Signal Processing and Renewable Energy
March 2022, (pp. 39-64)
ISSN: 2588-7327
eISSN: 2588-7335

A Brief Overview on Analysis and Feature Extraction of Electroencephalogram Signals

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Received: 09-Sep-2021, Revised: 03-Oct-2021, Accepted: 04-Oct -2021.

Abstract
Human brain cells are active even during sleep and communicate through electrical impulses. Electroencephalogram (EEG) signals can be used to extract the correct information from the human brain and classify it with different mental functions. Non-inventiveness, high temporal resolution, and relatively low financial cost are the reasons for the use of EEG widely in medical engineering research. Extraction of a feature is very important and fundamental for EEG signal classification. In this paper, some of the methods used to extract the features from EEG signals are reviewed. In biomedical research, the classification of EEG signals plays an important role. According to the principles of pattern recognition, the classification process has two stages: feature extraction and classification. This study explains the EEG signal classification. Features are extracted for different bands.

Keywords: Electroencephalogram signal, feature extraction, frequency range.

1. INTRODUCTION

Medical engineering is the application of engineering sciences in the field of medicine to diagnose and treat diseases. In this area, the goal is to meet the medical needs in the field of design, construction and maintenance of medical equipment and tools for the prevention, diagnosis and treatment of diseases with the help of engineering sciences [1,2].

So far, various studies have been conducted on the application of engineering sciences in medical engineering [3,4].

The brain is a very complex part of the human body [5,6,7]. So far, various brain signals that are easily visible and controllable have been suggested for brain computer interface (BCI) [8,9,10]. General architecture of an online brain-computer interface is shown in Fig. 1 [11,12].

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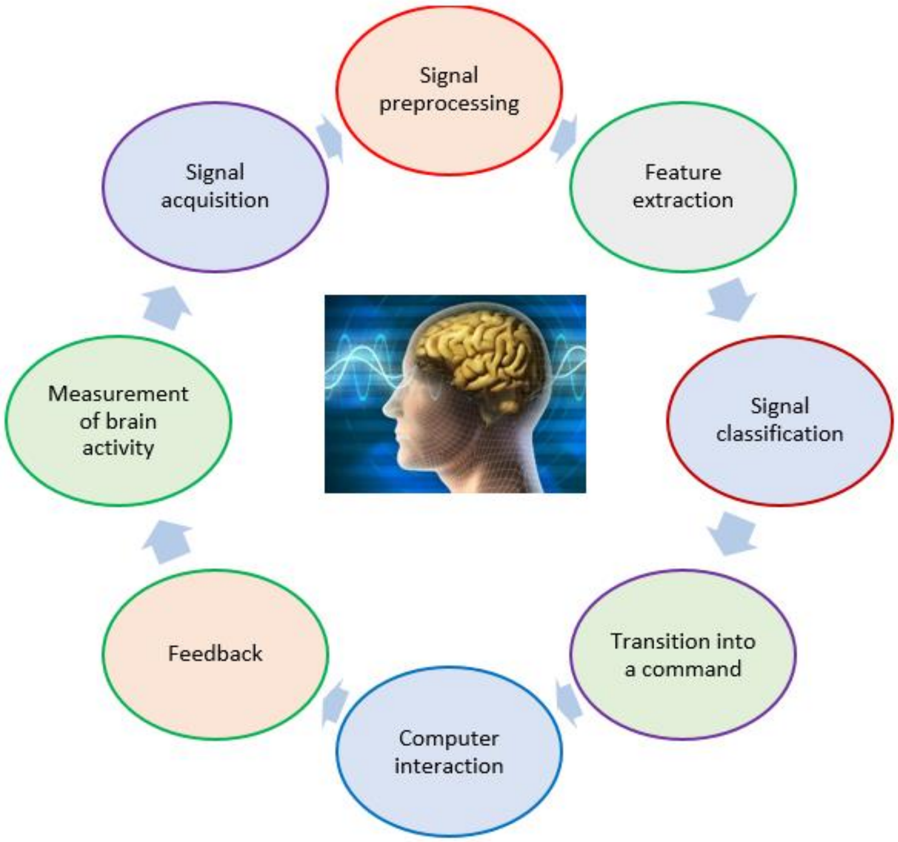


Fig. 1. Basic BCI system.

