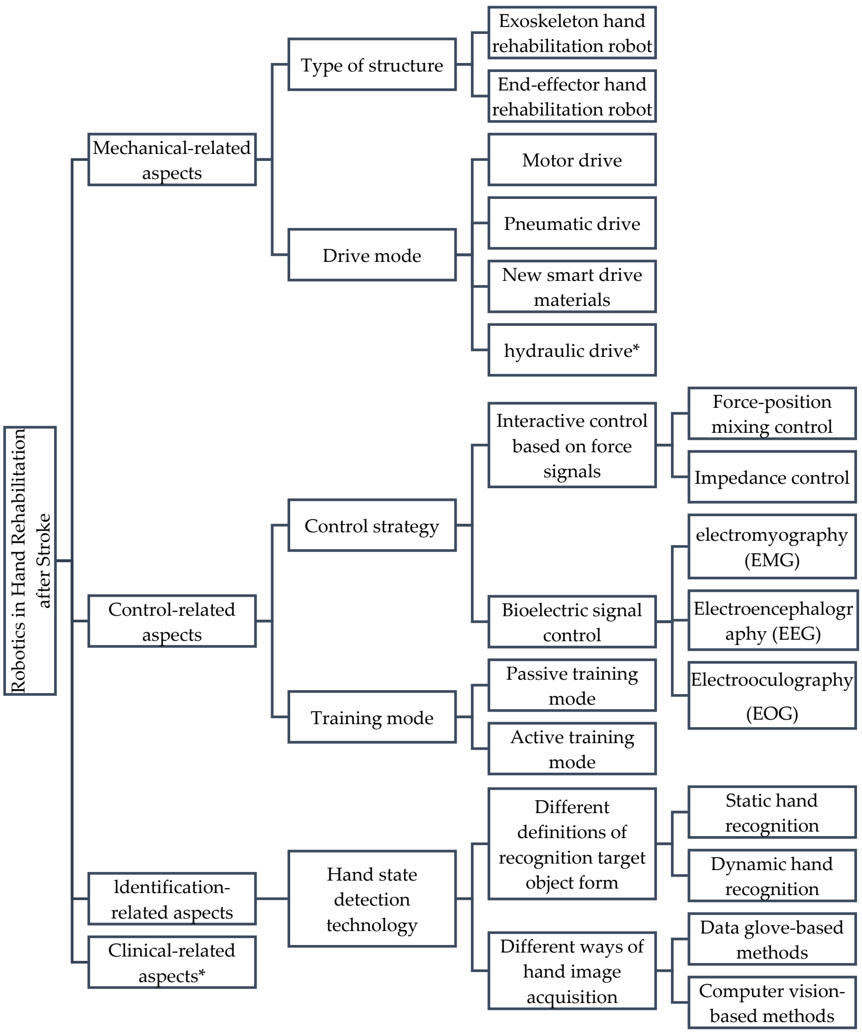


Figure 2. The basic outline of the contents is covered in this paper. The aspects marked with an asterisk (*) are beyond the scope of this article.

2. Materials and Methods

2.1. The Development of Hand Rehabilitation Robot

At present, hand rehabilitation robots for post-stroke can be divided into those fixed to a table and those movable or stationary to the patient's own body [17], e.g., hand rehabilitation robots fixed to a table: hand motion assist robots [18] and hand rehabilitation robots movable or stationary to the patient's own body: HX wearable robotic exoskeletons [19]. In this paper, the authors will focus only on mobile hand rehabilitation robots, which include exoskeleton hand rehabilitation robots and end-effector hand rehabilitation robots [20,21]. Exoskeleton style refers to devices in which the joints of the device are aligned with the patient's anatomical joints, allowing direct control of individual joints and thus reducing the risk of abnormal postures [22,23], such as in Cempini et al. [19] and Tong et al. [24]. The end-effector style is a device that applies force to the most distal end of the finger, allowing a simple initial setup at the cost of limited control of the proximal finger joint, e.g., Iqbal et al. [25].

2.1.1. The Exoskeleton Hand Rehabilitation Robot

Exoskeleton hand rehabilitation robots are similar to human limbs because they are connected to the patient at multiple points and their joint axes match those of human joints [26,27]. It is possible to train specific muscles by controlling joint movements under computational torque. Most exoskeletal robots are still based on rigid linkages. Existing hand rehabilitation robots enable finger flexion and extension movements, differing in that some designs do not enable independent movements of each finger, the choice of control signals varies, and the range of motion of the affected limb varies between rehabilitation robots. After nearly 30 years of development, the technology has become more mature, and in recent years there are still many researchers at home and abroad in innovative research, and several newer rigid exoskeleton-based hand rehabilitation robots will be introduced below.

In 2016, the exoskeletal rehabilitation hand HES, produced by 3D printing at the University of Florence [28,29] uses a cord for the transmission of driving forces and a linkage mechanism as a finger actuator while limiting joint movements to ensure safety. The HES is intended for patients with severe hand contractures to train them in hand extension, while hand flexion is performed by the patient. The maximum trajectory error after wear is 5 mm.

In 2017, a wire-controlled hand exoskeleton was designed by the Ulsan University of Science and Technology, South Korea [30,31], where each finger is driven by a separate linear motor, and each exoskeleton joint uses a four-link mechanism to measure the force on the finger and the joint movement angle using a force measuring sensor and a rotary potentiometer to limit the exoskeleton hand using the stroke of the linear motor. Bortoletto et al. [32] in Italy used springs as power transmission to reduce the risk of hand-filling blood pressure injuries during motion compared to traditional linkage rigid structural members. Decker et al. [33] designed an underdriven exoskeleton hand with a modular design of the mechanism to select different models of exoskeleton hand for wearing according to different hand sizes. Each finger is driven by a separate geared motor, and the force is transmitted to the linkage on the finger by a cord, and the movement angles of the MCP and PIP joints can reach 62° and 88°, respectively. Jo et al. [34] designed an exoskeleton hand with two linear motors driving the thumb and four fingers and used the fixed stroke of the linear motors to limit the motion of the exoskeleton hand. The finger actuators consisted of two sets of four-linked rods, preserving the natural motion of the DIP joints. The overall structure of the device is 3D printed. However, the motors are mounted on the back of the hand, which poses a risk of a crush injury to the affected hand.

In 2018, Sale et al. [35] from Italy invented an underdriven exoskeleton FEX with a "finger spine", which is driven by a single motor with four fingers and can be adapted to different hand sizes and can be well matched to the manual motion joints, while the MCP joints can be moved inward and outward, and the driving device is placed on the patient's small arm. The actuator is placed on the patient's small arm, connected and driven by Bowden wires, and each "spine" has a certain joint angle restriction to protect the affected hand within a normal joint angle. However, most of the weight of the device is located on the back of the affected finger, which increases the patient's sense of weight-bearing after being worn for a long time. In recent years, domestic research has also made some progress, and many universities have researched hand rehabilitation robots. The wearable hand rehabilitation robot system designed by Harbin Institute of Technology [36] uses a rack and pinion parallel sliding mechanism to achieve flexion/extension movements of the three joints of the finger as well as inward/abduction movements of the MCP joints, and the exoskeleton joint rotation center can coincide well with the human hand joint rotation center, and it can also adapt to different sizes of palms.

In 2019, the Department of Mechanical Engineering, UNIST, Ulsan, Korea invented a portable and spring-guided hand exoskeleton for exercising flexion/extension of the fingers [25], as shown in Figure 3. The exoskeleton was designed with a simple structure to help the finger move with one degree of freedom (DOF). The desired joint trajectory of the exoskeleton was determined based on the user joint ROM and general finger motion obtained through hand flexion and extension experiments. The design of the linkage structure was optimized to maximize the desired trajectory. When the finger deviates from the desired position, a spring attached to the structure generates a force to guide the finger to the desired posture.

