Detection of Epileptic Signal using EEG

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Abstract—*Epileptic seizure occurs as a result of abnormal transient disturbance in the electrical activities of the brain. The electrical activities of brain fluctuate frequently and can be analyzed using electroencephalogram (EEG) signals. Therefore, the EEG signals are commonly used signals for obtaining the information related to the states of brain. The EEG recordings of an epileptic patient contain a large amount of EEG data which may require time-consuming manual interpretations. Thus, automatic EEG signal analysis using advanced signal processing techniques with the statistical features plays a significant role to recognize epilepsy in EEG recordings and also reduce the computation complexity.*

Keywords— EEG; Feature Information;EEG Signal Analysis.

1. Introduction

Human brain is a highly complex system. The epilepsy is a common neurological disorder of human brain. It affects at least 50 million people of the world. The annual occurrence of epilepsy, 48 per 100,000 populations in developed countries was reported in Hirtz et al. (2007). The prevalence of epilepsy is higher in low and middle income countries than developed countries (2011). At least 50 % of the epileptic cases start developing at childhood or adolescence (WHO 2014). Occurrence of epilepsy can also be noticed in elderly people, which may require special considerations in treatment. If the patient with epilepsy are treated properly, then 60%–70% of them can lead to normal lives (WHO 2014). Therefore, study of epilepsy is an important research area in the field of the biomedical engineering. The electroencephalogram (EEG) signals are very useful to measure the electrical activity of the human brain. The EEG signals are commonly analyzed by experts in order to assess the states of the brain. The EEG based statistical measures are very helpful for diagnosis of neurological disorders specially epilepsy. Presence of spikes in EEG signals is main indication of epileptic seizure activity in the brain. Automatic detection of epileptic seizure by analyzing EEG signals using advanced signal processing techniques is very useful for diagnosis of epilepsy

1.1 Classification of Epileptic Seizure EEG Signals

Human brain is a highly complex system. The epilepsy is a common neurological disorder of human brain. It affects at least 50 million people of the world. The annual occurrence of epilepsy, 48 per 100,000 populations in developed countries was reported in Hirtz et al. (2007). The prevalence of epilepsy is higher in low and middle income countries than developed countries (2011). At least 50 % of the epileptic cases start developing at childhood or adolescence (WHO 2014). Occurrence of epilepsy can also be noticed in elderly people, which may require special considerations in treatment. If the patient with epilepsy are treated properly, then 60%–70% of them can lead to normal lives (WHO 2014). Therefore, study of epilepsy is an important research area in the field of the biomedical engineering. The electroencephalogram (EEG) signals are very useful to measure the electrical activity of the human brain. The EEG signals are commonly analyzed by experts in order to assess the states of the brain. The EEG based statistical measures are very helpful for diagnosis of neurological disorders specially epilepsy. Presence of spikes in EEG signals is main indication of epileptic seizure activity in the brain. Automatic detection of epileptic seizure by analyzing EEG signals using advanced signal processing techniques is very useful for diagnosis of epilepsy.

1.2. EEG Data Acquisition

In our work we analyzed EEG seizure recordings from ten epileptic patients prone to surgical treatment. Seizure recordings include normal, ictal and inter-ictal periods. We have acquired the EEG signals extra cranially from patients whose ages range between 2 and 60 years. The patients were diagnosed with temporal lobe epilepsy having partial and complex seizures. The Table 1 summarizes the patient’s clinical data that were used in our experiment. The 17 channel recordings were used, during 84 h, from the scalp. During the long recording of patients’ EEG data, the patients had 4 h of break after each 20 h of recording. During the break time, the physicians made inspection of the patient’s EEG and looked for patterns related to seizure. Two of the patients had simple partial seizures for a few seconds, during the break time. The simple partial seizures were related to abnormal motor function of the brain, when the patients feel convulsive motions such as muscle jerks. We applied the electrodes according to the 10–20 international system of electrode placement. Each signal was amplified and filtered

