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Research paper

Epileptic Seizure Detection In EEG Signals Using Non-Linear Analysis

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Abstract

Epilepsy is a chronic disorder of the central nervous system that occurs irregularly and unpredictably, due to the temporary electrical disturbances in the brain. According to World Health Organization (WHO), approximately 50 million people worldwide have epilepsy, making it one of the most common neurological diseases globally [1]. It predisposes individuals to experience recurrent seizures. Electroencephalogram (EEG) is a technique used to measure the electrical activity of the brain signals for the diagnosis of neurological disorders, and it also paves the way for seizure detection using scalp and intra-cranial EEGs as the input data. In this paper, we have proposed a method for non-linear feature based epileptic seizure detection by extracting five features namely Entropy, Mean, Skewness, Standard Deviation and Band Power. The classification techniques used are K-nearest neighbor (KNN) and Support vector machine (SVM) which gave an accuracy of 95.33% and 100% respectively.

Keywords: *Epilepsy, EEG, Seizure, Non- linear analysis, Entropy, Skewness, SVM, KNN.*

1. Introduction

As we all know brain is one of the most vital organs of human body controlling the coordination of human muscles and nerves. Any small disturbance in the electrical activity might lead to a disease called Epilepsy. Approximately 12 million people with epilepsy reside in India that contributes to about one-sixth of the global burden. Approximately one out of every three individuals with epilepsy continue to experience recurrent seizures even after the treatment with multiple anti-epileptic drugs[2].

Epilepsy is derived from a Greek word called epilambanein, which means 'to seize or attack' [3]. Seizures are temporary alterations in the brain functions that are caused due to improper electrical activities of a group of brain cells. It can be caused due to a various number of unrelated conditions such as damage to the brain due to high fever, toxicity, stroke, electrolytic imbalances, which sometimes results in loss of consciousness and control of bowel or bladder function. Here we are using EEG signals for the detection of epilepsy. EEG is a test in which we place several electrodes on the scalp and measure the electrical activity of the brain. The standardized electrode placement is as shown in figure 1. It is a non-invasive and low cost method to measure electrical activity of brain, it can be used for diagnosis of various diseases such as early dementia and seizure. Despite the presence of various other technologies such as Positron emission tomography (PET), Magnetic Resonance Imaging (MRI) etc., the EEG signals are widely used in the diagnosis and study of epileptic seizure because EEG signals provides ample of information regarding the function of the brain.

Since biomedical data can be acquired through sensors and peripheral devices, the analysis of bio signals reflects complex dynamics that has been widely studied in the area of nonlinear analysis. During the last few years, nonlinear dynamic methods have been successfully used in biomedical applications based on electromyogram (EMG), electroencephalogram (EEG), electrooculogram (EOG), magneto encephalogram (MEG) and electrocardiogram (ECG)data [4].

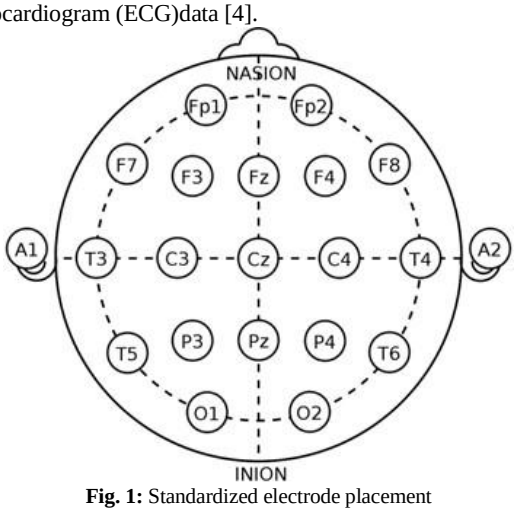

Fig. 1: Standardized electrode placement

Generally, EEG signals can be analyzed using linear and non-linear methods. In this paper the latter is used. Although linear approaches have been used in the past, non-linear analysis is prevailing now because it captures the subtle information that contains the underlying nonlinear EEG dynamics which cannot be obtained using linear methods.

