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# Electroencephalogram Signals Analysis: A Study

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## Abstract

Electroencephalography (EEG) is a process of extracting accurate information from the brain using electrodes attached to the scalp. In the area of biomedical signal processing, EEG signal has developed importance in the diagnosis, and treatment of abnormalities and brain diseases. It has revealed massive facilities to advance human life. In this paper, a state of art on EEG signal analysis is presented that aims to cover various signal processing and machine learning techniques to recognize the mental health conditions of the human being thereby paving a way to assist medical professionals, besides revealing future opportunities and scope available in this research domain.

**Keywords:** Electroencephalogram signals, Feature Extraction, Signal Processing.

## 1. Introduction

The human brain is an incredible part of the human body. The most complex part of our body is the brain. It consists of approximately a hundred billion neurons, interconnected via axons and neurons. Through synapses, the neurons receive stimulus which travels through the axon as electrical impulse helps control emotions, body movements, and other aspects of the body [1]. The electrical activities of the brain are detected by EEG signals. EEG signals have a very important role in clinical and research purposes. The fluctuating electric potential of the brain can be recorded by electroencephalography [2]. This potential electrical occurs by placing electrodes on the scalp and applying gel on it. The brain's activity reflects the EEG signal recorded by fixing the electrodes on the scalp. During the recording of the brain waves, it results in a high-resolution sequence within a short time. Epilepsy is primarily treated with EEG. The conditions that result in abnormalities of EEG data like coma, anesthesia, brain death, a disorder in sleep, etc. are treated using EEG. The brain-computer interference (BCI) is a mechanism that enables brain impulses to communicate within the globe. EEG is a treatment process for strokes, tumors, and other localized brain illnesses. In the BCI system, there are lots of options to determine brain pulses like EEG, MEG, MRI, ECoG, LPF, etc. In the market, we can get numerous electrode channels like 14 electrodes, 64 electrodes,128 electrodes, etc. The most consistent and regularly used is the BCI system. The range of frequency in which the EEG pulses are recorded is for delta the range is between 0.5-4.0 Hz, for theta the range is 4.0-8.0 Hz, for alpha the range is 8.0-13.0 Hz, and beta is less than 13.0 Hz. Placing 10 to 20 electrodes on the scalp of the brain the EEG pulses are determined. EEG has become the most efficient method of detecting brain pulses [3].

### *1.1 Brain-Computer Interference System (BCI)*

A (BCI) method is mainly of 4 phases. Signal Acquisition, Signal Pre-Processing, Feature Extraction, and Classification are the stages of BCI. The brain pulse is connected to the outside world with the help of a Brain-Computer Interface (BCI). Invasive and non-invasive are two techniques used in the BCI system. Bio-medical, robotics, surgery, etc. can get lots of benefits from it [4].

### 1.2 Signal acquisition of the brain

Some of the approaches assess the variance of electrical activities connected to different states of the brain, while others measure a variety of other characteristics. Non-invasive and invasive acquisition methods are two types of techniques. Intra–cortical electrode arrays and electrocorticography (ECoG, intracranial) are two types of invasive procedures. EEG, near-infrared spectroscopy (NIRS), functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and magnetoencephalography (MEG) are the non-invasive methods [5].

### *1.3 Signal Preprocessing*

At signal preprocessing of BCI, EEG filtering is done [4]. There are numerous approaches that are designed to remove the noise generated by a variety of skills from the EEG pulses. The major plan of this method is to generate a new set of resulting channels that enhance the separability of the data. Preprocessing of the signal includes the instruction of the EEG reports. Filtering, segmentation, and detrending were utilized to set up the EEG data for the next stages. Filtering and segmentation which is also named epoching are the methods of recognizing and exploiting data above a definite frequency or time array which is connected through the feature of brain action. After filtering is done the segmentation of EEG information is performed. After the processing method, the next step is to simplify the extraction of features and classifications process.