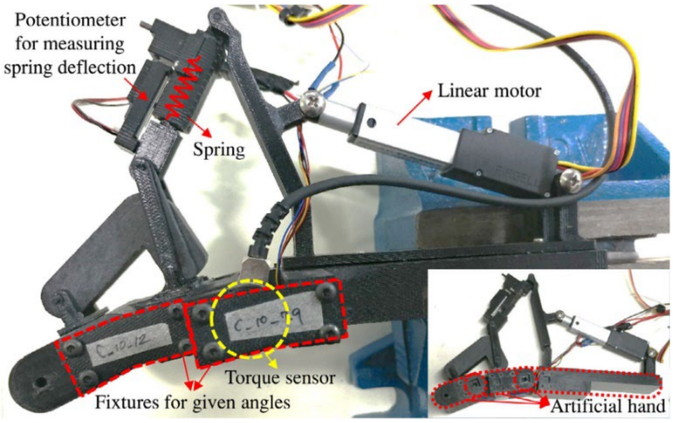


Figure 3. A portable and spring-guided hand exoskeleton.[25]

In 2019, D. Marconi et al. invented a HX-β orthosis (exoskeleton) with a SEA structure [37], as shown in Figure 4 introducing HandeXos-Beta (HX-β), a novel index finger-thumb exoskeleton for hand rehabilitation. The HX-β system features an innovative kinematic architecture that allows independent actuation of thumb flexion/extension and circumduction (opposition), thus enabling a variety of naturalistic and functional grip configurations. Furthermore, HX-β features a novel series-elastic actuators (SEA) architecture that directly measures externally transferred torque in real-time, and thus enables both position and torque-controlled modes of operation, allowing implementation of both robot-in-charge and user-in-charge exercise paradigms.

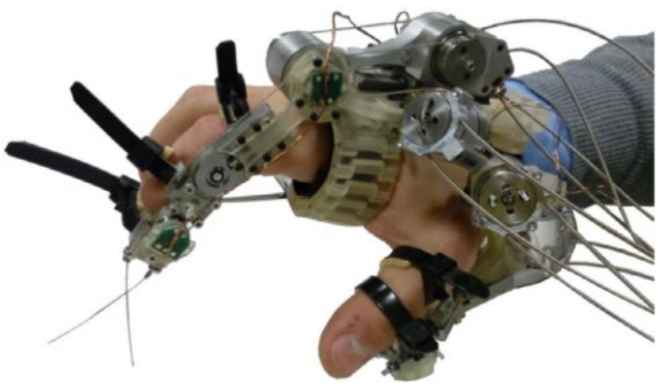


Figure 4. Close-up view of the HX-β orthosis (exoskeleton).[37]

The rigid exoskeleton type hand rehabilitation robot has been studied by many scholars because of its accurate motion transmission, precise control, and mechanical protection limit, but it has heavy mass, poor self-adaptability, and rigid impact. At present, researchers at home and abroad mainly reduce this deficiency in two ways: one is to reduce the weight of the exoskeleton by selecting lightweight materials, and the other is to use the rigid-flexible coupling method, in which the power drive of the rigid exoskeleton is rearranged and the elastic member is used as the power transmission member to eliminate the rigid impact of the exoskeleton and reduce the weight of the hand mechanism, so as to reduce the weight feeling at the back of the patient's hand.

2.1.2. The End-Effector Hand Rehabilitation Robot

The end-executing hand rehabilitation robot is connected to the patient's hand at a distal point with joints that do not match the joints of the human hand. The forces generated at the distal interface change the position of other joints simultaneously, making it difficult for individual joints to move individually [26,27]. This paper focuses on driven hand rehabilitation robots, which have been developed over the past 30 years and have become more mature in technology. There are still a lot of researchers in the innovative research, the following will introduce several new end-effector hand rehabilitation robots.

In 2015, the Robotics Laboratory of Seoul National University developed the Exo-Glove Poly, a wearable glove powered by tendons, which is a breakthrough from the rigid structure of previous gloves The Exo-Glove Poly has a built-in controller that receives electrical signals from the user's brain and then drives the three fingers of the flexible glove via a motor. Figure 5a shows a flexible glove made of polymer with two tendons on each finger, one on the dorsal side simulating the finger extensor tendon for finger extension and one across the ulnar and radial sides simulating the deep finger flexor for finger flexion [38–42]. The National University of Singapore has designed a flexible rehabilitation glove, shown in Figure 5b, which is pneumatically actuated. The main purpose of this rehabilitation hand is to help stroke and hemiplegic patients to stretch their hands to help restore muscles and prevent spasticity. The rehabilitation glove has an airbag on the back of each finger, and the airbag is driven to stretch the finger by punching air pressure into the airbag [43]. The device is simple in construction, lightweight in mass, and suitable for rehabilitation of patients with severe hemiplegia, but the rehabilitation hand is single-functional, enabling only hand extension, and the pneumatic needs to be supplied with an air pump, which limits portability and is noisy. Harvard University has designed a pneumatically actuated intelligent hand rehabilitation glove, shown in Figure 5c, which assists stroke and hemiplegic patients with hand extension and grasping movements. A new pneumatic actuator is implanted on the back of each finger of the rehabilitation glove to drive the finger movement. The actuator is made of two elastic materials with different stretching properties sewn together, and due to the different stretching properties, the actuator will bend and stretch during the process of inflation and deflation and drive the finger movement at the same time, and the bending mode of the actuator will change with different sewing modes of the materials [44,45]. The rehabilitation glove also has various sensors implanted in it, and patients can perform rich human-computer interaction rehabilitation training under the guidance of doctors after wearing it to help stroke and hemiplegic patients to have better rehabilitation.

(**a**)

(**b**)

(**c**)

Figure 5. (**a**) Close-up view of the Exo-Glove Poly; (**b**) Close-up view of the flexible rehabilitation glove designed by the National University of Singapore; (**c**) Close-up view of the Compliant Hand Based on a Novel Pneumatic Actuator designed by Harvard University. [38-45]

In 2016, Heidi C. Fischer et al. [46] developed a portable, actuated glove-orthosis, allowing free movement of each joint, as the abductor tendon's cable runs through a cable guide attached to the dorsal side of the glove, as shown in Figure 6. The guides form a bridge over each joint to allow joint flexion but prevent hyperextension of the joint. They are made of glass-filled nylon, using a selective laser sintering technique (SLS), and are sewn into each glove. For each finger, the single cable from the corresponding actuator is split into three cables to pass through the guides in order to provide greater lateral stability. Linear servo actuators (L12, Firgelli Technologies, Inc.,based in Victoria, BC, Canada,) move the cables to generate extended torque at each joint of the finger.