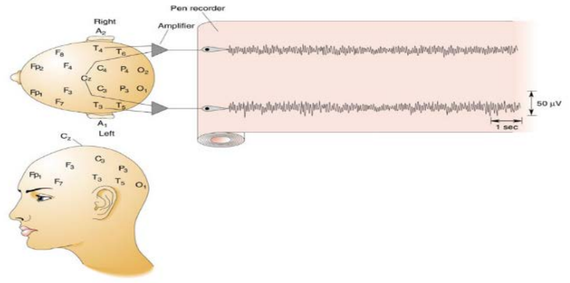


Fig: EEG Data Acquisition

Using a 1–40-Hz band pass filter. A four-pole Butterworth filter was used as a low-pass filter and as an antialiasing scheme. The sample rate of the EEG signal was 256 data per second and the record length for different signals varied between 1 and 3 min with varying sampling points. To implement our proposed method we have grouped the EEG time series as three classes; A, B corresponds to normal EEG and C to interracial, D and E ictal segment of the EEG signal. In Fig. 1 we present types of scalp EEG signals, from temporal lobe epileptic seizure recorded in a central right location C4 channel. In this figure, we can see normal, interracial, ictal segments of EEG signal. We have removed the major artifacts, e.g., due to hand, body movements or chewing. All recordings were done under video control in order to have an accurate determination of the different stages of the seizure evolution. The seizure activities on the recordings were visually labeled by a neurologist from the Department of Neurology at the Dongsan Medical Center, Taegu, South Korea. Therefore, we identified the types of EEG waveforms that occurs in normal and seizure epoch of EEG with the help of neurologist and used it as the reference in our experiment

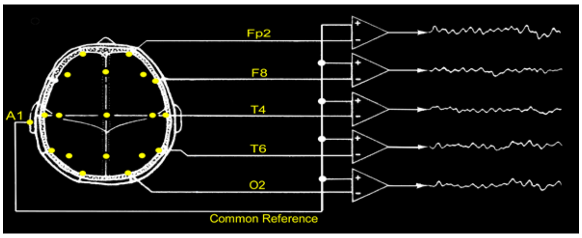


Fig: Data AcquisitionFrom Central Lobe

2. Features

We are extracting 8 features of the EEG signal of each lobe wise channels. It gives us the better accuracy for comparing the behavioral change in the EEG signal of epileptic patients and non-epileptic patients. The features we have extracted are given below:

A) Max
B) Standard deviation
C) Variance
D) Least significant value
E) Band power
F) Kurtosis
G) Skewness

2.1. Feature Selection

The above features of the EEG signal were extracted for the detection of epilepsy. But we have selected the features giving best results and high accuracy. The feature selection is done on statistical basis. Some of the features giving bad results. Few samples of the signal of epileptic patient shows non epileptic properties and vice versa. We classify them compare all the features and selects the features giving better accuracy and true results.

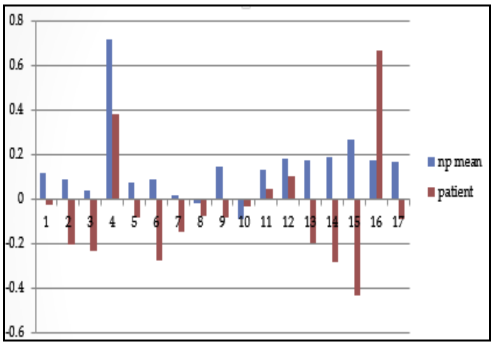
2.2. Feature Extraction

Feature extraction is an important step in pattern recognition and plays a vital role in detection and classification of EEG signals by extracting relevant information. Feature extraction can be understood as finding a set of parameters which effectively represent the information content of an observation while reducing the dimensionality. These parameters explore the property of two classes which has separate range of values for different classes. Two different area measures which are related with the variability of the signal are used here as a feature set. These area measures are computed for first four IMFs to create feature vector space. Final feature set consists of eight features for classification of normal and epileptic seizure EEG signals.

2. RESULTS:

Here are the results of our analysis on the EEG signals in the comparative form represented by graphical analysis. One can easily observe from the graphs given below whether the patient is epileptic or not:

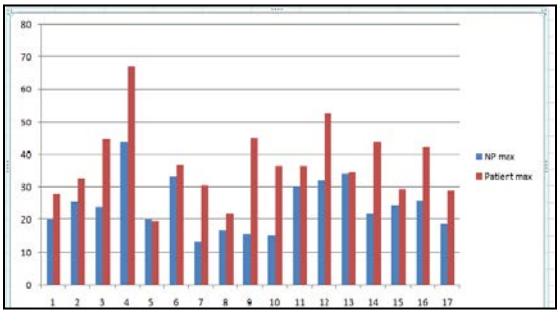
A) Mean



The mean of the data set is the arithmetic average of the elements in a data set obtained by adding all the values and dividing it by the number of values. In case of the data if in the form of frequency distribution.

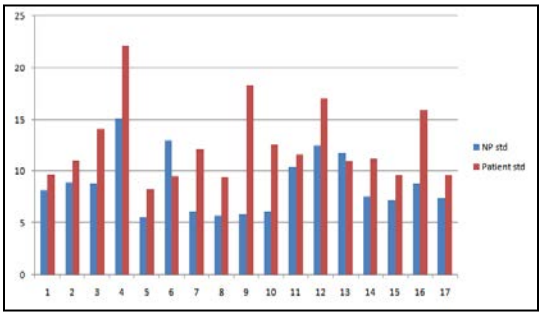
B) Max:

The highest possible value or the most significant value in a given data set is called maximum value (MAX).



