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Progress and Challenges in Brain-Computer Interface-Based Hand Rehabilitation Robots

Yanming Ba[1*], Hanjun Wang[2], Zhengyang Wang[3]

[1]*Eastern Michigan Joint College of Engineering, Beibu Gulf University, Qinzhou, China*
[2]*Shanghai World Foreign Language Academy, Shanghai, China*
[3]*School of Mechanical and Electrical Engineering, Beijing Institute of Graphic Communication, Beijing, China*
**Corresponding Author. Email: 2219401149@stu.bbgu.edu.cn*

Abstract. Converging trends in brain-computer interfaces (BCIs) and rehabilitation robotics have led to rapid advancements in BCI technology, positioning it as a promising innovation in the medical field. As a technology that establishes a direct connection between the human brain and computer systems, brain-computer interfaces are designed to interpret brainwave signals. These interfaces translate neural activity into commands that facilitate the control of external devices. As different development trajectories are followed, advancements in intelligent algorithms and machine learning technologies suggest that future BCI-based hand rehabilitation robots may achieve personalized training. These systems have the capacity to make precise adjustments to training protocols in real time based on brainwave signals. This adaptive training model has the potential to enhance treatment efficacy, increase patient engagement, and promote patient initiative in the rehabilitation process, thereby improving overall recovery outcomes. The integration of BCI with other advanced technologies is a future trend that merits further investigation. This paper reviews the current research status, advantages, and limitations of BCI-based hand rehabilitation robots. The analysis method employed in this study involves the identification and conclusion of the existing development characteristics and future trends of BCI-based hand rehabilitation robots for various applications under different development directions.

Keywords: brain-computer interface, hand rehabilitation robots, EEG, hand exoskeleton

1. Introduction

As neuroengineering and artificial intelligence continue to advance, integrating brain-computer interfaces (BCIs) with rehabilitation robots has become a popular area of research. BCI systems create a new pathway for transmitting information between the brain and external devices, which is independent of peripheral nerves and muscles. This technology enables patients who have lost motor function in a limb to control external devices via EEG signals from the BCI. This allows them to perform vital activities and enhances their independence. It also facilitates rehabilitation training for patients with motor impairments due to neural pathway dysfunction. BCIs assist in rebuilding neural connections and restoring motor capabilities [1].

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This paper primarily explores hand rehabilitation robots based on BCIs. As the most widely used feedback device in BCI-based upper limb rehabilitation systems, these robots accelerate patient recovery through motor imagery–based, BCI-assisted therapy. They also support rehabilitation therapists in providing sustained, repetitive training [2].

The paper summarizes recent advances in BCI-based hand rehabilitation robotics, covering BCI principles, architecture, and BCI-driven hand rehabilitation robots. Additionally, it compares the performance and practical rehabilitation outcomes of existing systems, analyzing their technical challenges and areas for improvement.

2. Brain-computer interface system

2.1. Basic principles

Electroencephalogram (EEG) signals reflect the state of neural activity in the brain. To monitor these signals in real time, multiple EEG sensor arrays are typically deployed in different brain regions to collect electrical signals from these regions in real time. These signals are then subjected to preprocessing, feature extraction, and pattern recognition to analyze specific thoughts or behavioral intentions within the brain. Feedback channels then relay this information or control commands to the brain, helping the user adjust their behavior to achieve optimal results. Furthermore, the rapid advancement of deep learning has made attention mechanisms indispensable for analyzing electroencephalography (EEG) signals, greatly improving brain-computer interface (BCI) applications [3]. Figure 1 shows the way BCI and attention mechanisms interact.

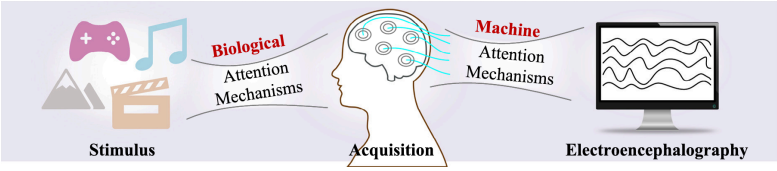

Figure 1. The way BCI and attention mechanisms interact [3]

A brain-computer interface (BCI) primarily consists of modules such as the user end, brain signal acquisition, brain signal processing and decoding, a control interface, external devices such as robots, and neural feedback. The user end is the system operator and the signal source for the BCI system.

