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When the Brain Can Talk: Bridging Engineering and Medicine in EEG-Based Brain-Computer Interface Systems

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Abstract—Brain–Computer Interfaces (BCIs) enable direct communication between our human brain and external systems by interpreting neural signals without relying on conventional neuromuscular pathways. Among different BCI technologies, electroencephalography (EEG)-based systems are widely adopted due to their non-invasive nature, low cost, and ease of implementation, making them suitable for both engineering and medical applications.We will provide a comprehensive review of EEG-based brain–computer interface systems from both engineering and medical perspectives. Examining the main components of BCI systems, including EEG signal acquisition, electrode placement, artifact and noise removal, feature extraction techniques, and classification methods used for decoding brain activity.a small experimental analysis using a multi-channel EEG dataset is presented to illustrate how engineering-based signal processing techniques can be applied to real EEG data.. In addition, several important applications are discussed, such as neurorehabilitation, assistive robotic control, and communication systems for individuals with severe motor impairments. Medical applications including epilepsy detection and seizure prediction, sleep monitoring and sleep stage analysis, the diagnosis and monitoring of neurodegenerative diseases such as Alzheimer's disease are also reviewed. The results of this review highlight the significant role of EEG-based BCI systems in bridging engineering technologies with medical applications by enabling more effective brain signal analysis and supporting assistive and diagnostic solutions. However, several challenges remain, low signal-to-noise ratio, inter-subject variability, and real-time performance limitations. Future research directions focus on improving EEG acquisition techniques and integrating advanced machine learning methods to enhance the reliability, accuracy, and practical usability of EEG-based brain–computer interface systems

Keywords—Brain-Computer Interface, EEG, Signal Processing, Machine Learning, Neurorehabilitation

I. INTRODUCTION

Brain–Computer Interfaces (BCIs) represent an emerging technology that enables direct communication between the human brain and external systems.that connects our brains to the outside world,by translating these signals into commands that can control external devices without relying on conventional neuromuscular pathways. This capability enables researchers and clinicians to better understand brain activity and develop innovative solutions for a wide range of medical and engineering applications.

In the medical field, BCIs play an important role in analyzing brain signals and supporting the diagnosis and treatment of various neurological conditions.because the brain is the controller of our body then we should give him more attention to understanding its neural activity provides valuable insights into brain-related disorders. Consequently, BCI technologies have attracted significant attention due to their potential in neurorehabilitation, neurological monitoring, and the development of assistive technologies for individuals with severe motor impairments.

Brain–Computer Interfaces can be classified into three main categories according to the method used to acquire neural signals: invasive, semi-invasive, and non-invasive systems. Invasive BCIs involve implanting electrodes directly into brain tissue, which allows high-quality neural recordings but requires surgical procedures. Semi-invasive BCIs place electrodes inside the skull but outside the brain tissue, offering a balance between signal quality and surgical risk. In contrast, non-invasive BCIs record brain signals from the scalp using techniques such as electroencephalography (EEG), making them safer and more practical for widespread research and medical applications.Table I summarizes the main differences between invasive, semi-invasive, and non-invasive BCI systems.

TABLE I. CLASSIFICATION OF BRAIN–COMPUTER INTERFACES

Type	Electrode Location	Advantages	Limitations
Invasive BCI	Inside brain	High signal quality	Requires surgery
Semi-invasive BCI	Inside skull but outside brain	Better signals than non-invasive	Requires surgery
Non-invasive BCI	On the scalp (EEG)	Safe and easy to implement	Lower signal quality

Among these categories, non-invasive BCIs—particularly EEG-based systems—have gained significant attention due to their safety, relatively low cost, and ease of implementation in both research and clinical environments.

Electroencephalography (EEG) is one of the most widely used techniques for acquiring brain signals in non-invasive brain–computer interface (BCI) systems,which make the process of detecting brain signals easier.It records the electrical activity of the brain using electrodes placed on the scalp. In EEG-based BCI systems, brain signals are first acquired through these electrodes and then preprocessed to remove noise and artifacts caused by factors such as eye movements and muscle activity. After preprocessing, feature extraction techniques are applied to obtain meaningful characteristics from the signals, such as signal power and frequency bands. These features are then analyzed using classification algorithms to interpret the user's intention and generate commands for external devices or medical analysis.

