

Analysis of Single Channel EEG features for Epilepsy Detection

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Abstract—Epilepsy is one of the brain disorders leads to abnormal electrical activity (seizure). The diagnosis and treatment of these seizures are challenging for neurophysiologist, which motivate the current researchers to develop automatic seizure detection system. In that the most important phases are feature extraction and classification. This paper analyses the features of healthy and ictal subjects for generic epilepsy detection and also for absence seizure detection with high order statistical features like Variance, Standard deviation (STD), Power, Skewness and Kurtosis. Many analyses had been done before with same techniques, but the features and methodology used are different in this paper work. So, better classification results have been obtained for ANN, than simple two classes SVM for both dataset.

Keywords—ANN; Confusion matrix; EEG; Epilepsy; feature extraction; ictal subject; SVM; rhythmic frequency; Sampling rate; Wavelet transform.

I. INTRODUCTION

Human brain plays a vital role related to the functions of nervous system. Electrical discharge in the form of EEG (Electroencephalography) from brain have been recorded are closely monitored for seizures, which is mostly used for diagnosing epilepsy. These signals [1] are captured with the help of electrodes (10 – 20 system) which is approved by International Federation of societies for EEG and Clinical Neurophysiology. Later those signals are preprocessed to obtain informative signal. In which, epilepsy is subdivided into three stages, 1. Normal 2. Ictal (with seizure) 3. Pre-ictal (recorded before seizure). These abnormal stages have been identified by extracting the informative features from different types of EEG frequencies. They are, delta (0.1 Hz – 3.5 Hz), theta (4 Hz – 7.5 Hz), alpha (8 Hz – 13 Hz), beta (14 Hz – 40 Hz), gamma (greater than 40 Hz). The diagnosis is done using quantitative analysis which have been followed several years which is shown in Fig.1. Among these one of the seizure type is absence seizure. Its frequency vary from 2 Hz to 3 Hz and it has a spike and wave pattern. This pattern lasts for 30 sec and mostly found in children's of 5 to 18 years. In general seizures are diagnosed with the main three patterns spike, wave and

spike and wave (SWD). An automatic SWD [2] was based on steepness of the signal. Some times in this the eye blink got misclassified as absence seizure. To overcome this [3] the maximum absolute value method has been used. In this differentiating maximum amplitude is tedious. To extract some valuable features [4] they used Short Time Fourier Transform (STFT). Later on Wavelet Transforms [5] [6] [7][8] and [9] are used for feature extraction. Recently Artificial Neural Network and linear models are used for absence seizure detection. This paper focuses on both spike wave for general seizure identification and spike and wave for absence seizure detection. In general common features have been taken for analysis which have been discussed under section III. The EEG signals of the normal and abnormal signals specifications, method of collection have been discussed in section II. The analysis part of the work have been discussed in section IV.

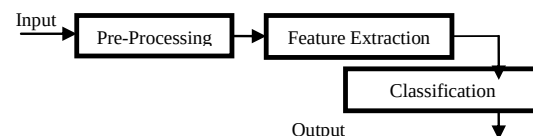


Figure 1. Analysis model

II. DATA COLLECTION

In this analysis work, Bonn university database which has been used by Andrzejak [10] have been used taken from the department of epileptology. Here two dataset named 'S' (ictal) and 'Z' (normal) have been taken, which are obtained by recording healthy subjects EEG signal with their eye open and ictal EEG signal from epileptogenic portion. Each dataset consist of 100 subjects. The sampling rate of the recorded data was 173.61 Hz and the time series contain spectral bandwidth of 0.5 Hz to 85 Hz. For absence seizure detection, the scalp EEG data have been used which are recorded using clinical setup of 16 channel with electrodes placed according to 10-20 international system from 5 subjects with normal state and

abnormal state recordings. The seizure data will last for more than 2 seconds and the data are recorded with the sampling frequency of 512 Hz with band pass filter from 1.0Hz to 70 Hz and to remove power line noise notch filter have been applied as 50 Hz. [17] proposed a novel method for secure transportation of railway systems has been proposed in this project. In existing methods, most of the methods are manual resulting in a lot of human errors. This project proposes a system which can be controlled automatically without any outside help. This project has a model concerning two train sections and a gate section. The railway sections are used to show the movement of trains and a gate section is used to show the happenings in the railway crossings. The scope of this project is to monitor the train sections to prevent collisions between two trains or between humans and trains and to avoid accidents in the railway crossings.

III. METHODOLOGY

In this section, data is processed in fivesteps for common seizure and absence seizure detection. Initially raw EEG data have been taken which is shown in Fig 2.