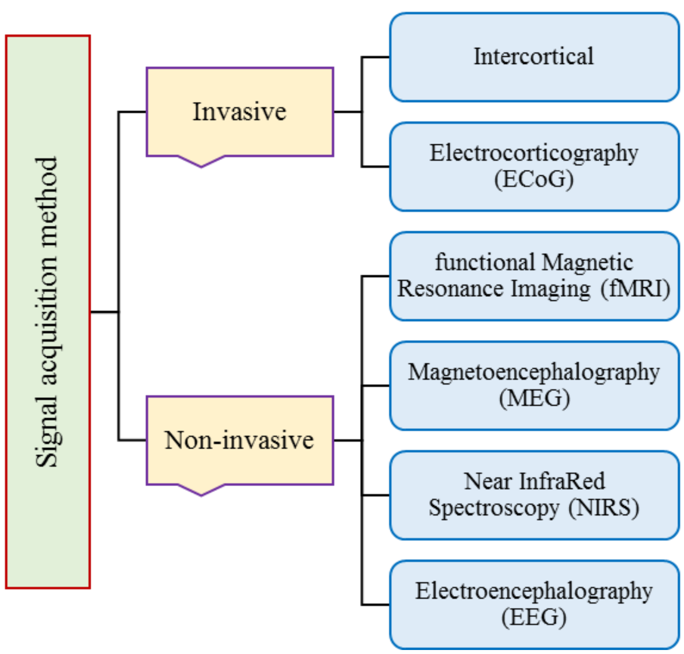


Fig. 2. Signal acquisition techniques for brain computer interface.

Table 1. ***A review run on studies on different aspects of EEG.***

Subject	References	Specifications (Summary of the review study)
Artifacts removal	[13]	Removal of artifacts from various sources is necessary for the pre-processing stage before analyzing the EEG data. An overview of existing methods for identifying and removing artifacts with their comparative advantages and limitations is provided.
	[14]	Artifacts are unwanted interference in the EEG signal that is caused by factors such as muscle activity, power line noise, and so on. Various techniques for receiving free EEG signals from artifacts to improve accuracy when extracting features and classifying data are proposed, and conventional methods for noise cancellation are reviewed.
Feature extraction	[15]	The physiological significance of EEG maturation characteristics and their relationship to neural growth in specific locations are shown in this paper. Intermittent multi-channel EEG monitoring is important for preterm infants because many of the features described are unclear when limited channel EEG monitors are used.
	[16]	Increasing the size of data challenges many methods of selecting specific features and extracting features. A number of widely used feature selection and feature extraction methods are analyzed. The purpose of this analysis is to show how to use these techniques to achieve high performance of learning algorithms to improve the accuracy of classification prediction.
	[17]	Feature selection involves a combination of searching and estimating the usefulness of features along with evaluating them according to specific learning plans. Genetic algorithm is one of the most widely used methods in selecting features in grouped systems. Investigation of the proposed feature selection algorithm uses the idea of evolutionary calculations of feature space to find the optimal feature subset.
Classification	[18]	EEG is a suitable signal for biometric authentication. Advanced methods in EEG-based authentication are reviewed in this paper, which includes various aspects such as different user tasks in EEG biometric authentication.
	[19]	Current functions and performance results of using deep learning for EEG classification are summarized. Tasks that used in-depth learning were divided into five general groups: mental workload, motion images, seizure detection, potential event detection, emotion recognition, and sleep scoring.

Fig. 2 shows the different methods for measuring brain activity signals in BCI. These techniques are divided into two groups: invasive such as ECoG [20,21] and non-invasive such as MEG [22,23], NIRS [24,25], fMRI [26,27], and EEG [28,29,30]. The electrical activity of the human brain can be detected using an electrode attached to the scalp in an EEG test [31,32].

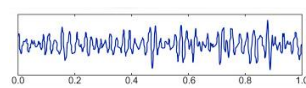
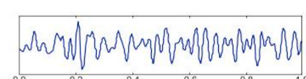
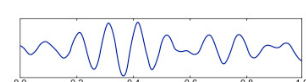
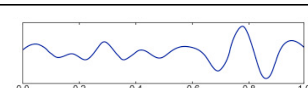
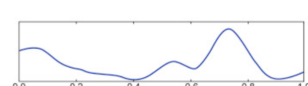
Changes in brain activity are shown by EEG results that can help diagnose brain conditions. EEG activity is quite small, measured in microvolts. In general, these signals are time-varying in nature and are unstable. It is a non-invasive imaging technique of the brain [33,34].

