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Recent advances in hand movement rehabilitation system and related strategies

Dapeng Wang[1,2,3,4], Chuizhou Meng[1,2,3,4,*], Mingyuan Wang[1,2,3,4], Dazhuang Liu[1,2,3,4], Teng Liu[1,2,3,4,*], Shijie Guo[1,2,3,4]

1 State Key Laboratory of Reliability and Intelligence of Electrical Equipment, Hebei University of Technology, Tianjin, 300401, China
2 Engineering Research Center of Ministry of Education for Intelligent Rehabilitation Device and Detection Technology, Hebei University of Technology, Tianjin, 300401, China
3 Hebei Key Laboratory of Smart Sensing and Human-Robot Interaction, Hebei University of Technology, Tianjin, 300401, China
4 School of Mechanical Engineering, Hebei University of Technology, Tianjin, 300401, China

* Correspondence author; E-mails: 2018108@hebut.edu.cn; wuqiu-liu@163.com.

Abstract: Hand movement disorders caused by neurological diseases like brachial plexus injuries significantly impact daily activities of patients. Compared with the upper-limb rehabilitation that is focused on the large movements of joints, the rehabilitation of the hand movements that are dexterous remains challenging due to its exceptional flexibility. This article aims to reviewing the latest research on the system and related strategies for hand movement rehabilitation. Firstly, the development on the cutting-edge sensing technologies, actuator-driven rehabilitation equipment and hand movement pattern recognition algorithms, all contributing to the design of the hand movement rehabilitation system, are introduced. Secondly, the various rehabilitation strategies, including the active rehabilitation, passive rehabilitation, and guided rehabilitation that are tailored for patients with different disability levels at varying rehabilitation stages, are reviewed. Furthermore, the limitations of current methods and techniques are discussed and future research directions are put forward.

Keywords: Hand movement rehabilitation; rehabilitation equipment; sensing technology; pattern recognition algorithm; rehabilitation strategy

1. Introduction

Nervous system diseases, such as stroke and brachial plexus injury, can result in unilateral or bilateral upper limb movement dysfunction, significantly impacting daily life of patients. In comparison to the arm with other parts of the upper limb that primarily serve to transfer the hand between positions in space for a wide range of movement, the hand is more flexible and thus dexterous, primarily responsible for intricate movements like grasping, pinching and manipulating objects [1]. Therefore, the recovery of the hand movement function poses greater challenges and thus requires more attention of study.

Over the past decade, the development of hand rehabilitation equipment that utilizes external robotic assistance and wearable equipment technology have drawn great research interest, with the main purpose of restoring the hand grasping ability [2,3]. However, because the hand motor impairment varies among patients at different illness stages, it is of significant to develop and adopt different rehabilitation strategies based on the degree or type of the specific motor impairment of the targeting patient [4]. For instance, patients with severe injuries would benefit from the robot-assisted approach that provides auxiliary force. While patients with milder motion-related injuries should be focused on the motor nerve recovery, where the guided rehabilitation approach with no direct supply of auxiliary force is more suited [5].

Nowadays, the study on the hand movement rehabilitation has become a hot research and development topic, and considerable progress has been made. Many related review articles introduce the recent development of commercial hand rehabilitation equipment and Do-It-Yourself (DIY) devices [6-8]. Although commercial products boast usable devices with system design, it is still necessary to timely review the latest academic findings to further stimulate innovation in the research field. Thus, this review article offers a comprehensive survey of the hand rehabilitation technology in the academic field instead of the commercial field, discussing the benefits, drawbacks, and prospects of various hand movement rehabilitation equipment and related strategies.

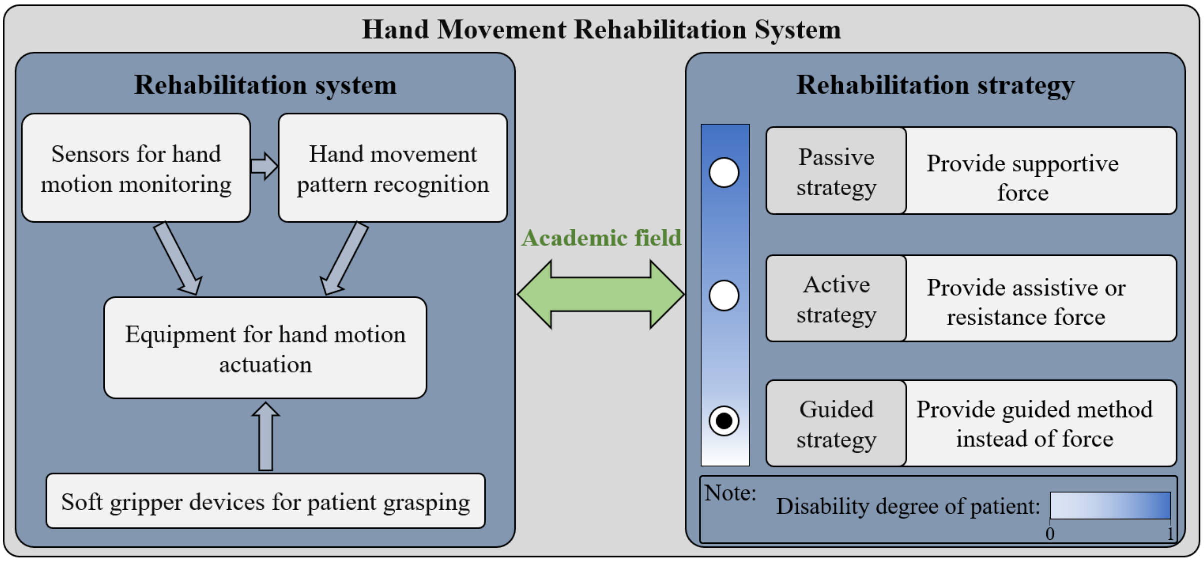

Figure 1. Main research contents of this review article.

As illustrated in Figure 1, the review content is organized as follows: Section 2 summarizes the recent developments of the hand rehabilitation system, which includes the key hardware of the sensing technology for hand movement monitoring and the hand rehabilitation equipment for hand movement actuation and the key software regarding the machine learning-based algorithms for hand movement recognition. Section 3 discusses the research on the hand rehabilitation strategies, including the active rehabilitation, the passive rehabilitation, and the guided rehabilitation. Section 4 outlines the future research prospects by highlighting the emerging research directions in hand rehabilitation. Finally, Section 5 concludes the whole article.

2. Development of hand movement rehabilitation system

Typically, a comprehensive hand movement rehabilitation system comprises three key components, *i.e.*, the hand movement monitoring by various sensors, the rehabilitation equipment for hand movement actuation, and the hand movement pattern recognition by some strategic algorithm. The hand movement monitoring acquires the real-time movement information of the hand, while the rehabilitation equipment performs the rehabilitation progress of the hand movement. The hand movement information is firstly analyzed by using the pattern recognition algorithm, upon which the control signals are decided to guide the actual motion of the hand rehabilitation equipment. The recent development of technologies regarding these three parts is summarized below.