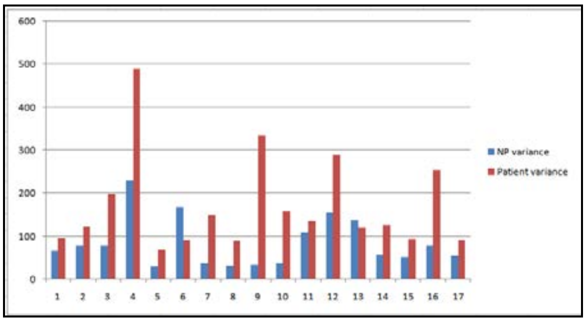
C) Standard Deviation:

It is the deviation of the signal at a particular sample from the reference point. The standard deviation of a data set in a frequency distribution.



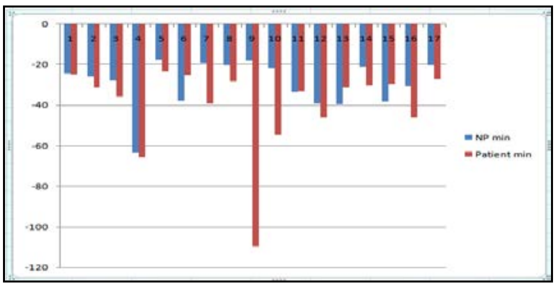
D) Variance:

The variance of data set is the arithmetic average of squared differences between the mean. Again, when we summarize a data set in frequency distribution.



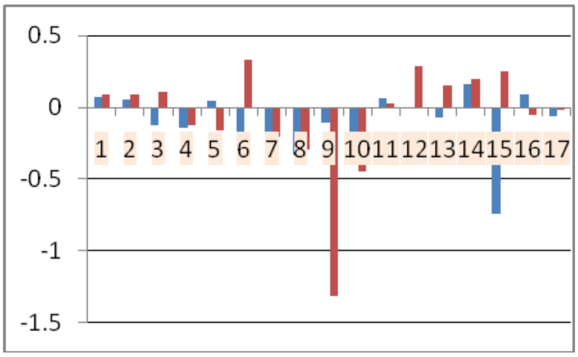
E) Least significant value

It is the minimum value in the given data set. The lowest possible value of the function at minimum point in a given data set is called Least significant value



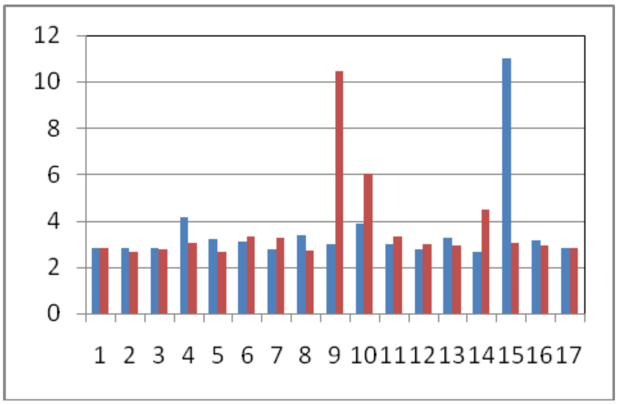
F) Band power:

The power spectrum band powers is reported as volts squared per Hz (v^2/Hz). It is the average power of the signal.

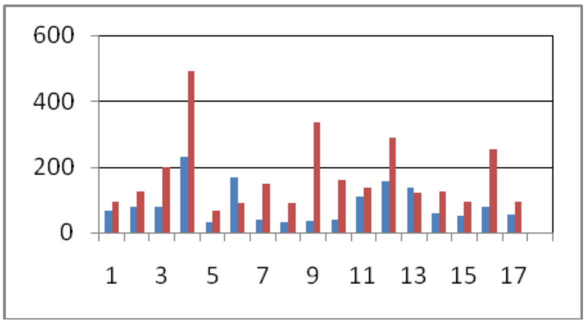


G)*Kurtosis:*

It is define as the second measure of peaked distributions of potential values of activity values in each trial.



H) Skewness:



From the above graph it can easily observed that the minimum value of epileptic patient is always greater than that of non-patient.

3. CONCLUSION:

Thus this project provides a effective way to detect the epilepsy with a system designed using statistical features with less computation time and complexity.In future this features can be used with the SVM classifier and an automatic epilepsy detection system can designed and can be used for the biomedical purpose thus enhancing to detection capabilities of the neuro surgeon.This paper has developed a novel approach for classification of the normal and epileptic seizure using EEG signals.

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