### *1.4 Feature Extraction*

Feature extraction is a method by which applicable information from the raw data is extracted for further classification purposes [6]. The applicable information extracted is not required to be in the form of raw data. Feature extraction includes extracting the applicable data from the digitized data with which proper classification can be done. The extraction of features is the largest part of a significant element of any classified process. The extraction of features includes biased information hence the accuracy of feature extraction affects classification accuracy. Extraction of features can be done in both frequency and time domains. Some examples of time domain analysis are common spatial patterns, autoregressive parameter estimation, and basic probability and statistical analysis. Some examples of frequency domain analysis are Fourier spectrum analysis and power spectral density estimation. Data reduction can also be achieved in the feature extraction process as only the relevant data is selected for classification purposes and thus reducing the processing time. There are many methods of feature extraction. (AR)Autoregression, (CSP)Common spatial pattern, (DWT) Discrete wavelet transform, (PWD)Power spectral density is the technique of extraction.

### *1.5 Classification*

Classification is an important state of Brain-computer interference [7]. After the signal is extracted from the feature the signal processing is then classified by the various classifier. The classifiers are easy to use. It gives good results. There are different types of classifiers. The main aim of classification is to convert neural data to control logical signals. A few classifiers can be listed as (LDA)Linear Discriminant Analysis, (QDA)Quadratic Discriminant Analysis, (LSM)Linear support vector, and (KNN)k- nearest neighbor.

## 2. Related work

Asieh Ahani (2013), study investigate that "mind-fullness meditation (MM), an inner psychological implementation is practiced through which a response relaxes but the state of mindset is nourished in [7]. To check the high-stress level also, MM carry out the high-stress level of the number of older people. Their study estimates the gesture methodologies of EEG. MM action was carried out for a growth sign through meditation and control conditions to support the quantification of the meditative remark. Collected data of respiration and EEG were analyzed six weeks later meditation intervention on 34 novice meditators. Analyzed collected data with spectral analysis to assess a goal mark for meditation with the support vector machine classification. In their study, they notice control condition and meditation differences in beta, alpha, and theta frequency bands. The result concludes that analysis of EEG spectral revealed a generalized increase in beta, and during meditation, theta EEG power compared to control. In the posterior and right lateral location, the increase of alpha EEG power during meditation compared to control.

Shih-Feng (2011) Along with his fellow researchers studied time-frequency analysis which is important and analytic tools are used for evaluating physiologic signals [8]. Their study was designed to detect the sampling frequency of 250 Hz during meditation through characterized of EEG recorded with 19 active electrodes. And through this study an acquired of new insights is obtained into the nature of EEG during meditation by the performed analyzed tools which records signal done by Fast Fourier Transform (FFT). Efficient segmentation in EEG signal processing is an important problem. At different electrodes exhibit behavior, the comparison between the recording time is strongly dependent on frequency and time.

Min Huang (2019) study investigates the meditation differences in between walking and sitting [9]. Identification of these four states is extracted and calibrated using the Rhythm feature, and these states are performed by the EEG signal of 7-day Zen participants. The performance of calibrated features with that of original features is compared. Their study classifies the accuracy of the proposed calibration methods is significantly improved. Vichivt Boonyahotra (2017) has aspired their study to probe and recognize inner wisdom training and meditation [10]. In their study, six healthy participants measured between 20-40 years of age were applied for EEG power spectra. All nine experiments were done equally to all the participants. While the EEG records the movement when the participants are urged to close their eyes for 3 minutes. During the observance activities of brainwave were recorded individually by EEG at one and three after the experiment began. The study conclude that inner wisdom meditation had accomplished on alpha, theta, and gamma frequency bands. Muhammad Zeeshan et.al. (2014) in their paper based on EEG signals have developed an effective way to classify the EEG signals [11]. The EEG signals were carried out on 2 electrodes c3 and c4. They have given a qualified revision on classification with a new advanced system. They used a self-organization map (MOP) based neural technique. For feature reduction principal component analysis has been worn. To categorize motor imagery EEG pulse, they have found the best approach by unsupervised and supervised features for an algorithm. SOM has been the best approach for EEG-sourced BCI devices. By using advanced processing signal techniques different diagnoses can be extracted from different feature diseases. Effects of different EEG signals events and hidden data from signals are used to extract from the processing signal method are examined. Frequency domain, time-frequency, linear and non-linear techniques like Hurst exponent(H), largest Lyapunov exponent (LLE), correlation dimension (CD), fractal dimension (FD), different entropies, higher order spectra (HOS). Using a classic normal EEG signal is discussed in recurrence plots and phase space in detail [12]. Akshaya R. Mane and his team (2015) compares different extraction of feature technique such as (ICA)Independent component Analysis, (WT)Wavelet Transform, (PCA)Principal component analysis, (AR)Autoregressive model, (EMD)Empirical mode decomposition. They have studied the significant measurement and distinguishing properties from different methodologies. They have concluded that high-quality performance does not obtain in the frequency domain method in EEG signal also time- frequency does not provide as much information as the frequency domain does. Hence, they suggested choosing the technique according to the mental task to get better performance [13].