1. Low pass filter have been applied.
2. Decompose data into five sub-bandwith discrete wavelet transform, which is shown in Fig 3. and Fig 4.
3. Features have been extracted from each sub-band.
4. Sum of feature values of all sub-bands,for each respective feature have been calculated.
5. Perform classification.
6. Repeat the above process for all subjects (generic seizure and absence seizure data) and Fig 5. shows the absence seizure spike and wave pattern.

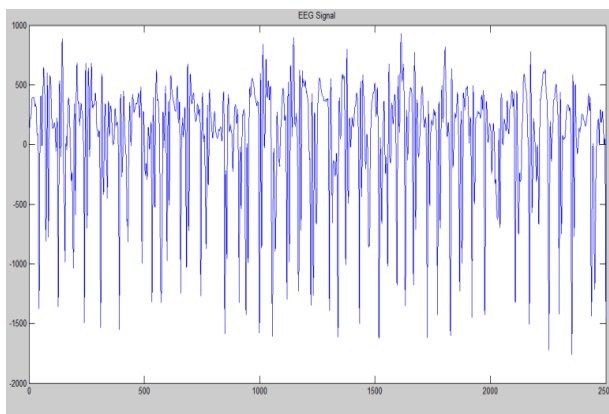


Figure 2.Raw EEG Signal

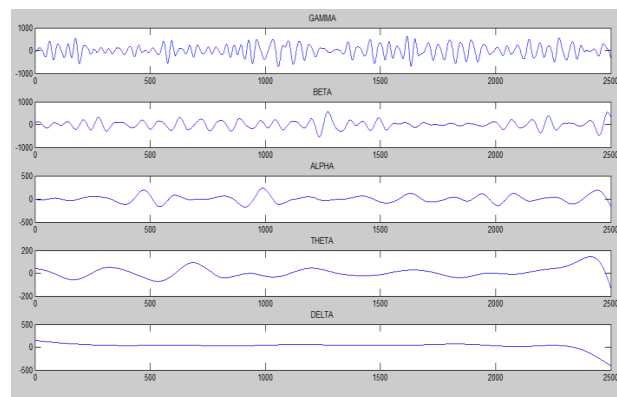


Figure 3.Five Sub-bands of EEG in time domain

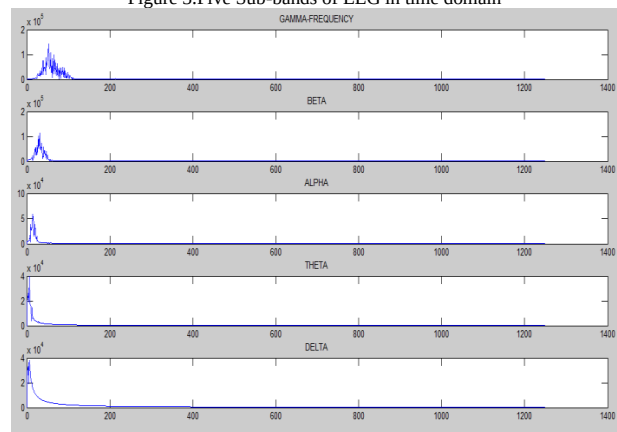


Figure 4.Five Sub-bands of EEG in Frequency domain

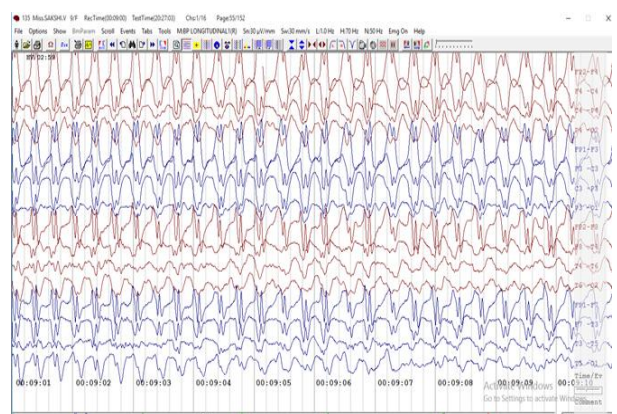


Figure 5.Absence Seizure signal

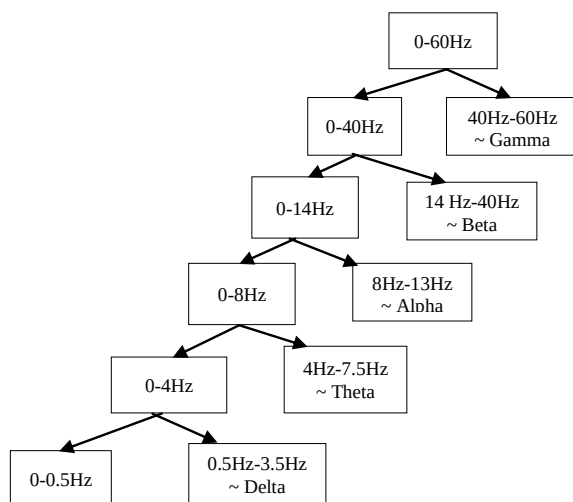


Figure 6. Decomposition of EEG signal into five sub bands

Here we considered 5 ictal and 5 normal subjects. Each subject's data are decomposed with the help of discrete wavelet transform [11] as a function which divides signal into five sub bands. Discrete Wavelet Transform acts as a barrier for noise and decompose input signal into five sub bands which have been shown in Fig 6. This method can do efficient de-noising on non-stationary EEG signal. From each sub band, following parameters are calculated for further analysis which are given in table 1.

TABLE 1 LIST OF FEATURES

Parameters	
Mean	Kurtosis
Maximum	Skewness
Minimum	Power
Variance	Total Power
Standard Deviation	Relative Power

Statistical features [12] which have been extracted from five sub-bands are given below with inference,

1. Mean: average of two or more values in sub band, which infers that healthy subject, have less average than abnormal subject.
Mathematical form: $\mu = \sum X/N$
2. Maximum: highest value in a set.
3. Minimum: lowest value in a set.
4. Variance: statistical dispersion of value, which infers that abnormal subject have high dispersion than normal subject.
Mathematical form: $\text{Var}(X) = E[(X - \mu)]^2$

5. Standard Deviation: dispersion of set of values from its mean, which infers that abnormal subject have high variation than normal subject.

$$\text{Mathematical Form: } \sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2}$$

μ - mean

6. Kurtosis: positive peaks of random variables, which infer that healthy subject have evenly distributed flatness than abnormal subject.

$$\text{Mathematical Form: } V_2 = \frac{\mu_4}{(\delta)^4}$$

δ = standard deviation

μ_4 = Fourth moment

7. Skewness: asymmetry of probability function and it's the standardized moment, which infers that healthy subject have low imbalance than abnormal subject.