The roles and functions of each component are as follows: The user's brain: The system operator and the primary signal source for the BCI. Brain signal acquisition: Acquires high-quality brain signals to ensure sensor safety, comfort, aesthetics, and ease of use. Brain signal processing and decoding: Includes three steps: brain signal preprocessing, brain signal feature value extraction, and brain activity pattern recognition and machine learning. Control interface: Converts logical control signals representing user intent into semantic control signals, and then into physical control signals. Robots and other peripherals: Include rehabilitation robots and intelligent prosthetics. Neurofeedback: Used to achieve bidirectional brain-computer interaction and promote the interconnection and interoperability of EEG and electronic signals [4].

2.2. Types of brain-computer interfaces

Brain-computer interfaces are categorized as invasive, semi-invasive, and non-invasive, depending on the depth of the implantation of electrodes into the brain for brain signal acquisition.

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Invasive BCIs involve implanting electrodes and other signal recording devices into specific locations within the brain through neurosurgery, enabling precise, high-throughput neural signal acquisition. This interface requires craniotomy to implant electrodes into the cerebral cortex, enabling more stable and reliable direct acquisition of EEG signals. This approach can be further categorized as cortical electrodes and deep-seated electrodes. The former involves implanting electrodes into the cerebral cortex, which can obtain higher EEG signals and more detailed brain activity data, but requires delicate surgery and inherently carries increased risks. The latter involves implanting electrodes deep within the brain to collect signals from deep neurons, stimulating specific brain nuclei to improve the symptoms of certain neurological disorders. Deep-seated electrodes can obtain higher-quality EEG data and precisely intervene in brain activity, offering unique therapeutic benefits for certain diseases. However, due to the difficulty in controlling the implantation location and depth, the potential for secondary infection increases. If a brain infection, electrode failure, or end-of-life condition occurs, the electrodes must be removed, necessitating a secondary craniotomy, significantly increasing the risk and complexity of the surgery.

Semi-invasive approaches involve implanting the brain-computer interface within the cranial cavity, outside the cerebral cortex, without direct contact with neurons. This approach typically requires electrodes to be implanted under the scalp, close to the dura mater, but without directly penetrating the cerebral cortex. A typical application is electrocorticography (ECG), commonly used for localizing epileptic lesions and guiding surgery. The advantages of this approach are high signal quality and relatively low surgical risk. However, its disadvantages include the need for craniotomy, which is somewhat traumatic for the patient and carries a correspondingly high cost.

Non-invasive brain-computer interfaces (BCIs) use wearable sensors attached to the scalp to record and interpret brain information. This approach eliminates the need for electrodes to be implanted in the brain; instead, wearable devices such as EEG caps, near-infrared helmets, or magnetic resonance imaging (MRI) head coils are attached to the scalp to obtain corresponding EEG data. EEG monitoring, a widely used method, falls into this category. This non-invasive method is highly safe, simple to use, and widely accepted by both physicians and patients. In addition to direct scalp acquisition, non-invasive BCI systems can also utilize near-infrared spectroscopy and transcranial magnetic stimulation (TMS).

3. Brain-computer interface-based hand rehabilitation robots

3.1. Classification

The literature cited in this paper focuses on two distinct research approaches. One approach involves using non-invasive brain-computer interfaces to monitor and record electroencephalograms (EEG). The other approach combines generated EEGs with electromyography (EMG) signals. The former aims to decode motor intentions from the brain or study cortical effects and differences in cortical rhythms within EEG frequencies. The latter builds on this foundation, using EMG signals to train models for hand rehabilitation robots or provide corrective signals for coordinated robot movement across multiple body parts (e.g., hand and wrist rehabilitation robots). Some of the examples presented in this paper also involve developing networks based on the combination of multiple signals to distinguish between different movement intentions.