Wan Amirah W.Azlan and his team (2008) says that an appropriate system for the extraction of feature is required to achieve the best results. Though there is various technique they have chosen the feature which is the majority used for schizophrenia. Hilbert-Huang transform, Principal Component Analysis, Independent component analysis, Local Discriminant Base are the techniques used in their resource. They have concluded that all the techniques are capable to distinguish the organized and alcoholic groups. They said that LDB is very effective to extract features [14].

Zhongwang Yang and his team (2017) perform the activity to understand brainwave movement through EEG signal extraction relate to Hilbert-Huang (HHT) and multivariate mode decomposition (MEMD) algorithms based on characteristics during the performance of exercise fatigue. And can help in the basis of scientific detection and treatment for fatigue injury and sports fatigue. Signal processing of experienced mode to multi-channel is extended by MEMD and solved by traditional algorithms. Scale alignment, self-adaptability, and modal aliasing are not suitable for this. Multi-time analyzing sequence; decomposition of multi-scale and EEG signal and multi-channel is suitable for this. After that, the real EEG signals flow through the MEMD, and the feature set is formed by the energy median, mean, and standard deviation calculated in different levels of the EEG bands. Later the extracted features extract and classify through the support vector machine (SVM) classifier. During exercise fatigue EEG signal extract, the feature method is proposed to show the simulation results effectively [15].

Chamila Dissanayaka [2014] and his team investigated the difference between a brain region and human (drowsiness, meditation, and awake) states by comparing coupling (also known as information flow) and coherence (also known as connectedness) accomplished in the study. Through each condition different region of information was estimated to measure the brain's flow or the coupling by a method known as The Directed Transfer Function (DTF). To measure the connectedness or coherence between brain area a method known as Welch and Minimum Variance Distortion-less Response (MVDR) were used. Analysis was conducted of 30 subjects comprising 10 meditating, 10 awake, and 10 drowsiness with six electrodes utilizing the EEG data. For individual subjects, five minutes of baseline and 15 minutes of exact condition comprising meditation, consciousness, and tiredness EEG data were recorded. Data analysis was moved out which consist of Kruskal-Wallis 9KW nonparametric examination of variance occurred Bonferroni alpha-correction by a post-hoc test. The outcome result of the study concludes that the spectral summary of the brain's coupling (or information flows) as well as its coherence (or connectedness) that change in surface awareness led to substantial difference [16].

U. Rajendra Acharya's (2018) research about Brain disorder disease in humans known as Epilepsy can affect anyone at random age. People suffer from Epilepsy nearly 50 million globally. Seizures are observed because of excessive discharge of electrical in brain cells. Focal(F) and non-focal (NF) types of Electroencephalogram (EEG) carry activity of brain information that estimates to identify affected areas by seizures. Generally, the Epileptic area of the brain is recorded by FEEG signals while unaffected Epileptic from brain regions is recorded by NFEEG signals. Correct detection is important to detect FEEG signals, they occur when and where as successful treatment of focal epilepsy can be treated by the surgical process. Also, highly trained personnel are required as all EEG signals are complex for the right explanation. To associate with the overcome challenge, a computer-aided detection (CAD) system to assist the FEEG signals of detection has developed and the presentation of nonlinear features in EEG signals containing Rhythms and concealed patterns can capture effectively. All-inclusive, this study constructs that the CAD system will benefit in providing clinicians with an accurate and objective paradigm for the localization of the Epileptogenic area [17].

Table 1: Brainwave Classification [18]

| **Wave** | **Frequency** | **Mental state** |
|---|---|---|
| Gamma | 40Hz or more | High level of order processing |
| Beta | 13 to 40Hz | Normal walking consciousness |
| Alpha | 8 to12Hz | Woke up but relaxed |
| Theta | 4 to7Hz | Less sleep or extreme relaxation |
| Delta | > 4Hz | Depth dreamless sleep |

EEG is a test that reads the electrical impulses of the brain by using numerous electrodes which transfer information from the brain to a machine that measures and records the data.

