© 2016 IJSRST | Volume 2 | Issue 4 | Print ISSN: 2395-6011 | Online ISSN: 2395-602X
Themed Section: Science and Technology

Classification of Epileptic & Non Epileptic EEG Signal Using Matlab

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ABSTRACT

Epilepsy is a typical incessant neurological issue. Epilepsy seizures are the consequence of the transient and surprising electrical aggravation of the cerebrum. Around 50 million individuals worldwide have epilepsy, and about two out of each three new cases are found in creating nations. Epilepsy will probably happen in youthful youngsters or individuals beyond 65 years old years; nonetheless, it can happen at any age. The identification of epilepsy is conceivable by investigating EEG signals. In this paper we are using a technique to classify normal & epileptic EEG signal using k-means clustering algorithm in MATLAB. Further the SVM & Discriminant classifier in MATLAB Machine learning toolbox is used to classify the epileptic and normal EEG signal & wavelet transform is used to process the EEG signal. After the implementation of the signals there is ~70% accuracy with SVM classifier and ~93% accuracy with discriminant classifier.

Keywords: Epilepsy seizures, SVM Classifier, MATLAB, k-means clustering, wavelet transform, Discriminant Classifier.

I. INTRODUCTION

The electroencephalogram (EEG) consists of a time series data of evoked potentials resulting from the systematic neural activities in a brain. The recording data of the human EEGs are carried out by placing the electrodes on the scalp, and plotted as voltage magnitude against time. The voltage of the EEG signal corresponds to its amplitude. The general voltage range of the scalp EEG lie between 10 and 100 µV**,** and in adults more frequently in the range of 10 and 50µV**.** In the frequency spectrum range of the EEG, the frequency range extends from ultraslow to ultra-fast frequency components. The extreme frequency ranges play no significant role in the clinical EEG. The general frequency range of interest lies between 0.1Hz and 100Hz for the classification purpose. The frequency range is generally classified into several frequency components, or delta rhythm (0.5 - 4Hz), theta rhythm (4 -8Hz), alpha rhythm (8 - 13Hz) and beta rhythm **(**13- 30Hz). For normal adults, the slow ranges (0.3 -7Hz) and the very fast range (>30Hz) are sparsely represented, and medium (8 - 13Hz) and fast (14 - 30Hz) components predominate.

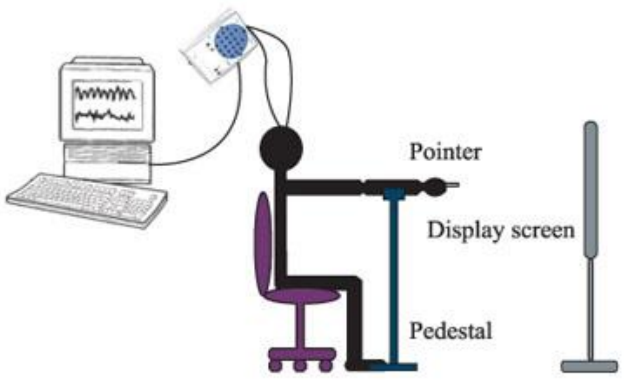

Fig 1: Position of the subject during data acquisition

One of the most common neurological diseases is Epilepsy which is very common in patients having epileptic seizures which are unpredictable and recurrent. To diagnose such disorder, EEGs or Scalp are used clinically, also this can be detected by using blood test. These signals can appear in many forms like, spikes, poly-spikes and waves. Ictal (i.e. state during epileptic seizure) EEG recordings are more reliable in diagnosing epilepsy than interictal (i.e. state between two epileptic seizures) recordings but they are expensive and difficult to obtain in patients with infrequent epileptic seizures.