Previous studies have shown significant progress in the use of EEG-based brain–computer interfaces for both engineering and medical applications. also in signal processing and machine learning techniques have enabled more accurate analysis of brain signals and improved the ability to decode neural activity. These developments have led to several practical applications, including robotic control systems and neurorehabilitation technologies that assist patients with motor impairments [1]. Moreover, EEG analysis has become an important tool in the medical field for monitoring brain activity and supporting the detection of neurological disorders such as epilepsy, sleep disorders, and neurodegenerative diseases including Alzheimer's disease [2].

Despite these advancements, many existing studies focus primarily on either technical system development or specific medical applications without providing a comprehensive perspective that connects engineering methodologies with clinical insights. Therefore, there is a need for a structured review that highlights how advances in EEG signal acquisition, signal processing, feature extraction, and classification techniques can contribute to both technological development and medical diagnosis.In this context, the present paper aims to provide a comprehensive overview of EEG-based brain–computer interface systems, emphasizing the relationship between engineering techniques and their medical applications in brain activity analysis, neurological monitoring, and assistive technologies. In addition, a simple experimental EEG data analysis is presented to demonstrate how signal processing techniques can be applied to real EEG recordings.s, emphasizing the relationship between engineering techniques and their medical applications in brain activity analysis, neurological monitoring, and assistive technologies.

II. EEG-BASED BRAIN–COMPUTER INTERFACE SYSTEMS

EEG-based brain–computer interface (BCI) systems follow a structured processing pipeline that converts neural activity into meaningful commands that can be used for device control or medical analysis. These systems typically consist of several stages, including signal acquisition, preprocessing, feature extraction, and classification. Each stage plays an important role in transforming raw brain signals into interpretable information that can support both engineering applications and medical analysis [3].

As illustrated in Fig. 1, the general architecture of an EEG-based BCI system begins with the acquisition of brain signals, followed by signal preprocessing and feature extraction. The extracted features are then interpreted using classification algorithms to produce decoded signals that can be used for device control or clinical interpretation.

A. EEG Signal Acquisition

The first stage in an EEG-based BCI system is signal acquisition, where brain activity is recorded using electroencephalography (EEG). The human brain contains billions of neurons that communicate through electrical impulses, generating measurable electrical signals. These signals can be detected using electrodes placed on specific locations on the scalp.

Because EEG signals have very small amplitudes, typically in the microvolt range, amplification is required before further processing. Therefore, the recorded signals pass through an amplifier, often including a low-noise amplifier (LNA), which increases signal strength while minimizing additional noise. After amplification, the signals are converted from analog to digital form using an analog-to-digital converter (ADC) so that they can be processed using computational techniques.

Electrode placement is commonly based on the internationally recognized 10–20 electrode placement system, which defines standardized electrode positions corresponding to different brain regions. However, many practical BCI applications do not require a large number of electrodes. In assistive technologies such as wheelchair control or prosthetic limb operation, a smaller number of electrodes is often sufficient. These electrodes are typically placed over the motor cortex, such as positions C3 and C4, where brain activity related to motor imagery can be effectively detected.

B. Signal Preprocessing

After acquisition, EEG signals usually contain various types of noise and artifacts that may affect signal quality and analysis accuracy. These artifacts can originate from several sources, including eye movements (electrooculogram – EOG), muscle activity (electromyogram – EMG), and external electrical interference.

The purpose of the preprocessing stage is to improve signal quality by reducing these unwanted components. Common preprocessing techniques include digital filtering, artifact removal algorithms, and signal normalization. By eliminating noise and artifacts, preprocessing produces a cleaner EEG signal that is more suitable for subsequent analysis.

C. Feature Extraction

After preprocessing, the next step is **feature extraction**, where meaningful characteristics are derived from the EEG signals. Instead of using the raw signal directly, feature extraction methods identify patterns that represent specific brain activities.

EEG signals are commonly analyzed using different frequency bands such as alpha, beta, and gamma rhythms [4].

