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An Overview of Brain-Computer Interface (BCI) Technology and Signal Processing Methods

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Abstract: Brain–machine interfaces are an emerging way that enables communication by using brain power, affecting the sensitive nerves and muscles. Over the last 20 years, this advancement in technology has motivated a lot of disabled patients. This continues to grow, helping more and more patients suffering from paralysis or any other disabilities. At present, extensive research is being conducted in this complex emerging field. Significant efforts have been directed towards implementing Brain-Computer Interface (BCI) systems in laboratory settings to assist individuals with disabilities, enabling them to perform tasks akin to those of able-bodied individuals. This manuscript will examine the current landscape and future potential of BCI technology, along with its correlation to various signal processing techniques. This review seeks to bridge the gap in understanding the influence of diverse signal processing methodologies on the efficacy of BCI systems. Consequently, the paper will cover advancements in the domains of signal acquisition and processing. In addition, the study is focused on analyzing all the previous studies done on improving signal quality. Moreover, the paper discusses how creating advanced algorithms significantly improves the interpretation of user intentions and commands.

Keywords: BCI, ECoG, Brain Waves, Motor Imagery

1. Introduction

In recent years, the utilization of brain-computer interfaces (BCIs) has significantly expanded. Numerous neurological studies analyzing trends from the past two decades underscore their importance.[1].

Brain-Computer Interface plays a huge role in communication and is specifically designed for individuals with disabilities. Many studies show how the quality of life has improved for people, especially for people suffering from neuro muscular disorders and spinal cord injury (SCI), and amyotrophic lateral sclerosis (ALS). Figure 1. Shows the common process involved in this process

Brain-Computer Interfaces (BCIs) are systems that help improve the quality of life of disabled individuals. This is done by providing new ways to interact with their environment, communicate, and access essential services. These systems work by passing conventional neuromuscular pathways. The initial stage of this technology involves capturing brain signals, processing them, and translating them into commands. These then help in controlling devices such as computers, prosthetics, or other electronic systems. Consequently, brain-computer interfaces (BCIs) demonstrate a considerable

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influence on applications within medical rehabilitation, assistive technology, and an array of pioneering disciplines. [2].

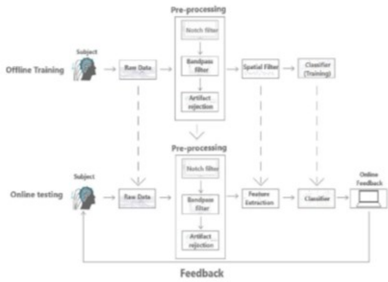

Figure 1: General working of EEG-based BCI[3]

1.1. Applications of BCI Technology

Brain-Computer Interfaces (BCIs) have been effectively deployed across various applications. This technology represents a dynamic and interdisciplinary domain that intertwines neuroscience, biomedical engineering, computer science, and clinical practice.[4].

BCIs can translate brain signals into control commands for artificial limbs, allowing amputees to perform tasks with prosthetic devices. Moreover, Users can control the movement of a computer cursor, motorized wheelchairs are also used for controlling purposes. The individual is able to maneuver the wheelchair solely through cognitive commands, enabling users to attain a level of autonomous mobility. Additional applications encompass text generation and speech synthesis. [2].

This also plays a vital role in assisting in the rehabilitation of stroke patients. This is achieved by promoting motor recovery through therapies. For instance, by developing training programs, one can gain recovery by improving cognitive functions and motor skills. Personalization and Adaptation over time, offering new ways to interact with virtual environments and Augmented Reality (AR) can enhance the experience in gaming. The domains of privacy, accessibility, affordability, as well as robotics and automation, represent just a few of the diverse applications of Brain-Computer Interfaces (BCIs).[5].

1.2. Components of BCI Systems

The major components of Brain-computer interface systems include Signal acquisition, which is achieved through methods like EEG and fNIRS. Signal processing overs the part of preprocessing the raw data. The data is cleaned by extracting meaningful features and classifying these features using machine learning.

The additional components encompass Signal Processing Techniques. The control interface subsequently facilitates the translation of these interpretations. The latter stages involve deriving insights from Real-time feedback. These user interfaces enhance interaction with the Brain-Computer Interface (BCI) system, while data management guarantees secure data storage.

2. Signal Acquisition Techniques

There are multiple technologies which can stimulate the careful examination of brain activity. Among these technologies include electroencephalography (EEG). EEG methods that are most widely used include Sensorimotor Rhythms (SMR) and Motor Imagery BCI (MIBCI).