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3.2. EEG

The key point in using an electroencephalogram (EEG) recorded by a brain-computer interface (BCI) and a hand rehabilitation robot is the connection between EEG decoding and robot interaction. Sun and others from KU Leuven compared the EEG representations of different movement modalities, including imagined (IM), passive (PM), and congruent imagined and passive (IPM) finger flexion. They also assessed motor intention detection performance in situations with and without exoskeleton assistance [5]. Their designed equipment is shown in Figure 2.

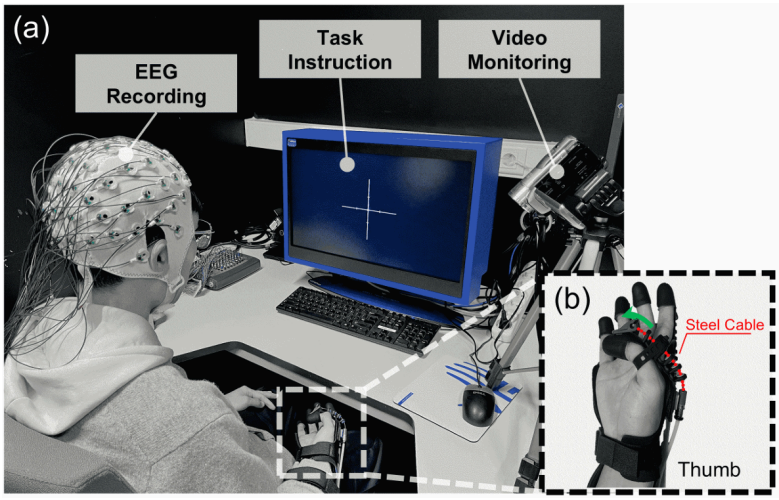

Figure 2. Full-scalp EEG signals recording device and hand exoskeleton [5]

Cristian F. Blanco-Diaz and others from the Federal University of Espirito Santo performed an electroencephalography (EEG) analysis combining a robotic glove to examine differences in cortical rhythms in the frequency domain, and compared it to the classical MI protocol based on static Action Observation (AO) They proposed a novel protocol based on motor imagery (MI) tasks and found that using the robotic glove generated a greater decrease in power (desynchronization) in the central parietal cortex of the brain [6]. The designed equipment is shown in Figure 3.

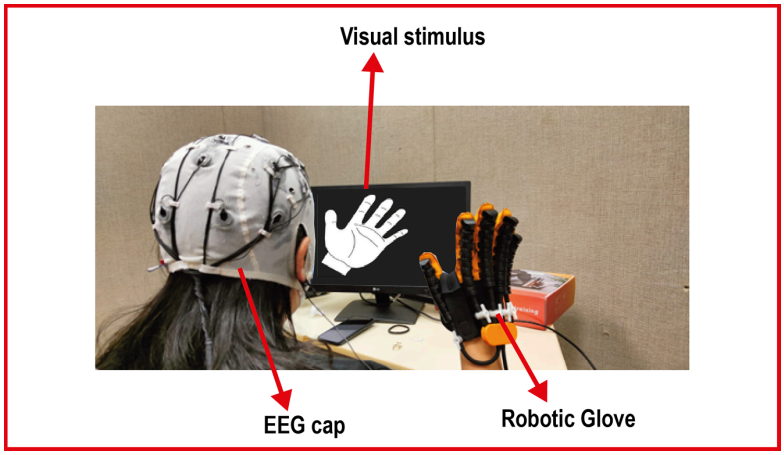

Figure 3. The equipment of a robotic glove that generates passive movements and EEG cap [6]

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3.3. Combination of EEG and EMG

Kim and others from Korea Advanced Institute of Science and Technology,designed a three-degrees of-freedom (3-DOF) soft wearable robots for integrated hand-wrist rehabilitation using both EEG and EMG signals. EEG signals classified rest and grasp states using a Riemannian geometry approach. Meanwhile, EMG signals from three forearm muscles detected reaching onset and triggered wrist adjustments [7]. The overview of the study is shown in Figure 4.