One of the most commonly used approaches is the analysis of **EEG frequency bands**, which correspond to different cognitive and physiological states of the brain. These frequency bands include :

- **Delta (0.5–4 Hz):** Associated with deep sleep and unconscious states.
- **Theta (4–8 Hz):** Linked to memory processing and drowsiness.
- **Alpha (8–13 Hz):** Commonly observed during relaxed wakefulness.
- **Beta (13–30 Hz):** Related to active thinking and concentration.
- **Gamma (>30 Hz):** Associated with higher cognitive processing and sensory perception

An overview of EEG frequency bands and their corresponding cognitive states, along with common feature extraction techniques, is shown in Fig.2.

Feature extraction techniques such as spectral analysis, wavelet transforms, and power spectral density estimation are often used to quantify these frequency components.

D. Classification and Signal Interpretation

The final stage of the EEG-BCI pipeline is classification, where machine learning algorithms are used to interpret the extracted features and determine the user's intended action or cognitive state. Classification models analyze patterns within the EEG features and convert them into decoded signals that can be used for device control or medical interpretation.

Common classification methods include support vector machines (SVM), k-nearest neighbor (KNN), artificial neural networks, and deep learning models. These algorithms enable the system to recognize patterns associated with specific brain activities, such as motor imagery.

Once the signals are successfully classified, the decoded information can be translated into commands for external devices. In medical and assistive applications, this capability allows patients to control devices such as wheelchairs or prosthetic limbs and supports clinical processes such as neurological monitoring, diagnosis, and rehabilitation.

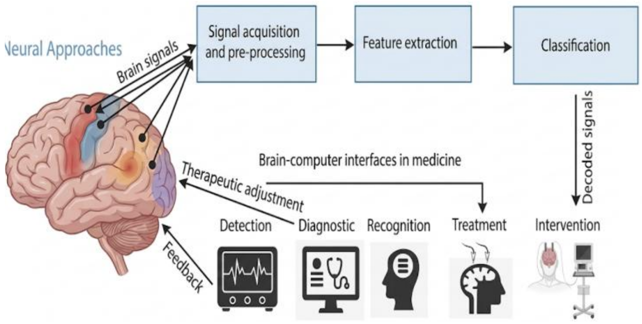

FIG. 1. GENERAL ARCHITECTURE OF AN EEG-BASED BRAIN–COMPUTER INTERFACE SYSTEM SHOWING THE MAIN PROCESSING STAGES FROM BRAIN SIGNAL ACQUISITION TO SIGNAL CLASSIFICATION AND MEDICAL APPLICATIONS.

III. APPLICATIONS OF EEG-BASED BRAIN–COMPUTER INTERFACE SYSTEMS

EEG-based brain–computer interface systems have attracted significant attention due to their wide range of practical applications in both engineering and medical fields. By analyzing neural signals and transforming them into meaningful information, these systems can either translate brain activity into control commands for external devices or provide valuable insights into neurological conditions. Consequently, EEG-based BCIs are increasingly used in assistive technologies as well as in neurological monitoring and diagnosis.

A. Brain-Controlled Assistive Systems

One of the most important engineering applications of EEG-based BCIs is the ability to convert brain signals into commands that can control external devices. In such systems, neural activity is recorded using EEG electrodes and processed using signal processing and machine learning techniques to interpret the user's intention.

A common approach used in these systems is motor imagery, where users imagine performing specific movements such as moving their hands or arms. These imagined movements produce distinguishable patterns in EEG signals, which can be detected and classified by the BCI system. The decoded signals can then be translated into control commands for various assistive devices.