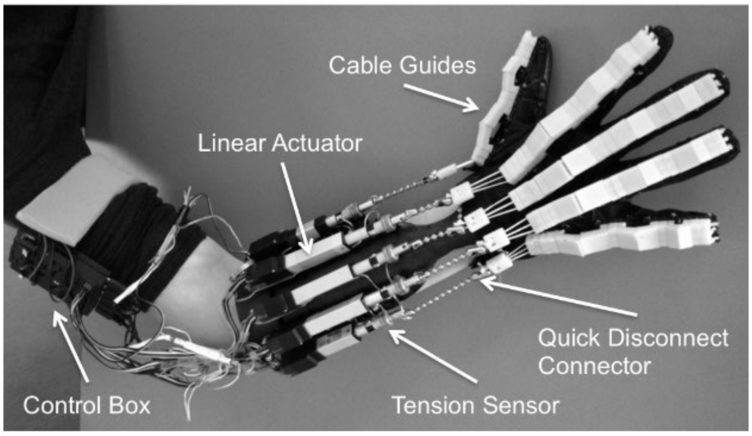


Figure 6. Close-up view of the portable, actuated glove-orthosis.[46]

In 2019, Xi'an Jiao tong University invented an attention-controlled hand exoskeleton for the rehabilitation of finger extension and flexion using a rigid-soft combined mechanism [47], as shown in Figure 7. Active rehabilitation training is achieved using an attentional value threshold measured by an electroencephalography (EEG) sensor as a brain-controlled switch for the hand exoskeleton. The spring layer flexes and slides due to the linear motion input provided by the linear motor, and then the structure becomes like a circular sector that supports the finger flexion/extension movement when the structure is attached to the finger.

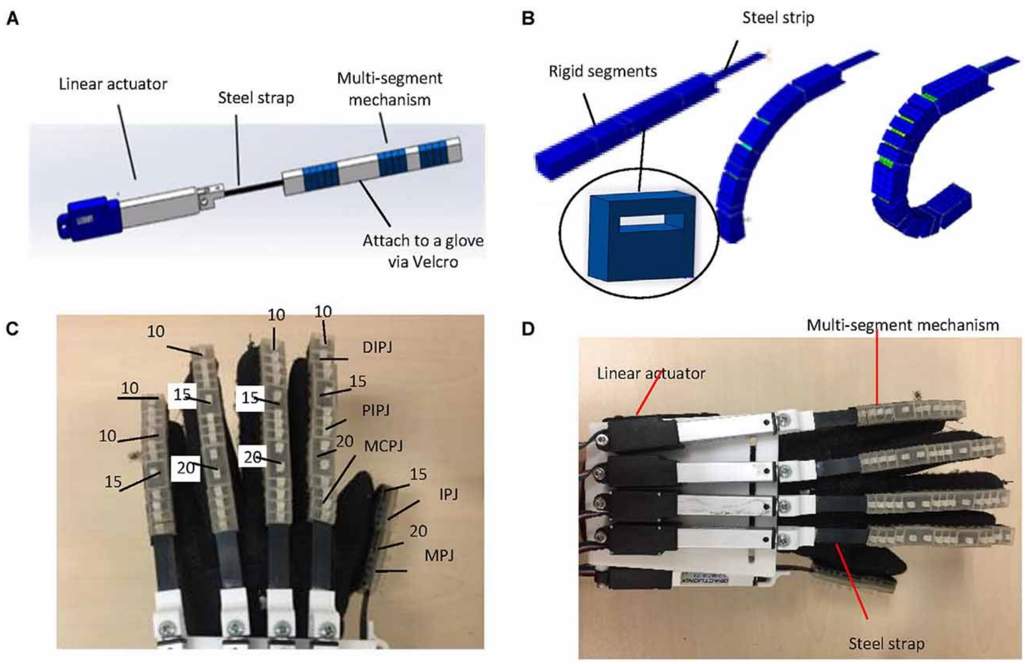
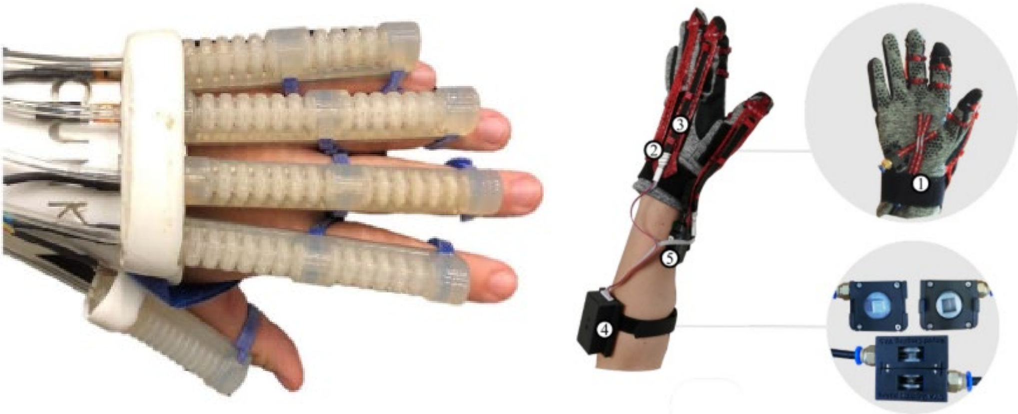


Figure 7. An attention-controlled hand exoskeleton. (**A**) CAD drawing of the index finger acuator; (**B**) bending motion generated by the proposed mutli-segment mechanism with a spring layer; (**C**) segment thicknesses (unit: mm); and (**D**) overview of the hand exoskeleton prototype.[47]

In 2020, Butzer, T. et al. designed the RELab tenoexo [48], a fully wearable assistive soft hand exoskeleton for everyday activities, as shown in Figure 8. It consists of a hand module attached to the hand and a backpack containing electronics, motors, and batteries. The backpack and the hand module are connected by a force transfer system based on a Bowden cable and can be connected by a clip mechanism. In the hand module, three DOFs enable power, precision and lateral gripping: combined actuated flexion/extension of 2–5 digits, separate actuated flexion/extension of the thumb, and manual lateral and pad opposition of the thumb. The two DC motors are controlled by force feedforward and actuate the finger and thumb flexion/extension separately via a rack and pinion mechanism. The Myo armband wireless surface electromyographic EMG sensor was used for monitoring.

Figure 8. Close-up view of the RELab tenoexo.[48]

In 2022, Zhi Qiang Tang et al. of the University of Hong Kong designed a probabilistic model-based learning control of a soft pneumatic glove for hand rehabilitation [49], as shown in Figure 9a. This soft-body pneumatic glove, a probabilistic model-based learning control method for an integrated "hand-soft-body robot" system and a task-oriented, intention-driven training model is proposed. Marek Sierotowicz et al. of the Institute of Robotics and Mechatronics, German Aerospace Center (DLR) designed an EMG-Driven machine learning control of a soft glove for grasping assistance and rehabilitation [50], as shown in Figure 9b. This glove is able to assist flexion of the index and middle finger, and flexion of the thumb, respectively, by means of a tendon-driven system. Two movements, namely flexion of the thumb and flexion of the fingers, are independently assisted by motors that pull and release the respective tendon cable. This glove has an intention recognition control system via EMG.



(**a**) (**b**)

Figure 9. (**a**) Close-up view of the probabilistic model-based learning control of a soft pneumatic glove; (**b**) Close-up view of the EMG-Driven machine learning control of a soft glove.[49,50]

Compiling an overview of hand rehabilitation robotics in recent years was shown in Table 1.

Table 1. Compiling an overview of hand rehabilitation robotics in recent years.

