Analysis of Epileptic Seizures in Wavelet Domain

K Najmah
MES College of Engineering, Kuttippuram, Kerala, India.

M Bedeeuzzaman
MES College of Engineering, Kuttippuram, Kerala, India.

Thasneem Fathima
National Institute of Technology, Calicut, Kerala, India

P K Saleema
MES College of Engineering, Kuttippuram, Kerala, India
.

ABSTRACT
Epilepsy is a neurological disorder that can be assessed by electroencephalogram (EEG). EEG signals, which are highly non-linear and non-stationary in nature, are very difficult to characterize and interpret. Wavelet transform is a very effective tool for analyzing non-stationary signals. A method of automatic detection of epileptic seizures from scalp EEG is discussed in this paper. EEG signals are undergone wavelet decomposition and features such as mean and variance are extracted. A linear classifier is used for classification and could achieve an accuracy of 97.19%.

General Terms
Biomedical Signal Processing, Pattern Recognition

Keywords
Epileptic seizure, EEG, wavelet transform, linear classifier

1. INTRODUCTION
An epileptic seizure is an abnormal excessive or synchronous neuronal activity in the brain. About 50 million people worldwide have epilepsy, and nearly 80% of epilepsy occurs in developing countries. The cause of most cases of epilepsy is unknown, although some people develop epilepsy as the result of brain injury, stroke, brain tumor, and drug and alcohol misuse. The electrographic signature of a seizure is composed of a continuous discharge of variable amplitude and frequency, polymorphic waveforms like spike and sharp wave complexes or electro cerebral inactivity observed over duration longer than the average duration of these abnormalities during interictal periods.

EEG is a device used to record cerebral activity, therefore it is one of the important tools for diagnosis and analysis of epilepsy. EEG contains a set of electric potential differences developed as a result of electrical impulses spreading from an active neural tissue throughout the conductive media of the brain. These measurements can be obtained either using sensors on the scalp or by placing special intra-cranial electrodes. The internationally recognized method to apply the location of electrodes in EEG recording is “10-20” system. The“10-20” refers to the actual distances between electrodes are either 10% or 20% of front-back or right-left distance of the skull.

Visual screening of the EEG is labor intensive, time consuming, and expensive. Therefore, automatic seizure detection is very necessary in medical world. Automatic seizure detection can also be used in real time situation. This will help to localize the brain area where seizure originates when surgical treatment is needed. Seizure detection can be classified as either seizure onset detection or seizure event detection. In seizure onset detection the purpose is to recognize the starting of seizure with shortest possible delay. The purpose of seizure event detection is to identify seizures with the highest possible accuracy. The automated seizure detection can be subdivided into preprocessing, feature extraction, and classification (Fig. 1).

Different types of artifacts affecting EEG are external and internal artifacts. In preprocessing step these artifacts are removed. Feature extraction simplifies the amount of resources required to describe a large set of data accurately. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task. Feature extraction is used to distinguish normal and seizure instances. In classification, all the extracted features of pattern are submitted to a classifier that distinguishes among different classes of samples, for example, normal and abnormal pattern.

The first valuable work in seizure detection was done by Gotman in 1982[1], which was later modified in 1990[2]. After this, different methods have been proposed to detect epileptic seizures. Liu et al [3] introduced a method based on wavelet transform and SVM (support vector machine) in long term intracranial EEG. An algorithm based on discrete wavelet transform is proposed for detection of seizures from the long-term intracranial EEG signal. In this work, sensitivity of 94.46%, accuracy of 95.337 and specificity of 95.26% were obtained.

T, Fathima et al[4] proposed another method for the analysis of EEG for seizure detection using wavelet based features. Normal and seizure EEG signals were decomposed at level 4 using Daubechies wavelet of order 2. Linear classifier was used here which classified healthy and seizure segments with the accuracy of 99.5%, sensitivity of 99.8% and specificity of 99.2%,

D. Wang et al[5] proposed a system for classification of EEG signals using wavelet packet transform. In the training stage cross validation method together with K- Nearest Neighbor classifier was used for hierarchical knowledge base (HKB) construction. During the testing stage discriminative rules from HKB were chosen for final classification. This method gives an accuracy of 99.449% with 10 fold cross validation.

M. Bedeeuzzaman et aI [6] proposed a method using MAD (Median absolute deviation) with other features like variance and entropy were used. These were calculated for each frame of EEG signal. They used linear classifier for classification. This method gives 100% accuracy in seizure detection.

S. M. Shafiul Alam and M. I. H. Bhuiyan [7] introduced a new approach that is EMD (Empirical mode decomposition) for seizure detection using the higher order statistical moments. The EMD is a process of extracting amplitude and frequency modulated oscillatory patterns from a time-series data. These were used as features to classify the EEG signals using an ANN (Artificial neural network). It reported 100% sensitivity, specificity, and accuracy.

