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Prognostication of Epilepsy by EEG Signals Using Wavelets

Antriksh Ojha
Student, Jaypee Univ. of Information Technology, Solan, Himachal Pradesh, INDIA
Email ID: anterikshojha.sanjai@gmail.com

Iresh Rastogi
Student, Jaypee Univ. of Information Technology, Solan, Himachal Pradesh, INDIA
Email ID: ireshrastogi@rediffmail.com

Aeshna Chawla
Student, Jaypee Univ. of Information Technology, Solan, Himachal Pradesh, INDIA
Email ID: aesha51294@gmail.com

Meenakshi Sood
Faculty, Jaypee Univ. of Information Technology, Solan, Himachal Pradesh, INDIA
Email ID: meenakshi.sood@juit.ac.in

Abstract - **In this paper, a comprehensive quantitative analysis of electroencephalogram signals is carried out. As nature of EEG signals is non-stationary, the visual inspection of EEG data lacks quantitative analysis and is time-consuming and inefficient. Wavelets provide a solution for analyzing and synthesizing signals, images, and data exhibiting regular behavior punctuated with abrupt changes. Attributes from the available database are extracted and analysis of signal with different wavelets is processed to detect and predict the type of disorders. This article proposes a method for reliable detection of epilepsy by using different wavelets asHaar wavelet, Coiflet wavelet, DBand symlet to the database signals and on the basis of which we are able to prognosticate. Db wavelet provides the optimum results and best serves our objective.**

Keywords–Electroencephalogram (EEG); Prognostication; Wavelet transform; Attributes; Skew; Kurtosis.

I. INTRODUCTION

Electroencephalogram(EEG) is an unique and a valuable measure that provides information about the electrical activity of human brain.These signals play an important role for examining and diagnosing of neurological disorders, as epilepsy, Alzheimer, sleep problems and so on [1]. The primeval methods of analyzing EEG signals are based on the linear mathematics, though linearity is not appropriate for investigation of chaotic and complex seizures. In real time devices such as central nervous system, social behavior, chemical reaction, which are complicated and extremely input-sensitive behavior that cannot be analyzed linearly.

It is recommended to use frequency – time domain methods as discrete wavelet transform analysis to display differentt behavior of the EEG as these signals are non-linear and a non-stationary signal. These signals can be easily described in the time and frequency domain and have excellentt time resolution and can be acquired non- invasively, which makes this technique more frequently used[2]. In the early days of digital processing, the most commonly used transform for signal representation was Fourier transform. However, bio-signals, characterized by a non-stationary time behavior would not produce the finest result if processed with Fourier transform. In this work, wavelet theorem has been used for analysis, diagnosis and processing of bio-signals for extracting features, firmness and de-noising purposes. Numerous wavelet families exist for signal characterization and selection of suitable wavelet is an open research issue[3]. A range of techniques for signal processing have already been proposed for characterization of non-stationary and non-linear signals like EEG [4].Because of their very complex nature, there seems a necessity to investigate their joint time-frequency localization for more discriminatory features. A nnumber of transformation methods ssuch as Wavelet Packet transform (WPT), Wigner Valley (WV) decompositionon, Wavelet Transform (WT), etc, are available for the representation of a signal in time-frequency domain[5].

The techniques used for the detection of seizures are divided into domain based five groups: time-frequency domain, time domain, frequency domain, soft computing domain and nonlinear based methods [7]. In this paper time-frequency domain techniques are used to analyze the signals using wavelet transform. This paper reviews epilepsy detection by the techniques used for EEG signal processing, from analysis of EEG data acquisition leading to classification methods of EEG signal. The technique employed in this paper involves- finding out the optimal wavelet to analyze the EEG signals. Further, Signals are statistically analyzed by calculating first, second and higher order statistical parameters. Section II presents the materials & methods employed for this research work. Section III gives the details of the proposed methodology adopted in this paper. Results are shown in section IV and the final conclusions are drawn.

II. MATERIALS AND METHODS

A. Acquisition of Signals

Encephalographic signals are acquired by a particular system using recording device comprising electrodes, amplifiers with filters, A/D converter. A standard International system is adopted for acquisition known as 10-20 electrode placement system for the designations of electrodes and physical placement on the scalp.The head is divided proportional to the prominent skull landmarks to cover all regions of the brain [6]. Electrode positioning are named as F (frontal), C (central), T (temporal), P (posterior), and O (occipital) as shown in figure 1.