$$\text{Mathematical Form: } V_1 = \frac{\mu_3}{(\delta)^3}$$

δ = standard deviation

μ_3 = Third moment

8. Power: energy consumed per unit time for the give's dataset.

$$\text{Mathematical Form: } P = \frac{1}{N} \sum_{n=0}^{N-1} x^2[n]$$

9. Total Power: summation of power calculated for each sub band.

Where power and total power infers that, normal subject have less power than abnormal subject.

10. Relative Power: power of each sub band divided by total power.

TABLE 2 EXTRACTED FEATURES OF NORMAL AND ABNORMAL SUBJECT

Subject/ Feature	Kurtosis	Skewness
Subject 1 (normal)	0.043043	-0.16528
Subject 2 (normal)	0.786949	-0.22406
Subject 3 (abnormal)	36.24253	-3.03034
Subject 4 (abnormal)	24.15231	0.796196

The above features in table 2 are given more importance than other features while classifying subjects. Here, classifications have been done with simple two classes SVM and ANN with perceptron. Where, x_i is input and y_i is class label (output). Classifications have been done with the help of svm_demo

function for each row in the dataset. Both the classifiers are examined with sufficient subjects.

IV. DATA ANALYSIS

The classes are labeled as 1 for epileptic subject and -1 for normal subject. To find the accuracy [13] of classification results confusion matrix have been used. Where TPR and TNR are calculated to figure out the sensitivity and specificity of classifier. Equations are given below for calculation and their performances are discussed in table 3.

$$\text{Sensitivity} = \frac{tp}{tp + fn} \times 100\%$$

$$\text{Specificity} = \frac{tn}{tn + fp} \times 100\%$$

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn} \times 100\%$$

TABLE 3 PERFORMANCE OF CLASSIFIERS

Measurement of ANN			
	Normal (N)	Abnormal (P)	
Normal (N)	4 (TN)	1 (FN)	Sensitivity, Specificity, Accuracy - 80%
Abnormal (P)	1 (FP)	4 (TP)	
Measurement of SVM			
	Normal (N)	Abnormal (P)	
Normal (N)	3 (TN)	2 (FN)	Sensitivity, Specificity, Accuracy - 60%
Abnormal (P)	2 (FP)	3(TP)	

V. CONCLUSION

Epileptic subject identification is a tough task, based on the high level statistical features. To classify subjects SVM and ANN classifiers have been used, in which features like kurtosis and skewness have been considered while selecting features and are used for classification. In this paper, ANN showed better result than the SVM. But this may not be suitable if an input have a continuous time series of data while taking absence seizure data and also the existing dataset has been used for generic epilepsy analysis. To overcome this further analysis is done with different set of data and analysis techniques.

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