A Review on Brain Computer Interface

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Abstract:

The utilization of Brain-Computer Interface (BCI) technology enables individuals to harness brain signals as an alternative means of communication and device control, bypassing traditional pathways involving peripheral nerves and muscles. Various methodologies are employed to gather data from brain sensors, which primarily monitor physiological processes. BCI represents a burgeoning field of research with diverse applications in the medical domain. This review delineates the present state and future potential of BCI technology, encompassing a comprehensive examination of BCI-related signals, functional components, and applications across multiple sectors. Specifically, we explore BCI's role in medicine, entertainment, gaming, safety, security, and biomedicine. Furthermore, we address current limitations, challenges impeding widespread clinical adoption, and envisage the trajectory of BCI technology in the future.

Keywords Brain computer interface · BCI · EEG

1 Introduction:

Throughout history, humanity has harbored an insatiable desire to explore every facet of the universe, leaving no stone unturned. The enigma of the human brain, once perceived as an impenetrable fortress, has long captivated the curiosity of mankind [1]. However, with the rapid advancement of technology, the chasm between humans and machines has begun to narrow. In 1970, pioneering research on Brain-Computer Interface (BCI) commenced at the University of California Los Angeles (UCLA), initially funded by the National Science Foundation and later supported by a contract from DARPA. BCI represents a direct communication pathway between the human brain and computers, effectively supplanting the natural connection between the central nervous system (CNS) and musculoskeletal system [2]. Initially conceived for biomedical applications aimed at restoring physical disabilities or enhancing athletic prowess, the scope of BCI research has since broadened to encompass non-medical domains. Recent endeavors have explored BCI's utility as a novel input mechanism and its potential to foster hands-free applications [4, 5]. Moreover, the benefits of BCI technology for healthy individuals have been extensively deliberated [6].

This research paper endeavors to elucidate the fundamentals of BCI, providing novice readers with comprehensive insights into its workings, rationale, and applications. Additionally, it delves into the myriad challenges confronting BCI adoption, along with potential avenues for mitigation, while also casting a gaze toward the future of this transformative technology.

1.1 Functions of BCI:

Invasive BCIs represent a category of interfaces that are surgically implanted directly into the brain, yielding the highest quality signals. The underlying function of a BCI application program revolves around observing user status or facilitating communication of their thoughts. The BCI system records brain waves and transmits them to the computer system to execute the intended task. These transmitted waves serve to convey ideas or manipulate objects.

1.1.1 Communication Bridge:

The Brain-Computer Interface (BCI) system serves as a vital conduit between the human brain and the external environment, obviating the need for conventional modes of information transmission. It facilitates the transmission of information to the human brain and interprets silent thoughts, thereby enabling individuals with disabilities to articulate their opinions and ideas through various means, including silent speech communication [7], spelling applications [8], and semantic categorization [9]. BCI-assistive robots play a pivotal role in enhancing the quality of life for individuals with disabilities, both personally and professionally, fostering collaboration and community-building endeavors [10].

1.1.2 User Status Monitoring:

Initially, BCI applications were directed towards individuals with disabilities characterized by limited mobility or speech impairments, aiming to offer alternative communication channels. However, with the significant advancements in this technology, BCIs may find utility among healthy users in specific contexts. They serve as a tool for physiological measurement, capturing and utilizing an individual's emotional and cognitive states.

Moreover, the scope of brain signal utilization has expanded to encompass the control of certain objects or the provision of alternatives, a function known as passive BCI [11]. The user status monitoring function of BCI is deemed valuable in the human-machine interface, adapting according to the estimated emotional or cognitive status of the user [6, 9]. It operates within shared control environments, determining the most appropriate control type for various scenarios. The subsequent section will delve into specific applications employing brain-computer interfaces.

2 Applications of BCI

Brain-computer interfaces (BCIs) have demonstrated extensive utility across diverse research domains. Initially developed to aid individuals with physical disabilities, this technology has transcended its original purpose and found applications in medical, neuroergonomics, smart environments, neuromarketing and advertisement, educational and self-regulation, games and entertainment, as well as security and authentication fields.

The applications of BCIs can be succinctly summarized as follows: summarized in Fig. 1 [12].

1.2 Medical Application

The healthcare field harnesses the potential of brain signals across various stages, including prevention, detection, diagnosis, rehabilitation, and recovery (Fig. 2) [13]. Medical prevention is crucial due to potential impairments and reduced alertness caused by factors like smoking and alcohol consumption [14–18]. Additionally, traffic accidents, a leading cause of fatalities and injuries, underscore the importance of preventive measures [19, 20]. Research focuses on understanding and mitigating factors contributing to accidents, such as motion sickness [21, 22].

BCI systems' capability to monitor mental states aids in predicting and detecting health issues like brain abnormalities (e.g., tumors), seizures (e.g., epilepsy), sleep disorders (e.g., narcolepsy), and brain swelling (e.g., encephalitis). EEG serves as a cost-effective alternative to MRI and CT scans for tumor detection, with studies exploring EEG-based tumor detection [23, 24] and breast cancer identification [25]. Systems like those proposed by Sharanreddy and Kulkarni [22] identify EEG abnormalities associated with tumors and seizures.