Notably, this section also summarizes the latest soft gripper devices. Although it does not directly contribute to a patient's hand motor rehabilitation, it can replace the patient's hand in performing grasping movements during rehabilitation

2.1. Sensing technology for hand movement monitoring

The monitoring of the hand movement status enables the capture of the current static position or dynamic gesture of the targeting hand, which is typically achieved using advanced wearable sensors. Intuitively, the vision-based sensors were firstly used for detection of the hand movement, which as a non-contact approach has been dedicated by considerable amount of efforts [9-11], but its practical adoption by patients is still challenging due to factors such as low sensitivity, light influence and privacy concerns, particularly in the context of hand movement rehabilitation, which requires the distinguishment of small difference in position and gesture. Up to date, the accurate hand movement detection mostly employs various kinds of wearable sensors in a close contact with the hand. Besides, sensors can also be implanted in the human body for the detection purpose, but despite of such specific application, they are not covered by this review article due to their intrinsic non-invasive nature [12]. Figure 2 shows the several types of sensors integrated on the glove or directly mounted on human arm for the wearable hand movement monitoring and their corresponding wearing positions.

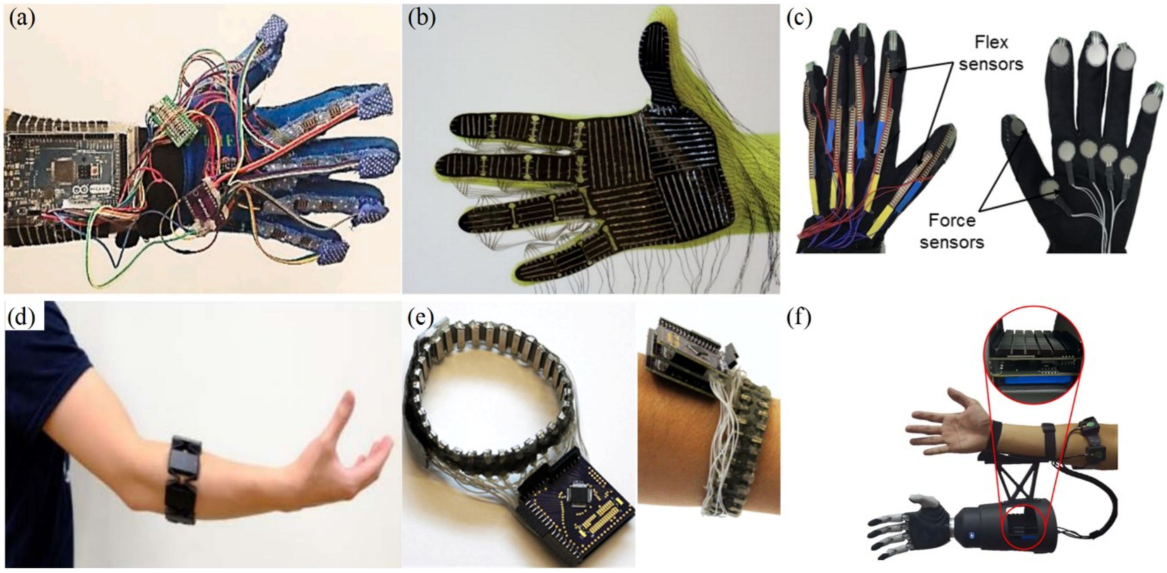

Figure 2. Different types of sensors integrated on glove or mounted on arm for hand movement monitoring: **(a)** IMU [13] Copyright© 2021, Elsevier; **(b)** strain sensor [14] Copyright© 2019, Springer Nature; **(c)** flex and force sensor [15] Copyright© 2021, IEEE; **(d)** sEMG sensor [16] Copyright © 2022, IEEE; **(e)** EIT sensor [17] Copyright© 2016, Publication History; **(f)** ultrasound sensor [18] Copyright © 2022, IEEE.

2.1.1 Mechanical sensor

The mechanical signal is the most direct result by hand motion and thus its acquisition is extensively utilized for hand movement monitoring. The commonly used mechanical sensing techniques include the detection of inertial, strain and flexibility on different parts of the hand.

The inertial sensing device is particularly based on the inertial measurement unit (IMU), and exhibits high sensitivity in the hand movement detection. Two approaches can be employed to detect the hand movement by using the IMUs. The original sensing information from the IMU includes the 3-axis accelerometer information and the 3-axis gyroscope information, and sometimes the 3-axis magnetometer information. As shown in Figure 2a, based on such information, the first approach is to employ the machine learning algorithms to determine the current gesture or movement state of the hand [13]. The second approach involves direct calculation of the current joint bending angle through the quaternion algorithm, enabling the assessment of the current state of the hand [19] . Currently the most commonly used way is to place multiple IMUs on each finger and the back of the hand for a comprehensive hand movement monitoring [20]. However, this method also takes the influence of the wrist movement into account on the hand movement monitoring, so the body movement such as arm swing can introduce inevitable but significant interference to the hand movement monitoring.

The strain sensing devices mainly work on the piezoresistive, capacitive and piezoelectric sensing principles, and can be easily integrated on the human palms [15] (Figure 2c) and even between fingers [21] to detect the hand movement. It is important to note that this sensing approach is non-susceptible to interference from the movement of human body or arm swing, which is advantageous over the IMUs. By sensing mechanism, the commonly used strain sensing devices can be categorized into the piezoresistive, capacitive, and piezoelectric types [22]. Piezoresistive sensors work on the measurement of resistance change due to the mechanical deformation, and are relatively simple to manufacture with easy circuit design for signal acquisition, but they are generally sensitive to environmental temperature variations (*i.e.*, sensing performance drifting upon temperature change). Capacitive sensors work on the measurement of capacitance change due to the distance change between two electrodes over one dielectric layer upon pressing, and offer a better temperature stability, but they suffer higher output impedance by environmental electromagnetic wave or human body paradise capacitance noise and thus require more complex design of the signal acquisition circuit. Piezoelectric sensors work on the produced voltage in response to applied mechanical stresses derived from the oriented dipoles in the intrinsic piezoelectric material, and are highly suitable for measuring quick dynamic responses, but they are not used for the static measurements. Given that the temperature of human body is very stable for a healthy person and for the design simplicity and cost reduction consideration, piezoresistive sensors are mostly in the research [23].

The flexibility sensing devices work on the resistance change of the sensor upon bending [24], which can be detected by designing a simple impedance voltage divider circuit and using digital-to-analog conversion. Similar to the IMUs, the flex sensor can also be used to measure the current bending angle of the finger through calculation of the raw sensing data, because the change of the resistance during the finger bending process shows a well linear relationship with the actual bending angle and can be expressed by a determined formula [25]. However, the flex sensors are usually long in shape, which makes them suitable for detecting finger bending but not effective in capturing the abduction-adduction movement between adjacent fingers.