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2.1. Electroencephalography (EEG)

Brain activity is captured using electroencephalography (EEG) to start BCI. The technology measures electrical activity with scalp electrodes. This also uses more invasive methods like intracortical neurone recording. Electrodes placed directly into brain tissue can capture these signals for a standardised system like the 10-20 system. After recording, signals are amplified and digitised for processing. This non-invasive approach records voltage fluctuations. Ionic current fluxes between neurones cause these oscillations. Signal processing reduces noise and improves quality. Later, pertinent features are extracted, filtered, and translated. Studies reveal that recent advances in spatial resolution and signal quality have made EEG essential for real-time BCI applications. Its low cost makes it easy to use. EEG records spontaneous oscillations that become event-related potentials. Information is packed into these signals. Analysis can be done by frequency, amplitude, and phase. EEG has drawbacks like any other technology. Recording muscular contractions (EMG) and ocular movements (EOG) shows these events. Ambient electrical noise makes measurements difficult [6].

Advanced preprocessing techniques, such as filtering and artifact rejection algorithms, are employed to mitigate these issues and enhance the signal quality. Additionally, EEG offers a relatively low spatial resolution. However, in comparison to other brain imaging techniques like fMRI or MEG, this technique is far simpler to use as the signals have to pass through the scalp, skull, and cerebrospinal fluid before these finally arrive to the electrodes. These factors make it a valuable tool in research and practical BCI applications.

Each EEG-BCI system begins by recording brain activity using electrodes. Studies show that EEG-BCI systems use a lesser number of electrodes. Studies also show that by using less than 20 electrodes, the cost can be largely minimized. Table 1. All the studies are in reference to the number of channels used[6].

Table 1: Analysis of the number of channels in reference to studies conducted [7]

Number of Channels	Percentage of studies conducted
1-2	20.33
3-8	21.61
9-16	10.05
17-31	19.16
32-64	14.49
65-128	14.37

2.2. Functional Near-Infrared Spectroscopy (fNIRS)

fNIRS is another technique used for brain activity monitoring. It is a type of noninvasive method. fNIRS functions on the principle that oxygenated and deoxygenated hemoglobin absorb near-infrared light at 590–1000 nm wavelengths. Recently, a lot of studies have been conducted with fNIRS to examine its impact.

This is done by using near-infrared light. fNIRS is less responsive to motion artifacts than EEG, making it a suitable choice for only certain BCI applications. By emitting light through the scalp and measuring the amount of light reflected after passing through the brain, fNIRS provides insights into it.

Compared to other techniques like fMRI or PET, fNIRS Is another technique after EEG that is simpler and easier to use. It can be used in clinical environments, research laboratories, and naturalistic conditions. The method offers a moderate spatial resolution, typically in the range of a few centimeters, and good temporal resolution. Just in a matter of seconds the signal performs the

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process. Like any other technology out there fNIRS some drawbacks as well. The technique is the most efficient when examining cortical activity, as the near-infrared light has limited penetration depth, which restricts its ability to measure activity in deeper brain structures by affecting light absorption and scattering.

3. Signal Processing Methods in BCIs

Signal processing in Brain-Computer Interfaces (BCIs) is a vital step that transforms raw brain signals into the type of information that is needed. This process goes through a lot of stages to ensure that the signals are clean, usable and have quality. The essential phases of signal processing involve initial data preprocessing, subsequent feature extraction, and finally, the classification stage.[6].

3.1. Preprocessing

This is the initial step in signal processing, where the raw brain signals are then sent for further analysis. This stage was all about filtering out noise and environmental interface. These noise and environmental interfaces can distort and weaken the signal.

Many other techniques such as low-pass filters and high-pass filters are designed to eliminate high and low-frequency drift respectively. Band-pass filters is another techniques that works by allowing only certain signals to pass through. these target the ones that are within a specific frequency range. Additionally, alternative methodologies, including Independent Component Analysis (ICA), are employed for these objectives.[4].

3.2. Feature Extraction

This is a step that occurs after preprocessing and focuses on identifying and extracting the information that's needed from the cleaned signals. Decoders are algorithms that interpret neural signals to determine the user's intended actions. These decoders convert brain activity into commands for controlling external devices. This step works by analyzing the brain signals in different domains. In the time-domain, features such as signal amplitude and event-related potentials (ERPs) are examined. In the frequency domain, power spectral density (PSD) and frequency band powers, including alpha, beta, and gamma, are essential concepts for analyzing signal characteristics.[4].

