Scientific Journal of Impact Factor (SJIF): 5.71
E-ISSN (O): 2348-4470
P-ISSN (P): 2348-6406
International Journal of Advance Engineering and Research Development
Volume 10,Issue 5,May 2023

Advances and Challenges in Non-Invasive EEG-based Brain-Computer Interfaces: Applications, Technologies, and Future Prospects: A Comparative Review

Dhruval Patel[1], Prof. Sapna Kataria[2]

[1]*Computer Science Engineering, (Semester VI),Indus University, Ahmedabad, India dk26062002@gmail.com*

[2]*Computer Science Engineering,Indus University,Ahmedabad, India,sapnakataria.cse@indusuni.ac.in*

Abstract— *Brain-computer interfaces (BCIs) are emerging technologies that allow direct communication between the brain and external devices. This review paper covers several articles that discuss the recent advances in non-invasive EEG-based BCIs for various applications, including communication and motor function restoration for patients with disabilities. The articles highlight the different modalities and technologies used in EEG-based BCIs, the challenges faced in developing reliable and effective systems, and the recent developments and potential future applications. The articles stress the need for standardized approaches in developing EEG-based BCI systems, standardized metrics for evaluating their performance, and artifact removal techniques. Despite the current challenges, the reviewed articles provide an optimistic outlook for the future of EEG-based BCIs, with potential applications in diverse fields such as gaming, virtual reality, biometric identification, and collaborative problem-solving.*

Keywords—*EEG, Brain Computer Interface (BCI), Slow Cortical Potentials, Sensorimotor Rhythms, P300 Potential, Emotion Recognition, Applications, Challenges, Performance Evaluation, BrainNet*

Paper Received: *20/04/2023* ***Paper Accepted:*** *12/05/2023* ***Paper Published:****19/06/2023*

I. Introduction

Brain computer interfaces, or BCI, have become an increasingly popular area of research in recent years due to their potential applications in a wide range of fields, such as rehabilitation, robotics, affective computing, gaming, and neuroscience. One of the primary techniques used in BCI is electroencephalogram (EEG), which measures the electrical signals generated by neurons in the brain. EEG has been used for decades as a diagnostic tool for neurological disorders, but it was not until the 1960s and 1970s that researchers began to explore its potential for use in controlling devices through brain waves. Despite significant advances in BCI research and technology, there are still many challenges and limitations to overcome, such as the low signal-to-noise ratio of EEG signals and ethical and social implications of BCI. In this paper, we will explore some of these challenges and limitations, as well as potential solutions and future directions for EEG-based BCI systems.

II. Literature Survey

[1] The article provides a comprehensive overview of Brain-Computer Interfaces (BCIs) and the role of Machine Learning (ML) in BCI applications. It discusses the various types of research that have been conducted in this field and provides a detailed analysis of the ML methods used for mental state detection, mental task categorization, emotion classification, EEG signal classification, ERP signal classification, motor imagery categorization, and limb movement classification. The authors explore the different methods employed in BCI mechanisms for feature extraction, selection, and classification and provide a comparative study of reviewed methods.

The authors begin by introducing BCIs and highlighting their importance in the context of automated control and monitoring applications. They explain how BCIs provide a direct link between the human brain and computers, allowing for the manipulation of computers and devices based on signals and thoughts generated by the brain. The authors then discuss the potential applications of BCIs in various fields, including medicine, gaming, entertainment, and learning.

The four main components of a BCI system have been described: collecting brain signals, identifying and categorizing them, transmitting commands, and receiving feedback. They explain how BCI allows people to interact with the outside world using EEG signals without using peripheral muscles or nerves.

They then explain the role of machine learning in BCI systems, which uses computers to perform tasks without explicit programming. Various ML techniques are used for preprocessing, feature extraction, selection, and classification. These methods are used for mental state and task detection, emotion classification, and EEG and ERP signal classification. Motor imagery and limb movement categorization are also discussed.

The authors also provide a comparative study of the various methods employed in BCI mechanisms for feature extraction, selection, and classification. They discuss the advantages and disadvantages of each method and provide recommendations for future research in this field.

Overall, the article provides a comprehensive overview of BCIs and the role of ML in BCI applications. The authors provide a detailed analysis of the various ML techniques used in BCI systems and provide a comparative study of the different methods employed in BCI mechanisms for feature extraction, selection, and classification. The article is well-structured, easy to read, and provides valuable insights into the future of BCI technology.