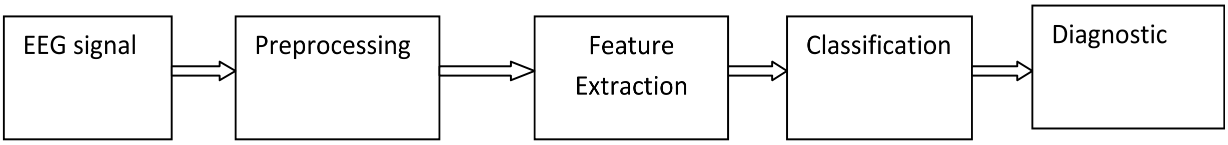

Fig1: EEG signal processing Steps

Nabeel Ahammad et.al [8] used interquartile range (IQR) and MAD with wavelet based features like Energy, entropy, standard deviation, mean, maximum, and minimum. They used latency and sensitivity to study the performance of the algorithm. A sensitivity of 98.5% has been achieved with an average latency of 1.76 seconds.

In this paper, we propose a patient specific detection method using discrete wavelet transform on scalp EEG data. Features such as mean and variance of ictal and interictal data are extracted and classified using a linear classifier. A specificity of 98.3% and sensitivity of 96.06% and an accuracy of 97.19% are achieved.

2. MATERIALS AND METHODS

2.1 Data Sets

CHB-MIT scalp EEG database collected from Boston Children's Hospital. The database consists of EEG recordings with intractable seizures recorded from pediatric subjects. Sampling rate of all signals is 256samples per second with a resolution of 16 bit. For recording, the international 10- 20 system of EEG is used. The EEG data set of each patient is segmented to records of typically one hour long.

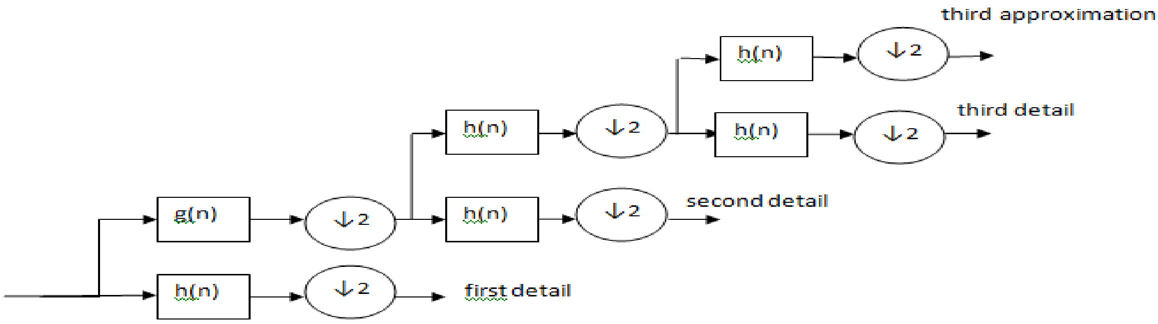

Fig2: multiresolution decomposition of signal

2.2 Wavelet Transform

Wavelet transform is mainly used to analyze non-stationary signals such that, at different frequencies of the signals different resolutions are used. It is the representation of the time function of signals in terms of simple blocks called wavelets which are in fact derived from mother wavelets by dilation and translation operation. The main advantage of wavelet transform is its variable window size due to which good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies are possible. Wavelet transform are of two types: first one is the continuous wavelet transform which is computed by changing the scale of the analysis window, shifting the window in time, multiplying by the signal, and integrating over all times .i.e,

$$\mathrm{CWT}(a,b) = \int_{-\infty}^{\infty} x(t)\Psi^{*}_{a,b}(t)\,dt$$

Where, x(t) represents the analyzed signal, ɑ represent the dilation/compression coefficient (scaling factor), and b represent shifting coefficient. And

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\,\Psi\left(\frac{t-b}{a}\right)$$

Ψ(t) represents the wavelet

The second category is discrete wavelet transform(DWT). In DWT, filters of different cut off frequencies are used to analyze the signal at different scales. The signal is passed through a series of highpass filters to analyze the high frequencies, and it is passed through a series of lowpass filters to analyze the low frequencies. Fig. 2 shows the multiresolution decomposition of signal using DWT.

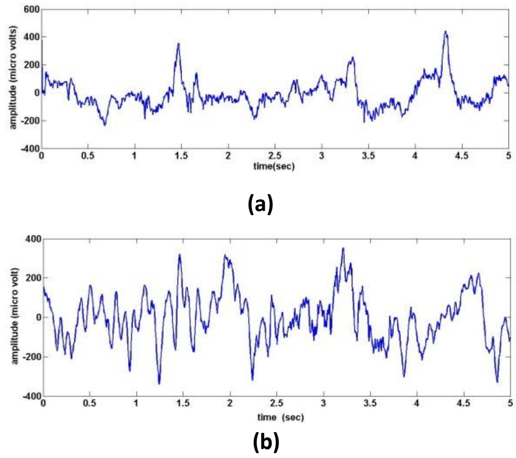

Fig3: (a) Interictal and (b) ictal EEG signals of a patient

2.3 Feature Extraction and Classification

Feature extraction is used to discard irrelevant informations and to represent relevant informations in a meaningful form.It reduces the dimensionality of input data into a set of features.These features are used for the classification of data into ictal and interictal.The features used are mean and variance.