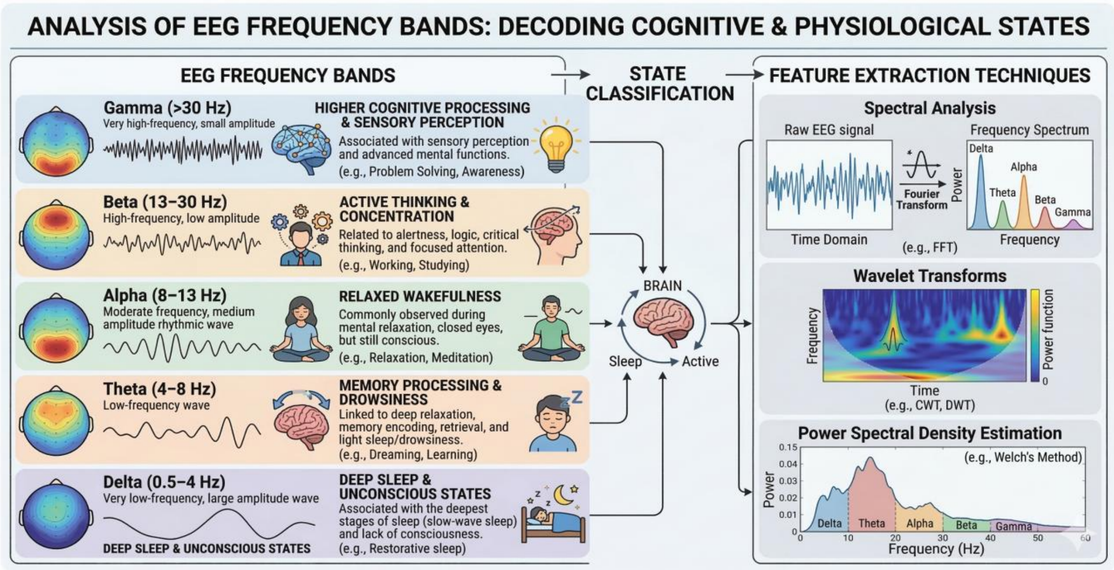

FIG. 2. EEG FREQUENCY BANDS AND FEATURE EXTRACTION TECHNIQUES

This capability has enabled the development of several assistive technologies designed to improve the quality of life for individuals with severe motor impairments. Examples include brain-controlled wheelchairs, robotic arms, and prosthetic limbs, where users can interact with their environment without relying on traditional muscular movements [5]. Such systems are particularly beneficial for patients suffering from paralysis, spinal cord injuries, or neurodegenerative diseases

B. Neurological Monitoring and Brain Disorder Analysis

In addition to assistive control, EEG-based BCI systems also play an important role in analyzing brain activity and supporting the detection and monitoring of neurological disorders. Since EEG signals reflect real-time neural activity, they provide valuable information about the functional state of the brain.

One important medical application is the detection and prediction of epileptic seizures. By analyzing abnormal electrical patterns in EEG signals, BCI systems can identify potential seizure activity and provide early warnings to patients. Such early detection systems may allow patients to take precautionary measures, such as avoiding dangerous situations or taking appropriate medication before a seizure occurs.

EEG analysis is also widely used in the study and monitoring of neurodegenerative diseases, including Alzheimer’s disease. Changes in EEG frequency patterns have been investigated as potential indicators of cognitive decline, which may support early diagnosis and long-term monitoring of disease progression.

Another important application is sleep monitoring, where EEG signals are used to analyze different sleep stages and detect sleep disorders. By examining variations in EEG frequency bands, researchers can classify sleep states and evaluate sleep quality.

In more advanced neurotechnological approaches, brain activity detection can also be integrated with neural stimulation systems, particularly in invasive BCI applications. In such systems, abnormal neural activity can trigger controlled stimulation signals that may help regulate or reduce certain neurological symptoms. These approaches are currently being explored for conditions such as epilepsy and Tourette syndrome.

Overall, these applications demonstrate that EEG-based BCI systems provide powerful tools for both engineering innovation and medical research. While assistive BCI technologies enable direct interaction between the brain and external devices, medical BCI applications contribute to improved understanding, monitoring.

IV. MEDICAL CHALLENGES AND LIMITATIONS OF EEG-BASED BCI SYSTEMS

Despite the promising applications of EEG-based brain–computer interface systems, several challenges still limit their reliability and widespread use in medical and assistive environments. These challenges arise mainly from the nature of EEG signals, patient variability, and practical usability issues.

A. Low Signal Amplitude and Artifacts

One of the main challenges in EEG-based systems is the extremely low amplitude of EEG signals, which are typically measured in microvolts. Because of this weak signal strength, EEG recordings can easily be affected by different types of artifacts such as eye movements (EOG), muscle activity, and other external interferences. These artifacts may lead to incorrect interpretations of brain activity. For example, in medical applications such as epilepsy detection, noise in the signal may sometimes produce false alarms. Therefore, improving signal processing techniques and artifact removal methods remains essential for increasing the accuracy of EEG-based BCI systems.