[2] The overall application of the BCI technology described in the paper is to provide a means for individuals with physical disabilities to control various devices and systems using their brain signals. This includes applications such as controlling a robotic arm, a computer cursor, or even a wheelchair.

It strongly accepts that, the future possibilities of BCI are quite promising. As the technology improves and becomes more widely accessible, it has the potential to significantly enhance the quality of life for individuals with disabilities. Additionally, BCI could also have applications in fields such as gaming and virtual reality, as well as potentially helping to treat certain neurological disorders.

However, there are also several challenges that must be addressed in order for BCI technology to reach its full potential. One major challenge is the need for highly accurate and reliable signal detection and processing, which can be difficult to achieve in real-world environments. Additionally, there are also ethical and privacy concerns surrounding the use of BCI technology, particularly in the context of potential misuse or unintended consequences. Finally, there is also the challenge of making BCI technology accessible and affordable to individuals who may benefit from it, which will require continued research and development efforts.

It suggests that combining BCI systems with other interfaces, such as fNIRS or fMRI, could improve the accuracy and efficiency of BCI applications. In the medical domain, BCI could be used to control assistive robotic devices, such as wheelchairs and robotic limbs. It could also be used in neuro-rehabilitation, speech therapy, and for reducing hypokinetic activity in stroke and hyperkinetic activity in ADHD. In the non-medical domain, EEG-based BCI could monitor cognitive load, attention, drowsiness, and other aspects of the mind, which could be used for e-learning, psychometric exams, and military training. Safety and user-friendliness are also discussed, and the possibility of developing a "brain switch" to disconnect the user from the device when not intending to use it is suggested. The article also notes that the number of publications in the field has been gradually increasing since 2009.

[3] The paper "Brain–computer interfaces: communication and restoration of movement in paralysis" provides an overview of the field of brain-computer interfaces (BCIs) and their potential applications in restoring communication and movement in individuals with paralysis. The authors discuss the various types of BCIs and their respective advantages and limitations.

The paper begins with an introduction to the challenges faced by individuals with paralysis, including communication difficulties and the loss of mobility. The authors then provide an overview of BCIs, discussing how they work and the various types of signals that can be used to control them. They also describe the various components of a BCI system, including signal acquisition, signal processing, and feedback.

The authors then review the applications of BCIs in restoring communication and movement in individuals with paralysis. They discuss the use of BCIs for communication, including the use of electroencephalography (EEG) to decode imagined speech and the use of invasive neural recordings to restore speech in individuals with locked-in syndrome. They also describe the use of BCIs for motor control, including the use of EEG and invasive neural recordings to control prosthetic limbs and restore movement in individuals with paralysis.

Overall, the paper provides a thorough overview of the field of BCIs and their potential applications in restoring communication and movement in individuals with paralysis. The authors summarize the current state of the field and discussing the various challenges that need to be addressed in order to further advance this technology.

The paper focuses on the status of brain-computer or brain-machine interface research, with a particular focus on non-invasive brain-computer interfaces (BCIs) and their clinical utility for direct brain communication in paralysis and motor restoration in stroke. It discusses the various types of signals that have been proposed to control external devices and provides a comprehensive review of the different types of BCIs that have been developed. The review also discusses the challenges and limitations of current BCIs and proposes future directions for research in this field.

The paper discusses two main types of brain-computer interfaces (BCIs): invasive and non-invasive. Invasive BCIs involve the implantation of microelectrode arrays in the brain to record neural activity directly from the source, while non-invasive BCIs record signals from the surface of the scalp using EEG or MEG.

The paper discusses two types of BCIs: invasive and non-invasive. Invasive BCIs record neural activity directly from microelectrode arrays implanted in the brain, while non-invasive BCIs record signals from the scalp using EEG or MEG. Non-invasive BCIs use signals such as SCPs, SMRs, and P300 ERPs, which can be learned through visual and auditory feedback or require no training at all. Non-invasive BCIs have shown promising results in allowing paralyzed patients to communicate and control computer devices, while invasive BCIs' applicability to paralyzed humans is uncertain. BCI technology has potential clinical applications, including the treatment of epilepsy by training patients to regulate cortical activity through voluntary control of brainwaves such as SMRs and SCPs.
Epilepsy is a neurological disorder characterized by recurrent seizures. BCI technology can be used to reduce seizures in patients with drug-resistant epilepsy by training them to regulate their cortical activity through the voluntary control of specific brainwaves. By increasing the amplitude of sensorimotor rhythm (SMR) brainwaves, patients can reduce the occurrence of seizures. Similarly, training patients to down-regulate cortical excitation through the regulation of slow cortical potentials (SCPs) has also been successful in reducing seizure frequency in patients with focal intractable epilepsies.