2.1.2 Electrical sensor

The brain utilizes electrical current of pulse signals that act on the skeletal muscles to communicate with the hand, resulting in changes of muscle volume and internal impedance. This working mechanism enables the execution of course or precise movement of the hand. Surface electromyography (sEMG) is a typical electrical signal to record the electrical activity of skeletal muscles [26]. Notably, sEMG is non-invasive and only requires adhesive electrodes that are able to be attached on the surface of skin to detect the EMG signals [27]. The effectiveness of sEMG signals in monitoring human activities has been successfully demonstrated in various practical applications, including the prosthetic and exoskeleton control [28,29], gesture recognition [16,30], gait analysis [31,32] and muscle fatigue assessment [33,34]. However, when using the sEMG detection equipment, insufficient contact between the electrodes of sensors and the skin of human body would introduce additional noise. Although wet adhesive electrodes are commonly used to mitigate such interference issue, they often leave the gel residue on the skin. On the other hand, dry electrodes are free of the sticky residue issue but may experience interface slippage, particularly in the unsupervised environment, leading to the movement artifact or noise [35].

To address the abovementioned issues, an appropriate and continuous preload must be applied to the electrode, typically achieved through the design of a tighter external package or a pressure-adjustable package [36]. In addition, sEMG sensors have the limitation in recording deep muscle activity, which poses challenges in distinguishing the motion of individual muscle.

Similarly, electrical impedance tomography (EIT), a non-invasive technique that reconstructs the internal conductivity distribution of an object from the voltage collected by external electrodes, has recently been effectively applied in the hand movement monitoring [37]. The advantages of the EIT approach include high temporal resolution, no radiation and low cost. But its drawbacks are also obvious, such as low spatial resolution, especially near the center of the targeting position [26]. On the other hand, researchers used to believe that the resistance impedance was a two-dimensional (2D) problem that is merely based on the ring arrangement of electrodes, but the latest finding implies that its actual distribution is more complicated that is a three-dimensional (3D) problem. So further research is still needed [38].

2.1.3 Acoustic sensor

It is known that the formation of gesture results in different acoustic behaviors at the relevant muscles or joints. This acoustic property can be collected by means of ultrasound imaging and bone conduction to analyze the movement of the hand. Ultrasound imaging can provide real-time dynamic information of the internal tissue of the relevant movement position of human body. Compared with sEMG sensors, it can not only collect the information of the superficial muscles, but also acquire the information of the deep muscles [39]. In addition, ultrasound imaging has the advantage of high spatial-temporal resolution (25-204 Hz and 0.5-5 mm) [40], which can detect the changes in muscle thickness, cross-sectional area, and contraction angle, and thus has been widely used in gesture recognition [41,42] and prosthetic control [43]. For the hand movement monitoring, the most commonly used ultrasound modes include A-mode (the one-dimensional (1D) mode, which provides the echo amplitude information) [44], B-mode (the 2D mode, which provides the grayscale images of tissue or organ sections) [45], and M-mode (the movement mode, which has a higher scanning frequency) [46]. However, the ultrasound imaging technique also has some disadvantages, such as the need for gel to connect the sensor with the skin to facilitate the ultrasound imaging and artifacts that are caused by the arm movement.

The vibrations of bones in body caused by human motion activity also transmit sound signals. The bone conduction sensing equipment, as an acoustic-based equipment, often consists of a vibrator and a receiver. The vibrator provides external vibration as an active device, and the receiver can convert the vibration signal of the bone into an electrical signal to perform the function of signal collection. However, the bone conduction sensing technique has not been widely used in the practical application of hand movement monitoring due to the low precision of pattern recognition [47].

Table 1 summarizes the sensing technologies based on different types of sensor devices that are discussed above, and appropriate sensing technology should be selected based on their sensing characteristics according to the actual application needs.

Table 1. Sensing technologies based on different types of sensor devices.

Sensing technology	Source	Year	Sensor device	Wearing position	Application direction
Mechanical signal-based	J. Li [48]	2021	IMU	Fingers	Hand movement rehabilitation
	B. S. Lin [19]	2017	IMU	Fingers	Evaluation of hand movement status
	Y. F. Dong [24]	2021	Flex sensor	Fingers	Gesture recognition
	S. Sundaram [15]	2021	Flex sensor and strain sensor	Fingers and between fingers	Hand movement rehabilitation
Electrical signal-based	Z. C. Tang [29]	2022	sEMG and Gyroscope	Arm	Prosthetic control
	T. Y. Pan [16]	2022	sEMG	Arm	Gesture recognition
	M. Nawaz [37]	2022	EIT	Wrist	Gesture recognition
Acoustic signal-based	Z. X. Lu [44]	2022	Ultrasound sensor	Arm	Gesture recognition
	J. N. Li [46]	2022	Ultrasound sensor	Arm	Hand Movement Monitoring

