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Wavelet Based Seizure Detection using Scalp EEG

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Abstract

Epilepsy, the most common neurological disorder characterized by sudden and recurrent neuronal firing in the brain can be detected by analyzing electro-encephalogram of the subject. EEG signal processing consists of three steps such as preprocessing, feature extraction and classification. In this paper, the wavelet transform based method have been applied for feature extraction in EEG signals. Eight features were extracted over wavelet coefficients. When trained on about 60% of data and tested on the remaining data using Linear classifier, the results obtained was an accuracy of 92.5%, sensitivity of 90.5%, and specificity of 94.5%.

Keywords: Classifiers, Electroencephalogram, Feature Extraction , Seizure, Wavelet transform.

Introduction

Epilepsy is the second most known (after stroke) neuronal disorder of the brain, caused by simultaneous abnormal firing of a cluster of neurons and influences very nearly 60 million worldwide [1]. The detection and diagnosis of epileptic seizures often require long duration monitoring of the patient’s electroencephalogram (EEG) signals. EEG is the most important diagnostic tool to analyze epileptic seizures. The frequency ranges of interest in the case of EEG are delta (0.5–4 Hz), theta (4–7 Hz), alpha (8–13 Hz) and beta (14–30 Hz). Based on the placement of electrodes during the recording of EEG, they can be classified into two: scalp and intracranial. In scalp EEG, electrodes are placed on scalp whereas in intracranial EEG, readings are taken from the exposed surface of the brain after opening the skull.

In one of the recent studies, a method based on high frequencyactivities using wavelet decomposition was introduced [17]. Analysis was done on a dataset of 36 hours of intracranial EEG, including 18 seizures. Results show a sensitivity of 72% and a median delay of 5.7 s. Higher order statistical moments such as variance, skewness, and kurtosis in empirical mode decomposition domain was used. Another method was proposed by Yadav et al. [2] using intracranial EEG was based on quantifying the sharpness of waveform. Single-channel test data resulted in a sensitivity of 87% and a specificity of 71% whereas the multichannel test data reported a sensitivity of 81% and a specificity of 58.9%. Fourier transform features were extracted from dual-tree complex wavelet sub bands for seizure detection.

Shoeb et al., [3] designed an EEG seizure detector and studied on CHB-MIT scalp EEG database. The EEG signal epochs of two seconds duration through a filter bank, composed of eight filters, spanning in the range of 0.5 to 25 Hz. Then, the feature vector was formed by measuring the energy of the output of each filter. The procedure was repeated for all the channels and detected

96% of the test seizures with median false detection rate of 2 false detection.

One of the many challenges in the automated detection of epileptic seizures is to draw a line of demarcation between seizure activity and non-seizure activity. To accomplish this task, identification of related features and there extraction from the EEG plays a key role. The work presented by Nidal Rafiuddin [4] is a part of an overall effort going on to develop a new method for automated detection of seizures. A wavelet based feature extraction technique has been adopted. Statistical features, Inter-quartile range (IQR) and Median Absolute Deviation (MAD) also form part of the feature vector. These feature vectors were used for the classification process. The classifier used was a simple LDA classifier which gave an average result of 80.16% detection accuracy. The algorithm was evaluated on 23 subjects with 195 seizures. The database used is the CHB-MIT scalp EEG database.

Khan et al. [5] a wavelet based technique was adopted to extract features from sliding epochs of 1 second that could differentiate between seizure and non-seizure activities. Eight features were extracted from each epoch and in all concatenated to form a feature vector. In this work, classified using simple LDA classifier, the algorithm was tested on 5 subjects and average results of 83% sensitivity and 100% specificity. Kiranyaz et al. [6] proposed a seizure detection method which uses time, frequency, time-frequency, and nonlinear features. The authors developed a collective network of binary classifiers along with a novel morphological filtering for the detection of EEG seizures. They studied their method to long duration CHB-MIT scalp EEG database and reported an average sensitivity of 89.01% with 25% training rate.

Samiee et al. [7] a novel feature extraction method is proposed based on the mapping of EEG signals into two dimensional space, resulting into a texture image. The texture image is constructed by mapping and scaling EEG signals and their associated frequency subbands into the gray-level image domain. Image texture analysis using gray level co-occurrence

matrix (GLCM) is then applied in order to extract multivariate features which are able to differentiate between seizure and seizure-free events. To evaluate the discriminative power of the proposed feature extraction method, a comparative study is performed, against other dedicated feature extraction methods. The comparative performance evaluations show that the proposed feature extraction method can outperform other state-of-art feature extraction methods with a low computational cost. With a training rate of 25%, the overall sensitivity of 70.19 and specificity of 97.74% are achieved in the classification of over 163 h of EEG records using support vector machine (SVM) classifiers with linear kernels and trained by the stochastic gradient descent (SGD) algorithm.