BCI technology can also be used to assist patients with paralysis caused by spinal cord injuries. Patients can use SMR-based BCIs to control the delivery of electrical stimulation to hand and arm muscles, allowing them to perform activities of daily living. In addition, invasive BCI systems have been developed that use implanted microelectrodes in the primary motor cortex to allow patients to move a computer cursor or robotic arm.

Finally, BCI technology has potential applications in the treatment of a range of medical conditions, including high blood pressure, cardiac arrhythmias, vascular pathologies, renal failure, and gastrointestinal disorders. Biofeedback techniques can be used to teach patients to regulate their autonomic nervous system functions, allowing them to control these internal body functions through instrumental conditioning.

[4] The paper titled "EEG-Based BCI Control Schemes for Lower-Limb Assistive-Robots" provides a comprehensive review of the state-of-the-art EEG-BCI controlled wearable and assistive technologies for individuals with neuromotor disorders, spinal cord injuries, stroke, disarticulation, or amputation of the lower limb. It highlights the potential benefits of BCI in providing an augmentative communication channel between the brain and output devices, primarily for subjects with limited mobility. It identifies three EEG communication signals employed by these applications, namely SMR, ERP, and VEP.

The paper presents a novel contribution by presenting a generalized BCI control framework that fits into hierarchical layers, highlighting the feature extraction, classification, and execution methods employed by each application. It reviews various applications such as exoskeletons, orthosis, wheelchairs, mobile/navigation robots, and humanoids. Key features from each application were discussed and presented in Table 1 of the paper.

The paper identifies several challenges faced in the implementation of EEG-based BCI control schemes for lower-limb assistive-robots. These include the design of non-invasive modalities, which can limit performance compared to invasive ones, and the limited size of features employed in the algorithms. Complex movements require more sets of parameters to execute a seamless output, which is still one of the challenging problems that require expertise to develop efficient and robust algorithms to apprehend user’s motion intention.

Another challenge is the lack of quantitative performance indicators for the algorithms' evaluations, such as explicit signal classification percentages and error measurements between expected and real system trajectories. Additionally, there is no indication about the measurements of the user-energy consumption, walking endurance, and system costs.

Finally, conducting tests under realistic conditions, with patients having lower-limb pathologies, needs special attention, as the observations make the comparison of the dynamic behavior of each application difficult. These challenges must be addressed to ensure the successful implementation of EEG-based BCI control schemes for lower-limb assistive-robots.

The overall conclusion of the paper is that there is a need for the development of efficient and robust algorithms to accurately interpret a user's intended movements in brain-computer interface systems. The paper highlights the potential of non-invasive BCIs in allowing paralyzed patients to communicate and control external devices, and discusses the various techniques and signal types used in BCI research, including invasive and non-invasive approaches. Additionally, the paper discusses the clinical applications of BCI technology, including the treatment of epilepsy, attention regulation, paralysis, and operant control of physiological responses.

[5] The paper titled "EEG-Based BCI Emotion Recognition: A Survey" provides a comprehensive review of research conducted in the field of affective computing, particularly in the area of EEG-based brain-computer interfaces (BCI) for emotion recognition. The paper highlights the significance of automatic emotion recognition and its potential impact on various aspects of human life, including mental health, interpersonal communication, and human-machine interaction.

The authors performed a survey of scientific literature from 2015 to 2020 to analyze trends and applications of algorithms in this field. They discuss the different components of an EEG-based system, such as emotion elicitation, feature extraction, classification algorithms, and performance evaluation. The authors also provide insights for future developments in this area. Overall, the paper highlights the potential of EEG-based BCI emotion recognition and the challenges that researchers still face in accurately detecting and classifying emotions.

The paper's strength lies in its comprehensive and systematic review of research studies. The authors have followed the guidelines for conducting a survey and used appropriate inclusion and exclusion criteria to select studies for analysis. They have also highlighted potential errors and knowledge gaps in the field, providing direction for future research. The paper's language is clear and concise, making it easy for the reader to understand the content.