2.2. Hand rehabilitation equipment for hand movement actuation

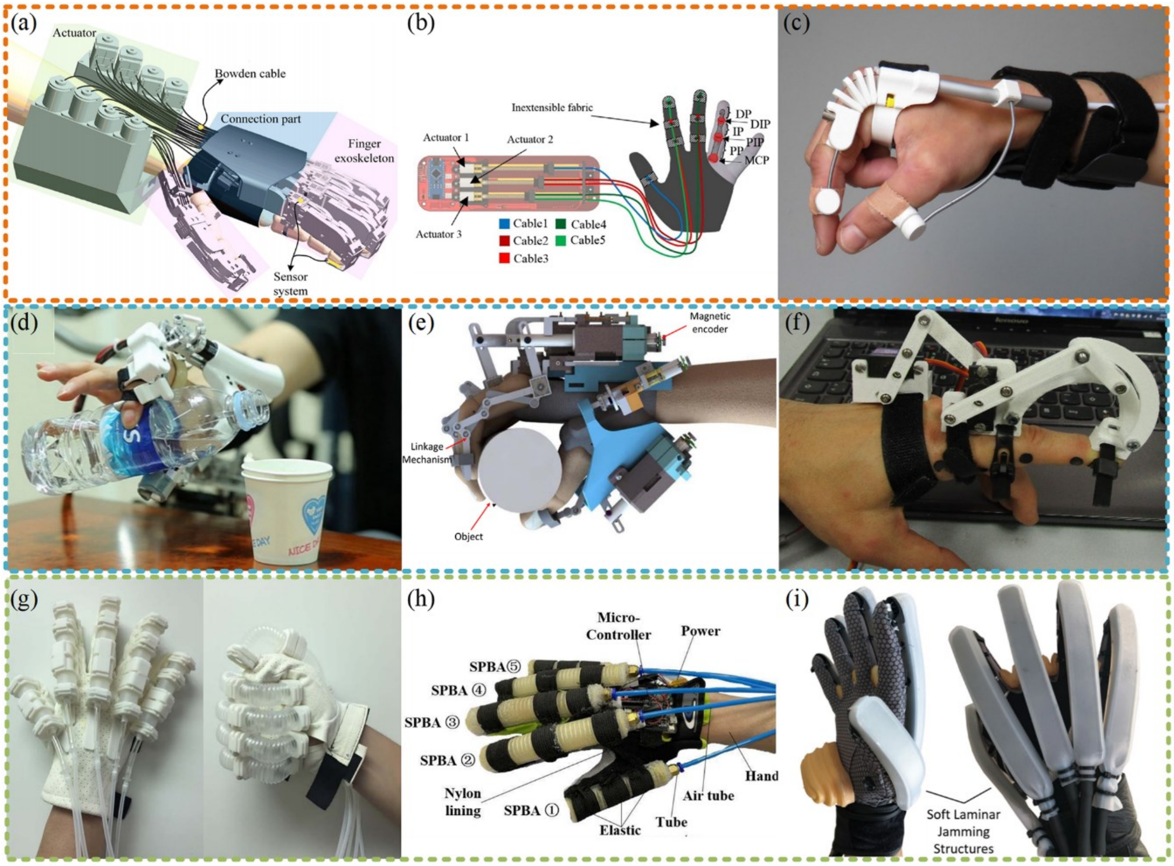

Figure 3. Three drive types of hand rehabilitation equipment: **(a-c)** tendon-cable drive [49-51]: [49] Copyright© 2022, IEEE, [50] Copyright© 2021, Elsevier, [51] Copyright© 2023,

IEEE; **(d-f)** connecting-rod drive [52-54]: [52] Copyright© 2019, IEEE, [53] Copyright© 2020, American Society of Mechanical Engineers, [54] Copyright© 2020, Applied Sciences; **(g-i)** pneumatic drive [55-57]: [55] Copyright© 2022, IEEE, [56] Copyright© 2022, IEEE, [57] Copyright© 2020, IEEE.

The hand movement rehabilitation equipment is another important component of the upper limb rehabilitation system. In the past decade, the advanced upper limb rehabilitation equipment both in academic and commercial market has achieved a great growth. Compared with the other parts of upper limb such as the elbow and arm, the hand as well as the fingers are required to perform finer movements. Therefore, the fine actuation of the hand movement rehabilitation equipment is important and is challenging from research and development point of view. According to the drive type of the hand rehabilitation equipment, it can be divided into three categories, *i.e.*, the tendon cable drive, the connecting rod drive, and the pneumatic drive. Figure 3 shows the three drive types of hand rehabilitation equipment that has been recently developed and reported in literature.

2.2.1 Tendon-cable drive

The exoskeleton-assisted rehabilitation equipment driven by tendon cables mainly uses motors to provide the torque and shorten the length of the cables to generate the tension. This working mechanism also leads to its main drawback of realization of only one-way finger-bending movement, and the return movement of the fingers needs to be achieved by patients or additional design of return-movement structure is needed [15]. In addition, the friction loss between the tendon cable and its external spool is inevitable, which is another issue. Recently several types of hand rehabilitation equipment based on the tendon-cable-driven mechanism have been developed. As shown in Figure 3b, Alnajjar *et al*. [50] proposed a tendon-cable-driven hand rehabilitation device, which was powered by a control box worn on the patient's forearm and used the dual linear actuators to enable the flexion motion of the index and middle fingers. To realize the return motion of the finger bending, an adjustable flexible rubber rope was used with design simplicity and weight reduction of the finger return structure. Yang *et al*. [49] proposed a portable cable-actuated exoskeleton glove and practically demonstrated its performance through clinical tests on nine patients with tendon injuries. Similarly, Haarman *et al*. [51] proposed a lightweight and compact exoskeleton structure to assist stroke patients in the training of the grasping motion.

2.2.2 Connecting-rod drive

The link structure is also employed in the structural design of the hand rehabilitation equipment. This rehabilitation equipment often relies on the external motors to provide power. To reduce the overall weight, lightweight materials are often used to fabricate the connecting rods through the 3D printing or similar technique. The main advantage of the hand rehabilitation equipment based on the link structure is that it can make the specified joints of the hand move in a precise manner through complex kinematics analysis. However, the connecting rod structure has limitation of large volume, which is challenging to achieve a compact structure of the whole equipment. In addition, the assembly of multiple motors on the wearable device for the purpose of overall size reduction and structural design simplicity would increase the overall weight of the equipment. Recently several types of hand rehabilitation equipment based on the connecting-rod-driven mechanism have been developed. As shown in Figure 3d, Hong *et al*. [52] proposed an underactuated hand exoskeleton to assist patients in training of the grasping motion. This mechanism consisted of an underactuated finger for grasp movement generation, a spherical four-bar linkage for power transmission, and a passive thumb link with a flexure hinge structure. Xia *et al*. [58] designed a hand exoskeleton system, which could realize 10 active degrees of freedom and provide an effective way for patients to recover at home.

2.2.3 Pneumatic drive

The pneumatic rehabilitation equipment utilizes compressed air as a power source. The main advantage is that the body of the equipment worn on the hand is relatively light, which is very important for long-term continuous treatment of patients. In addition, different functions, such as bending, expansion and contraction, and twisting, can be realized by optimizing the structural design of the air chamber. Furthermore, the pneumatic actuation generally does not cause devastating damage to the opponent during the recovery process. The disadvantage is that external equipment such as the air pumps and pressure tanks that requires sufficient external space is needed. In addition, the force provided to assist rehabilitation is often small, so it is usually used for the patients who still have some certain hand motion functions rather than the severely disabled patients. Recently several types of hand rehabilitation equipment based on the Pneumatic-driven mechanism have been developed. Guo *et al*. [55] proposed a soft pneumatic glove for hand function rehabilitation after stroke, and used a gas pressure sensor to monitor the movement status of the hand rehabilitation system in real time. Through a long-term comparison test with the conventional treatment and the robot-assisted treatment, the effectiveness of the proposed hand rehabilitation equipment was demonstrated. Gerez *et al*. [57] reported an exoskeleton glove actuated by a hybrid pneumatic and tendon-cable actuation. The glove was able to assisting the gripping motion, and its efficacy was demonstrated through the experiments of bending profile, force application, and grip quality evaluation.

It is worth mentioning that the hydraulic-driven hand rehabilitation equipment has also been developed [59,60], but due to the factors such as space, weight, and cost, it has not been widely used in the field of hand rehabilitation.

Some recently proposed hand rehabilitation devices with different drive types have been summarized in Table 2.

Table 2. Comparison of hand rehabilitation devices with different drive types in recent years.