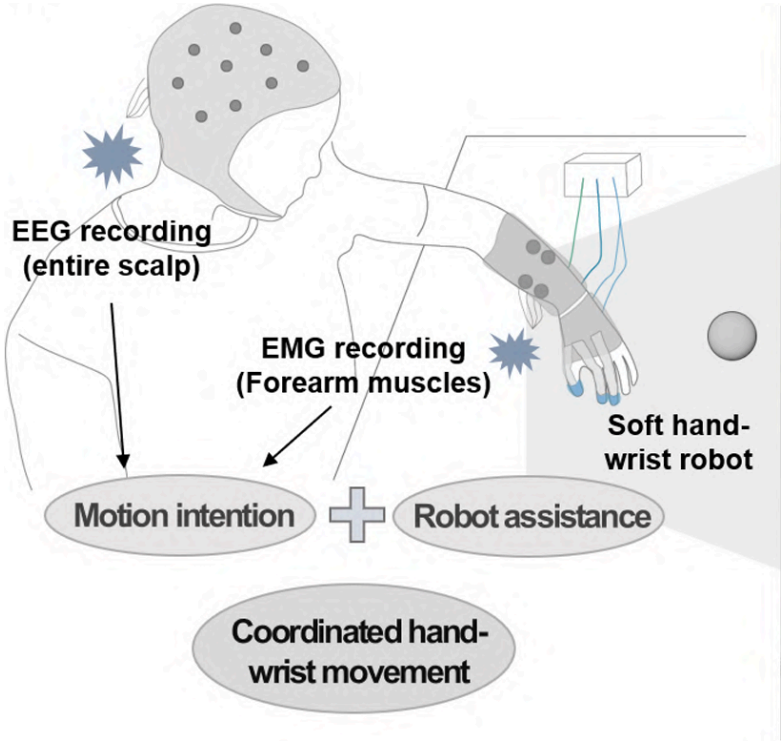

Figure 4. The concept of multimodal EEG-EMG human machine interface based on hand-wrist rehabilitation [7]

Soto-Florido and colleagues from the Pontificia Universidad Javeriana explored the integration of electroencephalography (EEG) and electromyography (EMG) signals for classifying five hand movements commonly used in rehabilitation therapy, including four finger pinches and full hand closure. The researchers acquired biological signals from healthy participants using a synchronized setup of EEG and EMG systems. The equipment is shown in Figure 5. Signal processing methods were applied to extract frequency features from the EEG and muscle activity features from the EMG. These features were then used to train machine learning models for classifying movement intention and execution. One model, Ensemble Bagged Trees, achieved 84.7% and 67.4% accuracy for movement execution and intention, respectively, when using EEG power spectral density features. These results suggest that integrating EEG-EMG analysis with machine learning could enhance stroke rehabilitation by improving patient monitoring and robotic-assisted therapy [8].