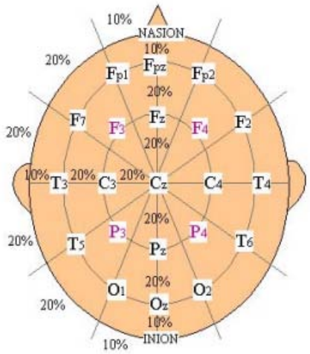


Fig. 1. Labelled 10-20 system of electrode placement

Each scalp electrode is positioned near certain brain centres, and each electrode position represents a lobe and number identifies hemisphere location. 'C'means central,'F' means frontal,'P'means parietal and T' means temporal lobe of brain. The signal acquired by the electrodes from the head surface is in microvolt range which is amplified by the amplifiers to bring them in Volts range that can be further digitized accurately. Thus the computer aided system can be to store and display obtained data and can be further processed.

B. Database Selection

The EEG database used in this study was provided by the University of Bonn [8]. This gathering contains EEG data coming from three different events, to be exact, healthy subjects, seizure-free intervals that is the inter-ictal states and during a seizure, that is ictal states. The perfect database constitutes three classes such as S, Z and F, each having 100 single channel EEG signals. The various human activities used for measuring the brain activity were Eye open (Z), Eye close (O), during ictal state (F), Seizure (S).

C. Attributes

In this work, statistical parameters such as energy, standard deviation and entropy [9] were calculated for the different categories of signals at each decomposition level.The various attributes used are Energy, Standard Deviation, Mean, Kurtosis, Skewness SNR and Entropy.The attributes of all the signals are calculated and tabulated to be used for classification.

III. METHODOLOGY ADOPTED

While recording EEG signal it gets contaminated by noise known as Artifacts which are caused byvarious factors, likeEOG (electro-oculogram), EMG (electromyogram) andline interference. To extract the accurate information from EEG signal, it must be noise free and without any Artifacts[11].After preprocessing of the signals, waveletsare used which divide data into various sub-components of frequency, and then each sub-component is analyzed with a particular resolution.

A. Wavelet transforms

EEG being a non –linear, non-stationary signal, using wavelet transform for the signal analysis is preferred over other transforms. Wavelet transformation is divided broadly into two major categories: Discrete wavelet transform and Continuous wavelet transform. The Continuous wavelet transform is normally used for feature detection and analyzing signals, whereas the latter is mostly used for compression and reconstruction of data. The frequency bands or sub-bands(subspaces) are scaled versions of a subspace[10]. This cause shifts in one of the generating function ψ in L2(R) i.e. the mother wavelet generates this subspace in all situations The frequency is generated by the functions basically called child wavelets.

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$

where ***a*** *b* define the scale and the shift is any real number. The coefficients are given as*:*

$$WT_{\psi}\{x\}(a,b)=\langle x,\psi_{a,b}\rangle=\int_{R}x(t)\psi_{a,b}(t)\,dt$$

By using all wavelets coefficients, it is not possible to analyse computationally, thus a discrete subset is sufficiently picked to reconstruct a signal of the upper half-plane from the corresponding wavelet coefficients, thus resulting in use of discrete wavelet transform[14]. Therefore, the child wavelets are**:**

$$\psi_{m,n}(t)=a^{-m/2}\psi\left(a^{-m}t-nb\right)$$

For finite energy a sufficient condition for the reconstruction of any signal x is given as :

$$x(t) = \sum_{m \in Z} \sum_{n \in Z} \langle x, \psi_{m,n} \rangle \cdot \psi_{m,n}(t)$$

where,

$$\{\psi_{m,n} : m, n \in Z\}$$

Some of the wavelets used in this research work are briefed in the following section :

Haar wavelet –Haar wavelet is a sequence of functions of rescaled "square-shaped" family and is considered to be the simplest wavelet among all.

The mother wavelet function $\psi(t)$ for haar wavelet is:

$$\boldsymbol{\psi(t)} = \begin{cases} \mathbf{1} & \mathbf{0} \leq \boldsymbol{t} < 1/2 \\ \mathbf{-1} & \frac{\mathbf{1}}{\mathbf{2}} \leq \boldsymbol{t} < 1 \\ & \mathbf{0} \qquad \text{otherwise} \end{cases}$$

The scaling function is :

$$\phi(t) = \begin{cases} 1 & 0 \leq t < 1 \\ 0 & \text{otherwise} \end{cases}$$

Daubechies wavelet-This wavelet, is a family of orthogonal wavelets that defiines a discrete wavelet transform and is classified by a maximum no. of disappearing moments [13].