Groups	Representative Works	Researchers	Actuated DoF	Driving Modes	Control Strategies	Force Transmission Mode
The exoskeleton hand rehabilitation robots	[51]	J. Iqbal et al.	4	Motor drive	Preset	Link
	[52]	D. Leonardis et al.	5	Motor drive	Preset	Link
	[28,29]	R. Conti et al.	4	Motor drive	Preset	Rope + Connecting rod
	[30,31]	S. Kim et al.	1	Motor drive	Preset	Link
	[33]	Decker et al.	5	Motor drive	Preset	Link
	[34]	I. Jo et al.	5	Motor drive	Preset	Link
	[35]	Sale et al.	4	Motor drive	Preset	Cable + chain
	[36]	F. Zhang et al.	6	Motor drive	Preset	Cable + Link
	[53]	A. Lince et al.	1	Motor drive	EMG	Cable + Link
	[54]	A. Bataller et al.	1	Motor drive	Preset	Link
	[25]	I. Jo et al.	1	Motor drive	Preset	Spring + Link
	[37]	D. Marconi et al.	5	SEA	Force Control	Link
The end-effector hand rehabilitation robots	[55]	Haghshenas-Jaryani, M. et al.	3	Hybrid Pneumatic	Preset	Pneumatic artificial muscle
	[56,57]	Polygerinos, P. et al.	5	Hydraulic	Preset	Rubber Return Spring
	[58]	Diftler, M.A. et al.	3	Motor drive	Force Control	Tendon/Cable-pulley
	[59]	Fischer, H.C et al.	5	Motor drive	Preset	Cable
	[60]	H. K. Yap et al.	5	Pneumatic	EMG	Flexible Actuators
	[61]	Y. Park et al.	3	Motor drive	Force Control	Cable
	[62]	B. W. K. Ang et al.	5	Pneumatic	EMG	Flexible Actuators
	[63]	B. B. Kang et al.	2	Motor drive	Force feedback control	Cable
	[64]	D. Popov et al.	4	Motor drive	Preset	Tendon
	[65]	L. Randazzo et al.	5	Motor drive	EEG	Artificial tendon
	[66]	Thielbar, K.O. et al.	5	Motor drive	Active task orientation	Tendon/Cable-pulley
	[67]	Chua, M.C. et al.	4	Pneumatic	Force control	Pneumatic artificial muscle
	[47]	M. Li et al.	5	Motor drive	EEG	Multi-Segment
	[48]	Butzer, T. et al.	2	DC motors	EMG	Spring blade
	[68]	Qiaoling Meng et al.	1	Motor drive	Force control	Tendon
	[49]	Zhi Qiang Tang et al.	5	Pneumatic	EMG	Pneumatic artificial muscle
	[50]	Marek Sierotowicz et al.	2	Motor drive	EMG	Tendon

2.2. Drive Mode of Hand Rehabilitation Robot

The choice of drive mode directly affects the system solutions, such as structural design and control system, and is the basis for the design of hand rehabilitation robots. Currently, common drive modes are hydraulic drive, motor drive, pneumatic drive, and new intelligent drive materials [69,70]. We summarized different drive modes in Table 2, in which we only summarized three types of drive modes, namely motor drive, pneumatic drive, and new intelligent drive materials because the hydraulic drive is not commonly used in hand rehabilitation.

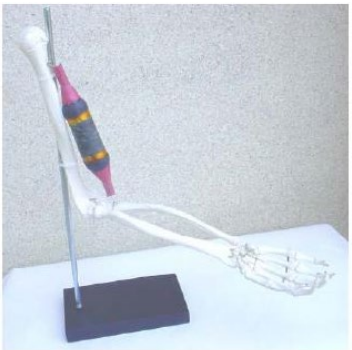
At present, most of the rehabilitation hand rehabilitation robots use motor drive mode, which has many advantages compared with other drive modes, such as easy control, no pollution, and low noise. Among the new drive modes, there is another widely used drive mode, pneumatic artificial muscle drive [71]. Pneumatic artificial muscle by air as the driving source generally consists of an easily deformable rubber capsule and the external play to limit the deformation of the mesh support. When the air pressure decreases, the pneumatic artificial muscle will return to its original length by the elasticity of the rubber and the external load. Figure 10 shows the pneumatic artificial muscle produced by FESTO.

Figure 10. The pneumatic artificial muscle produced by FESTO. [71]

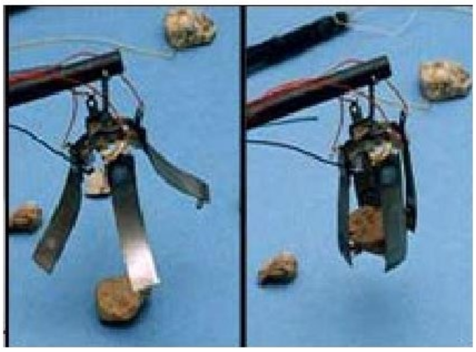
With the development of science and technology, the drive method has been developing more and more in the direction of flexibility, lightweight and high efficiency from the traditional electric motor, to pneumatic drive, and now to the new intelligent material drive [72]. Hydraulic drives now have some insurmountable constraints in some applications, many scholars at home and abroad hope to develop new drive materials to replace the traditional drive methods, which has given rise to many new intelligent drive materials, which have played their unique roles in different fields. Among the existing new intelligent drive materials, dielectric elastomers, IPMC, piezoelectric ceramics and shape memory alloy wires are the most typical drive materials. New intelligent drive materials, which are developed by scholars at home and abroad to overcome the traditional drive methods, are one of the development directions of drive innovation for future hand rehabilitation robots. Motor drive, pneumatic drive and new intelligent drive materials will have their own advantages and disadvantages, so researchers need to choose the most suitable drive mode in combination with the design requirements and continuously innovate.

Dielectric elastomer is often used to do research on bionic muscles, it is a new functional material with the advantages of high plasticity, flexibility, low noise, etc., and has a high efficiency of electrical and mechanical energy conversion [73], The dielectric elastomer bionic skeletal muscle experiment is shown in Figure 11a below. Some scholars hope to use it as a driving source for rehabilitation applications, but its driving conditions are very demanding, requiring ultra-high voltage to drive (~100 MV/m), and the poor robustness of control and low driving efficiency, seriously limit its application in rehabilitation driving; ion exchange membrane metal composite (IPMC), is formed by a class of precious metal cation exchange membrane, such as platinum through the chemical coating. When energized, the IPMC film will be bent and deformed in the direction of the anode, and the larger the energized voltage, the more obvious the bending amplitude. If an alternating current is applied, the film will oscillate as the positive and negative poles keep changing.

Using its special deformation response, it can be applied in some driving fields, as shown in Figure 11b for IPMC bionic gripper. It requires a low driving voltage of only 5 V to drive, but it must be driven in a humid environment or in a conductive environment, such as electrolyte, which is very demanding for the environment, and the mechanical conversion efficiency is relatively low.



(**a**)



(**b**)

Figure 11. (**a**) The dielectric elastomer bionic skeletal muscle experiment; (**b**) IPMC bionic gripper. [72,73]

Piezoelectric ceramics is one of the new smart materials with more applications and is a new type of micro-displacement device [74]. Because of its small size, high displacement resolution, fast response, high output force and high transduction efficiency, it is widely used in the fields of precision positioning, microelectromechanical systems, micro and nanomanufacturing technology and nano bioengineering. It has piezoelectric properties, i.e., it can convert electrical energy and mechanical energy to each other. In addition to piezoelectric properties, they also have many properties, such as elasticity and dielectric properties, but the high drive voltage and small maximum deformation rate limit their application in large stroke actuators.

Shape-memory alloy wire (SMA) is a unique new intelligent material that possesses two unique properties: shape memory effect and superelasticity [75,76]. After plastic deformation and permanent deformation of common metals, SMA wire can return to its original shape after heating to a certain temperature; at the same time, it can undergo great deformation and consume and absorb mechanical energy after applying a certain load to SMA wire under isothermal conditions, and it can return to its original shape after removing the load, showing a good damping effect. This is its superelasticity. In 2017, a wearable glove driven by shape memory alloy filaments was developed at Tehran University, Iran [77], as shown in Figure 12. Guides were set at the corresponding joints on the glove for fixing the SMA contraction path, and the force generated by the contraction of the SMA actuator was used to compensate for the lack of finger muscle force. Tests have shown that the glove can effectively achieve flexion-extension movements of the fingers within a certain range, with maximum flexion angles of 80°, 90°, and 70° at the DIP, PIP, and MCP joints. In addition, the glove can also effectively grip objects with a single fingertip force of 8 N or more during gripping.