Source	Year	Force Transmission	Driving Modes	Exoskeleton	End-Effector
L. Yang [49]	2022	Cable	Motor drive	√	-
F. Alnajjar [50]	2021	Cable	Motor drive	√	-
C. J. W. Haarman [51]	2023	Cable	Motor drive	√	-
F. Ennaiem [61]	2023	Cable	Motor drive	-	√
M. B. Hong [52]	2019	Link	Spring	√	-
T. Vanteddu [53]	2020	Link	Motor drive	√	-
G. Carbone [54]	2020	Link	Motor drive	√	-
A. Molaei [62]	2022	Link	Motor drive	-	√
N. Guo [55]	2022	Flexible pipe	Pneumatic	√	-
Y. L. Han [56]	2022	Flexible pipe	Pneumatic	√	-
L. Gerez [57]	2020	Flexible pipe	Pneumatic	√	-

2.3. Hand movement pattern recognition algorithm

In recent years, the pattern recognition algorithms have drawn extensive attention for the research on the hand movement monitoring. The role of pattern recognition algorithms in the field of hand rehabilitation is generally to monitor hand movements and recognize patients' subjective movement intentions. Although pattern recognition is not necessary for rehabilitation systems, it is currently a hot research topic related to hand movement rehabilitation. The application of the hand movement monitoring includes prosthetic control [63], sign language recognition [64] and hand rehabilitation [65]. The pattern recognition of hand movement monitoring can be divided into the traditional machine learning algorithm and the deep learning algorithm.

The traditional machine learning algorithm generally has three steps, *i.e.*, data preprocessing, feature extraction, and model building. For data preprocessing, information acquired by different types of sensors often has different data intensities. Therefore, the scalability of the data from different types of sensors needs to be considered. In this regard, the Max-min and z-score are the most widely used normalization algorithm, although these two methods inevitably weaken the differences in signals [66]. In addition, the data segmentation is another important step in recognition of the hand motion, and the feature extraction can be performed based the continuous data stream after segmentation. Although a method to dynamically segment the entire gesture formation process has been proposed [67], this method is often time-consuming. Therefore, to meet the real-time requirement for the data segmentation, a sliding data window is often established, and continuous data windows usually need a certain overlap rate (usually 50% is adopted) [25,68].

Manually extracting features is the next crucial step in the traditional machine learning, often performed in the time or frequency domain. Typical time domain features include mean, variance, maximum, root mean square, skewness, and kurtosis. Common frequency domain analysis methods, such as power spectral density, continuous wavelet transform, and discrete Fourier transform, have been widely used in the movement monitoring [69,70]. It is important to note that even though numerous features can be extracted from the continuous data streams, it does not mean the more the better. Many correlated features would increase the computational cost and even lead to the curse of dimensionality. Therefore, dimensionality reduction techniques have gained attention in recent years for feature extraction in the human activity recognition, particularly for the recognition of hand movements [71,72].

The commonly used traditional machine learning algorithms for the hand movement monitoring include Support Vector Machine (SVM), *k*-Nearest Neighbor (kNN), Decision Tree (DT), Multi-Layer Perceptron (MLP), and Random Forest (RF) [73]. It is worth noting that the classification performance of different algorithms for different gesture datasets is different. Therefore, multiple machine learning algorithms should be compared at the same time when performing the gesture pattern recognition, to get an optimal one. For instance, the performance of SVM and kNN are compared for gesture recognition using a capacitive sensor setup [74], and the performance of a system for Brazilian sign language recognition is compared with up to five traditional machine learning algorithms [25].

It is worth mentioning that the performance mostly relies on the manually extracted features, which requires significant expertise of the operator. In comparison, the deep learning algorithm can fit the features according to the input data and get the corresponding output without manual feature extraction and selection. The deep learning algorithm based on the convolutional neural networks (CNN) is a commonly used method for hand movement monitoring [75]. For controlling the robotic hand in a rehabilitation setting based on the movement intention, a model combining the CNN and attention mechanism (named CNN-Attention) was proposed [76], which showed high performance in continuously estimating the direction of the human hand movement. To facilitate the gesture recognition during the rehabilitation training, Li *et al*. [77] proposed an improved multi-channel convolutional neural network (IMC-CNN). By collecting sEMG signals, the classification accuracy of the 10 common gestures could reach up to 97.5%. Algorithms based on the recurrent neural networks (RNN) are usually used to process the timing-related information for the realization of the hand movement pattern recognition. For instance, Barron *et al*. [78] explored the performance of the RNN-based gesture recognition method in the electromechanical control of the upper limb prostheses, and the results showed that its performance was higher than that of the linear discriminant analysis (LDA) and MLP. A deep neural network that combines the convolutional layers with long short-term memory (LSTM) (named LSTM-CNN) was proposed by Xia *et al*. [79], the recognition accuracy on three public datasets was greater than 90% with verification, which showed good robustness and human activity pattern recognition performance.

Additionally, some template matching algorithms have also been proposed due to their small size with potential to be independent of the host system [80,81]. A hyper-dimensional computing algorithm has been recently reported, which does not depend on the host system and can directly perform the model training and updating on the external devices [30]. These studies have facilitated the shift of hand movement pattern recognition from the host system dependency to reliance on the wearable embedded electronic systems.

2.4. Soft gripper devices

In this study, soft gripper devices are also summarized since they can replace the grasp ability of patients during their rehabilitation process. Compared to traditional rigid grippers, soft gripper devices can adaptively grip objects of different sizes or shapes through flexible grippers or joints.

Cable-based underdriven soft grippers are currently the most widely researched in the academic field, and generally include cable-driven flexible joints as well as soft end-effectors. Compared to other soft grippers, the principle of cable-driven gripping is closer to that of the human hand. Although bending and even continuous bending can be well realized due to the structural properties of cables, the complex structural design and control of torsional motion remains a challenge. On the other hand, cable-driven devices have drawbacks in gripping flat structured objects since it is difficult to wrap the object completely. Figure 4a shows an underdriven robotic hand claw possessing a three-finger structure proposed by Lee *et al*. [82]. The proposed device can realize the grasping motion by means of a servomotor driving cables distributed along the finger-like structure. Recently, a new cellular mechanical metamaterial architecture has also been proposed and combined with cables to realize the grasping motion of the robotic hand [83].

