Electroencephalogram-Based Brain–Computer Interface System

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Researchers have discovered that brain–computer interface (BCI) techniques can improve communication between the brain and computer by decoding brain neural signals. There have been several attempts to investigate the application of BCI, but motor imagery (MI) has received the most attention since it causes the motor cortex to respond when a person mentally models a specific movement of limbs without activating their muscles.

brain computer interface | electroencephalogram | motor imagery | independent component analysis | features | entropy

1. Introduction

Common symptoms that have a substantial impact on the quality of life of stroke survivors include disability and cognitive impairment; stroke is the most frequent cause of disability and impairment [1]. Daily activities are significantly impacted by those impairments [2]. Recent studies have concentrated on developing effective therapies and rehabilitation programs for stroke victims. Helping the brain repair neuronal connections and make up for damaged circuits is the goal of therapy and rehabilitation. Though choosing the appropriate course of action can take weeks, it is still not yet possible to do so objectively [3].

Researchers have discovered in recent years that brain–computer interface (BCI) techniques can improve communication between the brain and computer by decoding brain neural signals [4][5]. There have been several attempts to investigate the application of BCI, but motor imagery (MI) has received the most attention since it causes the motor cortex to respond when a person mentally models a specific movement of limbs without activating their muscles [4]. Even in the presence of significant nerve injury, repetitive training based on MI encourages neuronal reorganization [6][7]. In conjunction with specific external assistive technologies, the MI-based system has the potential to significantly improve the quality of life for individuals with stroke, spinal cord injury, and amyotrophic lateral sclerosis [8][9].

Researchers used event-related desynchronization and event-related synchronization (ERD/ERS) to classify mental states [10][11], because the sensorimotor cortex attenuates oscillatory brain activity within specific frequency bands [12][13], which can be distinguished when the subject imagines moving different sides of the body [14][15]. Electroencephalogram (EEG) signals can be used to track a patient’s health and brain activity changes [16].

All prior research contributes significantly to the MI classification task. Classifiers such as support vector machines (SVM), linear discriminant analyses (LDA), and random forests (RF) have all been employed [5]. Nevertheless, most previous research only employs a single conventional filter during the preprocessing (denoising) stage, and most forecast MI EEG data analysis techniques overlook the benefits of using a hybrid filtering strategy for denoising the EEG signal before deploying algorithms. Most previous research has employed feature extraction approaches that are specific to a single domain, such as CSP or WT [17], during the feature extraction step. Existing research has not shown a variety of feature extraction and dimensionality reduction techniques to evaluate the MI EEG's complexity and irregularity, an area where much opportunity exists to enhance classification accuracy.

Apart from other studies, the preprocessing stage was where the conventional filters and independent component analysis (ICA) denoising technique were initially applied. Then, nonlinear features were retrieved, such as fractal dimension (FD), Hurst exponent (Hur), and Tsallis entropy ($TsEn$), as well as dispersion entropy ($DispEn$), as dynamic entropy parameters. Two-way analysis of variance (ANOVA) was used to statistically analyze four MI-based classes. Due to the effectiveness of the used features, they were combined into $CompEn$ integrated feature set. Laplacian Eigenmap (LE) dimensionality reduction algorithm was applied to the feature set to improve the classification performance of the motor imagery (MI)-based BCI stroke patients.

Not all of the time will a decision BCI MI-based EEG dataset system show promising outcomes; its advantages and disadvantages should be weighed carefully. In particular, unlike other methods that involve a great deal of training and expensive sensors, EEGs are a wireless, low-cost device that can automatically recognize MI from EEG data. When compared to magnetoencephalogram (MEG) systems, the proposed $CompEn$ integrated feature set can investigate complexity and irregularity over the entire spectrum of MI-based EEG data with normal throughput and can be mastered by a greater number of users.

2. Motor Imagery-Based Brain–Computer Interface

EEG is a non-invasive method for identifying conditions and symptoms that affect the brain. Numerous neurological conditions, including epilepsy, tumors, cerebrovascular lesions, depression, and trauma-related issues, can be diagnosed with its aid. An emerging method of direct brain-to-computer communication, known as EEG-based BCI, relies on the interpretation of features that are extracted from the EEG signal with higher resolution than those found in signals from other devices [18].

The EEG potentials recorded from the scalp's surface are bioelectric signals produced by the neuronal activity of the brain. Many researchers have been concentrating on the fundamentals of BCI in recent years through the interpretation of EEG-based commands and have worked on controlling a device with this approach [18]. These research studies continue to contribute to raising the quality of life for those who are paralyzed or have lost limbs such as their arms and legs [19]. An EEG-based BCI system that Mabrouk et al. [20] have created shows the user's EEG signals and accurately categorizes them as fictitious right and left hand movements.