Figure 12. Experimental prototype of the wearable glove driven by shape memory alloy.[77]

The most commonly used new drive modes in the field of hand rehabilitation robotics are pneumatic artificial muscle drive and shape memory alloy drive. Pneumatic artificial muscles are more widely studied and have been used in numerous applications. They can be used in a variety of harsh environments due to their clean seal and they also have excellent flexibility. The flexibility, high power density, and high output force of shape memory alloy wire all indicate that it is an excellent intelligent drive material. Both new drive modes are more outstanding in terms of comfort and are well suited for applications in hand rehabilitation. Relative to exoskeletons that use rigid links, soft Exo suits use low-modulus materials, often along with tendon actuation, to transmit movement assistance without imposing substantial movement constraints along non-actuated DOFs. The field has yet to fully establish corresponding best practices for providing gait assistance for poorly ambulatory individuals. In the future decade, scholars and researchers in the field of soft robotics will also continue to focus on innovative ways to apply new soft drive methods [78].

Table 2. Overview of drive modes for hand rehabilitation robots.

Drive types	Definition	Advantages	Disadvantages	Representative Works
Motor drive	Using electric equipment and adjusting the circuit parameters for power transmission and control	(1) The cable for connection has advantages of energy transfer convenience, signal transformation quickly (2) High level standard (3) Easily to achieve automatic control (4) Simple structure (5) Nonpolluting.	(1) It has a poor balance of movement load (2) It is easily influenced by external (3) Large inertia (4) Slow change (5) Large volume (6) Heavy.	[40,79,80]
Pneumatic drive	Taking the compressed air as the actuating medium for energy transmission and control	(1) Simple structure (2) Low cost (3) Small gas viscosity (4) It can realize stepless speed regulation (5) Nonpolluting	(1) The gas is easy to be compressed and leak (2) The speed is easy to change under the load (3) It is difficult to precise control, cannot be used under low temperature (4) The gas is difficult to seal (5) Working pressure is usually smaller than 0.8 Mpa, which only applies	[43,45]

		(6) Little resistance losing (7) Fire and explosion prevention, high flow rate (8) Working in high temperature.	to small power driving. Unsuitable for the high-power system.	
New smart drive materials	Smart materials that respond to changes in external environmental conditions or internal states, convert their own energy into mechanical energy and can be used as actuators for hand rehabilitation robots	(1) Light weight, malleable, flexible, low noise (2) Has a high efficiency of other energy conversion mechanical energy	(1) Harsh driving conditions (2) Poor robustness of control (3) Low drive efficiency	[72,77,81,82]

2.3. Control Strategy of Hand Rehabilitation Robot

The interaction control between the robot and the patient is a very important aspect in the research of hand rehabilitation robots, because the hand rehabilitation robot is interacting with the affected limb with impaired motor function, and the patient is the object with autonomous motor awareness. First, the interactive control creates a safe, comfortable, natural and active training environment for the patient, which prevents the patient's limbs from confronting the robot due to abnormal muscle activities, such as spasms and tremors and protects them from secondary injuries. Secondly, the interactive control will obtain the patient's active movement intention from the sensor signals and encourage the patient to actively participate in the movement to achieve the so-called active training, thus improving the rehabilitation effect. Depending on the signal used to obtain the active movement intention, the interaction control strategy between the robot and the patient can be basically divided into two categories: (1) control methods based on force signals; (2) control methods based on biomedical signals.

2.3.1. Interactive Control Based on Force Signals

In force signal-based interactive control, the force signal specifically refers to the force acting on the mechanical structure due to the contraction of the limb muscles, the interactive force. It can be measured directly by a force/moment sensor through clever mechanical design or estimated by a dynamic model of a human-machine hybrid system. Compared to biomedical signals, force signals have better determinism and are a more direct reflection of the patient's active movement intentions, making force-based interaction control relatively reliable and stable. However, since the acquisition of interaction forces usually depends on mechanical structures, which is not as convenient and flexible as the detection of biomedical signals, the application of this interaction control method is limited. Two of the most widely used force control strategies for interaction between rehabilitation robots and patients are force-position hybrid control and impedance control [83].

Force-position mixing control: The force-position hybrid control approach was first proposed by Raibert et al. to solve the problem of controlling a robot in a constrained environment [84], which can be simply described as the need to control the robot's position in some directions and the need to control the interaction forces between the mechanism and the external world in other directions. Therefore, in force-position hybrid control, when the robot is in contact with the external environment, its task space is naturally partitioned into two subspaces, namely, the position subspace and the force subspace, and the tracking control of position and force is accomplished in the corresponding subspaces [85]. The goal of interactive control of hand rehabilitation robots is to create a safe, comfortable, natural and actively supple training environment for paralyzed patients, and precise force trajectory tracking is rarely required. Therefore, the following literature review on force-position hybrid control is also related to upper limb rehabilitation robots, and the approach is also useful for the control of hand rehabilitation robots.

Impedance control: The control research of hand function rehabilitation robots is mainly focused on finger position control at this stage. The research on the control of the contact force between the functional hand rehabilitation robot and the human hand is less. In the 1980s, Hogan [86] proposed the well-known theory of impedance control method in the study of contact control between robot end and environment. Impedance control incorporates force and position into the same control system and has the advantages of less computational effort as well as greater robustness, making it an efficient method for dealing with machine human control that has been widely studied. Impedance control is essentially an indirect force control, characterized by not directly controlling the desired position and force, but by adjusting the corresponding dynamic relationship between the position (or velocity) and the force acting at the end of the robot in real-time, thus achieving a soft and compliant control of the robot. Impedance control is divided into two different control results based on force and position; force-based impedance control is achieved by controlling the joint drive torque to adjust the end contact force and displacement; while position-based impedance control is achieved by adjusting the position of the robot end according to the deviation of the contact force between the robot and the environment.

In the force-based impedance control method, the robot reflects the end impedance characteristics of the robot by controlling the robot joint torque through feedback based on the contact force between the end and the environment. In practical applications, the robot end position and contact force are detected in real-time, the desired force output is generated by the grid feedback position and desired impedance model, the difference between the desired force and the actual contact force is taken, and the control torque is calculated by the robot dynamics model based on the force error as the joint driving force so that the robot's system behaves as the desired impedance model characteristics. Therefore, the force-based impedance control must first determine the exact robot dynamics model before the desired impedance model and the exact contact force control can be achieved.

The position-based impedance control consists of two parts, the inner loop of position control and the outer loop of impedance control. The inner loop of position control processes the three data of the desired position, position compensation amount, and actual position to make the actual position of the robot track up to the desired position. The impedance control outer loop is to process the difference between the desired force and the actual force to get the position correction amount, and these will continuously adjust the target impedance model parameters by actually detecting the force between the robot and the environment, and then control the robot's position through the position controller to achieve force control. The literature mainly addresses the problems of the robot arm in terms of unstable impedance control force and position control safety collision avoidance and designs an impedance controller with linear decoupling position control in the operation space as the inner loop and uses the force error to adjust the reference trajectory in real-time to achieve effective force tracking impedance control and collision avoidance control of the robot arm. In the literature, an impedance control method based on the position inner loop was proposed for the gripping force tracking of the end-effector double-finger grasping of fruits and vegetables to reduce the damage of the robot in the picking process, which realized the flexible grasping of the robot, reduced the damage of the grasped fruits and vegetables, and ensured the picking quality.