Standard Frequency bands of the EEG signal

Most of EEG waves range from 0.5-500Hz, however the following four frequency bands are clinically relevant:

1. **Delta waves**: Delta waves frequency is up to 3 Hz. It is slowest wave having highest amplitude. It is dominant in infants up to one year and adults in deep sleep.
2. **Theta waves**: It is a slow wave with frequency range from 4 Hz to 7 Hz. It emerges with closing of the eyes and with relaxation. It is normally seen in young children and in adults.
3. **Alpha waves**: Alpha has frequency range from 7 Hz to 12 Hz. It is most commonly seen in adults. Alpha activity occurs rhythmically on both sides of the head. Alpha wave appears with closing eyes (relaxation state) and disappears normally with opening eyes/stress. It is treated as a normal waveform.
4. **Beta waves**: Beta activity is fast with small amplitude. It has frequency range from 14 Hz to 30 Hz. It is dominant in patients who are alert or anxious or who have their eyes open. Beta waves usually seen on both sides in symmetrical distribution and is most evident frontally. It is a normal rhythm and observed in all age groups. These mostly appear in frontal and central portion of the brain. The amplitude of the beta wave is less than 30µV.

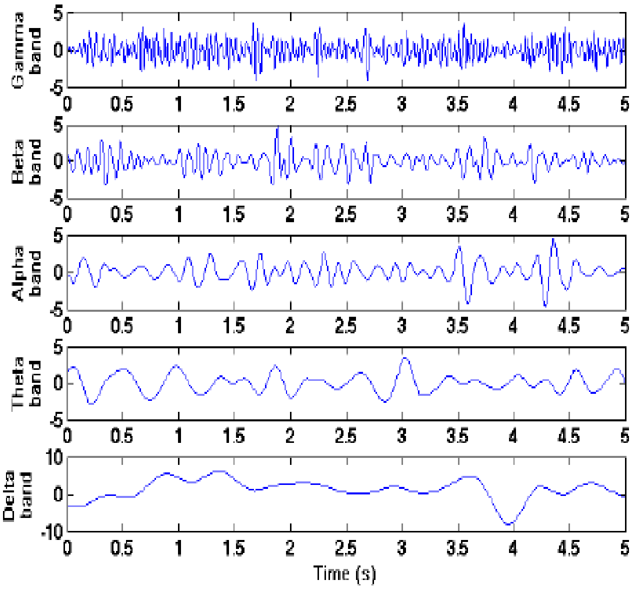

Figure 2. The five Frequency bands of normal EEG Signal

II. METHODOLOGY

The main aim of this work is to analyse EEG signals as epileptic or non-epileptic for the diagnosis of Epilepsy by using machine learning algorithms. In this, the signals which are epileptic in nature are focused on ictal discharge and non-epileptic signals are made up of normal and abnormal interictal discharges. The algorithm used to achieve this is:

1. Extraction of EEG Signals and normalization of the signal.
2. Extract statistical features to create a feature set.
3. Decompose the signal using wavelet decomposition.
4. Reduce the number of features of the feature set by using k-means Clustering to decrease runtime.
5. Use the reduced feature set to train the Support Vector Machine.
6. Compare the performance of the SVM trained on original and reduced feature set to separate epileptic from non-epileptic signals on a test data set.

The proposed strategy utilizes MWT and Time and frequency domain parameters and Machine learning to characterize the EEG signal for epilepsy seizure discovery. The underneath square graph demonstrates stream of proposed procedure.