B. Model Training and Personalization

Another important challenge is related to the training of machine learning models used for interpreting EEG signals. In many cases, the model requires sufficient training time and large amounts of EEG data in order to achieve reliable predictions. Generally, the longer and more representative the training process is, the higher the expected accuracy of the model. In addition, EEG signals vary significantly between individuals, which means that a model trained on one person may not perform equally well on another. For this reason, many BCI systems rely on personalized models that are trained specifically for each user to reduce prediction errors and improve overall performance.

C. User Comfort and Long-Term Monitoring

Another practical challenge involves the comfort of patients or users during long-term monitoring. Traditional EEG systems often require multiple electrodes attached to the scalp, sometimes using conductive gels, which can cause discomfort during prolonged use. This becomes particularly problematic in applications that require continuous monitoring, such as sleep analysis or neurological observation. To address this issue, researchers are currently developing wearable EEG devices, such as lightweight caps or headsets, that allow users to move more freely and use the system in daily life.

D. Clinical Validation and Medical Trials

Finally, for EEG-based BCI technologies to be widely adopted in healthcare, they must undergo rigorous clinical validation and medical trials. These processes are necessary to ensure that the system provides reliable and trustworthy information for medical decision-making. Clinical testing helps verify the safety, accuracy, and effectiveness of the technology before it can be implemented in real-world medical environments.

V. Future Directions of EEG-Based Brain–Computer Interface Systems

Although EEG-based brain–computer interface systems have achieved significant progress in recent years, many research directions are still being explored to improve their efficiency and practical usability. Future developments are expected to focus on improving signal analysis techniques, enhancing system adaptability, and integrating advanced technologies to support long-term medical and assistive applications.

One important direction for future research is the development of **adaptive and personalized BCI systems**. Since EEG signals differ from one individual to another and may also change over time due to aging or physiological conditions, future models may rely on continuous learning techniques that allow the system to adapt to the user's brain activity over long periods. Such systems could potentially learn the neural patterns of a specific individual and gradually improve their accuracy as more data becomes available.

Another promising direction is the integration of **advanced artificial intelligence techniques**, particularly deep learning models, for more accurate interpretation of complex EEG patterns. These approaches may help improve the detection of neurological abnormalities and enhance the performance of assistive BCI applications.

Future research is also focusing on the development of **wearable and portable EEG devices** that allow continuous monitoring of brain activity in real-life environments. Lightweight EEG headsets and dry-electrode technologies may make it possible to use BCI systems outside laboratory settings, enabling more practical medical monitoring and assistive control.

the long term, these developments may contribute to the creation of personalized neural assistance systems capable of continuously learning from users

Future research directions in EEG-based BCI systems are illustrated in Fig. 3.