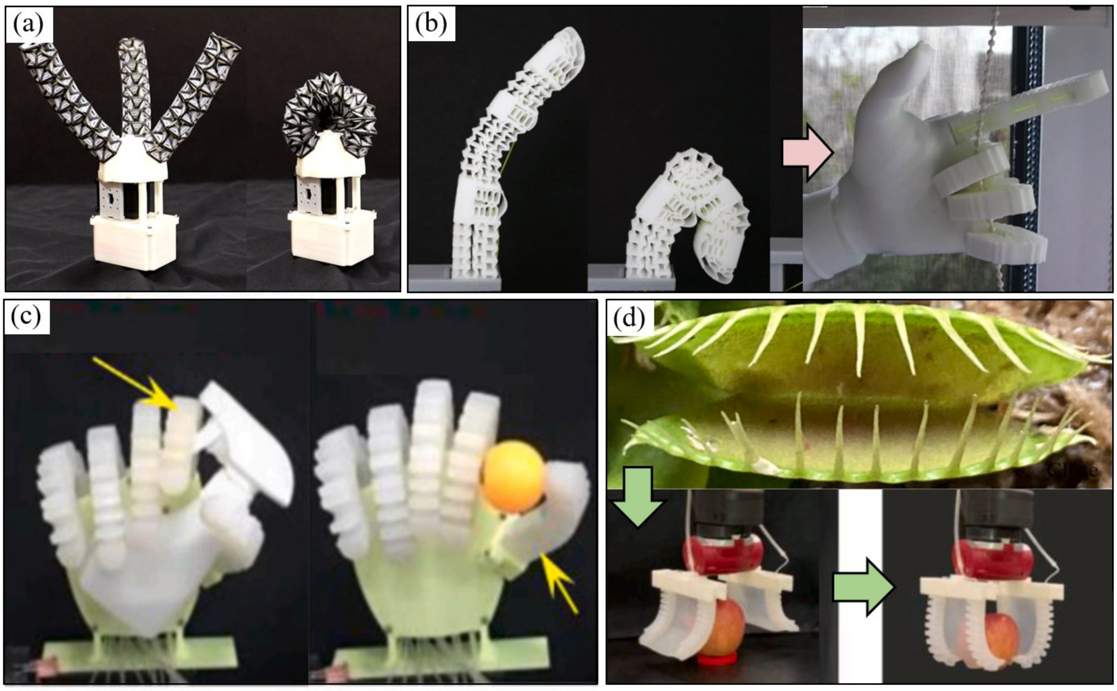

Figure 4. Typical different types of soft gripper equipment: **(a,b)** cable-based [82,83]: [82] Copyright© 2020, IEEE, [83] Copyright© 2023, IJB; **(c,d)** pneumatic-based [84,85]: [84] Copyright© 2023, Elsevier, [85] Copyright© 2022, Elsevier.

Pneumatic-based soft gripping devices mostly use contraction or expansion brakes to realize bending motions. Although some structural designs are capable of torsion but are seldom used in soft gripper design. For example, Wu *et al*. [84] designed a pneumatic soft finger structure with a composition of three independently actuated segments, which overcame the shortcomings of the traditional single-cavity soft finger structure with poor stability. The study produced an anthropomorphic hand with 15 degrees of freedom and tested it performing various gestures and piano playing tasks. The exploration of bionic gripping structures in nature has also received attention. Inspired by the Venus flytrap, Xiao *et al*. [85] proposed a soft pneumatic gripper hand with a large contact area, which can provide a human hand-like envelope and holding pattern.

Additionally, some soft grippers based on dielectric elastomers [86,87], shape memory alloys [88,89] and shape memory polymers [90] have been proposed, but the applications are not widespread.

3. Hand movement rehabilitation strategies

The hand movement disorders caused by stroke or other neurological diseases require a comprehensive and prolonged rehabilitation process. Different degrees of injury or stages of rehabilitation often necessitate different rehabilitation strategies. The rehabilitation strategy can be categorized into three types, *i.e.*, the passive rehabilitation strategy, the active rehabilitation strategy, and the guided rehabilitation strategy.

3.1. Passive rehabilitation

For patients with severe loss of hand movement ability, the basic functions such as hand grasping are often completely lost. In this case, the exoskeleton equipment or the end effector equipment must be used on patients to perform the hand rehabilitation.

It is important to note that the rehabilitation of the hand at this stage is often repeated in accordance with the prescribed motion path. The treatment plan must be customized by professional therapists based on the specific situation of each individual patient. This type of treatment, in which the therapist or rehabilitation system provides the rehabilitation program, is called the task therapy. For patients with affected finger extension and gripping difficulties, Gasser *et al*. [91] designed an assisted rehabilitation equipment and experimentally verified that the device could actually enhanced the grasping ability of the patient’s hand. Guo *et al*. [92] designed a low-cost exoskeleton rehabilitation equipment for patients with hand movement disorders, and used the topology optimization to complete the lightweight design of the hand rehabilitation robot. Although this rehabilitation method has been widely used in hand movement rehabilitation, it largely limits the active movement intention.

Furthermore, the majority of hand orthosis-based rehabilitation approach can be categorized as the passive rehabilitation. These devices are typically employed for patients with severe hand movement impairments and do not consider the patient's individual movement intention. As shown in Figure 5, Orthodontic devices typically lack power components and instead rely on structural design to harness the patient's manual dexterity [93]. Ates *et al*. [94] proposed an orthosis that encompasses both the wrist and fingers, offering antegrade assistance to aid patients in overcoming the excessive hand flexion. For patients with severe hand movement injuries caused by stroke, Yurkewich *et al*. [95] proposed a hand straightener glove that provides a wearable and comfortable solution for neuromuscular recovery related to finger movement.

Nevertheless, while orthoses offer an effective hand rehabilitation strategy, they often restrict the complete range of hand movement, preventing patients from achieving rehabilitation based on their voluntary motor intentions.

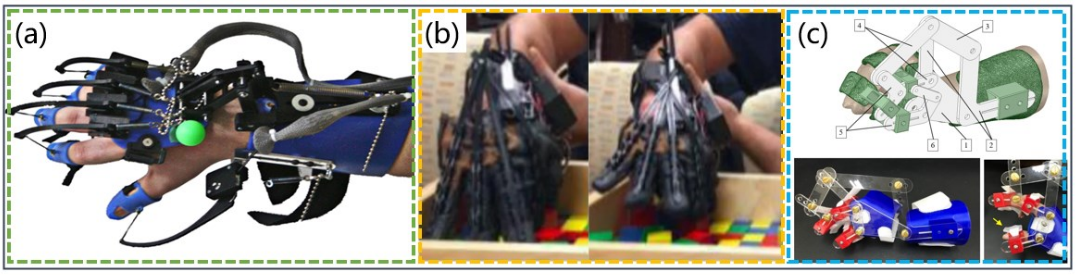

Figure 5. Different typical orthosis designs [94-96]: [94] Copyright© 2017, Autonomous Robots, [95] Copyright© 2020, Journal of Neuro Engineering and Rehabilitation, [96] Copyright© 2023, IEEE.

3.2. Active rehabilitation

Patients with moderate impairment of hand movement or those in the intermediate stage of rehabilitation typically possess some level of voluntary hand movement ability and can perform basic actions such as grasping. During this stage, patients often employ the active rehabilitation strategy to engage in the rehabilitation exercises.

Active rehabilitation strategy can be divided into the active adjuvant therapy and the active resistance therapy. Actually, no clear boundary exists between the active adjuvant therapy and the passive therapy, because both provide a certain amount of auxiliary force for the movement of the hand [97]. Xiao *et al* [98] designed an exoskeleton structure that combined a rotary-spatial-spatial-rotary (RSSR) mechanism with a double-parallelogram mechanism. This rehabilitation equipment utilized the surface electromechanical sensors to capture the movement intention to assist the hand movement. The active resistance therapy, which involves presenting challenging tasks to patients during the rehabilitation exercise, typically entails applying resistance force in the direction of finger rehabilitation instead of providing assistance force [6].