## 3. Mathematical Tools and Techniques

### 3.1 Discrete Wavelet Transform (DWT)

Wavelet Transform (WT) is a key function in the diagnostic field and recognition. WT reduces the time-varying in bio-medical signal, which consists of a lot of information points into a modest parameter that presents the pulses [19]. Because the EEG pulse is not constant, using a time-frequency domain technique such as the wavelet transform (WT), which is a spectral approximation approach in which various common functions may be described as an infinite series of wavelets, is a good way to extract features from raw data. The unique EEG signal is represented in the WT approach by wavelets, which are protected and simple building units. During dilation and translation, the wavelet generates these wavelets as part of derived functions, shifting actions adjacent to the time axis. Wavelet Transforms are divided into two types: continuous and discrete.

| | |
|---|---|
| [illegible] | (1.1) |

Here,

$H(z)$ shows the filter's $h$ $z$-transformation. The (HP)high pass filter's matching$z$-transformation is expressed as

$$G(z)=zH(-z^{-1}) \tag{1.2}$$

There are a number of benefits to precisely relating the character of the signal section inside a particular frequency range and enclosed time domain qualities, which offset the high computational and recollection necessities of the predictable convolution-based DWT completion.

### *3.2 Autoregressive Method*

The estimation of (PSD) power spectral density of EEG with various parametric approaches is done by a technique called the autoregressive method [20]. So, it does not have any issue with spectral leakage and gives a good result in frequency. By calculating the coefficient, we can get the estimation of power spectral density. Two technique of the autoregressive method is discussed below [20][21]:

### 3.3 Yule-Walker technique

Using Yule- walker process the PSD is estimated. The calculation method is specified below:

$$\tag{1.3}$$

$r_{xx}$ is expressed by

$$r_{xx}(m)=\frac{1}{N}\sum_{n=0}^{N-m-1} x^{*}(n)\,x(n+m) \tag{1.4}$$

Calculating on top of set of $(p + 1)$, the coefficients of are is as follows:

$$p_{xx}^{BU}(f)=\frac{\sigma^{2}wp}{\left|1+\sum_{K=1}^{p} a_p(k)e^{-j2\pi fk}\right|^{2}} \tag{1.5}$$

$$\sigma^{2}wp=E_f^{p}=r_{xx}(0)\prod_{k=1}^{p}\left[1-|a_k(k)|^{2}\right] \tag{1.6}$$

### 3.4 Burg's technique

The reflection coefficient is straight forwardly calculated without the autocorrelation technique. To satisfy Levison-Durbin recursion the backward and forward prediction error is reduced based on AR methods. The method is as follows:

$$p_{xx}^{BU}(f)=\frac{\hat{E}^{p}wp}{\left|1+\sum_{K=1}^{p} a_p(k)e^{-j2\pi fk}\right|^{2}} \tag{1.7}$$

Burg's method gives exact data value. It produces well packets which are sinusoid once it holds minimum level of noise. The Burg's method and Yule's- method is calculated in different process. The autoregressive method estimated good frequency resolution and spectral leakage.

### *3.5 Common Spatial Pattern (CSP)*

This strategy of CSP is first introduced by Ramsor to classify motor imagery. The spatial resolution of EEG is improved by CSP algorithm. The abnormality of EEG activity is detected by CSP [23]. In movement related pattern CSP has become the effective method. In BCI signal processing it has become the most effective method. It is a mathematical expression to obtain optimal spatial filtering by decomposing unprocessed EEG signals.

Though it is an effective method in acquiring EEG signals it has many disadvantages and limitation. The mathematical expressions are shown below:

| | |
|---|---|
| $C_1 = \frac{(X_1 X_1^T)}{Trace(X_1 X_1^T)}$ | (1.8) |
| $C_1 = \frac{(X_2 X_2^T)}{Trace(X_2 X_2^T)}$ | (1.9) |

The equation of covariance matrix together are expressed as:

| | |
|---|---|
| $C = C_1 + C_2 = U_0 \sum U_0^T$ | (2) |

$U_0$ = eigenvectors

$\sum$ =The covariance matrix C has a diagonal matrix of eigen values.

