BCI Application in Stroke Rehabilitation: Robotic Assisted System

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Abstract. Stroke remains a pervasive global health concern, exacting enduring motor, cognitive, and emotional tolls on affected individuals. The evolving landscape of neural interfaces has recently shown promising strides in reinstating lost sensorimotor functions. Non-invasive brain-computer interfaces (BCIs) have gained widespread recognition for their inherent advantages—simplicity, safety, and cost-effectiveness. The ongoing refinement of BCIs involves addressing previous technological and neurophysiological limitations, focusing on understanding distinctive neurophysiological alterations observed in individuals with disabilities. The exploration of brain connectivity attributes is pivotal in implementing BCI-based control systems. Emerging as a notable prospect for post-stroke motor rehabilitation, Brain-Computer Interface (BCI)-based therapy has made significant progress in restoring sensorimotor function. Revolutionary advancements have been made to traditional brain-computer interface (BCI) systems, which rely on brain signals obtained from electroencephalography (EEG) and rule-based translation algorithms. This comprehensive review delves into the realm of BCI Robotic Assisted Systems, offering a nuanced analysis of contributions from diverse researchers. It meticulously dissects these systems' advantages and limitations, providing valuable insights into their efficacy. Ongoing endeavors within the field prioritize enhancing the portability, simplicity, and cost-effectiveness of BCI technology, ultimately refining its overall usability. As research progresses, emphasizing larger sample sizes, there is a tangible potential to augment the reliability of BCI systems for stroke rehabilitation significantly. This trajectory holds promise for extending the benefits of BCI technology to a broader spectrum of patients, marking a transformative leap in neurorehabilitation methodologiest.

Keywords: Brain-Computer Interface (BCI), Robotic Assisted Systems (RAS), Stroke rehabilitation, Neurorehabilitation devices.

1. Introduction

A BCI is a computer-based framework that captures, deciphers, and transforms measurable neurophysiological signals into executable commands, steering a single or a sequence of output devices [1, 2]. These devices cater to diverse tasks contingent on the intended application. The spectrum of BCI-based systems is categorized into two broad divisions: invasive and non-invasive. The former involves techniques such as electrode arrays positioned directly on the brain's surface for electrocorticographic (ECoG) recordings or microelectrode arrays embedded within the cerebral cortex. Conversely, the latter non-invasive category stands out due to its portability, safety, comfort, and cost-effectiveness. Such systems primarily employ electroencephalogram (EEG) signals obtained via multiple electrodes placed on the scalp.

While both invasive and non-invasive approaches have exhibited impressive results in robotic and neuroprosthetic control, the recent strides in BCI research have propelled non-invasive techniques to the forefront [3]. Despite the historical disparities in reliability, accuracy, and speed, non-invasive BCIs are more accessible, safer, and cost-efficient. Moreover, ongoing developments in non-invasive BCI protocols aim to overcome past technical and neurophysiological constraints and align their performance with invasive BCIs.

Considering the distinctive neurophysiological patterns evident in individuals with disabilities compared to their neurotypical counterparts, a novel paradigm emerges: analyzing brain connectivity characteristics for BCI implementation. Simultaneously, commercial EEG-based BCI systems have gained momentum, rapidly and consistently identifying a limited set of mental states. These systems are progressively finding their way into consumer applications and gaining traction for controlling robots, often contingent on detecting the user's motor imagery status.

In this article, we delve into the evolving landscape of neural interfaces, focusing on non-invasive brain-computer interfaces (BCIs) and their potential applications in neurorehabilitation. As we navigate through the intricacies of motor recovery in neurological conditions such as stroke, spinal cord injury, and amyotrophic lateral sclerosis, the exploration of innovative approaches becomes imperative. The convergence of motor imagery (MI) and BCIs equipped with neurofeedback capabilities emerges as a promising avenue to enhance rehabilitation strategies. We unravel the distinctions between invasive and non-invasive BCIs, emphasizing the recent advancements that have propelled non-invasive techniques to the forefront. Furthermore, we explore the paradigm shift towards analyzing brain connectivity patterns for BCI implementation, shedding light on the unique neurophysiological signatures present in individuals with disabilities. Additionally, we touch upon the rising prominence of commercial EEG-based BCI systems, their applications in consumer settings, and their potential to revolutionize how we interact with technology, particularly in robotic control.