Mobility rehabilitation aims to restore or adapt mobility for patients with reduced mobility, such as stroke survivors. Stroke, caused by disrupted blood supply to the brain, can result in speech impairment, memory loss, or paralysis [26]. Research indicates that neuroplasticity allows for brain structure reorganization and motor function restoration post-stroke [27, 28, 29].

BCI-based neuroprosthetic devices, including prosthetic limbs, offer a solution for patients unable to regain mobility or communication abilities [30–33]. Such devices restore functionality and enhance quality of life for patients with disabilities.

1.1 Neuroergonomics and Smart Environment

Neuroergonomics integrates brain-computer interface (BCI) technology into smart environments, including smart homes, workplaces, and vehicles, enhancing safety, comfort, and physiological control in daily life. By monitoring the user's mental state, these environments can dynamically adjust to meet individual needs. The synergy between Internet of Things (IoT) and BCI technologies is anticipated, fostering further advancements in this field [34].

1.2 Neuromarketing and Advertisement

BCI research has extended into the realm of marketing, particularly in the field of neuromarketing. Studies have explored the advantages of utilizing electroencephalography (EEG) to evaluate the effectiveness of TV advertisements, including both commercial advertisements and political campaigns [35]. Researchers have also focused on assessing cognitive functions related to memorization of TV commercials, offering an alternative method for evaluating advertising effectiveness.

Educational and Self-Regulation

BCI technology has made inroads into the field of education and self-regulation. Neurofeedback, a technique aimed at enhancing brain performance by adjusting to individual brain activity, has been integrated into the education system. EEG signals are utilized to assess the clarity of information being studied, allowing for personalized interactions tailored to each learner's response [36]. Additionally, EEG-based emotional intelligence has been applied in sports competitions to manage stress levels [37]. Furthermore, BCI technology has been explored in the context of self-regulation and skill learning, particularly through functional Magnetic Resonance Imaging (fMRI) neurofeedback [28].

1.2 Games and Entertainment

Non-medical brain-computer interfaces find extensive use in entertainment and gaming applications. These interfaces leverage players' physiological functions such as brain signals, heartbeat, and facial expressions. For instance, in [38], various games are discussed where players control helicopters to navigate through 2D or 3D virtual worlds. Additionally, Tan and Nijholt [6] described a brain game specifically designed to reduce players' stress levels. In this game, players can only control the movement of a ball by relaxing, incentivizing calmness and providing a means for players to learn stress control while being entertained.

Security and Authentication

Security systems often utilize biometrics-based, knowledge-based, and object-based authentication methods. In this field, various applications include the detection of signal distortions through EEG and eye movement, as well as the identification of irregular behavior and suspicious objects, as discussed in [39]. In a scenario where multiple testers and viewers are observing the recording of a suspicious event, only EEG signals and precise eye movement can accurately identify potential targets, a capability not achievable through other methods [39].

Moreover, several researchers have explored the authentication of EEG signals generated from driving behavior as part of smart navigating systems. For instance, in [40, 41], a simplified driving simulator with mentally tasked conditions is employed to verify the driver's identity on demand.

1 Components of BCI System

A BCI system comprises several key components, as depicted in Fig. 3 [42]:

1. Signal Acquisition: This component records electrophysiological signals from the brain and transmits them for further processing. Brain signal acquisition methods include invasive and non-invasive techniques, as illustrated in Fig. 4 [13].
2. Preprocessing: The preprocessing component enhances the signal-to-noise ratio of the recorded signals. This step is crucial for improving the quality of the data before feature extraction.
3. Feature Extraction: Feature extraction aims to identify discriminative characteristics in the processed signals. These features provide valuable information for classification tasks while reducing the dimensionality of the data.
4. Classification: In the classification stage, machine learning algorithms or classifiers interpret the extracted features and classify them into relevant categories or commands. This step translates brain signals into actionable commands for controlling external devices or applications.
5. Application Interface: The final component of the BCI system is the application interface, which receives the output from the classification stage and translates it into commands or actions for interaction with external devices or software [3, 43].
By integrating these components, a BCI system enables users to communicate or control external devices using brain signals, offering new avenues for interaction and accessibility.

9. Challenges in BCI System

The utilization of brain signals for establishing a communication interface presents several challenges, encompassing technical and usability aspects:

1. Technical Challenges: These challenges primarily pertain to system obstacles, especially those related to the characteristics of EEG features. EEG signals are susceptible to various sources of noise and artifacts, which can degrade signal quality and complicate signal processing algorithms. Overcoming these technical hurdles requires advancements in signal processing techniques, artifact removal methods, and feature extraction algorithms.
2. Usability Challenges: Another set of challenges involves limitations that affect the level of human acceptance and usability of BCI systems. Usability challenges encompass factors such as user comfort, system reliability, ease of use, and adaptability to individual user needs. Designing BCI systems that are intuitive, user-friendly, and capable of seamlessly integrating into users' daily lives is essential for overcoming usability challenges.
Addressing these challenges requires interdisciplinary collaboration between researchers in neuroscience, engineering, computer science, and human-computer interaction. By tackling technical and usability challenges, BCI systems can realize their full potential in facilitating communication and control for users with diverse needs and abilities.