Most of the current research on hand function rehabilitation robot systems focuses on function realization in the bionic structure power source which mainly adopts a micro DC motor, a transmission method selects a linkage mechanism or rope wheel mechanism, and currently, for the selection of degrees of freedom, quality, institutional efficiency is to be further improved. In terms of control methods, based on multi-rigid body robot control methods, most scholars focus on the study of motion control of hand-functional rehabilitation robot systems, or the study of rehabilitation training patterns based on motion control, and a few scholars focus on the study of human-machine contact forces for hand-functional rehabilitation robots. There is a lack of in-depth research regarding human-machine interface modeling and contact force control methods for hand-functional rehabilitation robots.

2.3.2. Bioelectric Signal Control

Surface electromyography (sEMG), electroencephalography (EEG), and electrooculography (EOG) are mainly used for the interactive control of hand rehabilitation robots. Since these signals are acquired in a non-invasive manner, surface EMG and EEG are obtained in an operable way that does not require medical expertise, and their performance can be guaranteed.

sEMG signal control: Surface electromyographic signals (sEMG), acquired by non-invasive electrodes affixed to the skin surface, contain information about the motor state and motor commands of the neuromuscular system [87,88], reflecting the generation and propagation of action potentials from muscle motor units [89]. sEMG is currently widely used in prosthetic control, rehabilitation robot control, exoskeleton robot control, teleoperated robots, virtual reality, etc., [90–93] using machine learning algorithms The sEMG signal is used to decode the human motor intent and map it to the control output, which is used to establish an information channel between the patient and the robot to obtain biofeedback control during rehabilitation training [89,94–100]. The sEMG-generated EMG control allows the patient to participate in the actual control of the device, which is important for increasing the patient's awareness of active participation [101].

In the study by Iqram Hussain et al. [102]. It was emphasized that the degree of muscle changes due to stroke depends on the severity of the stroke and its effect on neuromuscular activity, and that accurate lower limb muscle selection is crucial for identifying stroke impaired gait impairments, as well as for hand muscles. Machine learning and deep learning methods applied to EMG detection techniques can effectively classify EMG pattern recognition, and since this review is biased towards an overview of hand rehabilitation robots, in general, the review of the bioelectric signal part will be systematically summarized in a subsequent study.

Unilateral limb dysfunction caused by stroke is one of the post-stroke symptoms and providing rehabilitation training to post-stroke patients can improve the patient's motor ability and thus the ability to perform daily activities. Bilateral training is a rehabilitation strategy based on natural limb coordination [103]. Bilateral training involves manipulating both hands together, with the participant using both hands to work together to accomplish the target task. It has been shown that simultaneous movement of both limbs helps the neuromuscular system to restore a degree of stability and improve the efficiency of the use of the damaged limb [104]. Training patients with a two-handed task improves the efficiency of grasping movements on the neurologically impaired side, accompanied by a reconfiguration of neural networks in the brain of the impaired hemisphere [105]. In healthy individuals, corticomotor control of spontaneous hand movements is derived from contralateral cortical areas because of the contralateral control of left and right-hand movements in humans; after stroke, the role of uncrossed fibers in the cerebrospinal pathway is redirected and the balance of limb control is shifted from the injured hemisphere to the contralateral hemisphere [106]. Therefore, bilateral training can contribute to motor function rehabilitation after stroke [107].

EEG signal control: The brain is the source of all human movement and thought, consisting of ten billion nerve cells that continuously process information obtained from the outside and efficiently send feedback instructions to various organs and structures of the body. Since the first recording of the human electroencephalogram (EEG) by German scientists in 1929 [108], the development of brain-computer interface technology has never stopped, and the dream of using EEG signals for control and communication with external devices has never ceased.

However, the EEG signals recorded for the first time by German scientists are quite random and non-linear. Brain activity is the most complex biological activity in the human body, and each area within it is relatively independent yet closely connected, either individually to accomplish a complex thinking activity, or in concert with each other to accomplish some imagination. In addition, compared to the power line interference in the air, the strength and assignment of EEG signals are very weak, and the signal-to-noise ratio of detectable EEG signals is also relatively unsatisfactory, and the waveform of the original EEG signal (raw EEG) appears to the naked eye to be no different from that of white noise interference waves, which are jittering in a chaotic manner. In 1937, the American scientist Jacques Vidal discovered the rhythm of EEG signals and realized the prototype of the brain-computer interface for the first time: using EEG signals to control the cursor to do two-dimensional movement [109]. According to this study, the integrated waves in the common frequency band of EEG signals between 0.5 and 35 Hz were decomposed into Delta (δ, 0.5~3 Hz), Theta (θ, 4~8 Hz), Alpha (α, 8~13 Hz), and Beta (β, 14~30 Hz) by frequency. The waveform vibration of EEG signals in each band also vaguely corresponds to different brain activities. With the development of society, the research of brain-computer interface technology has been gradually combined with practical engineering applications, and brain-computer interface platforms based on Brain-Computer Interface (BCI) [110] and Brain-Machine Interface (BMI) [86] have been introduced one after another, and EEG signals were steadily collected and analyzed, and eventually utilized as an effective operating command for electronic devices, thus facilitating our lives. While brain-computer interface technology is developing rapidly, the lives of elderly people with physical movement disorders and hemiplegic handicapped patients are gradually gaining attention, and the technical implementation of controlling external electronic devices through EEG signals is just perfect to overcome the obstacles in the lives of such people in terms of physical movement and to meet their rehabilitation training needs.

The utilization of EEG signals in existing brain-machine interface upper limb rehabilitation platforms is still at a low level, and the meaning of EEG signals in most frequency bands is not yet clear. At the same time, most of the existing EEG signal processing algorithms are not designed to be universally meaningful, considering the large individual differences in EEG signals. In the medical field, the research of EEG signals has achieved remarkable results, but there are no mature products for the integration of brain-machine interfaces with rehabilitation devices, and there are still many problems to be solved in the communication and integration of EEG signal processing algorithms and the lower computer. This thesis will explore the above aspects, propose reasonable solutions and verify them. The application of brain-computer interface technology on rehabilitation platforms is an interdisciplinary research field involving neuroscience, biomedicine, signal processing, circuits and systems, computer programming, communication technology, mechanical design, rehabilitation medicine, etc. It is a complex and young cutting-edge technology field.

Electrooculogram (EOG) [111] is also increasingly used by researchers in a wide variety of control systems. EOG signals are caused by the electrical potential difference between the cornea and the retina and can be used to reflect eye movements (e.g., gaze, blink, frown, etc.) [112]. Compared with limitations, such as weak EEG signals, susceptibility to environmental noise interference, and complex signal processing, EOG as a control signal for control systems has obvious advantages, such as obvious patterns, easy detection, EOG-based control systems that do not cause excessive discomfort to the user, low operation difficulty for users, etc. Currently, EOG-based control systems are used in wheelchair control [113], control of home appliances [114], and learning evaluation, etc.

The above three bioelectric signal control methods have their own advantages and disadvantages. In some high-level articles, researchers have combined the required functions of the hand rehabilitation robot and selected the appropriate control method or combined two of the bioelectrical signal control methods to obtain the optimal control system. For example, S.R. Soekadar et al. [115] published three papers, in 2014, 2015 and 2016, describing a novel brain/neuro-computer interaction (BNCI) system for controlling a hand exoskeleton robot that integrates electroencephalography (EEG) and electrooculography (EOG). Brain-computer interfaces (BMI) are developed to translate electronic or metabolic brain activity into control signals for machines or robots. Non-invasive BMI techniques may be a possible alternative, but do not achieve high reliability and are susceptible to signal artifacts, especially in everyday life settings. The fusion of biological signals related to eye movements works better. A hybrid system fusing biological signals from different sources (e.g., EEG and EOG) could achieve better performance in controlling the hand exoskeleton compared to a system using brain signals alone. A validation experimental paper of this system, also published in the journal science robotics, demonstrated that the use of this hybrid EEG/EOG-based BNCI system enabled the patient to regain full independence in daily life. Overall, future research should investigate this hybrid bioelectrical signal control system, as such systems can largely improve the applicability of assistive devices in real-life scenarios.