Later, Zabihi et al. in [8], proposed a novel real time seizure detection system which reconstructs seizure and seizure-free segments of EEG signals in higher dimensional space by employing time-delay embedding method. They achieved an average sensitivity of 88.27% using 25% training rate, with a two layered classifier system followed by morphological filtering operation.

Materials And Methods

A. Data Used

The CHB-MIT dataset is a publicly available database that contains 686 scalp EEG recordings from 22 patients treated at the Children’s Hospital in Boston [9]. The subjects had anticonvulsant medications withdrawn and EEG recordings were taken for up to several days after. Twenty-three sets of EEG recordings from 22 patients (5males, 17 females), aged between 1.5 and 22 years, are contained within the dataset (one patient has two sets of

EEG recordings 1.5 years apart). The database has a total number of 199 intractable seizures with at least three seizures per patient. The EEG data of each patient was segmented into records of one hour duration. Those containing one or more seizures are called seizure records and the remaining ones are labeled as non-seizure records. All EEG signals were recorded with a sampling frequency of 256 Hz and 16-bit resolution. Most of the EEG files contain 23 channels whereas a few contain 24 or 26 channels. Recording was done using the international 10–20 system of electrode placement scheme. A band pass filter was applied to each of the EEG segments to extract the EEG data in each of the frequency bands. Second order Butterworth filters were used as they offer good transition band characteristics at low coefficient orders.

B. Seizure Detection System

The brain is made up of millions of nerve cells called neurons. They generate electrical impulses and messages to produce thoughts, feelings and movement. A seizure occurs when the normal pattern of these impulses is disrupted, caused by the neurons rapidly firing all at once. This can cause changes in sensation, awareness and behaviour, or sometimes convulsions, muscle spasms or loss of consciousness, depending on where the seizure starts and spreads in the brain. There are many different types of seizures. Having some basic knowledge about seizures can help to recognise and know what to do when a seizure occurs. Most seizures are classified into two groups, partial and generalised [10].

Biomedical information processing involves the analysis of physiological measurements to provide useful information upon which clinician can take decisions. The main steps of a typical EEG measurement and processing system are shown in Fig 1.

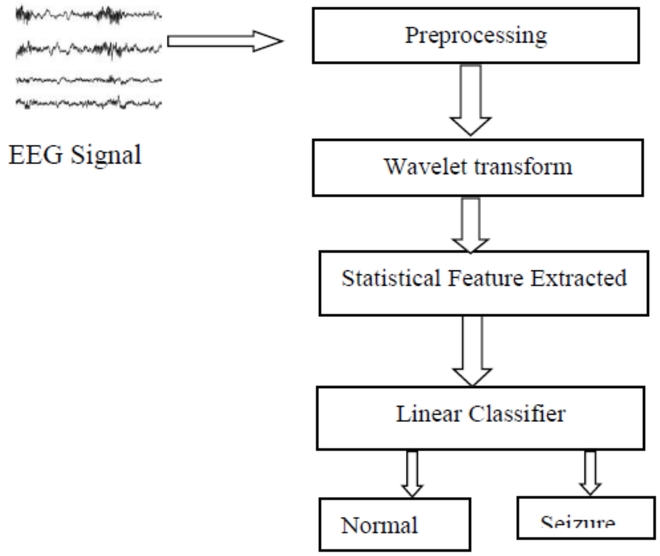

Fig 1: Seizure Detection System

Electroencephalography or EEG is a method which provides monitoring of brain neural activity using electrical signals. EEG provides information about functional state of brain more than structural functions. EEG signals are recorded by electrodes placed over the head.

C. Wavelet Transform (WT)

The wavelet transform is the next step designed to address the problem of non-stationary signals. The multi-resolution property in the time and frequency domains reduces the resolution problem which was encountered in STFT. The resolution problem exists in every transform regardless of the transforms used and is due to a physical limitation explained by the Heisenberg uncertainty principle. But in wavelet analysis, it is possible to analyze the signal by using an approach called the multi resolution analysis (MRA). The signal at different frequencies is analyzed at different resolutions. Every spectral component is not resolved equally as was the case in the STFT. MRA gives good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. MRA analysis makes sense especially when the signal contains high frequency components for short durations and low frequency components for long durations [10].