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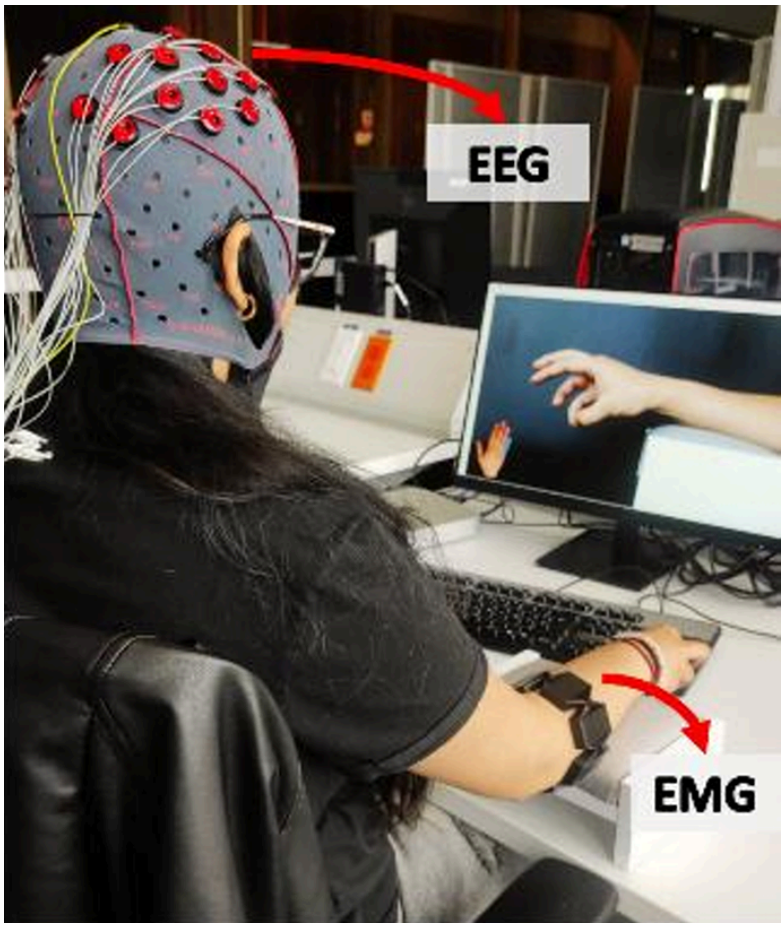

Figure 5. Exploring and integrating equipment [8]

3.4. Networks integrating EEG with algorithms and signals

To address the generalization challenges caused by reliance on active movement during upper-limb rehabilitation for stroke patients, Kang et al. designed a passive brain–computer interface (BCI) system that integrates exoskeleton actuation with EEG-response decoding. The core idea is to use a mechanical exoskeleton to assist the hand in performing passive grasping, thereby activating cortical sensory pathways and acquiring EEG data to improve the stability of neural signals elicited by passive movement, which in turn reduces the complexity of cross-subject model transfer.

The technology consists of a synchronized EEG monitoring module and a high-precision grasping exoskeleton. Ten stroke patients and twenty healthy subjects were enrolled in the study, and they all completed both active and passive gripping exercises. Through the analysis of ERP and mu/beta-band ERD/ERS patterns, as well as the evaluation of classification performance using EEGNet and the CSP algorithm, the researchers discovered that stroke patients' neural response characteristics under passive conditions were comparable to those of healthy participants, and that ERP amplitudes in healthy individuals were significantly enhanced and more stable under passive movement. Experimental data showed that EEGNet achieved an accuracy of 84.19% in distinguishing motor states on the affected versus unaffected sides in stroke patients—significantly outperforming active-task processing and conventional methods.

This work is the first to establish a systematic experimental framework (Figure 6) demonstrating that an “exoskeleton-driven passive feedback” mechanism can enhance neural signal stability and

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algorithmic adaptability in BCI decoding. It provides a theoretical basis for developing rehabilitation interfaces that do not require continuously stable intention outputs and further opens a feasible "perception–feedback–adjustment" pathway for clinical rehabilitation with BCI technology [9].

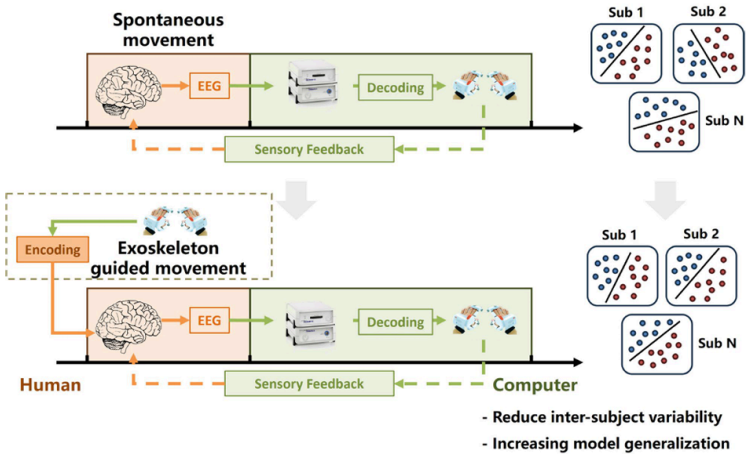

Figure 6. Schematic diagram of the exoskeleton-guided brain–computer interface rehabilitation model [9]

