Proceedings of the 6th International Conference on Biological Engineering and Medical Science
DOI: 10.54254/2753-8818/2026.39299

An Exploration of Non-Invasive Brain-Computer Interfaces in Rehabilitation Robotics

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Abstract. Brain-computer interfaces can directly read brain signals, enabling control of external devices without relying on hands or feet. Among these, non-invasive brain-computer interfaces require no surgical implantation, feature high safety, and possess great potential in rehabilitation robotics. This paper briefly introduces several common EEG operating modes, describes the basic workflow of EEG signal processing, lists practical BCI applications in rehabilitation robotics, analyzes existing technical challenges, and discusses prospective future developments. It is hoped that this paper will help readers understand this interdisciplinary field of biomedical engineering and provide a basic reference for assistive rehabilitation technologies for people with motor impairments.

Keywords: brain-computer interface, electroencephalogram, rehabilitation robotics, motor imagery, biomedical engineering

1. Introduction

As the population continues to age, conditions such as strokes and spinal cord injuries may cause motor impairments in some individuals. Some patients lose the ability to move their limbs, operate a mouse or keyboard, and struggle to communicate their thoughts. Traditional rehabilitation training mainly relies on machine-assisted passive limb movements, which achieve limited therapeutic effects [1, 2].

Brain-Computer Interfaces (BCIs) are an emerging interdisciplinary technology integrating biology, medicine, computer science and robotics. BCIs record brain electrical signals, convert human intentions into machine-readable commands, and realize direct control of robotic devices. Brain-Robot Interfaces (BRIs) represent a practical class of BCI applications. They can drive rehabilitation wheelchairs, robotic arms and exoskeletons to help patients complete daily tasks such as drinking or grasping objects, while supporting rehabilitation training to promote neural recovery.

BCIs are divided into invasive and non-invasive types. Invasive BCIs require surgical implantation of electrodes deep into brain tissue. Although they acquire high-quality signals, they carry risks of surgical infection and are generally not acceptable to most people. Non-invasive BCIs capture EEG signals from the scalp via head-mounted EEG caps. Without surgical procedures, they are relatively simple and safe to operate, suitable for daily use and rehabilitation scenarios. Currently, much popular science work and research are focusing on this technology. This article

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explains the fundamentals of non-invasive BCIs and rehabilitation robots in plain, easy-to-understand language.

2. Several operating modes of non-invasive brain-computer interfaces

Electroencephalographic (EEG) signals are faint electrical signals generated by neural activity in the brain when a person thinks or imagines something. Different operating modes (paradigms) produce EEG signals in different ways; they are categorized as active, reactive, and hybrid modes that combine multiple approaches.

2.1. Active mode: motor imagery

Motor imagery (MI) does not require external stimuli such as lights or sounds. Simply put, when a person imagines moving their hands or feet while keeping their body still, specific changes in EEG activity occur in the brain's motor regions. For example, imagining clenching the left hand or walking with both feet causes the EEG rhythms in the corresponding brain regions to increase or decrease. The device detects these changes and outputs control signals accordingly.

The advantages of this mode are significant: the control logic aligns with our actual limb movements. During rehabilitation training, when patients actively imagine movements, it stimulates brain activity, which aids in the repair of damaged nerves. It is currently used to control rehabilitation wheelchairs, robotic arms, and rehabilitation exoskeletons.

However, it also has drawbacks: the number of control commands it can execute is limited, typically only 3-4 [3]; brain signals vary significantly from person to person; some individuals require repeated practice before the device can accurately interpret their thoughts; and it is difficult to perform fine motor tasks such as picking up small objects.

2.2. Reactive mode

Reactive mode requires external visual or auditory stimuli. When the brain is stimulated, it generates corresponding electroencephalographic (EEG) signals, which the machine reads to determine the person's intent [4, 5]. The two main types are SSVEP and P300.

Steady-State Visual Evoked Potentials (SSVEP): Several icons that flash continuously are displayed on the screen, each at a different frequency. When a person's eyes fixate on a specific flashing icon, the visual cortex generates EEG waves matching the flashing frequency. By detecting this frequency, the device identifies which command the user has selected.

Its advantages include the lack of need for extensive training, the ability to configure numerous control commands, and the capability to control a robotic arm to perform actions such as grasping and rotating. The disadvantage is that the user must keep staring at the flashing screen, which can cause eye strain over time; if the user has poor vision, this method is unlikely to function properly.

P300 Event-Related Potential: Multiple icons flash randomly on the screen. When the desired icon lights up, a specific electrical potential—known as the P300 signal—appears in the brain approximately 300 milliseconds later. The machine captures this signal to determine the user's selection.

The P300 is suitable for selection-based operations, such as switching a robot's operating mode. However, since it is best suited for discrete operations like "selecting a target," it is difficult to use it to control a robot's continuous, gradual movement; therefore, it is rarely used for precise motion control.

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2.3. Hybrid modes

Each individual mode has its limitations. Therefore, researchers combine two or more signal types to form hybrid modes. For example, the P300 can be used to select the object to be manipulated, while the SSVEP is used to control the robot's movement to avoid obstacles; in addition to EEG, electromyographic signals from facial muscles can be incorporated for secondary confirmation.

Hybrid modes can leverage the strengths of each component to compensate for their weaknesses, thereby improving the system's recognition accuracy. However, this also increases the complexity of the equipment and software and the workload involved in data processing. For instance, the NOIR system developed abroad integrates motor imagery, visual evoked potentials, and electromyography signals. Users need only specify a general target, and the robot independently executes the specific movements, thereby reducing the difficulty of manual control.