In principle, both WT and STFT are similar. The main difference is that the time-window is not fixed in the wavelet transform analysis, but scaled across the levels of WT. It includes speaking to a period work As far as simple, altered fabricating blocks, termed wavelets. The main advantage of the WT is that it has a varying window size, being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time-frequency resolution in all frequency ranges. The WT of a signal is the decomposition of the signal over a set of functions obtained after dilatation and translation of an analyzing wavelet. In continuous wavelet transform (CWT), the width of the window is adjustable which solves the resolution problem. Here the signal is multiplied with a function called wavelet similar to the window function in STFT. The CWT is defined as follows:

$$W(s,\tau)=\int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{|s|}}\psi^{*}\left(\frac{t-\tau}{s}\right)dt=< f(t),\psi_{s,\tau}(t)>$$

Where (f(t)) represents the analyzed signal, s and τ represent the scaling factor and translation along the time axis, respectively, and the superscript asterisk denotes the complex conjugation. $\psi_{\tau,s}(t)$ is the wavelet. Continuous, in the context of the WT, implies that the scaling and translation parameters τ and s change continuously. High scales (low frequencies) correspond to global information of a signal, whereas low scales (high frequencies) correspond to detailed information of a hidden pattern in the signal. However, calculating wavelet coefficients for every possible scale can represent a considerable effort and result in a vast amount of data. Therefore discrete wavelet transform (DWT) is often used. In the discrete wavelet transform, various cut off frequencies at multiple scales are used to analyze the signal. Various filtering techniques are used to represent the digital signal with respect to time. The signal is passed through a series of low pass filters to analyze the low frequencies and high pass filters to analyze the high frequencies.

The procedure of multiresolution decomposition of a signal $x[n]$, where h[n] and g[n] are low pass and high pass filters, respectively. Each stage of this scheme consists of two digital filters and two downsamplers by 2. Filtering operation will alter the resolution of the signal, which is defined as a measure of the amount of detail information in the signal and the scale is changed by down sampling operation. Down sampling a signal corresponds to reducing the sampling rate, or removing some of the samples of the signal. Sub sampling or down sampling by a factor n reduces the number of samples in the signal n times. The first filter, g[n] is highpass in nature, and the second, h[n] is its mirror version, low-pass in nature. The downsampled outputs of first high-pass and low-pass filters provide the detail, $D1$ and the approximation, $A1$, respectively. The first approximation, $A1$ is further decomposed and this process is continued.

One level of wavelet decomposition can be mathematically expressed as follows:

$$y_h(k)=\sum_n x(n)\,g(2k-n)$$

$$y_l(k)=\sum_n x(n)\,h(2k-n)$$

where yh(k) and yl(k) are the outputs of the high pass and low pass filters, respectively, after sub-sampling by 2. This decomposition, which is also called as sub-band coding, halves the time resolution and doubles the frequency resolution. . Then, the outputs from both filters are decimated by 2 to obtain the detail coefficients and the approximation coefficients at level 1 (A1 and D1). The approximation coefficients are then sent to the second stage to repeat the procedure. Finally, the signal is decomposed at the expected level.

The following features are extracted from D5 coefficient to represent the time-frequency distribution of the EEG signals.

1. Mean of the wavelet coefficients in each sub band.
2. Maximum of the wavelet coefficients in each sub band.
3. Minimum of the wavelet coefficients in each sub band.
4. Standard deviation of the wavelet coefficients in each sub band.
5. Entropy of the wavelet coefficients in each sub band.
6. IQR of the wavelet coefficients in each sub band.
7. RMS value of the wavelet coefficients in each sub band..

D. Classifier

With the extracted features, classification is to be done. complex classification methods are chosen for the normal and seizure discrimination. Apart from this, simple linear classifiers are taken for this study. In a linear classifier, a linear combination of features are compared which decides the class membership and simple and computationally efficient [13]. Performance evaluation of the classifier are done using the metrics. Sensitivity, Specificity and Accuracy. This is based on the values of true negative (TN), true positive (TP), false negative (FN) and false positive (FP). During classification, the labels ‘0’ and ‘1’ are assigned for normal and seizure data respectively.

Results And Discussion

The epileptic seizure patient dataset that is available from the physionet. The data used has already gone through the pre-processing steps, the record was sampled at 256 Hz with 16-bit resolution. Only one channel data is used in this work and one channel normal and seizure data is shown in fig 3.1.