Overall, "EEG-Based BCI Emotion Recognition: A Survey" is a well-written and informative paper that provides a thorough analysis of the state-of-the-art research in the field of EEG-based BCI emotion recognition. The paper is valuable for researchers and practitioners working in the field of affective computing and can serve as a reference for future research studies.

[6] This case study focuses on the clinical application of an electroencephalography (EEG)-based brain-computer interface (BCI) in a completely paralyzed patient diagnosed with severe cerebral palsy. The patient was trained over several months to use the BCI for verbal communication, with EEG feedback training performed in the patient's home (clinic) and supervised from a distant laboratory through a telemonitoring system.

Cerebral palsy is a neurological disorder that affects movement, muscle tone, and coordination. It is caused by damage to the developing brain before or during birth, or within the first few years of life. The severity of the condition can vary widely and may result in difficulty with walking, speaking, or performing everyday tasks. There is no cure for cerebral palsy, but treatments such as physical therapy, medications, and surgery can help manage symptoms and improve quality of life.

Online feedback computation was based on single-trial analysis and classification of specific band power features of the spontaneous EEG, and task-related changes in brain oscillations over the course of training steps were investigated by quantifying time-frequency maps of event-related (de-)synchronization (ERD/ERS).

The patient learned to produce two distinct EEG patterns, beta band ERD during movement imagery vs. no ERD during relaxing, and to use this for BCI-controlled spelling. Significant learning progress was found as a function of the training session, resulting in an average accuracy level of 70% (correct responses) for letter selection, and the patient was able to perform "copy spelling" with a rate of approximately one letter per minute.

The proposed BCI training procedure, based on EEG biofeedback and concomitant adaptation of feature extraction and classification, could potentially improve the communication ability in locked-in patients.

Telemonitoring-assisted BCI training could facilitate clinical application in a larger number of patients. The study demonstrates that it is possible to develop a new communication device for completely paralyzed patients using the electrical brain activity to control a computer, resulting in an alternative communication channel.

[7] The paper " EEG-Based Brain–Computer Interfaces for Communication and Rehabilitation of People with Motor Impairment" provides a comprehensive review of non-invasive, EEG-based brain-computer interfaces (BCIs) that are designed to enable communication and restore motor function in patients with motor impairment. The paper highlights three different BCI modalities - slow cortical potentials, sensorimotor rhythms, and P300 potentials, as operational mechanisms for communication. It also reviews BCI systems for restoring motor function in patients with spinal cord injury and chronic stroke.

The paper provides an in-depth analysis of the advantages and limitations of these approaches, highlighting the challenges that need to be addressed in the future. The paper notes that current technological assistive solutions have several limitations, including extensive user training and the inability to adapt to patient needs, particularly at later stages of the disease. The paper provides a critical analysis of various technologies used in assistive devices such as "SmartNav" and eye gaze technology and notes the challenges faced in using these technologies, including the "Midas touch problem."

Overall, the paper provides an excellent starting point for researchers interested in the development of EEG-based BCIs for motor-impaired patients.

[8] The article provides a comprehensive review of EEG-based Brain-Computer Interfaces (BCIs). It covers popular BCI applications, control signals, feature extraction, classification algorithms, and performance evaluation metrics. The challenges faced by EEG-based BCI systems are also discussed, including the lack of a general BCI standard, poor ITR for any type of effective BCI application, and the need for standardized BCI metrics. The article concludes that if these concerns can be addressed, BCI systems could be an emerging means of human-machine interaction in the foreseeable future.

The article discusses various recent applications of EEG-based BCIs, including spelling systems, wheelchair control, robot control, mental workload, virtual reality, gaming, environment control, driver fatigue monitoring, biometric identification, emotion recognition, and collaborative problem-solving through BrainNet. It also highlights some notable recent developments, such as Facebook's research project that aims to restore the communication ability of disabled people through their thoughts at a speed of 100 words per minute, Neuralink's ultrafine threads embedded into the brain to recognize neural activity, and BrainNet, which is the first multi-person non-invasive direct brain-to-brain interface for collaborative problem-solving.

Some of the challenges faced by EEG-based BCI systems mentioned in the article are:

- Lack of a general BCI standard: There is a lack of a standardized approach in the development of EEG-based BCI systems, which hinders their generalizability and makes it difficult to compare results across studies.

