ABSTRACT

Electroencephalogram (EEG) is an important technique for detecting epileptic seizures. In this paper a method of classification of EEG signal into normal, interictal and ictal classes is presented. Statistical measures such as median absolute deviation (MAD), variance and entropy showing the dispersion and rhythmicity, were calculated for each frame of EEG signals. The classification was done using a linear classifier. The direct time domain approach adopted without resorting into any kind of transformations yields an accuracy of 100%.

Index Terms— Electroencephalogram, Feature Extraction, Median Absolute Deviation, Classification

1. INTRODUCTION

Epilepsy is a neurological disorder characterized by recurrent seizures that happen due to repetitive and paroxysmal discharge of brain cells [1]. It shows the clinical signs of an excessive and hyper synchronous neuronal activity in the brain. Three to five per cent of the world populations have a seizure sometime in their life and half to one per cent of the population have active epilepsy [2]. Since discovery, EEG is the main diagnostic tool for detecting these transient and unexpected electrical disturbances of the brain. Difficulties attached to the visual inspection of bulky multi-channel EEG data necessitate the automation of seizure detection process.

Several algorithms have been developed for automatic seizure detection in recent years. Guler et al [3] have reported an accuracy of 96.79% using Recurrent Neural Network (RNN). They found that dynamical measures, especially Lyapunov exponents can serve as clinically useful parameters and contain significant amount of information about the signal. Khan and Gotman [4] developed a wavelet based method for seizure detection, examining how different frequency ranges fluctuate compared to the background. Detection sensitivity reported was close to 90% and the false detections were found to be 0.5 per hour. Mohseni et al [5] suggested a method based on time-frequency analysis. This method was developed by focusing on two most often used time-frequency distributions: the pseudo Wigner-Ville and the smoothed pseudo Wigner-Ville distributions. Wavelet-chaos-neural networks [6] have also been reported with an accuracy of 96.7% using a feature space consisting of nine parameters acquired through the chaos analysis of wavelet sub-bands. The detection technique based on smoothed pseudo Wigner-Ville (SPWVD) distributions [7], found to give an accuracy of 99.28%. In the said method, features measuring the fractional energy of specific time-frequency windows are calculated. Then these features are used as inputs in an artificial neural network. Ubeyli [8] suggested a method in which mean, maximum, minimum and standard deviations were calculated in wavelet sub-bands. These features were given to a two-level neural network by which a classification accuracy of 94.83% was reported.

Praveen Kumar et al [9] used wavelet, spectral and sample entropies along with two neural network models, namely Recurrent Elman Network (REN) and Radial Basis Network (RBN) for seizure detection. Among the different entropy features used they found the best performance with wavelet entropy features with REN. It has showed a classification accuracy of 99.75% in normal vs. epileptic and 94.5% in normal vs. interictal cases. In a scheme based on the Discrete Wavelet Transform (DWT) followed by Probabilistic Neural Network (PNN) [10], the detection accuracy is found to be 99.33%. Here the EEG data were subjected to six level decomposition and approximate energy values of the wavelet coefficients at all nodes of the down sampled tree were used as the feature vector to characterize the epileptic activity.

One of the common characteristics of the methods described is the transform based approach of feature extraction. Also most of them use classifiers which require rigorous training. In this paper, a seizure detection method based on the time domain analysis of EEG signal is presented. Three statistical features including median absolute deviation (MAD) were used in this method. The classification based on linear discriminant function was done which showed an accuracy of 100%.
2. MATERIALS AND METHODS

In this paper the seizure detection problem is approached as a three-group classification problem. The following three classes were considered in this work: a) Healthy subjects (normal EEG), b) epileptic subjects during a seizure-free interval (interictal EEG), and c) epileptic subjects during a seizure (ictal EEG). A general schematic of the method adopted for classifying the three groups is shown in Fig. 1. Each channel of the EEG signals is divided into frames of predetermined length. Three statistical features viz variance, median absolute deviation and entropy, were extracted for each frame. The size of the feature vector is reduced by selecting minimum, maximum, mean and standard deviation of these features. Based on these parameters the linear classifier classifies the EEG data into any of the above three classes.

2.1 Data Used

The database used for this study is a sub-set of the publicly available one [11] which have been widely used by the researchers [3, 6-8]. The sub-set, corresponding to normal (set A), interictal (set D) and ictal (set E) had 100 single channel EEG segments. Set A consists of segments taken from surface EEG recordings that were carried out in an awakened state with eyes open. Sets D and E are taken from EEG archive of pre surgical diagnosis. While set D contains activity measured from the epileptogenic zone during seizure free intervals only, set E contains seizure activity alone. The data were recorded with the same 128-channel amplifier system and digitized at 173.61 Hz sampling rate and 12 bit A/D resolution. The EEG data used has already gone through the pre-processing steps and artefacts were removed after visual inspection. A band-pass filter having a pass band of 0.53–40 Hz (12 dB/oct) was used to select the EEG signal of desired band.

