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Applications of Brain-Computer Interfaces in Medical Rehabilitation

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Abstract. Brain-computer interface (BCIs) technology is an advanced innovation that facilitates direct communication between the brain and external devices, effectively bypassing damaged neuromuscular pathways. By promoting neuroplasticity through real-time feedback during motor imagery tasks, BCIs enhance motor recovery without requiring actual movement, which is especially beneficial for individuals with severe motor impairments. This paper examines the application of BCI systems in medical rehabilitation, with a focus on enhancing motor function recovery and communication for patients affected by stroke, spinal cord injuries, and neuromuscular disorders such as ALS. However, BCIs still face significant challenges, including low signal quality, user fatigue, and variability in neural patterns. The study concludes by discussing current limitations and proposing future directions such as adaptive learning algorithms, improved signal acquisition methods, and greater personalization. These advances are essential for maximizing BCI effectiveness, expanding its clinical adoption, and improving the quality of life for individuals with severe motor impairments.

Keywords: BCI, Medical Rehabilitation, EEG, Application

1. Introduction

The increasing prevalence of neurological disorders, such as stroke and progressive neuromuscular diseases, presents significant challenges for rehabilitation. Traditional rehabilitation methods often fall short in addressing the complex needs of these patients, leading to limited recovery outcomes. In this context, brain-computer interfaces (BCIs) have emerged as a promising alternative, leveraging the brain's ability to adapt and reorganize through neuroplasticity. By enabling direct communication between the brain and external devices, BCIs offer new avenues for enhancing motor function and improving quality of life. As research in this field advances, understanding the efficacy and implementation of BCI technologies becomes critical for optimizing rehabilitation strategies and outcomes.

This paper reviews the medical application of BCIs in neurorehabilitation, particularly for stroke survivors and patients with progressive neuromuscular disorders. Through comparative analysis, It explores how BCIs promote neuroplasticity and evaluates the added benefits of hybrid systems like BCI-FES. This study aims to provide insights into how BCI technologies can be effectively implemented in rehabilitation programs, which will be essential for widespread clinical adoption.

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2. Technical overview

The concept of brain computer interfaces BCI or sometimes called as brain machine interfaces BMI first appeared in the early 1970s. Dr. Jacques Vidal proved the patterns from the brain could turn into commands to a computer directly [1]. BCI technology involves five key steps: signal acquisition, preprocessing, feature extraction, classification, and device control & feedback. Neural signals are collected, filtered for accuracy, and their features (e.g., amplitude, frequency, ERPs) are extracted. These features are then translated into commands using deep learning techniques and sent to external devices like bionic limbs, with feedback provided to the user [2-4].

BCIs primarily benefit patients with motor disabilities, such as stroke survivors, spinal cord injury patients, and those with traumatic brain injuries. Wolpaw suggested categorizing BCI users by their remaining neuromuscular control rather than medical diagnosis [5]. Therefore, based on his suggestion, the users can be separated into three groups.

Completely locked-in patients (e.g., late - stage ALS, brainstem stroke) have no detectable neuromuscular function. SCP - based systems, which require minimal input, can help establish basic communication. Partially locked - in patients (e.g., mid - stage ALS, severe cerebral palsy) have limited motor control but can use non - invasive BCI systems for communication and as a backup when physical control degrades. SMR - based cursor control has enabled some patients to make voluntary selections. Patients with significant voluntary function (e.g., using switch - based systems or joysticks) can benefit from BCI as an alternative access method when conventional systems become impractical due to disease progression [6].

3. Applications of brain-computer interfaces in medical rehabilitation

BCI's main functions are twofold: direct control of assistive technologies and neurorehabilitation [7]. Direct control bypasses damaged pathways, enabling use of devices like robotic limbs and communication tools. Neurorehabilitation focuses on promoting neuroplasticity and emotional recovery post - injury. Research shows BCI can improve daily life; Birbaumer demonstrated it reduces depression and anxiety by restoring control [8].