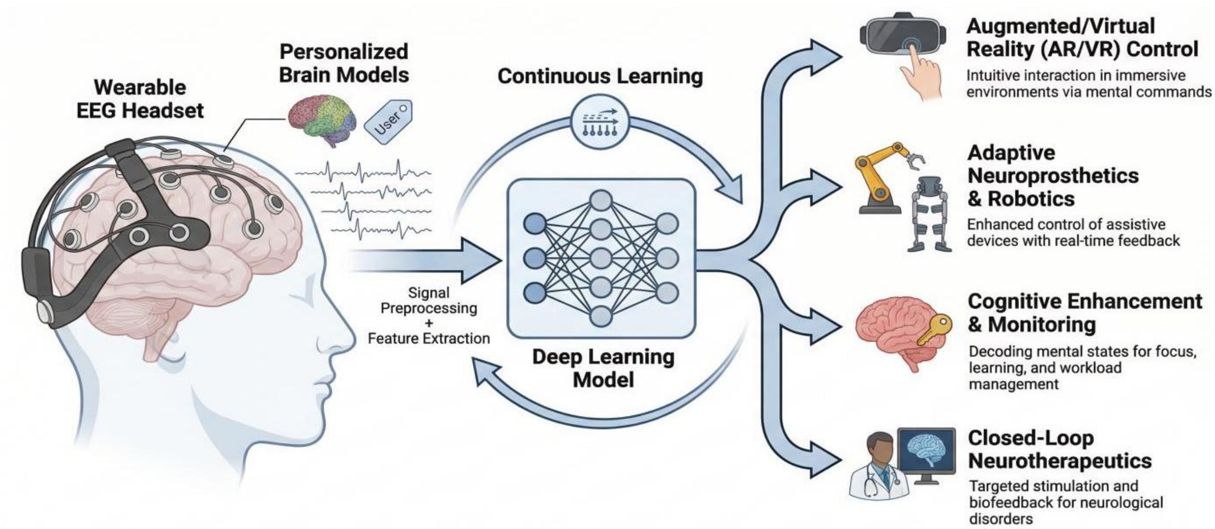

FIG. 3. FUTURE DIRECTIONS OF EEG-BASED BRAIN–COMPUTER INTERFACE SYSTEMS, INCLUDING WEARABLE EEG DEVICES, PERSONALIZED BRAIN MODELS, CONTINUOUS ***learning***, AND AI-DRIVEN APPLICATIONS.

IV. EXPERIMENTAL EEG DATA ANALYSIS

To illustrate how engineering-based signal processing techniques can be applied to EEG data, an experimental analysis was performed using a publicly available EEG dataset obtained from Kaggle. The dataset contains multi-channel EEG recordings collected from electrodes placed on different regions of the scalp.

Each EEG channel represents electrical brain activity recorded from a specific brain region. The dataset was analyzed to explore statistical and frequency-based characteristics of EEG signals and to investigate potential relationships between different brain regions.

First, correlation analysis was performed to examine relationships between EEG channels. A correlation matrix was computed and visualized to identify possible functional connectivity patterns between different brain regions. In addition, spectral analysis using Fast Fourier Transform (FFT) was applied to selected EEG channels to observe variations in electrical brain activity over time.