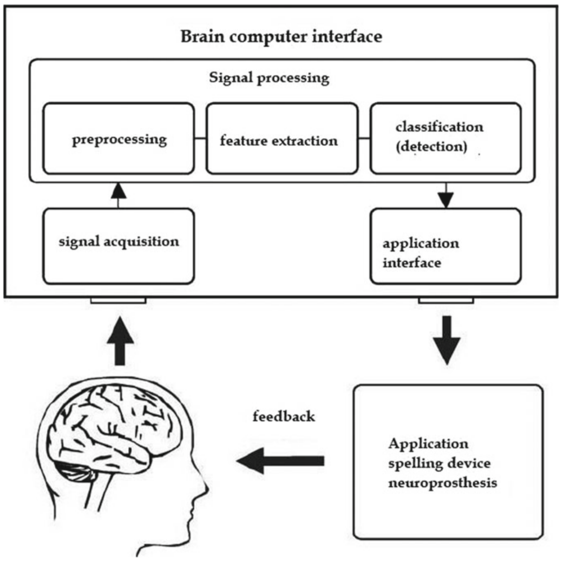

Fig. 3 Components of a BCI system

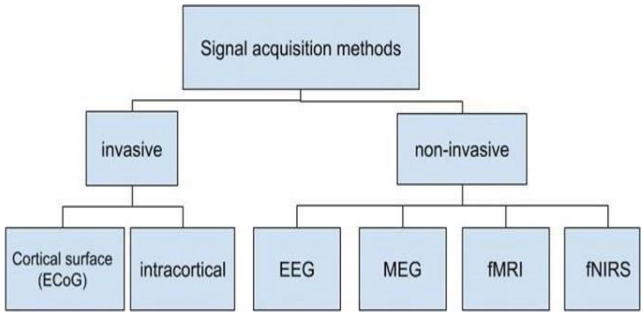

Fig. 4 Brain acquisition methods

1.1 Usability Challenges

User acceptance of BCI technology utilization presents a significant limitation, as highlighted in [4]. One aspect contributing to this limitation is the training process required for discriminating between different classes of brain signals. This training typically occurs either during the classifier calibration phase or in the initial phases of system use [45]. Additionally, sweating is a common issue encountered when wearing prosthetic devices, which can pose challenges in managing the device's energy consumption efficiently. These factors underscore the importance of addressing usability concerns and optimizing BCI systems to enhance user acceptance and functionality in real-world scenarios.

1.2 Technical Challenges

Detecting the chaotic behavior of neural ensembles within the highly complex, nonlinear, and nonstationary human brain presents a significant challenge for BCI technology [5, 46]. The nonstationary nature of electrophysiological brain signals is a primary obstacle in the development of effective BCI systems. Variability in EEG signals due to psychological and emotional states induced by different activities or conversations further complicates signal analysis [47]. Noise, including artifacts from changes in electrode position and environmental factors, also contributes to the nonstationarity problem in BCI technology.

To maintain high spatial accuracy, signals are typically recorded from multiple channels. However, the amount of data required to adequately describe these signals increases exponentially with the dimensionality of the vectors, posing a challenge for feature extraction methods [44]. These methods are crucial for identifying distinguishing features within the data. Ideally, a large number of training samples for each class should be used, typically five to ten times the number of dimensions. However, in high-dimensional environments, sustaining this approach becomes impractical, leading to the "curse of dimensionality" in BCI systems [48]. Addressing these challenges is essential for advancing the capabilities and reliability of BCI technology in practical applications.

2 Conclusion

The human brain, with its highly complex structure, generates signals that reflect the user's intentions and control behaviors, influenced by information from various body parts and organs. Brain-Computer Interface (BCI) technology acts as a conduit between the human brain and computers or devices, offering a range of applications across different sectors such as medical, organizational, transportation, gaming, entertainment, security, and authentication.

This study highlights the five stages of BCI, including signal acquisition, preprocessing, feature extraction, feature classification, and application interface. Various devices are employed to capture brain signals, enabling users to perform tasks solely through their thoughts, bypassing the need for functional but paralyzed organs.

Despite its potential, BCI faces challenges such as understanding brain activity, usability issues, capturing minute details, and hardware limitations. However, overcoming these challenges holds the promise of enhancing decision-making abilities and manipulating the human body's responses to different situations in novel ways.

Looking ahead, advancements in BCI have the potential to revolutionize human interaction, facilitating communication and connectivity through neural signals. Ultimately, the progression towards connecting individuals through neural signals represents a significant step forward in human-computer interaction.

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