3.1. Motor function rehabilitation

One of the key applications of BCI in the medical sector is to rehabilitate the motor control of paralyzed patients. These patients' neural pathways are disrupted, hence brain signals cannot be passed to their destination, so BCI then can act as a bridge to bypass the damaged areas. Wolpaw demonstrated a control of a two dimensional signal by a non-invasive BCI system [9]. Some studies worked on SMR based systems for restoration of motor control [10]. The process works as patients are being asked to imagine moving a limb, while BCI will then detect the featured brain signals and turn them into commands for the robotic arm. There's a number of studies showing using BCI helps neurological recovery and so motor function will then improve as well. This indicates BCI is an effective therapeutic tool to aid post-stroke rehabilitation [11]. Hence, it also supports a home-based recovery and reduces long term physical disability.

3.2. Communication

BCI technology restores communication for patients who have lost voluntary muscle control but remain cognitively intact, particularly for Group 1 (completely locked - in patients due to diseases like ALS or brain stroke) [5]. These patients lack detectable neuromuscular function, rendering

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traditional aids like eye - tracking unusable. BCI becomes their sole communication method, allowing them to maintain autonomy and social interaction.

BCI also supports Group 2 patients, who retain very limited voluntary control (e.g., eye blinks, facial twitches) due to mid - stage ALS or severe cerebral palsy [12]. While they can use conventional assistive technologies, these require significant effort and may become fatiguing. BCI serves as a reliable, consistent backup system, remaining functional even if the disease progresses.

Several EEG - based BCI systems have been developed for communication. The P300 - based BCI is widely used due to its ease of use and low training requirements. It detects the P300 event - related potential (a positive voltage change occurring 300 milliseconds after a target stimulus) to identify user selections from a matrix of letters or icons. This system is effective in home environments and suitable for both Group 1 and Group 2. However, it relies on visual attention, has slower communication speed, and shows performance variability across individuals [13].

The sensorimotor rhythm (SMR) - based BCI detects changes in Mu (8 - 12 Hz) and Beta (18 - 26 Hz) frequency bands in response to motor imagery. Users can control cursor movements or make selections through event - related desynchronization (ERD) and synchronization (ERS). This system is suitable for Group 2 patients with some voluntary control and cognitive capacity. It offers continuous, flexible control but requires considerable training and clear SMR patterns for effective use [7, 14].

The slow cortical potential (SCP) - based BCI detects slow voltage shifts (0.5 - 10 seconds) from the cortical surface. Users learn to control these shifts for binary communication. This system is primarily for Group 1 patients, allowing basic communication even without motor function. However, it requires extensive training and only provides binary output [15].

3.3. Neurorehabilitation

BCI shows promise in neurorehabilitation as a therapeutic tool for patients with impaired neuromuscular function [10]. During stroke recovery, BCI promotes neuroplasticity by reorganizing neural pathways through targeted, repetitive neural activity. It detects motor imagery signals via EEG and provides immediate visual or haptic feedback, strengthening weakened neural connections and improving motor function. Unlike traditional therapies, BCI engages the brain directly without requiring physical movement, enhancing recovery by inducing neural firing patterns that imitate actual movement and bypass damaged regions [16-17].

A study on 28 hospitalized subacute stroke patients with severe motor deficits showed that those who received 1 - month BCI - supported motor imagery (MI) training had better functional outcomes and increased FMA scores compared to those without BCI support [17]. This highlights the benefits of early BCI intervention in the subacute phase, leveraging heightened neuroplasticity to accelerate cortical reorganization and reduce upper limb impairments. Meta - analyses of randomized controlled trials also confirm BCI's efficacy in enhancing motor outcomes, with patients showing greater improvements in daily activities and functional motor scores compared to those receiving standard physiotherapy [16].

Personalized BCI feedback tailored to a patient's unique brain signals further optimizes recovery by promoting more effective cortical reorganization [18]. Hybrid BCI - FES systems, which combine brain - signal - reading BCIs with muscle - stimulating FES, enhance therapeutic outcomes by creating a closed loop. EEG detects the intent to move, triggers FES to stimulate muscles, and generates sensory feedback to the brain, promoting stronger cortical reorganization [19]. This hybrid approach is particularly effective for upper limb fine motor control and hand function recovery,

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which are often difficult to restore after stroke. It remains beneficial in the chronic phase, continuing to promote neuroplasticity even after spontaneous recovery has plateaued.