During the active rehabilitation, the hand has a certain ability to move independently, and does not need to rely entirely on the treatment plan designed by professional therapists. Therefore, the mirror therapy, in which the affected side is rehabilitated by imitating the movement of the healthy side, is proposed, and applied in the treatment strategy. Unlike the task therapy, the mirror therapy incorporates the subjective motion intention of the patients. For instance, Chen *et al*. [15] introduced a flexible and wearable hand rehabilitation system for patients with hand paralysis. The system captured the movement data from the healthy hand and utilized the pattern recognition algorithm to guide the movement of a motor-driven equipment on the affected hand, thereby conducting the mirror therapy process. Similarly, for the home-based rehabilitation, Yang *et al*. [99] proposed a system that mirrors the rehabilitation of the affected hand by collecting movement information of the unaffected hand and transmitting it to an exoskeleton device.

Active rehabilitation therapy provides an effective rehabilitation plan for patients with certain hand movement abilities. In contrast to passive rehabilitation strategies, active rehabilitation therapy focuses more on the patient's subjective motor intentions. However, both above schemes directly or indirectly provide force for hand movements to assist in patient rehabilitation. While this method is effective, it may not be the optimal solution for patients with minor hand movement injuries or those in advanced stages of rehabilitation [100].

3.3. Guided rehabilitation

Patients in the advanced stage of hand movement rehabilitation or those with mild symptoms, typically do not require external robotic equipment for assistance in their rehabilitation. During this stage, a wearable guided rehabilitation equipment is enough to help the patients perform the effective rehabilitation exercises.

As shown in Figure 6, guided rehabilitation strategy mainly includes four methods, *i.e.*, vibration stimulation, electrical stimulation, force feedback and audiovisual feedback. The vibrohaptic-based devices, representing the typical mechanical haptic technique, can deliver comfortable tactile feedback to the skin where it is attached. The real tactile perception could be achieved by adjusting the vibration frequency of the mounted vibrotactile actuators on skin [101]. The rehabilitation method utilizing the vibrotactile stimulation strategy was also proposed and validated for the hand movement impairment in the stroke patients [102]. In order to achieve the tactile feedback on the finger parts, a loop that could provide both the vibratory and thermal feedback was proposed [103]. Although this work is not directly applicable to the rehabilitation therapy, the guided rehabilitation strategy based on the vibration approach provides an encouraging idea. On the other hand, the electrical stimulation exhibits characteristics of high resolution and fast response. The working principle involves stimulating the human body through electrodes placed on the upper limb. Although it does not provide direct and comfortable feedback compared with the vibrotactile approach, it has also been accepted by the subjects [104].

Force feedback primarily comprises pressure and shear force feedback, can provide patients with a natural feeling when touching objects. Han *et al*. [105] introduced a micro dielectric fluid sensor for pressure feedback with attributes of high strain and rapid response. Its operation involves applying voltage to elongate and create protrusions on a silicone film, thus delivering pressure feedback. Similarly, a pressure feedback device that relies on balloon inflation to apply pressure to the skin directly below was proposed by Molina *et al*. [106], providing continuous tactile feedback to the wearing forearm. Shear force feedback is commonly achieved via direct skin contact, involving skin traction or torsion. Pan *et al*. [107] used wrist tactile perception to develop a real-time skin stretching feedback device worn on the dorsal side of the wrist, offering individuals extra sensory input for balance training.

Above-mentioned guided rehabilitation devices often rely on wearable devices to provide feedback through direct or indirect contact with the skin of the hand. Audiovisual feedback methods, especially those based on virtual reality systems, encourage patients' engagement in rehabilitation training. Colomer *et al*. [108] introduced a cost-effective, portable virtual reality rehabilitation system. This system can provide customized training for arms, hands, and fingers by combining virtual environments with tangible objects, and providing audio-visual feedback based on the patient's performance in the virtual environment. The interaction between natural gestures and immersive virtual reality environments simulates real-life interactions, benefiting the rehabilitation of patients' motor nerves and muscles. Juan *et al*. [109] proposed a complete set of virtual reality applications that assist patients in rehabilitation through three series games, allowing patients to detach from a large amount of medical equipment and tedious rehabilitation exercises.

It is worth noting, the thermal stimulation, which can provide a distinctive thermal sensation and can also serve as an effective guided modality. Nonetheless, its utilization has been limited due to the slow heating and cooling process, resulting in limited adoption range [110].

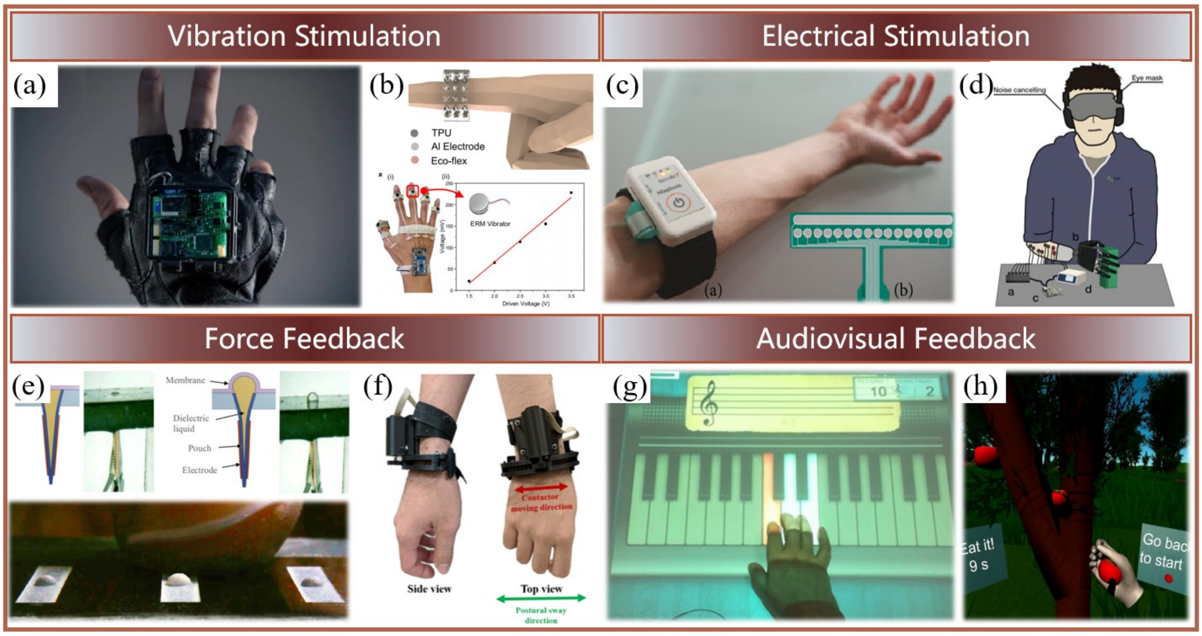

Figure 6. Typical guided rehabilitation strategy related equipment: **(a-b)** Vibration Stimulation [103,111]: [103] Copyright©2022, Nature Communications, [111] Copyright© 2021, Journal Neuroengineering and Rehabilitation; **(c-d)** Electrical Stimulation [104,112]: [104] Copyright© 2019, Applied Bionics And Biomechanics, [112] Copyright© 2017, Scientific Reports; **(e-f)** Force Feedback [105,107]: [105] Copyright© 2020, IEEE, [107] Copyright© 2017, IEEE; **(g-h)** Audiovisual Feedback [108,109]: [108] Copyright© 2016, Journal of NeuroEngineering and Rehabilitation, [109] Copyright© 2023, Virtual Reality.