2.4. Training Mode of Hand Rehabilitation Robot

The current training mode of hand rehabilitation robots can be divided into active training mode and passive training mode according to the source of motion signals.

2.4.1. Passive Training Mode

Continuous Passive Motion (CPM) rehabilitation therapy is a method proposed by Canadian orthopedic surgeon Robot Salto [116], which not only maintains the compliance of normal periarticular soft tissues but also accelerates the recovery of articular cartilage and calcified tissues. By repeatedly training the joint mobility, the stiffness of the joint can be stopped and the contracture can be prevented. Because this treatment is effective in preventing contractures and altering the inhibitory state of the central nervous system and promoting behavioral responsiveness, passive joint movement training has now become a routine tool in the clinical treatment of stroke patients. In this study, a passive rehabilitation training model was designed to restore the grip of the patient’s fingers by helping the affected hand to move according to the set training movements.

2.4.2. Active Training Mode

Active Repetitive Motion (ARM) rehabilitation therapy has a human-computer interaction system that allows patients to actively participate in rehabilitation training. It senses the motion parameters of the rehabilitation hand and joins the control session while displaying them on the interactive interface. The main research results include the Hand Mentor TM rehabilitation hand designed by the Deaconess Health System in the United States and the ARM rehabilitation hand developed by the University of Victoria in Canada. The Hand Mentor TM was designed by Deaconess Health System [117]. In addition to continuous passive flexion and abduction training, this rehabilitation hand has the ability to sense the pressure caused by finger flexor spasms and compulsively induce finger movement training. The size of the glove can be adjusted to fit most adult left and right hand sizes. The device is stable and reliable and is one of the more mature hand rehabilitation devices already in use in U.S. rehabilitation medical institutions.

2.5. Hand State Detection Technology

As an important communication tool for people, the human hand contains rich contents, and people can understand and transmit information to each other conveniently, intuitively, and naturally. In recent years, with the development and widespread application of computer technology, human-computer interaction technology has thus been rapidly developed and advanced and has become a hot research issue in computer vision.

Hand state detection technology plays a crucial role in the field of hand rehabilitation robotics. Hand state detection technology can effectively verify that the device designed by the researcher is consistent with the biology of the human hand and the kinematics of the hand to ensure that it will not cause secondary damage to the affected hand. Another application of hand state detection technology, which can be used to drive active conscious hand rehabilitation in the bad hand by performing gesture recognition in the good hand, is both convenient and effective. However, because of the complexity and diversity of hand gestures in time and space, coupled with the fact that the hand is a part of the human body with numerous complex deformations, gesture recognition is an extremely challenging and difficult research topic.

The generalized hand gesture recognition flow chart is shown in Figure 13. When the user's hand motion signal is obtained, the user's hand is first detected and motion tracked, then feature extraction and analysis are performed by hand trajectory extraction, hand shape feature extraction, and gesture modeling, respectively, and finally gesture recognition is performed. Among them, the part of hand motion analysis within the dashed box is the core content of gesture recognition, so how to get accurate motion analysis is the key to a gesture recognition system.

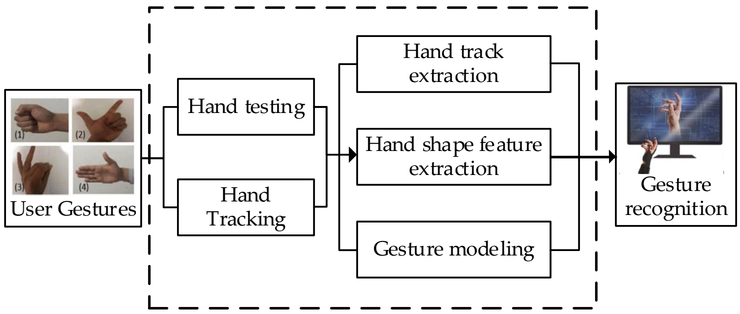


Figure 13. Generic gesture recognition flow chart.

Hand motion analysis techniques have been researched and explored by numerous scientists and have led to great achievements and applications. At the beginning of the research, hand motion analysis was conducted through hardware devices interacting with computers, and many devices and sensors were used to study hand motion, such as common optical cameras. Such devices are simple and inexpensive, but the limitations of two-dimensional images make it difficult to locate and segment targets quickly from complex and variable backgrounds. Other kinds of wearable sensor devices, such as electronic gloves, can provide high-precision position information and hand movements that can identify many complex behaviors, but such devices require a lot of precise debugging before use and are not convenient for ordinary people to use and operate. In addition, such devices need to be worn on the body, hindering the natural interaction between people and machines. This, coupled with their expensive price makes ordinary people discouraged. In order to get rid of the reliance on sensors and other devices and give the ordinary a better experience, a large number of researchers began to study how to achieve efficient and friendly natural human-machine interaction without contact.

According to different technical criteria, hand motion analysis techniques can be divided into different categories. According to the different definitions of recognition target object form, hand gesture recognition can be divided into static hand recognition and dynamic hand recognition; according to the different ways of hand image acquisition, we can divide hand recognition into data glove-based methods and computer vision-based methods. The computer vision-based methods can be divided into recognition methods based on ordinary optical cameras and recognition methods based on depth cameras.

2.5.1. Static Hand Recognition and Dynamic Hand Recognition

Research in static hand recognition has focused on work in the area of hand posture and hand shape. There are many related studies in China, for example, Rmeki Ziemlinski et al. have proposed a special static hand recognition method. The object of study for dynamic hand recognition is a set of continuous hand movements, where a dynamic hand forms a trajectory in the model parameter space that is composed of a series of continuous static images over a period of time and includes rotational, deformation and displacement movements of the hand in space [118,119].

The timeliness requirement of dynamic hand motion recognition is very high, and since its recognition object is real-time input hand data and requires a real-time response to the input, the algorithmic speed of the recognition system is required to be higher, and research experts in this field have invested a lot of time, effort and enthusiasm, while various algorithms for dynamic hand motion recognition have been proposed.

2.5.2. Data Glove-Based Approach and Computer Vision-Based Approach

Regarding the research related to hand motion recognition technology, the initial research mainly focused on inventing a special hardware device for interacting with computers, such as data gloves, i.e., the user needs to wear a pair of sensors with a shape similar to ordinary gloves, and the computer uses this device and position tracking technology to measure the trajectory and timing information of hand motion in three-dimensional space and obtain rich hand position, finger bending degree and other hand motion information. The advantages of the data glove-based hand motion recognition system are the high recognition rate of the system and the ease of implementation of the technology. Many studies have been conducted using typical sensing device approaches, such as data gloves. For example, Liang et al. at National Taiwan University used a single VPL company's data glove as an input device and technically recognized 250 basic words in a Taiwanese gesture textbook with a recognition rate of 90.5% [120]. Christopher Lee and Xu et al. at Carnegie I Mellon University completed a gesture control system that can manipulate robots using gestures using data gloves in 1995 [121]. Kadous used PowerGloves as a hand input device to recognize word sets consisting of 95 isolated words with a correct rate of 80% [122]. Vogler and Metaxas studied the recognition of 53 sign languages with a probability of 89.9% by combining data gloves and gesture recognition, using a position locator and three cameras perpendicular to each other as input devices [123].