Abnormal electrical discharge by the EEG is possible in some abnormalities in the brain. Over time, the use of EEG signals in the field of health to diagnose brain disorders has increased widely [35,36].

According to studies conducted by a number of researchers, irregular and complex EEG signals can provide information about basic neural activity in the brain [37]. To automatically detect brain abnormalities, the signals generated by the EEG recorder must be prepared to perform further processing [38,39].

EEG measurements are commonly used in various fields of medical research such as mental states [40], epilepsy diagnosis [41,42], drowsiness detection system [43], detection of deep sedation [44], motion sickness [45], for seizures treatment [46], addiction diagnosis [47], and other applications [48,49,50]. Typical EEG classification pipelines include artifact removal [51,52], feature extraction [53,54], and classification [55,56]. A review run on studies on different aspects of EEG is show in Table 1.

Table 2. ***Five frequency bands of EEG.***

Brainwave type	General characteristics	Location	Amplitude	Signal waveform
Gamma [57,58]	Indicates anxiety, stress, meditation. Gamma-band activity participates in various cerebral functions. Within the gamma-band frequency range, it is possible to differentiate between low gamma-band oscillations and high gamma-band oscillations.	Frontal-central areas	Smallest	
Beta [59,60]	The temporal and frontal lobes are the most commonly used areas for recording. It is considered a natural rhythm, that is predominant in patients who are alert or anxious or have their eyes open. This shows alert mode, especially when the subject is in dynamic thinking modeor focus mode.	Parietal, somatosensory, frontal, and motor areas	Very low	
Alpha [61,62]	It appears when the eye is closed and relaxed, and disappears when the eye is opened or alerted by any mechanism. Alpha rhythm characteristic can be found in any area of the brain.	Occipital and parietal regions	Low	
Theta [63,64]	It is perfectly normal in children up to 13 years old and asleep, but it is abnormal in awake adults.	Hippocampus region	Low-medium	
Delta [65,66]	In general, these waves are recorded from the occipital lobe. Appears at brain injuries, learning problems, inability to think. That dominant rhythm is normal in infants up to one year and stages 3 and 4 of sleep.	Mostly in thalamus region	High	

EEG can be used to measure different states of the brain [67,68]. EEG signals can be recorded in two ways: unipolar or bipolar. The unipolar method is mostly used. In this method, the potential of the electrode in an active electrode is measured. A set of special oscillations called rhythms make up the EEG signals [69]. In terms of EEG frequency components recorded in the channel, EEG signal can be analyzed [70,71].

EEG energy in the frequency domain is concentrated in specific bands (normal brain rhythms) that are referred to in this section. The types of EEG waves are divided into five frequencies based on their frequency range [72,73]. The types of EEG waves are: delta [74], theta [75], alpha [76], beta [77], and gamma [78], which are shown in Fig. 3 of the frequency range with the characteristics of each [79,80]. The frequency range and state of the brain of beta signal are shown in Fig. 4 [81]. Band power feature reflects the power in these five bands at each electrode position [82,83]. Table 2 describes the five frequency bands of EEG signal [84,85]. the frequency of the EEG signal refers to rhythmic repetitive activity (in Hz) [86]. They can have different properties such as: rhythmic, arrhythmic, and dysrhythmic [87,88].

The dynamics of EEG signals during emotional brain states during visual stimulation are evaluated in [89] for an accurate understanding of emotional EEG patterns. Three EEG time series channels are used and EEG signals from 5 subjects are recorded in three emotional categories of disgust, neutral, and happy. Also, RQA is used to study the morphological changes of EEG in different emotional states and ANOVA and t tests are performed to detect significant differences in the measurement of RQA EEGs.