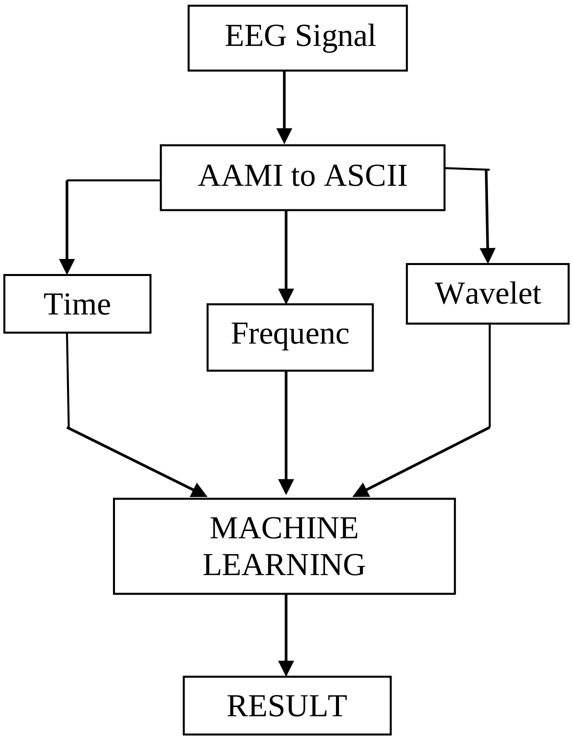

Figure 3. Flow chart for the Process

The EEG database is collected from Klinik for Epileptologie, which provides free access to web to large collections of recorded physiologic signals. EEG signals are recorded with machines having sampling frequency of 4090 Hz with 1000 samples/sec. This data set contains the signals of 10 users of both patients having epileptic seizures or non-epileptic seizures. Each user contains 4090 sample values.

The EEG sign is changed over into ASCII arrange and put away in the temp.txt record utilizing MAT to ASCII converter. The yield of the converter is given as a data to MWT, the mind sign is disintegrated and the anomalies of the sign are dictated by utilizing the T&F process. At that point the T&F yield is prepared by utilizing Machine learning. The multi-wavelet transform thought begins from the speculation of scalar wavelets. Rather than one scaling capacity and one wavelet, various scaling capacities and wavelets are utilized. This prompts more level of opportunity in developing wavelets. In this way contradicted to scalar wavelets, properties, for example, smaller backing, orthogonally, symmetry, vanishing minutes, short backing can be accumulated all the while in multi-wavelets.

In this T&F, MWT is utilized to separate the components of EEG sign. The MWT utilizes numerous scaling capacities and various wavelet capacities. The vector documentation of scaling capacity and wavelet capacity is as per the following.

$$\Phi(x) = [\Phi_1(x), \Phi_2(x), \ldots\ldots \Phi_n(x)]^T$$
$$\Psi(x) = [\Psi\_1\,(x), \Psi\_2\,(x), \ldots\ldots \Psi\_n\,(x)]^T$$

Where, T is denoted as the vector response and n > 1 is an integer. The wavelet relation of low pass filter and high pass filter is as follows.

$$\Phi(x) = \sqrt{2}\sum_{k\in Z} H_k \Phi(2x-k)$$
$$\Psi(x) = \sqrt{2}\sum_{k\in Z} G_k \Psi(2x-k)$$

Where, H_k is the low pass filter coefficient and G_k is the high pass filter coefficient. The initial basis condition of scaling function and wavelet function is given below.

$$\Phi(x) = \begin{cases} 1 & x = 0 \\ 0 & otherwise \end{cases}$$
$$\Psi(x) = \begin{cases} 1 & x = 1/2 \\ 0 & otherwise \end{cases}$$

These are the initial basis condition of scaling and wavelet function of MWT.

The decomposition of MWT is calculated by using the following formulas. The decomposition of low frequency component is calculated as,

$$A_{i-1} = \sum_k H_k A_{i,2k+n}$$

The decomposition of high frequency component is calculated as,

$$D_{i-1} = \sum_k G_k D_{i,2k+n}$$

Using the above two formulas, the decomposition of MWT is calculated.

Model was created for identifying the most suitable combination of dimensionality reduction technique paired with SVM that gave the highest sensitivity and specificity in classifying epileptic and non-epileptic data.

III. RESULTS AND DISCUSSIONS

In this section a great amount of heed has been paid as the entire research work deals with active results for different EEG signals.

Ten different patients are taken for our existing research work. In this research work a single patient recording length is approximately 4090 samples, recorded at a rate 1000 samples per second, for duration of 4.9 seconds. In the advent of such recordings it is important to analyze the time domain representation of the signal in such cases. Figure 3 and 4 shows results of time domain waveforms as given in the database for visualizing it with respect to its mean.