2.2 Feature Extraction and Classification

Feature extraction is the process of discarding the irrelevant information to the extent possible and representing relevant data in a compact and meaningful form [12]. The probability distribution function is an important characteristic which gives significant time domain information regarding the signal. Plotting this for different classes of signal will help to highlight their differences. A histogram is a simple way to show the probability distribution. Hence the histograms of the three classes were compared in order to gather the statistical characteristics. Fig. 2 shows an exemplar plot for the first channel of each class. The histogram of the same data is given in Fig. 3. By analyzing the two figures it can
be inferred that the seizure has larger mean value and higher sample amplitudes. Further, the distribution has a long tail; it is highly skewed and has large deviation from the mean value. Also the larger deviations in the distributions shown indicate the presence of outliers.

The observable difference in the spread characteristics of three different cases leads to the selection of two measures of statistical dispersion: median absolute deviation (MAD) and coefficient of variation (CoV). MAD is much more resilient to outliers in a data set. As large deviations are possible with the seizure signals, a median based measure of dispersion will naturally be a good choice.

For a data set \( X = x_1, x_2, \ldots, x_n \) MAD is defined as the median of the absolute deviations from the data’s median.

\[
\text{MAD} = \text{median} \left( |X - \text{median}(X)| \right)
\]  

(1)

This is a variation of the absolute deviation that is even less affected by extremes in the tail because the data in the tails have less influence on the calculation of the median than they do on the mean.

Coefficient of variation is the ratio of standard deviation to mean. The variance of a real-valued random variable is its second central moment. It is a way to capture the distribution’s scale or degree of being spread out. Skewness and Kurtosis are the third and fourth moments respectively of a distribution function about the mean. Skewness gives a measure of asymmetry. Higher kurtosis means more of the variance is due to infrequent large deviations, as opposed to frequent modestly-sized deviations. The rhythmicity expected with seizure data and the related lower degree of randomness justifies the inclusion of entropy in the feature list.

Among the features cited above, the variance, skewness, kurtosis, CoV [13] and entropy [14] were already used as features for EEG analysis, whereas the median absolute deviation is a new feature in this set.

To select the best set of features, class separability criterion for binary classification is being used with both two class cases, [one involves sets A (normal) and E (seizure); the other involves sets D (interictal) and E (seizure)]. Table 1 shows the significance of each feature for separating the two groups in terms of the absolute value of the criterion. Out of the 6 features considered, median absolute deviation, variance and entropy are found to be ahead of others.

The average values of selected features are given in Table 2. The increased dispersion of seizure data in comparison with the normal and interictal ones explains the high values of MAD and variance for Set E. The table also testifies the fact that seizure data will have lesser entropy value due to its rhythmicity comparing to the unpredictable normal and interictal data.

The classification is achieved in this work using a linear classifier based on linear discriminant analysis [15]. This classifier makes a decision based on the value of the linear combination of the features.

### 3. RESULTS AND DISCUSSION

Each of the 100 channels is partitioned into 16 frames and 3 different features per channel are computed for each frame. This results into a feature set consisting of 3 feature vectors of 100 dimensions, corresponding to each frame. In order to reduce the dimensionality and computational complexity mean, minimum, maximum and standard deviation of each extracted feature were evaluated. This reduces the feature set into one having 12 vectors in each frame. Here the training set was formed by choosing features from the 10 frames and the rest 6 frames used for testing. Both training and test sets were mutually exclusive.

The performance of the classifiers can be determined by the computation of specificity, sensitivity and total classification accuracy which can be defined as given below:

\[
\text{Sensitivity} = \frac{\text{TP}}{\text{TP}+\text{FN}}
\]

(2)

\[
\text{Specificity} = \frac{\text{TN}}{\text{TN}+\text{FP}}
\]

(3)

\[
\text{Accuracy} = \frac{(\text{Sensitivity}+\text{Specificity})}{2}
\]

(4)

where TP= True Positive, TN= True Negative, FP= False Positive and FN= False Negative. The results obtained in this work in comparison with the earlier works based on the same data sets are summarized in the Table 3.

It is evident from the Table 3 that there is an improvement in the performance by using the proposed method. It gives cent-percent result for all the three measures. As compared to the complex/transforms based...
approach for feature extraction and the use of non-linear/complex classifiers, the method proposed uses simple statistical features with a linear classifier. It reduces the computational complexity and gives better accuracy. Though the maximum accuracy was achieved by this method, the study is having some limitations as well. The EEG data sets used were artefact free. So when confronting with the real life situation, the accuracy of the proposed method will be slightly inferior to the reported one. Further, the data sets used can be said to be of shorter duration for seizure analysis purpose.

4. CONCLUSION

A seizure detection method using new statistical feature set and a linear classifier is presented, which shows 100% accuracy. The ranking of features showed that the MAD was the best among the 6 features used for classification. The combination of statistical features those quantify the dispersion characteristics (median absolute deviation and variance) and rhythmicity (entropy) help to improve the performance of the proposed seizure detection scheme over the recently reported works using the same database. Estimation of mean, maximum, minimum and standard deviation from the extracted features reduces the size of feature vector. This reduces the complexity of classifier. All this is achieved without sacrificing the overall classification performance.

5. REFERENCES