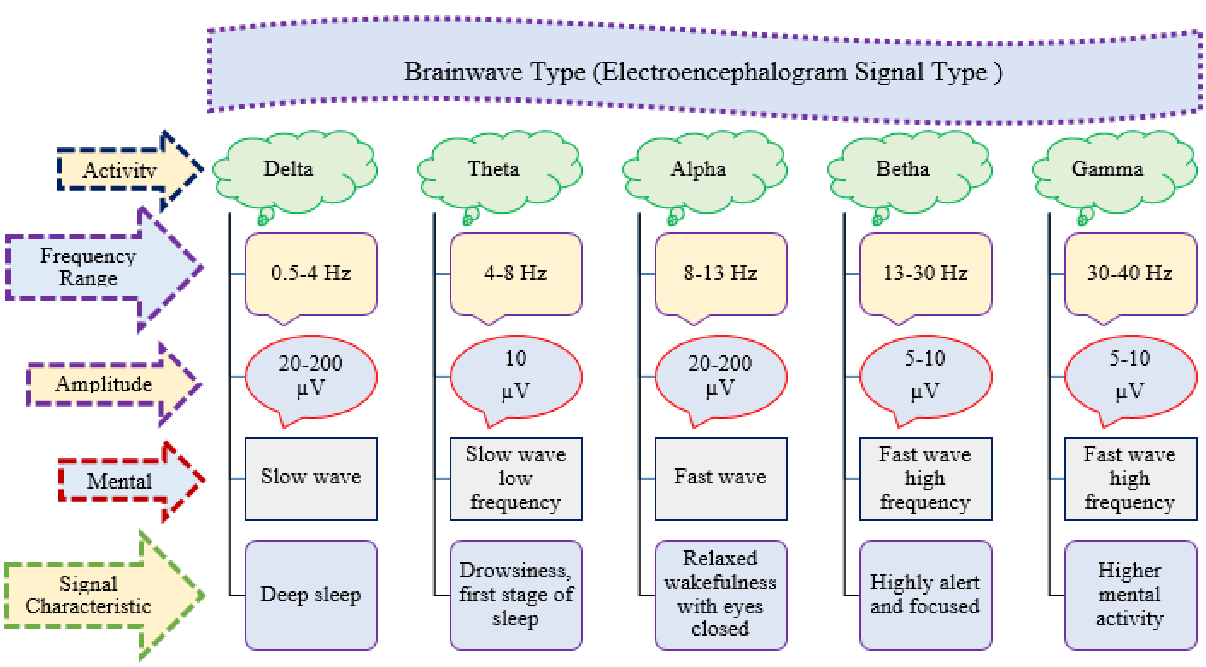


Fig. 3. Electroencephalogram signals characteristics.

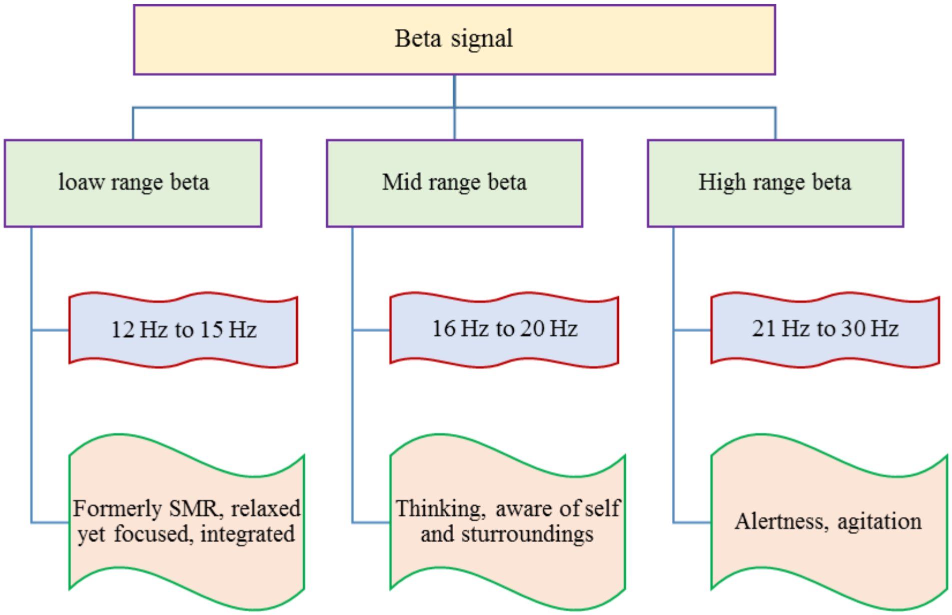


Fig. 4. Brainwave beta type.