Coiflet Wavelet- These are a type of discrete wavelets that contains some scaling functions with disappearing moments[12].Hence the two functions -the wavelet & scaling function must be normalized by a factor1/sqrt(2). Mathematically, Coiflet wavelet can be represented as:

$$B_k = (-1)^k C_{N-1-k}$$

here N - wavelet index, k - coefficient index , B – wavelet coefficient and C – coefficient of scaling function.

B. Design flow

The signals are taken from the database available online. Inspection for signal distortions among basic evaluation of the EEG traces is called artifacts. In comparison to signal sequences not going through by any large contamination typically it is a sequence with higher amplitude. So artifacts and excessive noise will be eliminated from the signal. After the detachment of noise and artifacts, the signal would be categorized into following mentioned the frequencies' (0.5-3 Hz) ϴ(3-8 Hz) α(8-12 Hz) β(12-38 Hz)γ(38-42 Hz).

For the final processing of the signal, various wavelets transform are used. Once the signal is passed through the wavelets, the attributes used for the analysis of the EEG signals are selected.

For all the 300 signals of ictal, normal and inter-ictal, attributes from all the coefficients are calculated and normalized in the max-min range. The main aim of data normalization is to improve the levels of signals of interest, while attenuating or rejecting unwanted signals. Finally the attributes of all the signals are used for training the classifier and then classifying the signals for epilepsy using SVM classifier.

IV. RESULTS AND DISCUSSION

The data taken from Bonn University comprises EEG signals for three types of patients – Ictal, Inter-ictal and healthy man, with each categories comprising of a dataset of 100 patients. In this work we have used different wavelets – Haar Wavelet, Symlet Wavelet, Coiflet Wavelet and Daubechies Wavelets to divide a single EEG signal into 5 different signals – delta, theta, alpha, beta, and gamma in frequency domain .

Figure 2 shows the Extracted features of Ictal and healthy patients respectively. These features are extracted using coiflet wavelet. Features includes mean, standard deviation, variance, skewness, kurtosis, energy which is scaled to x10^6, power, maximum/minimum value, and entropy.

Figure 3 shows the results of a single patient (from each state i.e. Ictal, inter-ictal and healthy) of EEG using Symlet wavelet. Figure 3 (i) shows the categorization of EEG signal of an ictal patient. In this the delta signal has high number of peaks which shows high order of randomness and instability of mind. The beta and gamma signals have very high frequency and rise and drops in the signal values.

Similarly, Figure 3 (ii) shows the categorization of EEG signal of a healthy patient. In this the delta signal has least number of peaks which shows low order of randomness and stability of mind. The beta and gamma signals have very high frequency and less rise and drop in the signal values.

Figure 3 (iii) shows the categorization of EEG signal of an inter-ictal patient. In this the delta signal has high number of peaks with respect to the healthy patient but low number of peaks with respect to ictal state patient which shows moderate order of randomness and less stability of mind. The beta and gamma signals have very high frequency and less rise and drops in the signal values compared to the ictal patient

	Ictal				
Parameters	DELTA	THETA	ALPHA	BETA	GAMMA
Mean	12.84092	-0.02618	0.067574	-0.01545	0.003532
Standard Deviation	256.8643	177.181	106.4368	41.23028	10.4266
Variance	65979.29	31393.11	11328.79	1699.936	108.714
Skewness	0.160399	-0.10393	-0.07169	0.034158	0.390759
Kurtosis	2.46269	3.027537	3.81717	7.686291	14.19022
Energy (scaled to x10^6)	270.9267	128.5862	46.40274	6.96294	0.445292
Power	66128.08	31385.45	11326.03	1699.522	108.6874
Max value	839.297	572.8943	377.6055	254.2637	92.86517
Min value	-614.652	-564.015	-551.005	-248.357	-76.8315
Entropy	0.049991	-0.00015	0.000635	-0.00037	0.000339

(a)