The rest of this paper is organized as follows. Section II describes the methodology which has the following the steps: Data acquisition, signal pre-processing, feature extraction and classification and then, in section III we discuss about the results. Finally section IV gives the conclusion.

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2. Methodology

Our proposed system for the detection of epilepsy includes the following four stages as depicted in figure 2, namely data acquisition, pre-processing of EEG recordings, feature extraction, and classification.

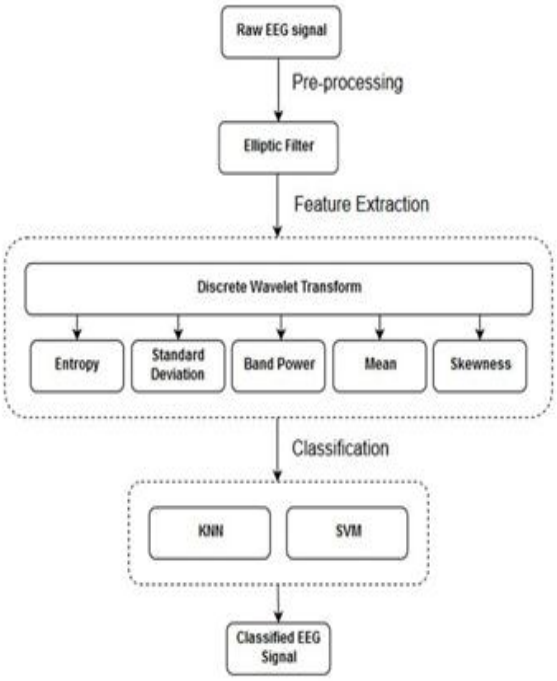

Fig. 2: Flowchart depicting the methodology

A. Data Acquisition

In this paper, we have used an EEG database which has been provided by University of BONN, Germany [5]. This dataset contains five sets, namely A, B, C, D, and E. Each set contains 100 single-channel EEG segments each of 23.6 seconds duration[6]. Sets A and B were recorded using scalp EEGs, they were carried out on healthy individuals using a standardized electrode placement scheme. The individuals were relaxed in an awake state with open eyes (set A) and closed eyes (set B), respectively. Sets C, D, and E were recorded using intracranial EEGs from epileptic subjects in which sets C and D were recorded during the seizure free intervals whereas set E was recorded during seizures as shown in table 1. The sampling rate used to record the data was 173.61 Hz. We have also used another database provided by TUH EEG Epilepsy Corpus. This corpus is a subset of the TUH EEG Corpus and contains sessions from patients with epilepsy [7].

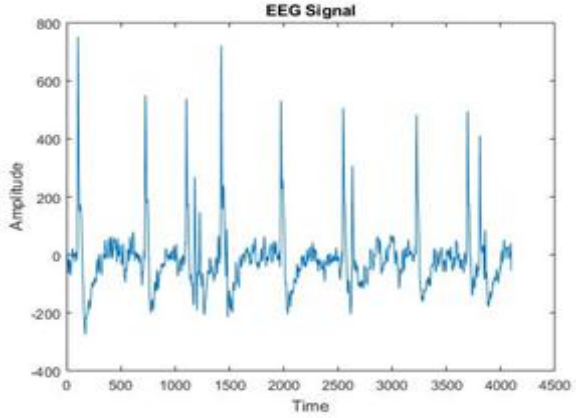

Fig. 3: Raw EEG signal

Table 1: Epilepsy database

Database	Class	Description
A	Healthy	Surface EEG recordings of healthy subjects in eye open condition
B	Healthy	Surface EEG recordings of healthy subjects in eye closed condition
C	Inter-Seizure	Seizure free segment recorded from hippocampal formation of the opposite hemisphere of the brain
D	Inter-Seizure	Seizure free segment recorded in the epileptogenic zone
E	Seizure	Seizure segment

B. Pre-Processing of Acquired Data for Filtering the Artefacts

EEG is designed to record cerebral activity. The activity recorded that is not arising from the cerebral region is termed as artefact. It can be divided into physiologic and non-physiologic artefacts. The scalp EEG data is often corrupted by these artefacts which prevent the extraction of useful information from the data. The raw EEG data is as shown in figure 3. Filtering is a common technique used for removing artefacts from EEG [6]. Thus, the acquired EEG signal is treated using a pre-processing block which contains the elliptic filter that removes noise from the brain patterns as shown in figure 4. It also improves the signal-to-noise ratio of the EEG and efficiently limits the signals to a specified frequency range. The reason for choosing an elliptic filter is that it has an extremely sharp cut-off frequency and the ripples are distributed equally across both the pass-band stop-band. Hence the error is minimized on both sides of the cut-off frequency.