2. Robotic Assisted Systems Mechanism

Robotics Assisted Systems (RAS) within the domain of Brain-Computer Interface (BCI) technology embody a sophisticated amalgamation wherein brain signals seamlessly interface with robotic devices, ushering in an era of direct cerebral control and interaction with robotic entities. This mutually beneficial relationship facilitates the elimination of manual controls and empowers individuals to exert influence over the actions, movements, or tasks executed by these robotic counterparts by utilizing their neural signals.

Diving into the intricate components that constitute the bedrock of RAS, a triad of pivotal elements collaboratively works in concert to realize its extraordinary functionality:

Brain-Computer Interface (BCI): Positioned at the epicenter of the system, the Brain-Computer Interface serves as the neural hub responsible for acquiring and processing intricate brain signals emanating from the user. These signals undergo a meticulous decoding process, precisely revealing the user's intentions, commands, or desired actions.

Robotic Devices: The second cornerstone of RAS encompasses a diverse array of robotic devices, ranging from rudimentary robotic arms to cutting-edge exoskeletons. Infused with motors and sensors, these devices exhibit a broad spectrum of complexity, enabling them to seamlessly execute myriad physical tasks. Translating neural commands into tangible actions becomes a reality as these robotic entities become conduits to embody the user's intentions.

Brain-to-Robot Communication: The third and pivotal facet, Brain-to-Robot Communication, functions as the crucial bridge connecting decoded brain signals with the orchestrated actions of the robotic system. The BCI facilitates this seamless communication pathway, which ensures a fluid exchange between the user's brain and the robotic entity. Delicately extracted from neural signals, the captured intentions are expertly transmuted into precise actions or movements, epitomizing the harmonious synergy between human cognition and robotic execution. This intricate interplay marks the pinnacle of BCI technology, underscoring the transformative potential of Robotics Assisted Systems in shaping the future landscape of human-robot interactions.

2.1. Mecury Robotic Platform

To exemplify the principles of RAS, a notable research endeavor undertaken by Dr. Alkinoos and colleagues introduces the Mercury robotic platform [4]. This platform showcases a sophisticated robotic arm capable of a range of movements, spanning from shoulder to thumb joints. With two integrated motors, the platform can grasp small objects using a 3D printed gripper.

The current generation of the Mercury robotic arm is depicted in three distinct visuals (Figure 1):