3.5. Vision-based perception and soft robotic hand actuation in BCI system design

The Rho team developed an integrated multi-grasp rehabilitation system that combines visual intention recognition with control of a soft exoskeleton glove, aiming to improve interaction accuracy and training diversity for stroke patients across multiple action patterns. By integrating an RGB-D camera with a depth-enhanced attention mechanism, the proposed DEEPOSE-Net can precisely extract spatial relationships between the user's hand and surrounding objects, enabling intention recognition for five common hand actions (e.g., cylindrical grasp, spherical grasp, lateral pinch, three-finger pinch, and thumb–finger opposition).

The system's eight-degree-of-freedom soft glove employs active tendons to drive finger flexion and thumb opposition, while passive tendons provide finger extension, yielding strong dynamic adaptability. In experiments, five healthy participants and three chronic-phase stroke patients completed a "grasp–move–place" task. DEEPOSE-Net achieved intention-recognition accuracies of 90.4% for the healthy group and 80.3% for the patient group, with no significant inter-subject variability in posture classification within each cohort. In most task scenarios, the glove effectively assisted precise action execution.

This study addresses the twin challenges of insufficient recognition accuracy and pronounced individual differences in multi-posture training, while replacing traditional electrophysiological acquisition with a non-contact, vision-based intention-capture approach. As such, it provides key technical support for building highly adaptive, widely applicable home-based rehabilitation systems. Compared with the EEG/EMG-centered pathway emphasized in this paper, the vision-perception approach focuses more on capturing and executing "external behavioral intention," which can substantially reduce calibration costs and user burden; however, because its intention signals are not derived directly from cortical activity, it is less suitable as primary evidence for assessing neuroplasticity [10]. Figure 7 shows the intention and hand-posture recognition via DEEPOSE-Net, followed by execution with an 8-degree-of-freedom soft robotic glove.

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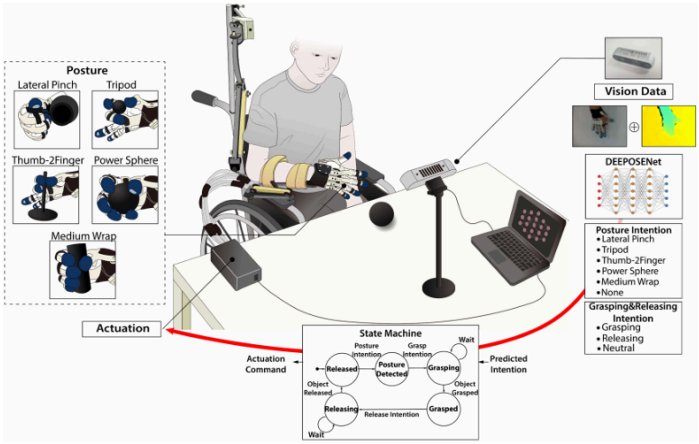

Figure 7. Intention and hand-posture recognition via DEEPOSE-Net, followed by execution with an 8-degree-of-freedom soft robotic glove [10]

4. Existing limitations and future prospects

Among the signals that can be recorded by existing brain-computer interfaces, electroencephalography (EEG) remains the mainstream choice for brain-computer interface (BCI) rehabilitation research due to its non-invasive, low-cost, and easily scalable nature. However, ECoG is limited to a few high-precision medical scenarios, such as intractable epilepsy or paralysis control, due to surgical risks and resource constraints. Future advancements in flexible electrodes and wireless transmission could enable minimally invasive ECoG applications for severe rehabilitation. Nevertheless, EEG will remain the core technology for accessible rehabilitation. Furthermore, high-precision models developed from healthy subjects may be ineffective for stroke patients and may require personalized calibration due to spasticity, electromyographic degeneration, and diminished neural responses. Existing device support and adaptive grasping strategies also contribute to deficiencies in system integration.