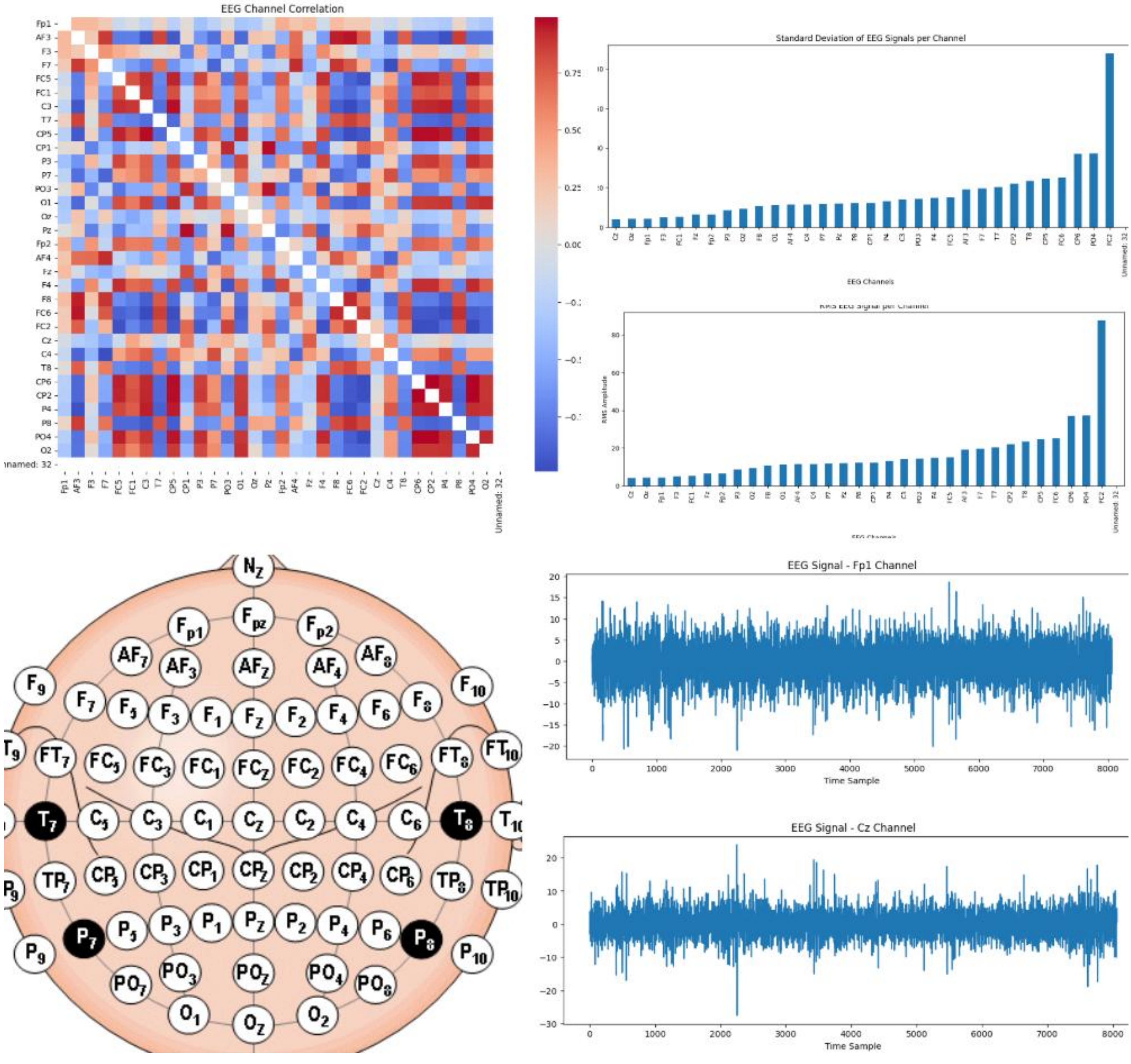

FIG. 4. EXPERIMENTAL EEG SIGNAL ANALYSIS INCLUDING CORRELATION HEATMAP BETWEEN EEG CHANNELS, EEG WAVEFORM VISUALIZATION, SIGNAL VARIABILITY ACROSS CHANNELS (STANDARD DEVIATION), AND RMS SIGNAL AMPLITUDE REPRESENTING SIGNAL STRENGTH.

It can be observed that certain EEG channels exhibit higher variability and signal strength compared to others. In particular, the FC2 channel demonstrates significantly higher standard deviation and RMS values, which may indicate strong neural activity or possible signal artifacts.

VI. CONCLUSION

Brain–Computer Interface (BCI) systems are becoming an important bridge between engineering and medicine. By understanding BCI technologies and the processing of electroencephalography signals, Previous researches are able to explore the interaction between the human brain and the external world. Making an interaction that enables the development of assistive technologies such as robotic control systems and intelligent medical monitoring tools, allowing brain signals to be translated into commands that control external devices and systems.

In this paper,We review the main components of EEG-based BCI systems , including signal acquisition, preprocessing techniques, feature extraction methods, and machine learning approaches used to interpret brain activity. Beside that a simple experimental EEG data analysis was presented to illustrate how engineering-based signal processing techniques can be applied to real EEG recordings and how these analyses can provide insights into patterns of neural activity.

We should give some attention to analysis EEG based BCI for valuable opportunities for improving the understanding and management of neurological disorders such as epilepsy and Alzheimer's disease. At the same time, several challenges still remain, including signal noise, variability between users, and the need for reliable clinical validation.

The next research in EEG-based BCI systems is expected to focus on improving signal analysis techniques, developing wearable and user-friendly EEG devices, and designing more adaptive and personalized machine learning models that can learn from users over time. Such advancements may further strengthen the role of BCI systems in both assistive technologies and medical applications, opening new possibilities for more effective interaction between the human brain and modern technological systems.To let the brain talk…

REFERENCES

[1] Y. Li, X. Zhang, and H. Liu, "EEG-based motor imagery brain–computer interface for robotic finger control," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 33, pp. 120–130, 2025.

[2] M. Chen, R. Wang, and J. Huang, "Brain–computer interface applications in neurological rehabilitation after stroke and spinal cord injury," Frontiers in Neuroscience, vol. 18, pp. 1–12, 2024.

[3] S. Sanei and J. A. Chambers, EEG Signal Processing. Hoboken, NJ, USA: Wiley, 2007.

[4] G. Pfurtscheller and F. H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: Basic principles," Clinical Neurophysiology, vol. 110, no. 11, pp. 1842–1857, Nov. 1999.

[5] B. Blankertz, G. Dornhege, M. Krauledat, K. Müller, and G. Curio, "The non-invasive Berlin Brain–Computer Interface: Fast acquisition of effective performance in untrained subjects," NeuroImage, vol. 37, no. 2, pp. 539–550, Aug. 2007.