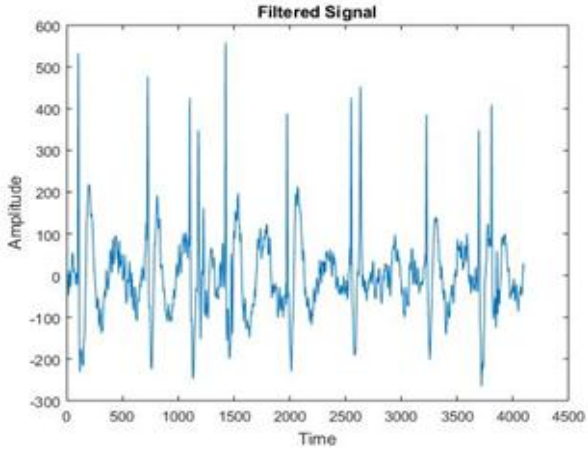

Fig. 4: Filtered EEG signal

C. Feature Extraction

Feature Extraction is a procedure of identifying a feature vector from an EEG pattern. A feature consists of most vital information necessary for pattern processing. Features can be obtained from filtered EEG data using various techniques. Each feature can singularly symbolize the original data, but only when various features are combined can they be used for practical applications. For achieving better performance, diverse features are usually utilized in a combination.

All physiological signals are non-stationary and cannot be analyzed completely by the classical time-domain analysis or frequency-domain techniques like Fourier Transform. Thus we are combining DWT with certain statistical features as shown in figure 2. DWT is a signal processing tool that captures small changes in the EEG signal by representing the signal in multi-scale time-frequency domains in terms of approximate (Ax) and detail (Dx) coefficients.

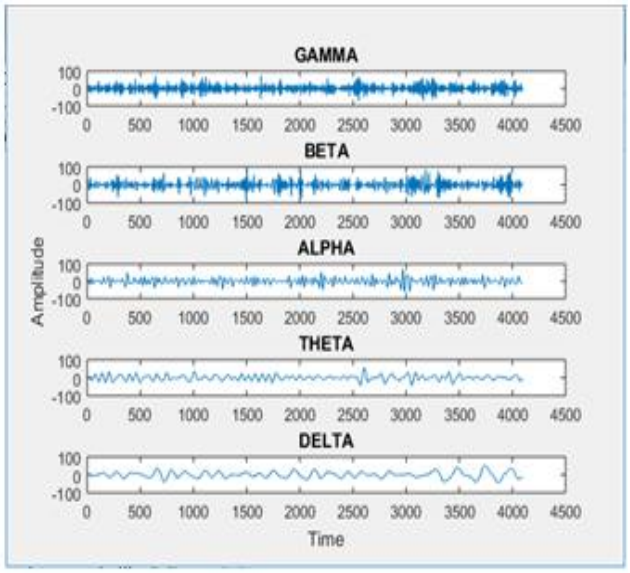

Fig. 5: DWT Coefficients

A recent review paper [8] showed that db4 is the most widely used and the authors suggested that it is the most suitable for epilepsy diagnosis or seizure detection. Hence we have used a six-level decomposition based on the Daubechies 4 (Db4) wavelet [6, 8, 9]. Only the D3, D4, D5, D6, and A6 coefficients are used for feature extraction to represent the EEG sub-bands in the spectrum[9]. These wavelet coefficients correspond to several EEG sub-bands namely delta, theta, alpha, beta and gamma. Further information regarding DWT is given in [10]. Figure 5 shows an example of the DWT outputs (different labelled EEG sub-bands). EEG sub-bands with higher frequency i.e., beta and gamma have lower magnitude or power than lower frequency sub-bands i.e., delta, theta and alpha. We have combined the discrete wavelet transform (DWT) with several statistical functions to build more efficient feature vectors as mentioned below.