The current limitations primarily focus on three aspects. First is variability in signal characteristics across populations. While non-invasive electroencephalography (EEG) offers operational simplicity, its recordings are susceptible to interference from muscle contractions, postural changes, and external noise. Models trained on healthy subjects typically have significantly lower predictive accuracy when applied to stroke patients, requiring multiple personalized adjustments. However, invasive signal enhancement methods face challenges in achieving widespread adoption due to high surgical risks and substantial costs. Second, device and interaction systems: Exoskeletons and flexible gloves must balance degrees of freedom, weight, wearability, and safety. However, cable routing design, sensor latency processing, and redundancy in protective mechanisms can significantly impact the user experience. Passive or semi-active control methods still have shortcomings when it comes to stabilizing "continuous intent" and turning it into "continuous action." Third, algorithms and validation mechanisms: Single-source data has poor interference resistance, and small sample sizes with significant labeling discrepancies are common. Training tasks lack unified standards, and datasets are difficult to cross-validate. The absence of long-term tracking to correlate functional recovery with neural changes hinders cross-study comparisons and reproducibility. Future approaches could integrate additional algorithms to develop models that dynamically track intent while resisting somatosensory interference. Alternatively, incorporating visual perception could enable adaptive assistance tailored to specific scenarios.

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The primary focus of optimization should be signal acquisition and integration. Due to the susceptibility of standalone EEG signals to interference, it is recommended that EEG be maintained as the primary data source and augmented with EMG monitoring or visual intent recognition technologies to enhance overall reliability. When patients perform grasping, moving, and placing tasks, analyzing overall movement intent through EEG activity while verifying specific action phases with visual input or EMG signals can effectively reduce misjudgment rates and minimize signal fluctuations. Additionally, detailed optimization standards are urgently needed for device structural design and wear comfort. The total weight of the flexible hand protection gear must be strictly controlled so users can wear it continuously during routine training without experiencing significant fatigue. To accommodate frequent training sessions in home environments, it is recommended to limit wear duration to under one minute. Furthermore, glove designs should incorporate instant release mechanisms to ensure the drive system ceases operation immediately when users experience discomfort or abnormal conditions, thereby safeguarding user safety. Regarding algorithm architecture and training methods, there should be a gradual evolution from single-action recognition to coherent motion tracking. For example, training programs could include 5-10 daily tasks with dynamically adjusted movement paths, rather than relying solely on start-end point detection. A dual mechanism of "instant calibration and real-time optimization" can be adopted. Initial deployment requires only 10 to 15 minutes of personalized model training, followed by brief daily automatic corrections to maintain model stability.

Finally, subject numbers must be increased and unified assessment standards adopted during clinical trials and validation phases. For example, it is recommended that a systematic rehabilitation training program lasting no less than eight weeks be implemented. This program involves monitoring patients' task completion rates, reaction times, and functional recovery trend curves while using standardized scales to quantitatively evaluate rehabilitation outcomes. This approach clarifies future optimization directions and advances the implementation of personalized, integrated robotic solutions.

5. Conclusion

In the future, hand rehabilitation robots based on brain-computer interfaces will be upgraded comprehensively in terms of their structure, drive mechanisms, and training modes. Primary development efforts will focus primarily on signal acquisition and recognition for brain-computer interfaces. While integrating multimodal neural interfaces with soft/exoskeletal robots offers new paradigms for hand rehabilitation, challenges such as proprioceptive interference, poor patient adaptability, and insufficient continuous control precision must be overcome. Future efforts should prioritize innovations in decoding algorithms, such as incorporating deep and adaptive learning mechanisms, enhancing the integration and fusion of multimodal sensory information, and advancing technology translation through rigorous, large-scale clinical trials. Only by achieving the leap from "functional substitution" to "facilitating neural remodeling" can rehabilitation become proactive and personalized. This will allow hybrid robots to surpass traditional solutions in efficiency and intelligence, greatly improving patients' rehabilitation outcomes and quality of life.

Authors contribution

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

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