Automatic classification of focal and non-focal electroencephalogram signals using discrete Fourier transform-based rhythms is proposed in [90], which is used to classify derived features (MF and RMS) as a set of input features using the class. The LS-SVM device classification is provided. Also in this data set, for automatic classification of 50 pairs of focal and non-focal pairs, the classification accuracy is 89.7% and for 750 pairs of EEG signals, the classification accuracy is 89.52%.

For multilevel mental fatigue EEG classification, two feature selection approaches are presented in [91], in which RF is combined with the heuristic INIT or with the RFE. 12 subjects were evaluated. RF with RFE achieved its lowest test error rate of 12.3% using 24 top-ranked features, whereas RF with INIT reached its lowest test error rate of 15.1% using 64 top-ranked features, compared to a test error rate of 22.1% using all 304 features.

In [92], the improvement of gamma band activity detection when a filter based on experimental state analysis is added to the pre-processing block of single-channel EEG signals, is investigated and shown that by improving EEG processing, clinical applications of activity the gamma band expands.

In [93], a study of 44 patients with depressive disorders showed that resting beta activity could be a useful biomarker for predicting future quality of life outcomes in patients. Initially, after considering the pharmacological effects in longitudinal studies in patients with high beta band strength (20-30 Hz), significantly predicted QOL at 3-year follow-up ($p=0.01$ and $\beta=0.38$).

For smokers, an EEG pattern study based on the theta, alpha, and beta band in [94] is presented that PSD is used. For this study, 33-male smokers and 33 non-smokers were sampled and EEG data were recorded for 5 minutes. From the sampling results it can be stated that for smokers compared to non-smoker is higher theta band power and higher alpha band power.

EEG signals are used to record the internal structure and activity of the brain. This paper provides an overview of important strategies for extracting electroencephalogram signal features. The contribution of this review paper are:

- Different EEG signals are compared in terms of bands, mental, frequency range, and applications.
- EEG signals have been classified into five categories based on kind of the rhythms.
- EEG signals studies have been reviewed in terms of characteristics, feature extraction methods, and events.
- Relationships between EEG waveform frequency bands and different cognitive processes are presented.

This paper consists of three sections. After stating the importance of the issue in the second part, the five main frequency bands of the EEG waveform are expressed. The EEG signal has a different amplitude and width for each person. EEG has a short duration time and signal length is not enough to evaluate the frequency characteristics. Therefore, one of the main issues in identification systems is the extraction of EEG features. The most used feature extraction methods are mentioned in section 2. There are several events that affect the signal. In the second 3, a number of them are examined. Finally, the conclusion is stated in Section 4.

2. FEATURE EXTRACTION TECHNIQ-UES

EEG is neurophysiological test conducted to capture neuronal actions of the brain. Manual screening of EEG signals to detect the event is complicated for users because EEG signals consist of the inherent complexity of the brain and are recorded in microvolts [95]. The study of EEG signals with linear frequency and time domain methods is complex because EEG signals are nonlinear, contain a lot of noise and inherently oscillating [96]. Therefore, nonlinear parametric amplitude-frequency-time methods are used to analyze EEG signals.

A variety of methods have been widely used to extract the features from EEG signals [97,98], including time frequency distributions (TFD) [99,100], wavelet transform (WT) [101,102], eigenvector methods (EM) [103], fast Fourier transform (FFT) [104] and auto regressive method (ARM) [105], and so on.

Feature extraction is an important step in the process of EEG signal classification [106, 107]. The purpose of feature extraction is to show raw EEG signals or processed by related ideal quantities that display the task information contained in the signals [108]. EEG signals feature extraction methods are listed in Table 3.

2.1. Time Frequency Distributions (TFD)

TFDs characterize nonstationary signals over a time-frequency plane. These methods require noise-free signals to provide good performance. Also, they may serve as a basis for signal synthesis, coding, and processing [109,110]. Feature extraction using this method is based on energy, frequency, and main path length [111].