Shannon Entropy (SE)

Entropy is a thermodynamic quantity describing the amount of disorder in the system. Higher the disorder of the system, higher is the entropy [10]. Shannon's Entropy is a measure of data spread and is most commonly used to assess the dynamical order of a system. The main advantage of Shannon entropy is that, it is better adapted to normal distributions.

$$\boldsymbol{SE = -\sum_{i=1}^{k} p_i log_2 p_i} \quad (\mathbf{1})$$

In which$k$ is the number of unique values in the discrete data and $p_i$is the probability or normalized frequency of unique values.The entropy levels that we have obtained for epilepsy and non-epilepsy datasets are in the range of -9.5×10^9 to -3.9×10^6 and -6.2×10^7 to -9.2×10^5 respectively.

Mean (μ)

The arithmetic mean of a time series is the average expected value. It corresponds to the center of a set of values. The mean is calculated for each and every sub-band signal and is given by,

$$\mu = \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{i=1}^{n} \boldsymbol{x_i} \quad (\mathbf{2})$$

Where$n$ is the number of terms and x_i is the value of each individual item in the list of numbers being averaged.The mean values that we have obtained for epilepsy and non-epilepsy datasets lie in the range of -1.96 to 1.41 and -0.39 to 0.56 respectively.

Standard Deviation (σ)

Standard deviation is a measure that is used to quantify the amount of variation or dispersion of a set of data values. It is given as,

$$\boldsymbol{\sigma} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N}}\sum_{n=1}^{N} (\boldsymbol{s_n} - \mu)^2} \quad (\mathbf{3})$$

Wheres_n is discrete time series of data with length$N$ and μ is the mean of the discrete data [9].The range of standard deviation values vary between 12.72 to 419.22 and 6.03 to 70.05 for epilepsy and non-epilepsy datasets respectively.

Skewness (S)

Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. It is given by,

$$\boldsymbol{S} = \frac{\boldsymbol{E(x - \mu)^4}}{\boldsymbol{\sigma^4}} \quad (\mathbf{4})$$

Where μ is the mean of signal$x$,σ is the standard deviation of x and E(t) represents the expected value of the quantity t.The levels of skewness that we have obtained are -3.02 to 5.57 and -0.59 to 1.19 for epilepsy and non-epilepsy datasets respectively.

Band power

Band power gives the average power of the input signal. It uses a modified periodogram to determine the average power in the frequency range. The average power is computed by integrating the power spectral density (PSD) estimated by,

$$\boldsymbol{BP} = \frac{\mathbf{1}}{\boldsymbol{N}}\sum_{n=1}^{N} (\boldsymbol{s_n})^2 \quad (\mathbf{5})$$

Wheres_n is discrete time series of data with length N [8].We have observed that the values of band power range between 161.91 to 17.57×10^4 and 36.37 to 4096.62 for epilepsy and non-epilepsy datasets respectively.

D. Classification

The next step is the design of appropriate classifiers that can separate epileptic from non-epileptic segments of the EEG signals. Having in mind the nature of the EEG signals and possible changes in their statistical properties it is desired to use robust classifiers. A robust classifier utilizes values of independent features as input to predict the corresponding class to which an independent variable belongs. It has a number of parameters that require training from a training dataset. A trained classifier will model the association between classes and corresponding features and is capable of identifying new instances in an unseen testing dataset. We employed the following classification methods to demonstrate the effectiveness of this study's proposed technique.

K-nearest Neighbour (KNN)

The K-nearest-neighbor (KNN) algorithm measures the distance between a query scenario and a set of scenarios in the data set and it is a memory based learning technique used to classify samples based on the closest training samples existing in the n-dimensional space[11]. It does not perform comparison with trained models for classification. A user defined constant, k is used to determine to which class the test samples belong to based on the majority votes. Typically, k is a small positive integer value. This method gave us an accuracy of 95.33%.