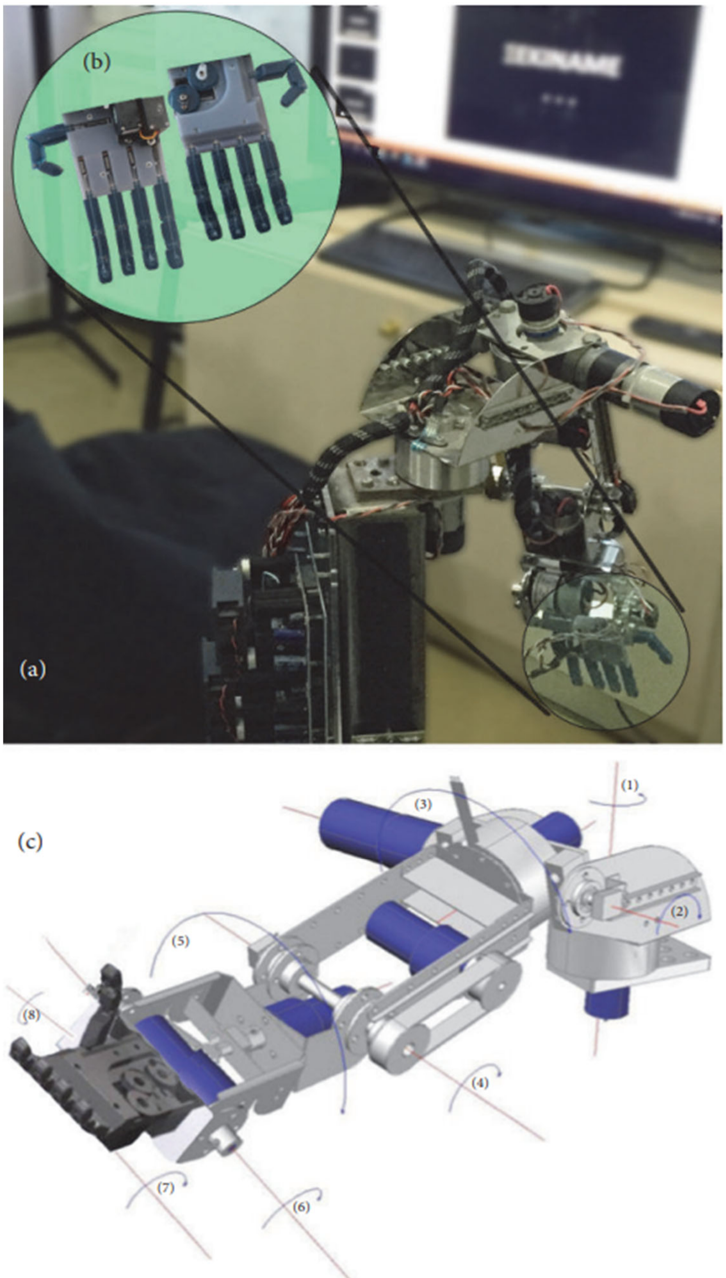

Figure 1. Mercury robotic arm [4]. (a) portrays the robotic arm's precise placement during experimental trials. (b) showcases the innovative 3D printed gripper in action. (c) illustrates the robotic arm's structure, complete with eight distinct degrees of freedom that grant it exceptional flexibility and versatility.

A meticulously orchestrated sequential process is implemented to explicate the operational workflow of this advanced system. Initially, users are presented with instructional content, typically in the form of a video, elucidating specific actions intended for the robotic platform.

Subsequently, during the Neural Signal Acquisition stage, the user's brain signals are meticulously recorded through the Brain-Computer Interface (BCI) interface, capturing the intricacies of their neural activity. These recorded electroencephalogram (EEG) signals are then transmitted to a dedicated BCI device for sophisticated processing.

The translated neural signals undergo a meticulous decoding process, translating the user's unique neural activity into discernible robotic commands. These decoded commands are then seamlessly transmitted to the robotic arm, triggering the precise execution of the intended actions with remarkable accuracy.

The culmination of this intricate process results in direct visual feedback for the user. With keen anticipation, they can observe the fluid actions and movements of the robotic arm, witnessing a tangible manifestation of their neural intentions. This seamless integration of instruction, neural signal processing, and tangible robotic response underscores the transformative potential of this technology in enhancing human-robot interactions.

3. Success of RAS

The success of brain-computer interface (BCI) applications spans different fields, especially in the multifaceted fields of solving neurological diseases and improving cognitive abilities [5, 6]. The broad use of BCI technology is demonstrated in a variety of applications, including neuroprocessing, wheelchairs, home environments, humanoid robots, and the rehabilitation of individuals recovering from stroke or spinal cord injury. In addition to alleviating motor deficits, brain-computer interfaces have shown great promise in addressing higher-order cortical dysfunction. This includes improving working memory and inhibitory control in those with attention-deficit/hyperactivity disorder (ADHD), and fostering social and emotional skills in those on the autistic spectrum, and aiding in the recovery of cognitive deficits associated with dementia [7]. Furthermore, brain-computer interfaces make a significant contribution to maintaining cognitive abilities in healthy older adults, thus promoting successful aging and mitigating the social challenges of an aging population.

The integration of electrooculogram (EOG) and steady-state visual evoked potential (SSVEP) signals revealed noteworthy potential in specific experimental settings using hybrid BCI systems. EOG-based switches exhibit commendable efficiency in selectively deactivating or activating robotic arm control systems, introducing flexibility and user convenience [8]. Notably, the incorporation of blink-based cancel commands further enhances the effectiveness of the system in navigating complex tasks, as demonstrated by the asynchronous operation of the robotic arm. The experiment demonstrated participants' skillful control of a robotic arm via a hybrid BCI system to perform subtle movements such as grasping, lifting, and repositioning target objects [9]. The efficacy of this system was evident when blinking was used to cancel inappropriate commands, as a reduction in the number of commands executed by the robotic arm was observed, thereby improving overall control efficiency. These empirical findings highlight the excellent versatility and utility of BCI technology, especially in the field of robot control for complex and demanding tasks.