2.2. Fast Fourier Transform (FFT)

EEG consists of time series data of evoked potentials resulting from systematic neural activity in the brain. FFT is a simple algorithm for efficient calculation of discrete Fourier transform. In this method, the EEG signal is decomposed into a number of sine functions with different frequencies, amplitudes and phases. FFT is just an algorithm used for fast computation of the DFT [112,113].

2.3. Eigenvector Methods (EM)

To estimate the frequencies and signal power of faulty noise measurements, eigenvector methods based on an eigen-decomposition of the correlation matrix are used [114,115]. When the SNR is low, high-frequency

Table 3. ***EEG signals feature extraction methods.***

Analysis method	Method name	Description	Advantages	Disadvantages
Frequency domain	Eigenvector	They are used to calculate the frequency and power of signals from artificial measurements.	Eigen has the potential to decompose to communicate even artificially faulty signals.	They must be calculated for each problem. There are no special vectors for the degenerate case that are not perfect degrees.
	Autoregressive	The variable in question is usually predicted using a linear combination of the variable's past values.	The AR model explicitly accounts for autocorrelation in the error allowing for valid inference to be made.	It is difficult to get transient features from EEG signals.
	Fast Fourier transformer	It converts the signal into individual spectral components and provides frequency information about the signal.	The speed increases as the number of calculations required to analyze the waveform decreases.	The narrow bandwidth transformed by super-heroism is also the most limiting factor of this method.
Both time and frequency domain	Wavelet transform	Wavelet transform decomposes a signal onto a basis of functions. It is suitable for the time-frequency analysis.	Signal analysis is possible at different scales simultaneously. The length of time that the energy of the decomposition functions is localized varies depending on the amplitude of the operating frequencies.	Its discretization is less efficient and natural. It does not give information about the time of occurrence of the signal components. The calculations are compressed during accurate analysis
	Time frequency distribution	The pre-processing step is necessary to get rid of all kinds of artifacts. The windowing process is required in the preprocessing module.	It is more suitable for nonstationary signals.	Noiseless EEG signals or a well-de-noised signal should be used.

eigenvector methods can still produce frequency spectra of high resolution. These methods are suitable for signals that can be thought of as consisting of several specific sinusoids buried in noise [116,117].

2.4. Wavelet Transform (WT)

Similar to Fourier transform, WT decomposes a signal onto a basis of functions [118]. Various WT such as Tunable-Q wavelet, dual tree complex, and orthogonal wavelet filter bank have been used in pre-processing and feature extraction of EEG signals to detect the event [119,120].

Its main advantage is that any favorable interaction between time and frequency resolution is provided, in other words the time window length becomes larger at low frequencies and smaller for large frequencies [121].

2.5. Auto Regressive Method (ARM)

AR model is widely used in system identification and signal processing. It is a time series model and uses observations of previous time steps as input to the regression equation to predict the value in the next time step. The AR model coefficients are used as characteristic vectors in the BCI system [122,123].

3. VARIOUS EVENTS AND EEG SIGNAL EVENTS EFFECT ON EEG SIGNALS

Recent advances in biomedical signal processing have led to the development of various techniques for multi-resolution analysis of EEG signals and diagnosis of disease status. The effect of various events such as epilepsy [124,125], addiction, and sleep on the EEG signal is examined in this section.

3.1. Epilepsy, Epileptic Seizures and Their Effects on EEG Signals

Epilepsy is the most common neurological disorder in humans. It is a serious neurological condition [126].
In epilepsy, brain activity becomes abnormal and anyone can have epilepsy. Periods of unusual behavior, emotions, and sometimes loss of consciousness are the effects of epilepsy.

Electrical signals in the brain are disrupted in epilepsy. Sometimes there is a sudden explosion of electrical activity that causes a seizure. In most cases, the cause is unknown.

Recorded EEG signals contain valuable information for understanding epilepsy. Traditional intelligent methods for detecting epileptic EEG signals consider two conditions: (a) the training data set and the test data set have the same distribution, and (b) the available data are sufficient for training. In practice, these two conditions are not always achievable and reduce the ability of the intelligent detection model obtained to detect epileptic EEG signals [127,128].

A DIC-MV fuzzy clustering algorithm for automatic detection of epileptic EEG data is presented in [129]. This algorithm uses correlation information between each view and controls the importance of each view to improve the final clustering performance. Experimental results show that this algorithm has better clustering performance than traditional clustering algorithms for processing multi-index EEG data.