Support Vector Machine (SVM)

In binary classification, support vector machine is one of the most commonly employed supervised learning models. For pattern classification, SVM is a powerful tool and it is based on the statistical learning theory and structural risk minimization. The algorithm involves training with feature vectors of signals of two different classes for normal and epileptic to learn a decision boundarythat separates these two classes [12]. Once the decision boundary is learned, the support vector machine algorithm determines the class membership of a newly observed feature vector based on which side of the boundary the vector falls.SVM classifier gave us an accuracy of 100%.

3. Results and Discussions

In this section, we present results from a set of experiments that were performed to evaluate the performance of our approach. We calculate features such as Band power, Entropy, Mean, Skewness and Standard deviation of the Bonn data sets Z, O, and S for every second. The above features were calculated for all the five bands in the EEG signal namely Gamma, Beta, Alpha, Theta and Delta. The results of the three data sets from the five bands were used as the classification features to input into the trained classifier. The results of classification performances are shown in table 2. We can see that Delta versus Alpha band gave us an accuracy of 100%. Also we can observe that Beta and Alpha bands when tested against any of the train sets gave us better accuracy when compared to the other bands. Since we were getting accurate results for the Bonn dataset we wanted to test our algorithm against other dataset. So we used the epilepsy dataset available from Temple University Hospital (TUH). A train set consisting of both TUH epilepsy and Bonn non-epilepsy data was created and tested against various bands as shown in table 3. We observed that an accuracy of 99.5% and 97% was obtained when it was tested against epilepsy data from TUH and Bonn University respectively.

Table 2: Bonn University classification accuracy

Train	Test	Classifier	Accuracy
Gamma	Gamma	SVM	90%
	Beta		92%
	Alpha		92%
	Theta		73%
	Delta		51%
Beta	Gamma	SVM	92.67%
	Beta		98%
	Alpha		83.33%
	Theta		61.33%
	Delta		44%
Alpha	Gamma	SVM	90.67%
	Beta		95.33%
	Alpha		98.67%
	Theta		90.67%
	Delta		82.67%
Theta	Gamma	KNN	85%
	Beta		94.67%
	Alpha		95.33%
	Theta		94.67%
	Delta		73.33%
Delta	Gamma	SVM	86%
	Beta		94%
	Alpha		100%
	Theta		94%
	Delta		86%

Table 3: TUH and Bonn University classification accuracy

TRAIN	TEST	CLASSIFIER	ACCURACY
TUH epilepsy dataset+ Bonn non-epilepsy dataset	TUH epilepsy	SVM	
	Gamma		96%
	Beta		99.5% 95%
	Alpha		88% 78.5%
	Theta		
	Delta		
	BONN epilepsy	SVM	
	Gamma		91%
	Beta		96% 97% 97%
	Alpha		97%
	Theta		
	Delta		

4. Conclusion and Future Scope

Within a supervised-learning model, we use EEG signals to classify epileptic and non-epileptic records. Most of the previous efforts in this area has concentrated on detecting seizures using data from a single source. In this, the focus has been to generalize seizure detection across a number of subjects from two different sources (Bonn and Temple University database).

An arduous, methodical approach to data pre-processing was done and features were extracted from the raw EEG signals using various feature-ranking methods and it was classified using SVM or KNN. Experimental results presented in this paper show that these features are able to capture variations, which are essential for classification of EEG signals. It has also been observed that the combination of features is quite nominal for the classification of EEG signals. The proposed method has provided better classification accuracy as compared to the existing methods. However, it is necessary to study and validate our proposed approach on an even larger dataset prior to implementing it for clinical purposes.

Future work can comprise the use of regression analysis. This would help to foresee the early indications of a seizure and not just when the seizure occurs. Further, more advanced classification algorithms and methods may be considered, including advanced ANN architectures. The scrutiny and assessment of features, such

as fractal dimension and cepstrum analysis, autocorrelation, zero crossing and correlation dimension can also be done. This will include the recognition of different types of seizure activity and how well classifiers can differentiate between them. In all, it demonstrates that classification techniques provide an interesting line of enquiry when separating seizure and non-seizure data.

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