3. Basic process of EEG signal processing

The raw EEG signals collected from the scalp are very weak and are contaminated with various types of noise caused by blinking, clenching teeth, and power supply fluctuations; therefore, they cannot be used directly to control a robot. A complete system consists of several steps: signal acquisition, preprocessing, feature extraction, command output, and feedback.

3.1. Signal acquisition

EEG acquisition primarily relies on an EEG cap and a signal amplifier. Electrodes are distributed across the scalp according to the international 10-20 system. Electrodes fall into three categories: wet electrodes require the application of conductive gel; they provide clear signals and are commonly used in laboratories, but are cumbersome to wear; dry electrodes do not require gel and are ready to use immediately, but their signal quality is somewhat lower; semi-dry electrodes fall between the two and represent the future direction for portable devices.

3.2. Signal preprocessing

Preprocessing involves "noise reduction" of the raw signal. Filters are used to remove unwanted frequency components and eliminate interference caused by 50-hertz AC power in the home. Interference signals caused by blinking or clenching the teeth are typically separated using independent component analysis (ICA) algorithms, leaving only the true brain activity signals.

3.3. Feature extraction and pattern recognition

After noise reduction, features representing the user's thoughts must be extracted from the signal. Traditional methods rely on manual selection of signal features, followed by classification using simple machine learning algorithms.

Deep learning has now also been introduced into EEG analysis. Convolutional neural networks can directly read EEG data and automatically identify useful features. Recurrent neural networks are well-suited for processing EEG waves that vary over time. However, deep learning requires a large amount of experimental data and involves significant computational demands, which poses certain challenges for real-time robot control.

Once recognition is complete, the results are converted into commands and sent to the rehabilitation robot. The robot then performs the action and feeds back visual information and other

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data to the user, forming a complete closed-loop system.

4. Current practical challenges

Although brain-controlled rehabilitation robotic systems have achieved significant results in the laboratory, there are still many challenges to overcome before they can be used by the general public in daily life.

First, EEG signals are inherently unstable. They are extremely weak; fatigue and stress can alter brainwave patterns, and brain signals vary greatly from person to person. Even for the same person, signals can change over time, requiring frequent recalibration of the equipment. For patients with brain injuries, EEG signals are even more complex.

Second, control capabilities are not yet optimal. The number of motor imagery commands is limited; SSVEP paradigms can easily cause visual fatigue; and P300 is not suitable for continuous movement. Currently, most experiments can only perform simple actions such as moving forward or grasping, making it difficult to achieve the complex and precise movements required in daily life. Deep learning models are computationally intensive, and the robot's real-time response speed requires further improvement.

Third, transitioning from the laboratory to real-world environments is challenging. Currently, many tests are conducted in quiet, ideal laboratory settings. Real-world rooms, however, are subject to interference from lighting and noise. Specialized equipment is expensive, and wet-electrode EEG caps are complex to operate, making them impractical for repeated use in hospitals or homes. Furthermore, there is a lack of unified industry standards.

Fourth, there are concerns regarding personal data security. EEG signals contain private information such as a person's emotions and physical state. If stored or transmitted improperly, there is a risk of data breaches, necessitating the establishment of relevant ethical guidelines.

5. Outlook for future development

First, improve data acquisition hardware. Develop lighter, more comfortable dry electrodes and flexible electrodes that are easy to wear and more resistant to interference, and create low-cost, home-use EEG data acquisition devices.

Second, optimize algorithms and operating modes. Develop hybrid brain-computer interfaces and research adaptive systems, where devices can automatically adjust operating parameters based on a person's mental state, reducing the need for repeated calibration. Incorporate the "shared autonomy" approach: the human brain sets overarching goals, while robots use cameras to automatically execute detailed movements, thereby reducing the cognitive load on the brain.

Third, advance testing and application in real-world scenarios. Conduct more trials involving the general public and patients to accumulate real-world usage data. Integrate brain-computer interfaces with functional electrical stimulation and virtual reality. When the brain sends signals indicating imagined movements, the machine uses electrical stimulation to trigger muscle contractions in the patient; sensory feedback from the body is then transmitted back to the brain, forming a closed-loop system that enhances neurological rehabilitation.

Fourth, prioritize public outreach and talent development. Brain-computer interfaces fall under the field of biomedical engineering, integrating multiple disciplines such as biology, computer science, and robotics. Conducting public outreach programs for middle school students can spark their interest in interdisciplinary fields and help cultivate future talent for this sector.

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6. Conclusion

Non-invasive brain-computer interfaces do not require surgery; by reading electroencephalographic (EEG) signals from the scalp, they enable the human brain to directly control rehabilitation robots, offering new hope to people with limb movement disorders. Motor imagery, SSVEP, P300, and various hybrid modes have undergone extensive experimental validation in rehabilitation wheelchairs, robotic arms, and exoskeletons.

However, due to objective limitations such as the weak nature of EEG signals and significant individual variations, this technology still faces numerous challenges that need to be addressed. In the future, with continuous advancements in electrode materials and computer algorithms, brain-computer interface (BCI) rehabilitation robots may find their way into hospital rehabilitation departments and even ordinary households. For adolescents, BCI is also a cutting-edge field in biomedical engineering that is well worth exploring.

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