Researchers addressed limitations associated with non-invasive brain-computer interfaces (BCIs) based on electroencephalographic (EEG) signals [10]. Two critical limitations were identified: the challenge of reliable BCI command detection as EEG epoch length decreases, hindering the achievement of high information transfer rates, and the incorrect interpretation of EEG signals as commands when there is no task being performed by the patient.

Yajun Zhou, Shenghong He, Qiyun Huang, and Yuanqing Li conducted a study with the goal of addressing the difficulty of accurately differentiating between the idle and control states in an asynchronous brain-computer interface (BCI) based on electroencephalography (EEG) [11]. The suggested remedy entails a brand-new hybrid BCI system that integrates blink-related electrooculography (EOG) signals with steady-state visual evoked potentials (SSVEPs) in the EEG signal.

The twelve character-corresponding buttons that make up the graphical user interface (GUI) flicker at different fixed frequencies and phases to elicit SSVEPs and change sizes simultaneously for highlighting. While their EEG and EOG signals are being collected, users choose a character by focusing on its frequency-phase stimulus and blinking their eyelids in time with its highlighting. Multifrequency band-based canonical correlation analysis (CCA) is applied to the EEG data in order to discover SSVEPs, and user blinks are identified by analysis of the EOG data. The findings of SSVEP and blink detection are then used to determine the target character.

Ten healthy participants participated in the studies, and the average information transfer rate (ITR) was 105.52 bits/min; the average accuracy was 95.42%; the average reaction time was 1.34 s; and the average false-positive rate (FPR) was 0.8%. According to the study's findings, the suggested hybrid asynchronous BCI system shows promise for real-world use in control and communication by producing a number of instructions with a high ITR and low FPR. (Zhou et al., 2020).

This novel method, which combines SSVEP and EOG signals, represents a noteworthy advancement toward the creation of dependable and effective BCIs, exhibiting encouraging outcomes with implications for communication and control applications in the future. The study provides valuable insights into the ongoing evolution of hybrid BCI systems and their potential impact on enhancing user experience and performance in various contexts.

4. Conclusion

This article provides an insightful exploration into the nuanced analysis and comprehensive review of various experiments and research initiatives conducted by domain experts. These efforts have elucidated the basic working principles and broad range of brain-computer interfaces applications. The recent emergence of new paradigms and advances in non-invasive brain-computer interface protocols represents a collective effort to overcome previous technological and neurophysiological limitations. Complex changes in neurophysiology within brain networks after spinal cord injury (SCI) are considered key considerations in designing resilient and sustainable non-invasive brain-computer interfaces specifically tailored for motor recovery and rehabilitation. However, the effectiveness of any rehabilitation strategy extends beyond the realm of technology. It includes user perception, satisfaction, overall experience and performance. Despite considerable progress, opportunities for enhancements remain, consistent with the technology's inherently early stage. While challenges, particularly related to cost, continue to pose obstacles, the overall potential and transformative impact remain undeniable. The challenge at the forefront is deciphering the complexity of brain activity, especially in scenarios involving multiple categories, for which huge obstacles remain. Encouragingly, integrating functional connectivity features into BCI class classification holds promise for solving this complex challenge. Of note, patients are currently being tested on their upper limbs due to limited range of motion, highlighting the need for further innovation to meet the needs of different patients. Safety issues and economic feasibility also deserve careful consideration as BCIs continue to be developed and implemented in clinical settings. As we look toward the future, the trajectory of BCI neurorehabilitation systems has the potential to be transformative by incorporating advanced flexible electronics. The continued development of this technology will redefine the boundaries of what is achievable in the field of neurorehabilitation. Looking to the future, brain-computer interfaces are not only rehabilitation tools, but also dynamic adaptive systems that meet individual needs, creating a new era of collaboration between human cognition and technological innovation. As we anticipate continued advances, the prospect of brain-computer interfaces revolutionizing neurorehabilitation remains an enticing and promising frontier, promising unprecedented levels of neurological recovery.

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