Then, a conversion (P $= \sum_p^{-\frac{1}{2}} U_0^T$) is applied to the average covariance matrices for both classes as Eq.

| | |
|---|---|
| $S_1 = P C_1 P^T$ | (2.1) |
| $S_2 = P C_2 P^T$ | (2.2) |

S1 and S2 contain the similar eigenvectors, and the mixture of the related eigen values for both are equal to one. It can be expressed as:

| | |
|---|---|
| $S_1 = U \sum_1 U$ | (2.3) |
| $S_2 = U \sum_2 U$ | (2.4) |
| $\sum_1 + \sum_2 = I$ | (2.5) |

$S_1$ have the maximum value of eigen vector, $S_2$ have the least value of eigen vector

| | |
|---|---|
| $W = U^T P$ | (2.6) |

The independent component off EEG data is:

| | |
|---|---|
| $Y = W X$ | (2.7) |

The process of common spatial patterns (CSP) designs spatial filters to obtain variances in the filtered time sequence information are finest for discrimination.

The main aim of CSP is to discover M spatial filters, it linearly changes the input signals by following equation:

| | |
|---|---|
| $S_{csp}(t) = W^T x(t)$ | (2.8) |

where s(t) = vector of input signals at time *t* from all the channels:

| | |
|---|---|
| $ScR_C = \frac{1}{K}\sum_i S_c^i (s_c^{i})^T$ | (2.9) |

A matrix W is determined in CSP technique:

| | |
|---|---|
| $W^T R_1 W = \lambda_1$ | (3) |
| $W^T R_2 W = \lambda_2$ | (3.1) |

### *3.6 Power Spectral Density (PSD)*

PSD is one of the techniques used for feature extraction process. PSD is used in narrow band signal and in signal processing. PSD distributes the power signal over frequency as role of frequency it shows the energy of power[22].

| | |
|---|---|
| $P(f) = \frac{1}{NT}\left\lvert \sum_{n=0}^{N-1} x_{(n)} w(n) e^{-j2\pi fn} \right\rvert$ | (3.2) |

### *3.7 Bagging Classifier*

Decisions in use from diverse learners be able to joint into single forecast. Simply combining individual decision in an organization's folder is voting. This method is used for boosting and bagging[24]. Individual models are bagged and boosted in a variety of ways. Models in bagging are given the same weights, but adding successful models in boosting are given greater weighting, as an executive may base his or her decisions on a variety of experts' suggestions.

Algorithm 1
Bagging algorithm 1
Input : data D = {($x_1,y_1$),($x_2,y_2$),…………($x_m,y_m$)}
Learning of base algorithm £
Number based learners L
method:

1) t = 1,…,….,L
2) $h_t = \mathcal{L}(D, D_{bs})$ distribution of bootstrap
3) $E$nd

Bagging Output: H(x) = $\arg$ Max $\sum_{t=1}^{T} I(h_t(x) = y)$

### *3.8 Boosting Classifier*

Boosting is a process in which a strong classifier is created with the weaker ones. It is an algorithm of a machine learning. In machine learning boosting helps in removing the conflicts and unfairness. The boosting was used to combine a large number of models in order to build this concept by attempting to find models that complement each other
ALGORITHM
Input of sample distribusion D
Learning of Base algorithm £;
Number based learners L.

PROCESS:

1) $D_1 = D$. % Initialized distributor
2) t=1,…,., L
3) [illegible] % Trained a weaker learner for distributed $D_t$
4) [illegible]; % Evalute the error $h_t$
5) $D_{t+1} =$ Adjusted_ Distribution ($D_t, L_t$)
6) $End$
7) BOOSTING OUTPUT: H(x) = combined_ outputs ({[illegible]})

## Conclusion

This study presents a general idea on EEG signal analysis for wellbeing assessment using various signal processing and machine learning techniques. It spans a detailed study on various signal processing techniques for feature extraction followed by the classifications of EEG signals for abnormality detection. The EEG analysis proves instrumental to know the mental condition of the human being including detection of the left handedness and right handedness of persons. In spite of challenges present in the EEG signals analysis mainly due to its non-linearity, non-stationary, low amplitude and low frequency characteristics, still there is a tremendous scope to implement recent signal processing and machine learning tools for proper analysis of EEG signals to extract the clinical information at early stage and help the neurologists.

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