3.3. Classification

The last stage is the final stage, where the extracted features are used to separate brain states and categorize them at places where they belong.

This process involves applying machine learning algorithms to translate the features into control commands. Machine learning algorithms play a pivotal role in decoding brain signals. Linear classifiers, such as Linear Discriminant Analysis (LDA) are used to establish simple decision boundaries to separate different brain states. Non-linear classifiers, like Support Vector Machines (SVM) and neural networks, can predict more complex relationships in the data. Advanced techniques, including deep learning. Recent studies have shown noteworthy advancements in classification accuracy and real-time performance.[8].

3.4. Adaptive Filtering

A decoder can be interpreted as having the ability to convert neural signals into instructions that external devices can understand. However, decoders based on different filters and classifications have certain aspects related to them. Adaptive filtering techniques are used to make the signals high quality. Methods such as the Kalman Filter and Independent Component Analysis (ICA) are commonly used.

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The Kalman filter is an algorithm that works on the principle of repercussion. This step is mostly done to optimize performance.

The main principle of adaptive filtering involves using an algorithm that adjusts the filter's coefficients to minimize a specific error criterion. One of the most used adaptive filtering algorithms is the Least Mean Squares (LMS) algorithm. Adaptive filters can help solve issues like echo in communication.

3.5. Feature Extraction Methods

Time-domain analysis is a method which inspects the signal based on time variation in the context of EEG (electroencephalography). This involves examining the amplitude and timing of recorded electrical activity in the brain. Time-domain analysis is effective in elucidating event-related potentials (ERPs), which are neural responses elicited when an organism reacts to a particular stimulus.[9].

However, by examining different frequency bands, researchers can gain insights into different states of cognitive and emotional processing.

Time-frequency analysis utilizes both time and frequency information, allowing for a more comprehensive understanding of non-stationary signals. The condition for it to work is that its statistical properties must change over time. One of the methods used for time-frequency analysis is the Wavelet Transform.

3.6. Feature Selection Methods

These methods rely on statistical tests to evaluate the relevance of each feature by measuring how well it distinguishes between classes. Features that demonstrate strong statistical significance (i.e., those that show substantial differences in their distribution between classes) are considered relevant and are retained. This process helps reduce the feature space by eliminating features that do not contribute to class differentiation or might introduce noise into the model.

Common statistical tests include t-tests, ANOVA which is the Analysis of Variance, and chi-square tests. For example, a t-test can determine if the mean values of a feature are significantly different between two classes. In comparison, ANOVA can be used when comparing more than two classes.

Machine learning algorithms for feature selection utilize techniques like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) to reduce dimensionality and select the most relevant features. The primary goal of the LDA algorithm is to use a hyperplane to distinguish between different classes. It seeks to identify directions in the feature space such that the features' variation within the same class is reduced, while the variation between different classes is increased. By projecting the initial features onto these principal components, Principal Component Analysis (PCA) effectively diminishes the dimensionality of the dataset. This process emphasizes the directions exhibiting the highest variance, which may consequently omit features that provide minimal information.[10].

4. Conclusion

The electrical stimulations inside the brain produce signals sensitive to the scalp or within the brain. This paper provides an overview of Brain-Computer Interface (BCI) technology by highlighting signal processing methods. Advances in signal acquisition techniques like EEG and fNIRS, and improvements in machine learning and adaptive filtering, have greatly enhanced BCI performance. No matter how many advancements have been made, studies show that challenges remain, particularly in integrating multiple modalities and achieving the goal of real-time processing. The findings of this research highlight the importance of continued innovation in signal processing techniques to advance BCI technology. BCI research should address these obstacles to increase its efficacy and usability, potentially expanding their benefits for disabled users. Additionally, multidisciplinary teams must collaborate to solve these problems. Researchers can build new data fusion and interpretation methods using neurology, engineering, and computer science. AI can provide adaptive systems that learn from user interactions, improving BCI responsiveness. User-centred design should also be emphasised to ensure accessibility and comfort, especially for end-users with diverse technological proficiency. As BCI research progresses, an ethical framework that prioritises participant well-being and agency is essential. A collaborative and inclusive research environment can speed breakthroughs for scientists and assistive technology users.

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