A strategy for constructing a TSK-FLS based on transducer transmission learning to identify epileptic EEG signals is presented in [130]. TSK transfer learning algorithms for regression and binary classification are built to build the corresponding TSK FLS, respectively. Both algorithms are mostly used to perform a multi-class classification to detect epileptic EEG signals. Their performance in the EEG epilepsy dataset represents promise in dealing with situations where the training and test datasets vary according to the distribution of the data.

In [131], an EEG classification method based on the prediction error of the AR model has been performed to detect EEG signals between control subjects and patients with epilepsy without epileptic form discharges. Twenty-three patients with non-discharge generalized epilepsy were studied in their EEG recordings and 23 age control groups for whom EEG recordings were performed using EEG features based on the prediction error of the classification AR model. The results showed that the accuracy, area under the curve, true positive rate, and true negative rate were 85.17%, 87.54%, 89.98%, and 81.81%, respectively.

Feature extraction based on image processing algorithms for automatic detection of epileptic activity in brain EEG signal display using an efficient classification method is proposed in [132] and CNGP and CTP for elimination automatic artifact brain maps are provided. The results also show that the LSSVM classifier with Gaussian RBF nucleus is able to detect epileptic brain map with high accuracy.

Literature [133], examines the common moment signals and frequencies at the EWT signal compatible frequency scales, and the Boston-Massachusetts Children's Hospital EEG database (CHB-MIT) is studied. Using a step, the features extracted from each oscillation level are processed and the common features are calculated to achieve better seizure discrimination and without seizures during the EEG signal period. Using six classifications, the proposed detection method was evaluated, and the means of sensitivity, specificity, and accuracy were set at 97.91%, 99.57, and 99.41, respectively.

a) Decoding brain signals

Decoding motor commands from non-invasive neural signals measured is important in brain-computer interface research [134,135]. The brain signal decoding algorithm is an important part of the BCI, because its function determines the performance of the interface [136,137].

In [138], when participants execute, observe, or imagine complex paths of upper limb movement, the movement instructions are decoded in three dimensions after EEG recording. The results show that linear receivers are an efficient and powerful method for decoding motor commands. Contamination of brain signals related to eye movement is also a serious problem for decoding motion signals from EEG data.

In [139], a decoding algorithm with a small-dimensional feature matrix optimized to detect the motion of a finger using EEG signals is proposed and implemented. That, to classify the two types of finger movements, a degree attribute extraction algorithm based on graph theory with SVM is proposed, which considers three factors:

frequency band, amplitude, and ERD amplitude.

A spike detection algorithm using the frequency band amplitude feature and classification of the core support vector device for intracranial EEG data is proposed in [140]. The algorithm consists of two steps: FFT algorithm is used to extract various features and then these features are used selectively and used to detect spikes in educational sets. Medium performance with 98.44 sensitivity, 100% selectivity and 99.54 accuracy is achieved for the performance of this algorithm.

In [141] by examining linear and nonlinear regression methods and using the estimated target EEG signals in the occipital region, the ear-EEG decoding accuracy in relation to the SSVEP pattern is increased. Given the predictive diversity of regression methods, an ECR framework has been proposed to reduce prediction errors by adding an additional nonlinear regression process. The ability to decode the proposed framework online with a short window size is demonstrated. The average accuracy was 91.11 9 9.9, 90.52 67 8.67, 96.96 12 12.13 and 78.79 12 12.59%.

3.2. Sleep and Drowsiness and Their Effects on EEG Signals

During human life, sleep plays an important role in health and wellness. Getting enough sleep at night protects a person's mental and physical health. And adds to the improvement of quality of life. Sleep-related, such as insomnia, sleep apnea syndrome, depression, schizophrenia, narcolepsy, and other neurological disorders are some of the sleep-related disorders. By reducing the memory capacity and speed of processing a person's brain information, drowsiness is determined, which creates risks in the workplace in real time for the person. Sleep screening and analysis is a significant tool in assessing these disorders.

Sleep disorders are a number of conditions that affect the ability to sleep well on a regular basis. For a variety of reasons, such as health problems and high stress, sleep disorders are on the rise.