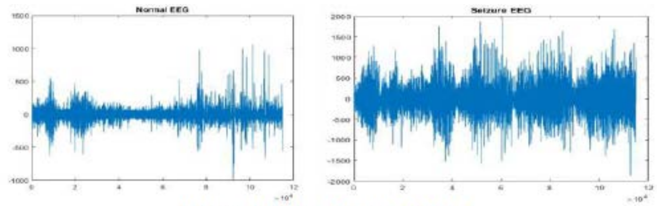

Fig 3.1. One channel data

The normal and seizure data is framed for a length of one seconds is shown in fig 3.2.

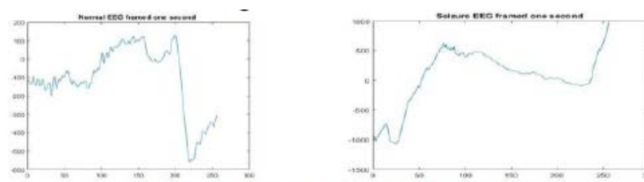
Fig 3.3. Data framed at one seconds

Selection of appropriate wavelet and the number of decomposition levels is very important in analysis of signals using the WT. The number of decomposition levels is chosen based on the dominant frequency components of the signal. Using discrete wavelet transform (DWT), decomposed to 5 level of wavelet decomposition using Daubechies (db4) wavelets. From the decomposition process, low frequency wavelet coefficient of 5th level, A5 (approximate coefficient) encompassing the frequency band 0-4 Hz and higher frequency wavelet coefficients of 5th, 4th, and 3rd levels D5, D4, and D3 (detail coefficients) each comprising of frequency range 4-8 Hz, 8-16 Hz, and 16-32 Hz respectively were retained for extracting features. The reason to select these frequency ranges with the respective lower and upper bound being 0 Hz and 32 Hz is that seizure activity predominantly lies below 30 Hz. As a result, this frequency range can be employed for classifying between seizure & non seizure.

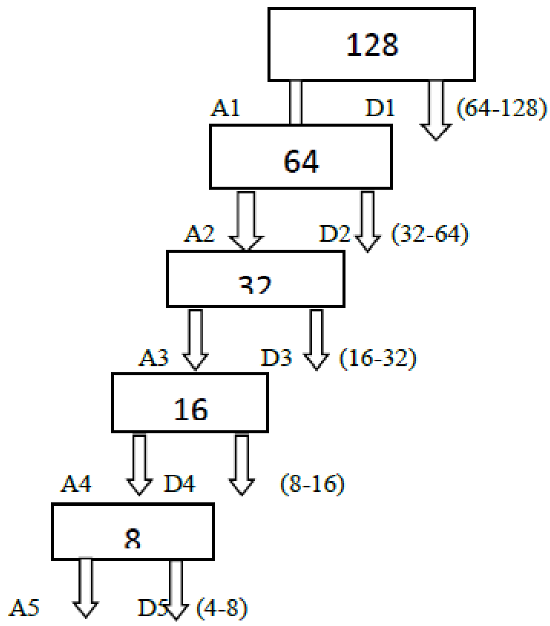

Fig 4 Five level wavelet Decomposition

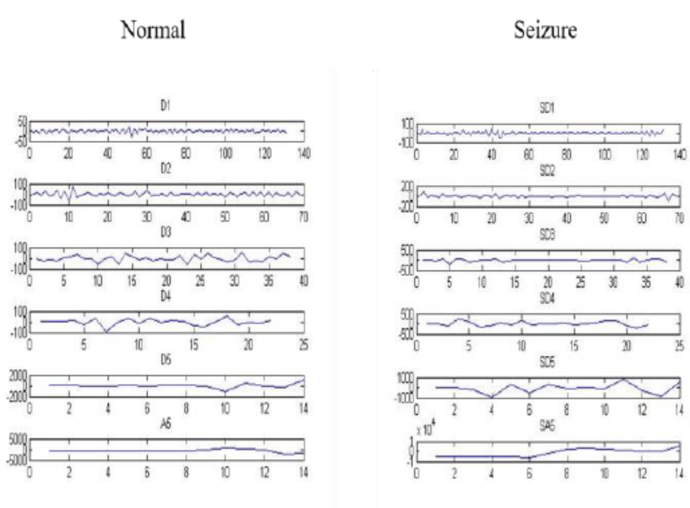

Fig 5 Five level decompostion of EEG

The performance of the algorithm is measured in terms of sensitivity, specificity, accuracy. For the performance evaluation of the classifiers, we have computed three well known parameters called.