For a dataset $X = x_1, x_2 \ldots\ldots x_n$, the mean is given by,

$$\mu = \frac{x1 + x2 \ldots\ldots xn}{n}$$

And variance, which is the measure of statistical dispersion is given by,

$$\mathrm{Var}(X) = \mathrm{E}[(X - \mu)^2]$$

For classification of extracted features we use a linear classifier. A decision based on the value of linear combination of the features is used for classification in this classifier.

3. RESULTS AND DISCUSSION

The ictal and interictal portions of the EEG signal of a single patient are divided into frames of one second duration. A five level wavelet decomposition is done on each of the frames. Features are extracted from approximation of fifth level(A5) and details of fifth(D5), fourth(D4) and third (D3) levels. The rest of the detail coefficients are discarded since they are out of frequency ranges of interest. Features extracted are mean and variance. These means and variances correspond to the data of 23 channels. Inorder to reduce the dimensionality, overall mean of the extracted features of 23 channels are computed and given to classifier. Five seconds of ictal and interictal EEG for the first channel is given in Fig. 3. Table 1 shows the features for a single frame of both interictal and ictal data.

A linear classifier is used to classify into ictal and interictal data. Features of 60% of the ictal and interictal data are used for training and the features of remaining 40% are used for testing. The total duration of ictal data is 442seconds. Training set is formed using 265 seconds from ictal as well as interictal data and next 178s econds data is used for testing .

The performance of a classifier is assessed by using the measures such as specifity, sensitivity and accuracy .

$$\text{Specificity} = \frac{\text{No :of true negative desicions}}{\text{No :of actually negative cases}} = \frac{\text{TN}}{\text{TN+FP}}$$

$$\text{Sensitivity} = \frac{\text{No :of true positive decisions}}{\text{No :of actually positive cases}} = \frac{\text{TP}}{\text{TP+FN}}$$

$$\text{Accuracy} = \frac{\text{specifity + sensitivity}}{2}$$

Where TP = true positive, TN = true negative, FP = false positive and FN = false negative

The performance measures obtained for the proposed work is shown in Table 2. The data we used are originally artifacts free. Therefore, in practical cases,the proposed method may not give same performance as achieved.

Table 1 Features extracted for first frame of first channel

FRAME	A5		D5		D4		D3	
	MEAN	*VARIANCE*	*MEAN*	*VARIANCE*	*MEAN*	*VARIANCE*	*MEAN*	*VARIANCE*
INTER ICTAL	0.30	5.15282×10^5	13.02	1.02590×10^5	-2.23	2.7167×10^4	2.99	9932.12
ICTAL	37.27	1.50727×10^5	-37.91	1.14985×10^5	-1.05	3.3090×10^4	0.11	3743.448

4. CONCLUSION

A lot of works have been done and still being developed in the area of automatic epileptic seizure detection. Majority of these works are aimed for automatic detection of seizures from intracranial EEG data.A very few effective works are proposed for scalp EEG data. Intracranial EEG requires surgical invasion and on the other hand scalp EEG recording is non-invasive.An effective automatic seizure detection algorithm using scalp EEG data would have been very useful for developing appropriate treatment strategies and research studies.The proposed method uses scalp EEG data. This methodology using discrete wavelet transform and linearclassifier could achieve an accuracy of 97.19%. Since we used an originally artifacts free data and it may not be true in the practical scenarios.

Table 2. Performance measures

specificity	sensitivity	accuracy
98.3%	96.06%	97.19%

5. REFERENCES

[1] Gotman,J. 1982. Automatic Recognition of Epileptic Seizures in the EEG. Electroencephal. Clin. Neurophys. 54, 530-540.

[2] Gotman,J. 1990. Automatic Seizure Detection: Improvements and Evaluation. Electroencephal. Clin. Neurophys. 76, 317-324.

[3] Y. Liu, W. Zhou, Q. Yuan, S. Chen. 2012. Automatic Seizure Detection Using Wavelet Transform and SVM in Long-Term Intracranial EEG, IEEE Trans Neural Syst Rehabil Eng. 20, 749-755.

[4] Fathima,T., Bedeeuzzaman,M., Joseph,P.K. 2013 Wavelet based features for classification of normal, ictal and interictal EEG signals. J. Med. Health Info.301-305

[5] Fathima,T., Bedeeuzzaman,M., Farooq,O., Khan Y.U.2011. Wavelet Based features for epileptic seizure detection, MES J. Technol. Manag. 2, 108-112.

[6] Wang, D., Miao, D., Xie, C. 2011. Best basis-based wavelet packet entropy feature extraction and hierarchical EEG classification for epileptic detection, Expert Syst. Appl. 38, 14314-14320.

[7] Shafiul Alam S. M., Bhuiyan M I H. 2013. Detection of Seizure and Epilepsy Using Higher Order Statistics in the EMD Domain. IEEE J. Biomed. Health Inform. 17, 312-318.

[8] Ahammad, N., Fathima, T., Joseph,P. Detection of Epileptic Seizure Event and Onset Using EEG. Hindawi Publishing Corporation .BioMed Research International Volume 2014, Article ID 450573, 7 pages.