BCI - FES also reduces spasticity by reconditioning neural pathways, decreasing muscle stiffness and involuntary contractions, thereby improving comfort and mobility in the affected limb and enhancing independence and quality of life [17]. For patients with severe paralysis or incomplete spinal cord injuries, integrating robotics with BCI - FES provides guided or amplified motion, ensuring quality practice and enhancing brain engagement and motor relearning [7]. Adaptive BCI - FES systems can learn each patient's unique brain patterns to adjust stimulation for better results. Long - term use of BCI - FES systems helps preserve brain changes and leads to lasting improvements in real - life tasks.

4. Challenges and future prospects

4.1. Challenges

BCI signal is the foundation of the entire system, hence the therapeutic effectiveness will depend on it, with accurate signal detection ensuring the brain receives correct, timely feedback, will be essential for promoting neuroplasticity. While a bad signal will lead to bad feedback, it may activate the wrong muscle, produce no movement, or trigger unintended actions. Hence confuses the brain, slows down learning, and can even reinforce incorrect neural pathways. In addition leading to our primary challenges in BCI systems, signal quality and reliability. Since brain signals measured on the scalp typically range in microvolts, causing them to be susceptible to interference from eye blinks, muscle activity, and electrical noise, hence affecting accuracy and reliability, these noises Artifacts from physiological and environmental sources may interfere with the true neural signals leading to wrong feedback. Moreover, motor imagery signals are usually very weak compared to the brain’s overall activity, so these signals may be hidden under background brain activity and external noise. While variability in signal quality also reduces reliability and causes inconsistent system behaviour [2]. To improve signal quality and reliability, advanced signal processing techniques can be used, such as using machine learning to filter noise or a better sensor design to capture more detailed signals [20].

Additionally, user fatigue is also a significant challenge for BCI usability. Operating a BCI often requires continuous mental focus, which can be mentally exhausting over time. As cognitive fatigue builds, signal quality deteriorates, leading to performance declines and user frustration. This not only hinders system effectiveness but also reduces user motivation and long-term engagement [2]. This could be improved by developing intelligent algorithms that adapt to how tired or focused the user is, adjusting the system to make it easier to use over time [10].

4.2. Future prospects

The future of BCI technology will focus on accuracy, adaptability, and real-world integration. Emerging developments in machine learning are expected to enhance the decoding of neural signals in variable conditions. Hybrid BCIs that combine EEG with other modalities like EMG or fNIRS promise greater signal stability and richer information. Future systems with development of adaptive algorithms will also be increasingly personalized. In clinical settings, BCIs are projected to play a central role in neurorehabilitation for conditions such as stroke, spinal cord injury, and neurodegenerative disorders. Beyond healthcare, consumer applications are expanding into fields such as gaming, augmented reality, and smart device control. Meanwhile, invasive BCIs—such as

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Neuralink and Synchron—offer potential for high-fidelity communication, motor restoration, and even cognitive enhancement, though they raise significant ethical and safety considerations. As AI, robotics, and neuroscience continue to converge, BCI systems are likely to become more intuitive, autonomous, and embedded in daily life. However, achieving this future will require addressing current challenges in signal quality and mental workload to ensure broad, reliable, and ethical deployment.

5. Conclusion

Brain-computer interfaces have emerged as a powerful tool in the field of medical rehabilitation, offering new avenues for restoring motor function and communication in patients with severe neuromuscular impairments. By translating brain signals into actionable commands, BCIs bypass damaged motor pathways and promote neuroplasticity, especially when paired with technologies like functional electrical stimulation or robotic devices. These systems have shown significant effect in stroke recovery, enabling improvements in fine motor control even during the chronic phase. However, despite significant advancements, BCIs still face challenges such as low signal quality and cognitive fatigue. Future progress will depend on the development of adaptive learning algorithms, improved hardware design, and user-centered system personalization. As these challenges are addressed, BCIs are expected to evolve into more intelligent, reliable, adaptive and accessible tools, not only for rehabilitation but also for broader applications in assistive technology and human-computer interaction. BCIs have great potential to enhance independence, quality of life, and long-term recovery for individuals with severe motor deficits.

However, the current study also has some limitations. Firstly, the sample size of the study is relatively small, which may limit the generalizability of the findings. Future research should aim to include a larger and more diverse population to better understand the effectiveness of BCIs across different patient groups. Secondly, the study focuses primarily on the technical aspects of BCI systems, but less attention is given to the long - term psychological and social impacts on users. Future research should also explore how BCIs affect users' mental health and social integration over extended periods.

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