$$\text{Sensitivity} = TP/TP + FN \quad (6)$$

$$\text{Specificity} = TN/TN + FP \quad (7)$$

$$\text{Accuracy} = \frac{(TP + TN)}{TP + FP + TN + FN} \quad (8)$$

Where TP (True positive) is the number of truly detected seizure epochs, FN (False negative) is the number of seizure detected as non-seizure epochs, TN (True negative) is the number of truly classified non-seizure epochs, FP (False positive) is the number non-seizure detected as seizure epochs.The patient data from one channel is framed at one second. Then features are extracted from normal and seizure data. The features extracted here were Standard deviation, Entropy, Mean Absolute Deviation (MAD), Rms value, Inter Quartile Range (IQR), Minimum and Maximum. The extracted features were submitted to Linear classifier. Data framed into one second then frames taken for each category is 449, 269 frames taken for training and 180 frames taken for testing at first channel and the result for first frame is given in Table 1.

Table 1 Sample feature for first frame

Features	Normal	Seizure
Stansard Deviation	93.43	4.139
Entropy	.9402	1.551
MAD	72.37	3.431
Rms Value	91.39	4.127
IQR	9.34	6.571
Minimum	-182.06	-8.871
Maximum	149.9	7.810

A linear classifier achieves this by making a classification decision based on the value of a linear combination of the characteristics. The linear classifier confusion matrix is given Table2. Using linear classifier sensitivity is 95.5%, specificity is 100% and accuracy 97.7% is obtained.

Table 2 linear confusion matrix

	Normal	Seizure
Normal	172	8
Seizure	0	180

The same procedure repeated for different patients and one channels data of 24 patients is taken and the classifiers results is given in Table 3.

Table 3 Results of different patient

Patient	Specificity	Sensitivity	Accuracy
1	100	95.5	97.7
2	100	91.6	95.8
3	94.4	98.1	96.2
4	94.1	86.0	90.1
5	100	97.3	98.6
6	100	100	100
7	84.6	94.8	89.7
8	100	91.8	95.9
9	100	100	100
10	100	97.1	98.5
11	100	86.3	93.1
12	61.4	43.7	52.5
13	100	88	94
14	100	95.6	97.2
15	78.8	98.4	88.6
16	85.7	42.8	64.2
17	100	95.5	97.7
18	99.2	96	97.6
19	78.9	97.8	88.4
20	100	97.4	97.8
21	98.7	87.5	93.1
22	97.8	94.5	96.1
23	97.2	91.6	95.8
24	98	94.1	96.1
Average	94.5	90.5	92.5

Comparison of existing seizure detection methods studied on CHB-MIT database. Kiranyaz et al, developed a collective network of binary classifiers along with a novel morphological filtering for the detection of EEG seizures. An average sensitivity of 89.01% with 25% training rate. Later, Zabihi et al (8) achieved an average sensitivity of 88.27% using 25% training rate, with a two layered classifier system followed by morphological filtering operation. Comparison is given Table.

Table 4 Comparison with related work

Authoura and year	Patients-	Spec % Sens %a ccu%
Rafiuddin et al [2011]	23-23	NR-NR-80.16
khan et al[2012]	5-NR	100-83.6-91.0
Kiranyaz et al [2014]	21-18	94.71-89.7-NR
Zabihi et al [2016]	23-23	93.21-88.27-93.11
This work	24 -1	94.5-90.5-92.2

Conclusion And Future Work

The EEG signals are commonly utilized to clinically review brain activities. The detection of epileptic seizures from the EEG signals is an important process in the diagnosis of epilepsy seizures. The CHB MIT data has been decomposed with daubechies wavelet of order 4 and seven features such as Standard deviation, Entropy, Mad, Rms value, IQR, Minimum and Maximum. were computed over the wavelet coefficients at fifth levels. Wavelet based technique in combination with statistical measures was adopted to extract features from sliding epochs of one second that could differentiate between seizure and non-seizure activities.

The classifier used is linear, performance of classifier is measured in terms of the metrics like accuracy, specificity and sensitivity. The sensitivity of linear classifier are 90.5%, accuracy is 92.5 and specificity is 94.5. A better way would be to develop a method for improving the performance of the classifiers using the same dataset.

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