- Poor ITR for any type of effective BCI application: The Information Transfer Rate (ITR) measures the speed and accuracy of communication between the user and the BCI system. The ITR of current EEG-based BCI systems is still too low for practical applications, which limits their effectiveness.

- Need for standardized BCI metrics: The development of standardized metrics for evaluating the performance of EEG-based BCI systems is essential to ensure their reliability and reproducibility.

- Artifact removal: EEG signals are susceptible to various types of artifacts, such as muscle activity, eye movements, and environmental noise, which can interfere with the accuracy of BCI systems. Developing robust algorithms to remove these artifacts is an ongoing challenge.

- Feature extraction: Extracting relevant features from EEG signals is a critical step in the development of EEG-based BCI systems. However, determining the optimal feature extraction technique for a specific EEG control
  signal modality remains a challenge.

Serial Number	Conclusion and Inference	Variation from previous papers
1	EEG-based BCI systems are a promising technology for the restoration of motor function in patients with disabilities, particularly those with spinal cord injuries or stroke.	The paper focuses on the potential use of EEG-based BCIs for motor function restoration rather than communication, which was the focus of some of the earlier papers.
2	The use of EEG-based BCIs for communication is a promising field of research, but there are still several challenges that need to be addressed, including low accuracy and limited communication speed.	The paper focuses specifically on the use of EEG-based BCIs for communication, which sets it apart from some of the other papers that cover a wider range of applications.
3	The use of EEG-based BCIs for human-robot interaction is a promising area of research, with potential applications in areas such as rehabilitation and assistance for people with disabilities.	This paper focuses specifically on the use of EEG-based BCIs for human-robot interaction, which sets it apart from some of the other papers that cover a wider range of applications.
4	The development of hybrid EEG-fNIRS BCIs has the potential to address some of the limitations of EEG-based BCIs, such as poor spatial resolution. However, there are still several challenges that need to be addressed in this area of research.	The paper focuses on hybrid EEG-fNIRS BCIs, which is a newer area of research that builds upon the findings of earlier studies on EEG-based BCIs.
5	The use of mobile EEG-based BCIs has the potential to enable more natural and flexible communication and control of devices. However, there are still several challenges that need to be addressed to improve the usability and reliability of these systems.	This paper focuses specifically on the use of mobile EEG-based BCIs, which sets it apart from some of the other papers that cover a wider range of applications.
6	The case study highlights the potential of EEG-based BCIs for rehabilitation of patients with severe brain injury, but also demonstrates the challenges and limitations of these systems in a clinical setting.	This paper is a case study rather than a review paper, so it provides a more in-depth analysis of a specific application of EEG-based BCIs.
7	EEG-based BCIs have the potential to enable communication and restore motor function in patients with motor impairment, but current technological assistive solutions have several limitations that need to be addressed.	The paper provides a more comprehensive review of the challenges and limitations of EEG-based BCIs for motor function restoration and communication compared to some of the earlier papers that focused on more specific applications.
8	EEG-based BCIs have a wide range of potential applications, including spelling systems, wheelchair control, robot control, mental workload, virtual reality, gaming, environment control, driver fatigue monitoring, biometric identification, emotion recognition, and collaborative problem-solving. However, there are still several challenges that need to be addressed in the development of EEG-based BCIs, such as the lack of a general BCI standard and poor ITR for any type of effective BCI application.	The paper provides a more comprehensive overview of the potential applications of EEG-based BCIs compared to some of the earlier papers that focused on more specific applications. It also highlights recent notable developments in the field.

III. Conclusion

In conclusion, the reviewed articles highlight the potential of EEG-based Brain-Computer Interfaces (BCIs) for a wide range of applications, including communication, rehabilitation, and human-machine interaction. These BCIs operate by translating electrical brain signals into computer commands and have shown promise in restoring motor function and enabling communication in individuals with motor impairment. However, the reviewed articles also highlight several challenges that need to be addressed for EEG-based BCIs to become more practical and reliable, including the lack of a standardized approach, poor

Information Transfer Rate (ITR), the need for standardized metrics, artifact removal, feature extraction, and selecting appropriate classification algorithms. Despite these challenges, the reviewed articles demonstrate the potential of EEG-based BCIs to transform the field of assistive technology and human-machine interaction in the foreseeable future.

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