Depending on the type of sleep disorder, people may find it difficult to fall asleep and feel very tired during the day. Lack of sleep can have a negative effect on energy, mood, concentration and overall health of the body.

Feature extraction is performed as an essential preprocessing step to reduce data and perform automatic sleep staging [142,143].

Three different schemes for extracting features from EEG signals including relative spectral band energy, It acara distance and harmonic parameters are presented in [144]. AR modeling has been used for spectral estimation. The performance of these schemes has been compared with the aim of selecting the optimal set of features for specific, sensitive and accurate neural-fuzzy classification of sleep stages.

The classification of EEG signals for the determination of the state of sleep of a patient is studied in [145], which the PSD matrices as the feature for the distinction between different classes of EEG signals is used.

An apnea frame detection method based on the EMD of wavelet reconstructed delta wave of EEG signal is proposed in [146], which begins with WT an EEG frame and reconstructing the low frequency delta wave from the approximate coefficients. The proposed method is applied to each patient and overall patients. Sensitivity and specificity rates of 80.43%, 85.59%, and 77.87% respectively on overall patients. This method is an efficient method for detecting apnea and non-apnea frames when only EEG signal is available and can be a great tool for PSG sleep apnea diagnosis.

The EEG-based automatic drowsiness detection method has been suggested in [147], which the CVMD is used to investigate the unstable behavior of EEG in the diagnosis of drowsiness. Homogeneous clusters created by CVMD are decomposed into finite band states. Then the oscillation mode features are extracted in terms of several features and fed as input to the least squares vector machine classification.

In [148], WT is used to detect drowsiness and alertness of EEG signals. Alpha and beta channels are considered EEG signals. 84.98% sensitivity and 98.65% rating were reported.

The non-static property of the EEG signal is investigated by TQWT in [149], in which TQWT decomposes the EEG signal into sub-band, which is mostly used to extract the features. Different classifications are considered. Awareness and drowsiness EEG signals assess the differential performance of TQWT-based features with the KW test. The results of the KW-test show that the proposed features effectively differentiate between wakefulness and drowsiness. According to the results, the best accuracy score of 91,842% is generated by the ELM classifier.

3.3. Migraine and Their Effects on EEG Signals

Migraine is a long-term neurovascular disease that can be caused by many factors and causes severe pain and disorders of the autonomic nervous system [150].

It is usually a moderate to severe headache. Migraine is felt as a throbbing pain on one side of the head. There are symptoms such as feeling sick, sick, and hypersensitivity to light or sound in some people. Migraine is a common disease that affects 1 in 5 women and 1 in 15 men.

Migraines are different from headaches. Headache symptoms include pain in the head, face, or upper neck. It can also have different frequencies and intensities. But migraine is a very painful primary headache disorder, and usually causes symptoms that are more severe and debilitating than the headache.

The two feature extraction methods (parametric and non-parametric) and the two classification methods in order to achieve optimal compositional diagnostic accuracy are compared in [151]. Features are selected using a GA, and then given to a vector machine for classification and linear segregation analysis. In this study, the highest migraine detection accuracy of 93% was obtained using the Welch method to extract the EEG feature along with the support vector device for classification.

A migraine analysis method using EEG signals to characterize migraine patients with aura is proposed in [152]. Three brain characteristics using brain network analysis of alpha phase synchronization; transient abnormality analysis and finally joint time-frequency analysis are extracted, which the wavelet scale and AR modeling are used. Findings suggest electrical features for the predisposition of migraine which can lead to possible preventative interventions in the future.

4. CONCLUSION

EEG is an effective non-invasive measurement method used to monitor the electrical activities of the brain. EEG signals are used intermittently among physiological signals because they represent brain activity. EEG signals contain a lot of information about brain function and detect abnormalities in the human brain. In other words, different brain functions produce EEG signals. The recorded waveforms reflect the cortical electrical activity. The voltage of the EEG signal corresponds to its amplitude. EEG signals have different rhythms depending on the frequency bands occupied. The EEG signal can be analyzed in terms of its frequency components. The main frequencies of the human EEG waves are: delta, theta, alpha, beta, and gamma. A number of diseases are identified by the nature and occurrence of these waves. A critical part of EEG classification is features extraction. Classically, feature selection methods are divided into two categories: filtering methods and wrapper methods.

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