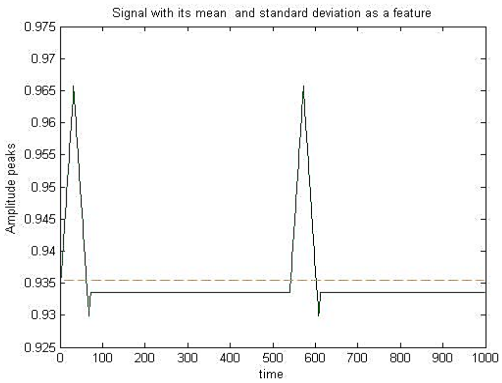

Figure 4. Original non epileptic waveform showing amplitude (µV) on y-axis and time(sec) on x-axis.

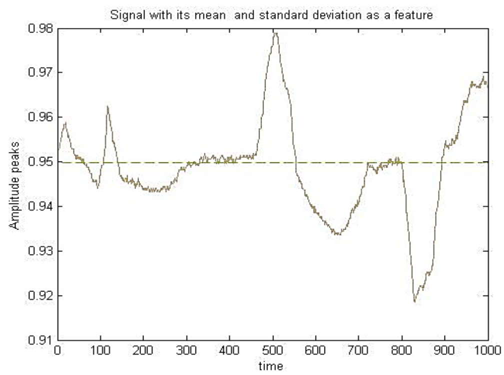

Figure 5. Epileptic waveforms measured for 1000 samples showing amplitude (µV) on y-axis and time(sec) on x-axis.

Similarly visualizing waveforms evaluation will be generated for both epileptic and non-epileptic signal by applying fast fourier transform. Figure 6 and 7 shows a similar type of distinguished waveforms for both signals.

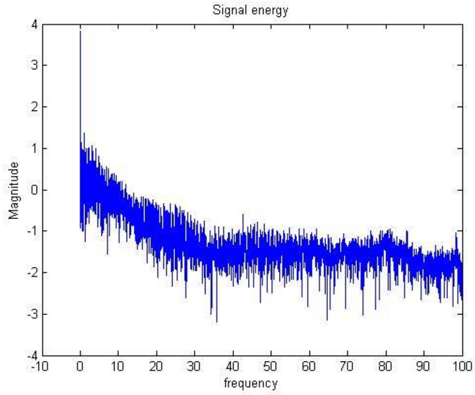

Figure 6. EEG epileptic signal for frequency domain visualization.

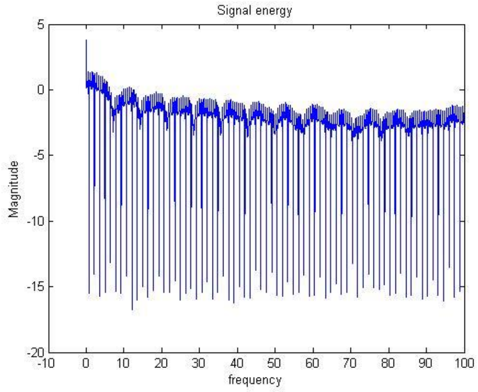

Figure 7: EEG non epileptic signal for frequency domain

Now it is most important for the current work to introduce the classification technique which is of utmost importance, when any arbitrary signal is given in this then how much will be recognition score, so most importantly there will be two different techniques for complete work analysis, i.e. support vector machine and discriminant analysis.

Table 1: Matching Score for two classification techniques.

S.No	Feature names	Feature classifier	Score
1.	T&F , wavlet	SVM	70%
2.	T&F , wavelet	Discrminant	93%

IV. CONCLUSION

As per the work conducted in this paper the number of observation taken was 10. Each observation as EEG signal is composite signal of multiple frequencies comprising 7200 samples. Similarly in a similar manner the second important point is complete analysis has been done in time and frequency domain as well as wavelet transform has been included as features. For individual signal three time domain features were calculated one frequency domain energy, and one level four decomposition has been found. Later stage is a verification stage where two different classifier has been used where first is support vector machine the other is linear discriminant analysis.

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