According to studies conducted by [21], the active EEG frequency bands and brain regions that contribute to cognitive load fluctuate based on the learning state. Moreover, they reported variations in EEG frequency bands in specific brain regions under cognitive stress when performing activities involving human–computer interaction [22].

EEG is, therefore, trustworthy and among the most sensitive indicators of brain activities for determining mental burden brought on by cognitive processing [23].

Recognizing the most pronounced marks from EEG signals is essential to detecting and identifying brain features as well as assessing the EEG signal variable under evaluation [3]. From a clinical standpoint, the neurologist interprets the post-stroke patient's EEG signal by looking at wave rhythms, amplitudes, asymmetries, changes in magnitudes, the presence of waves, and the ratio between waves [24][25].

The recorded wave activities could be distorted, though, by a variety of artifacts [26][27]. The abnormal behavior of the brain can typically be imitated or superimposed by these artifacts. Additionally, significant artifacts that conflict with EEG, such as eye blinks and ocular movements, cardiac artifacts, muscle activities, and noise from power lines, may cross EEG frequencies [28]. Thus, it is challenging to categorize EEG signals due to noise [29].

In order to improve our understanding of how the brain works, it is crucial to quantify the complexity of the EEG signal [30]. This allows us to obtain insight into the process and distinguishing characteristics of the signal. When examining the complexity changes caused by events in the functional areas of the brain, nonlinear parameters are very useful indicators [31]. It should be noted that nonlinear parameters are frequently employed for a range of neurophysiological investigations and applications utilizing EEG signals [32]. The EEG signal is difficult to acquire, process, and analyze due to its complexity and nonstationarity. When data processing for feature extraction is properly prioritized, significant information about the neurophysiological conditions in the brain can be gleaned.

Due to the numerous redundant data reductions and transformations involved in data processing, one must be extremely careful when selecting the best methodology to prevent information loss. Using advocates of nonlinear discrete dynamical systems, the authors of previously published studies have examined changes in the temporal dynamics of the EEG signal under moderate to demanding mental stimulation. However, it has been suggested that the brain in the majority of these cases functions as a nested network of coupled dynamical systems that maintains spatial and temporal dynamics and can be identified through nonlinear biomarkers of EEG signal [5][24].

The most recent techniques for EEG analysis for MI-based BCI are shown in **Table 1**, which also includes feature extraction and classification methods as well as various denoising techniques. Bandpass filters and notch filters have been used as denoising techniques in many studies, see [33][34][35], but blind source separation algorithms (BSS) have also been used with ICA in other studies (see [36][37][38]). As in [17][33][35][38], CSP was also the most widely used feature extraction technique. In reality, different EEG-based BCI datasets show differences in the brain regions associated with MI-BCI, making it difficult for conventional methods of feature extraction to demonstrate accurate classification of different classes.

Table 1. State-of-the-art: various denoising, feature extraction, and classification approaches are used in EEG analysis for MI-based BCI.

Study	Denoising Technique	Feature Extraction	Classifiers
Liu et al. [33]	Bandpass filter (0.5–100) Hz, notch filter	CSP	SVM, KNN
Krishna et al. [34]	Moving average filter, band pass filter	Cross-correlation	SVM, KNN, LDA, NB, DT
Rejer et al. [36]	FastICA algorithm	Power band	SVM
Assi et al. [37]	Temporal filtering, spatial filtering, K means-ICA	Band power, DWT-band power, DWT-coherence, DWT-PLV	LDA and SVM
Selim et al. [17]	Butterworth filter	CSP	SVM
Ghumman et al. [38]	ICA	CSP	SVM
Narayan et al. [35]	Butterworth filter (8 to 30) Hz, notch filter, ICA	CSP, PCA	SVM, LDA
Al-Qazzaz et al. [5]	Conventional filtering, AICA WT denoising technique	Time domain, frequency domain, entropy domain	SVM, KNN, RF

dynamical parameters. The complexity and irregularity characteristics used in this research, however, may aid in understanding how specific spatial information of brain functions changes over time [39]. The majority of EEG-BCI-based motor imagery studies published in the literature concentrate on separating left from right hand or foot motor imagery [19].

As a result, this issue could be resolved by using more effective features that are compatible with the complexity of the brain and that can be used to elicit the unique performance of subjects following motor imagery (MI)-based BCI rehabilitation.

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