As the above experiments and applications require the user to bring a special glove device, which hinders the natural interaction between people and machines, coupled with its high price to discourage ordinary people, after that, scientists are committed to marking hand research, that is, by placing specific markings on the hand, such as in the wrist and fingers stickers or painted with special color stripes, the computer recognizes the movement of such colors to identify the corresponding action. For example, Dvais and Shah used colored gloves with highlighted markings between the fingers as input to a hand motion recognition system, resulting in the recognition of seven different hand motions [124]. While this approach brought breakthroughs and convenience in recognition technology, it also caused a great deal of trouble for the user and hindered truly natural human-computer interaction. Finally, scientists finally focused their attention and attention on the natural hand, and through dedicated hardware devices detached from the human hand and offline training, some researchers succeeded in studying a vision-based hand motion recognition system.

In terms of general optical camera-based hand motion recognition methods, some of the more representative research results include Starner et al. in which American gestures in which 40 short sentences with lexical words are randomly composed with a final recognition rate of up to 99.2% [125]. Grboel and Assma recognized 262 isolated words by extracting features from video footage and then using Hidden Markov (Freeman and Roth et al. proposed a hand motion recognition system based on directional histograms, and Canesta, Inc. of San Jose, CA, USA, introduced a personal handheld computer (PDA) in 2004, which uses a 3D image above the keyboard to recognize human movements on the keyboard to control the input of the machine [126].

Currently, there has been much research on hand motion analysis methods in the field of human-computer interaction, but due to the complex multilateral nature of human hands, how to achieve effective and accurate hand segmentation and fingertip recognition is still a problem to be improved and solved.

In conclusion, hand motion analysis technology has a broad development and application prospect and is a research hotspot in the field of human-computer interaction, which deserves a lot of human and material resources for research and development. We believe that in the near future, the hand motion analysis system will contribute unique advantages to changing people's quality of life.

3. Discussion

The purpose of this paper is to (i) describe the existing research on hand rehabilitation robots, and (ii) describe the drive modes, control strategies, training modes, and hand state detection techniques of hand rehabilitation robots. The results show that in the existing research on commercial hand rehabilitation robots, it is important to focus not only on the mechanical structure part but most importantly on the system control and hand state monitoring aspects of hand rehabilitation robots in order to have the best hand rehabilitation results. In particular, commercial hand rehabilitation robots, cannot be separated from clinical trials. A successful technology needs to undergo extensive controlled trials before it can be brought to market quickly. For example, the research process of S.R. Soekadar et al. [115] is a relatively complete one, from problem formulation to practice to validation.

In the face of the severe situation of the aging population and a large number of stroke and hemiplegia patients, the research on hand functional rehabilitation robots will remain a relatively cutting-edge and popular field that can be explored in depth in recent years and in the coming decades. This paper reviews the development of hand rehabilitation robots, Drive mode, Control strategy, Training mode and Hand state detection technology. The problem is still a key and difficult issue in this field. Based on the summary of this paper, there are still many areas that need to be improved and enhanced in the future research of hand rehabilitation robots:

1. Portability and comfort of hand rehabilitation robots. Although the hand rehabilitation robot has slowly changed from a rigid exoskeleton to a flexible wearable type, its weight has been greatly reduced, but its drive still uses motors or air pumps, which makes it difficult to carry for a long time and limits the scope of use of the hand rehabilitation robot. Moreover, the biological characteristics and kinematics of the human hand should be fully considered to avoid secondary injuries to the patient's hand.
2. Diversity and flexibility of human-robot interactions. Most of the same kind on the market cannot realize EEG signal control, and the product cannot be remotely and instantly monitored during operation, the patient cannot independently conduct rehabilitation training, and there is little effective feedback data available for extraction,

and the training rhythm cannot be independently fine-tuned during the rehabilitation process.

3. Accuracy of hand state recognition. Improving the accuracy, stability, real-time and adaptiveness of hand detection and tracking is of great academic value and practical engineering significance for the control and detection of hand rehabilitation robots.
4. VR virtual task-oriented enhanced active rehabilitation training. Many hand rehabilitation robots have been combined with virtual reality technology. It is believed that as virtual reality (VR) technology continues to mature, future hand rehabilitation training will also be more interesting.

In order to optimize the difficult trade-off between functionality and usability typical of hand functional rehabilitation robotics in everyday life, we have identified the above four future directions that are of great interest. As shown in Figure 14, we have compiled a conceptual figure of robotic solutions in post-stroke hand rehabilitation. Future work should include several of these directions of development as a way to address the specific needs and desires of the user to control the device.

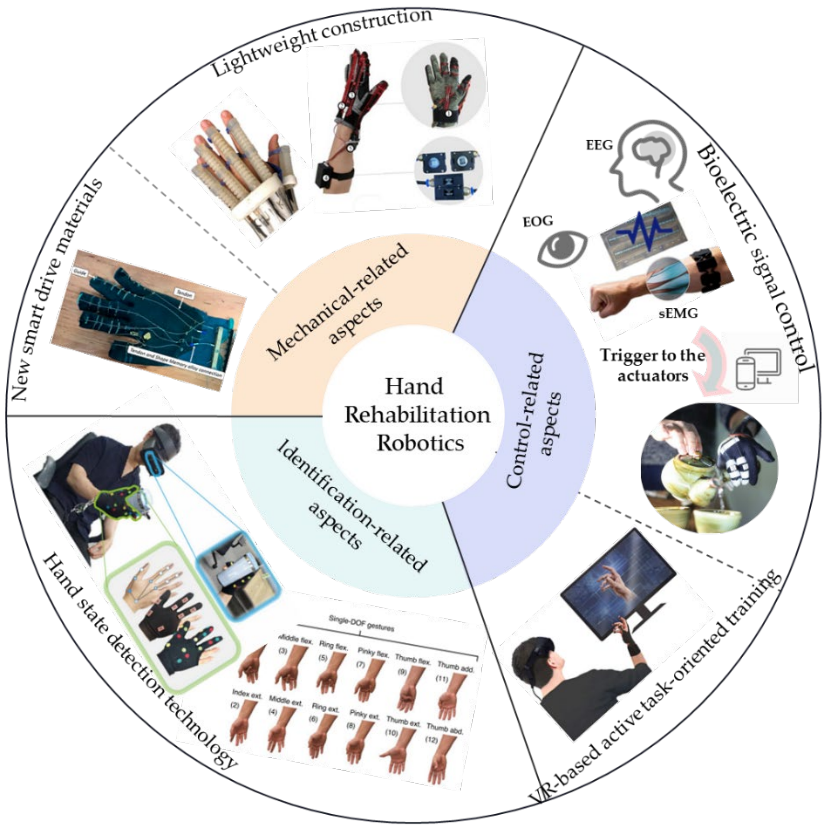


Figure 14. The conceptual figure of robotic solutions in post-stroke hand rehabilitation.

4. Conclusions

The purpose of this review is to explore the research concerning hand rehabilitation robotics, review its current research status in recent years, and summarize the future development trends in the hope that they will be useful to researchers in this research field. This review summarizes the technology in this paper with a systematic approach. Specifically, we provide an overview of the development of hand rehabilitation robots, drive modes, training modes, and control strategies in the reviewed literature. Finally, we discuss the future directions of hand rehabilitation robots. The results show that the development trends in recent years are more inclined to pursue new lightweight materials as a way to improve manual adaptability, studying intelligent control methods for human-computer interaction in hand function rehabilitation robots, improving the robustness and accuracy of control, and VR virtual task orientation to enhance the effect of active rehabilitation training. This paper will be useful in helping researchers understand the current state of the art regarding robotic technology for post-stroke hand rehabilitation in recent years.

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