Table 3 summarizes the comparison of these three rehabilitation strategies in aspects of application range, application stage, rehabilitation equipment and their working characteristics.

Table 3. Comparison of different modes of hand exercise rehabilitation.

Rehabilitation strategy	Application range	Application stage	Rehabilitation equipment	Working characteristic
Passive rehabilitation	With severe loss of hand motion function	Early stage of rehabilitation	Exoskeletons, orthotics, etc.	Provide external force to assist hand movement, mainly task therapy
Active rehabilitation	With small hand motion function	Mid stage of rehabilitation	Exoskeletons, end effectors, etc.	Provide external force to assist or resist hand movement
Guided rehabilitation	With basic hand motion function	Late stage of rehabilitation	Vibration motors, virtual reality, etc.	Do not directly provide assistance

4. Emerging research directions

Hand motor rehabilitation systems and associated rehabilitation strategies have been reviewed and summarized in previous sections, respectively. In this section, emerging research directions for hand rehabilitation devices are given. This mainly includes the research of advanced functional materials, large-scale sensor array technology and fine-grained hand movement rehabilitation equipment (Figure 7).

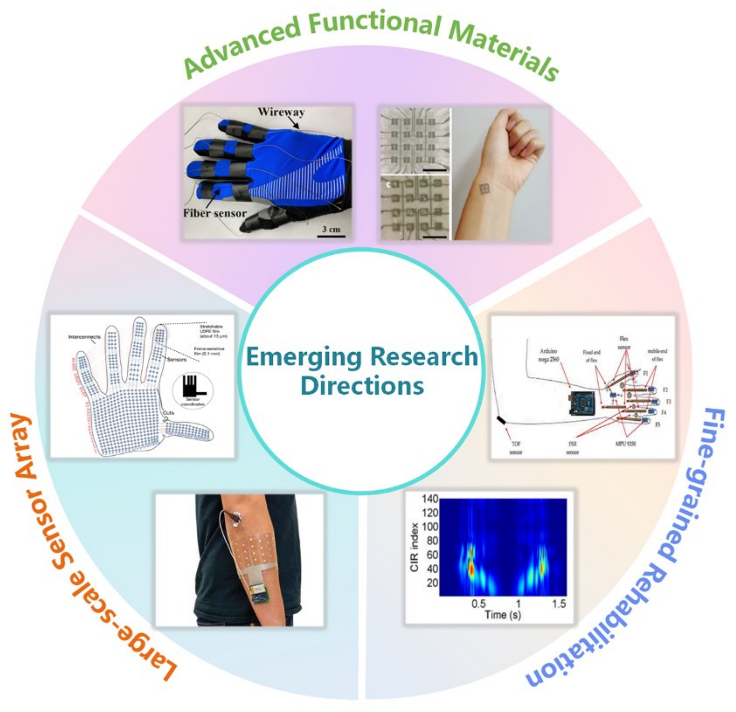

Figure 7. Emerging research directions of the hand movement rehabilitation equipment.

4.1. Advanced functional materials for sensing and actuation

With the development trend of miniaturization and intelligentization of the overall hand movement rehabilitation equipment, new requirements are put forward for the sensors that are integrated in the full system. Material is an important factor affecting the performance of sensors, and many studies have focused on the research of new types of sensors based on advanced functional materials, which exhibit the comprehensive merits of flexibility, elasticity and robustness as well as high sensitivity and wide measurement range to capture information related to a broad aspects of finger bending [113], pressure [114], temperature [115] and other parameters.

In addition, new flexible actuation technologies, particularly those utilizing artificial muscles, have the potential to replace the conventional rigid motor-driven systems or space-consuming pneumatics, representing a promising way for the development of next-generation driving approach. Nevertheless, the utilization of artificial muscles for the rehabilitation equipment that is intimate with human skins is still limited due to their ultrahigh voltage requirement, which would arise the safety concern [116,117].

4.2. Large-scale sensor array technology

The human hand possesses the remarkable dexterity, and the advent of large-scale array sensing technology holds the potential for effective acquisition of the comprehensive hand movement information through wearable devices. It has been reported that the integration of 548 low-cost sensors into a large-scale sensor array for smart object recognition during the human hand grasping operation [14]. However, the hardware complexity associated with this large-scale array sensing approach confines numerous studies to the high-performance laboratory computers. In addition, the large-scale array sensing matrix inevitably introduces crosstalk among individual sensors, which manifests as noise that often retains the same characteristics as the original sensing signal. This issue makes it challenging to eliminate the interference by using the conventional filtering technique [118], which further puts forward new requirements for the large-scale array sensing technology.

4.3. Fine-grained hand movement rehabilitation equipment

Despite the progressive development of the hand movement rehabilitation equipment, there are still challenges in realizing the hand rehabilitation with fine movements. For instance, for the finger bending rehabilitation, the focus is often limited to the positional movement of the fingertip or the overall grasping ability, while overlooking the movement of individual joints [119]. For an advanced rehabilitation system, it is necessary not only to focus on the rehabilitation of the whole finger, but also to be able to individually train each finger joint.

Moreover, the human hand also exhibits the abduction-adduction movement between adjacent fingers in addition to the flexion-extension movement [13], which puts forward higher requirements for the development of fine-grained hand rehabilitation equipment. The strategy of placing IMU schemes in the fingers has achieved the recognition of the finger abduction-adduction movement [120]. The ultrasonic finger motion perception and recognition system based on Channel Impulse Response (CIR) has also achieved high-precision hand motion recognition [121]. But such kind of research is rare and needs further investigation.

5. Conclusion

The development of the hand rehabilitation equipment that utilizes external robotic assistance and wearable equipment technology have drawn great research interest and gained a great progress. This review article firstly introduces the latest finding in the hand movement rehabilitation system, which covers the advanced sensing technologies, new driving mechanisms and related hand movement pattern recognition algorithms. Patients with different disability levels at varying rehabilitation stages should employ tailored rehabilitation strategies to attain the optimal rehabilitation outcome. Subsequently, a comprehensive review was conducted on three typical rehabilitation strategies, including active rehabilitation, passive rehabilitation, and guided rehabilitation. Then, corresponding application scope and latest research results were provided. Finally, the development prospects of hand motion rehabilitation equipment are anticipated. Sensor design based on advanced materials, large-scale sensor array technology, and fine-grained hand motion monitoring technology will become hot research topics in the academic field.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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