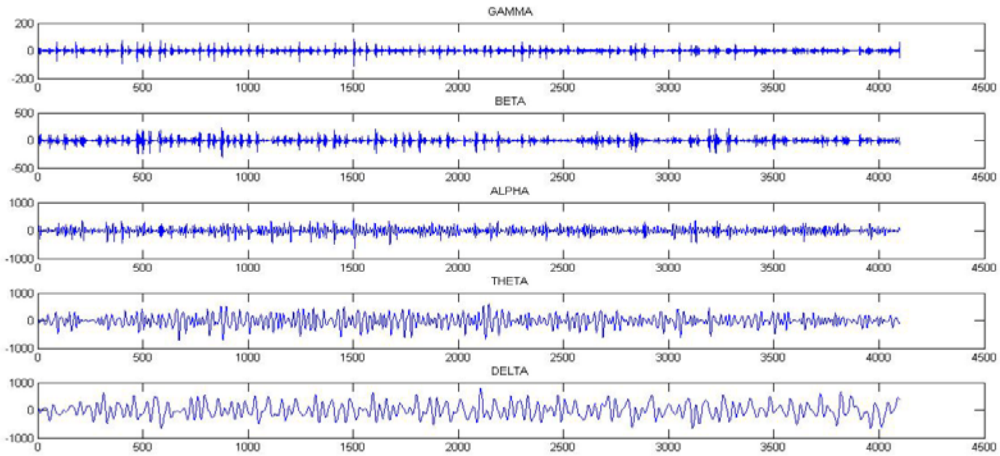
Fig. 2. Extracted Features using coiflet wavelet for (a) ictal state patient.

Figure 4 shows the graphs of the extracted features in comparison with all three states of mind (i.e. ictal, inter-ictal and healthy). The observations noted here are- Skewness and Kurtosis value is greatest in Inter-Ictal patient and least in Seizure patient. Energy value is greatest in Seizure patient and least in healthy individual. Entropy is positive in Seizure patient and negative in Healthy individual.

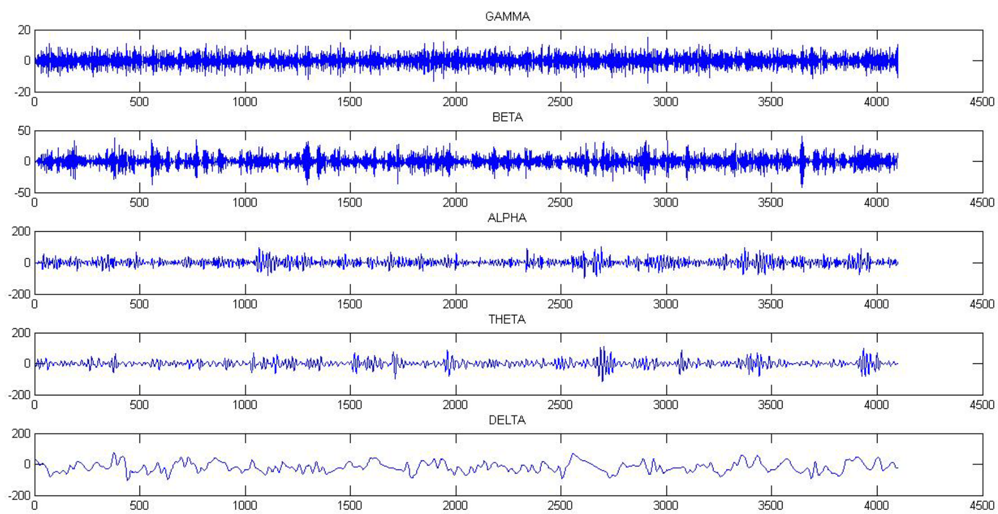
	Healthy				
Parameters	DELTA	THETA	ALPHA	BETA	GAMMA
Mean	-17.9943	-0.00632	0.000507	-0.0004	0.001287
Standard Deviation	31.5458	20.69438	22.47593	8.848159	3.207651
Variance	995.1376	428.2573	505.1676	78.28992	10.28902
Skewness	0.297508	-0.04749	0.152259	-0.04787	0.011297
Kurtosis	2.752754	4.473829	4.915403	3.804421	3.36615
Energy (scaled to x10^6)	5.402677	1.754142	2.069166	0.320676	0.042144
Power	1318.691	428.1528	505.0443	78.27081	10.28651
Max value	73.40109	89.37174	131.3493	36.44718	12.88376
Min value	-102.51	-95.0303	-98.5605	-40.3406	-12.8102
Entropy	-0.57042	-0.00031	2.26E-05	-4.5E-05	0.000401

(b)

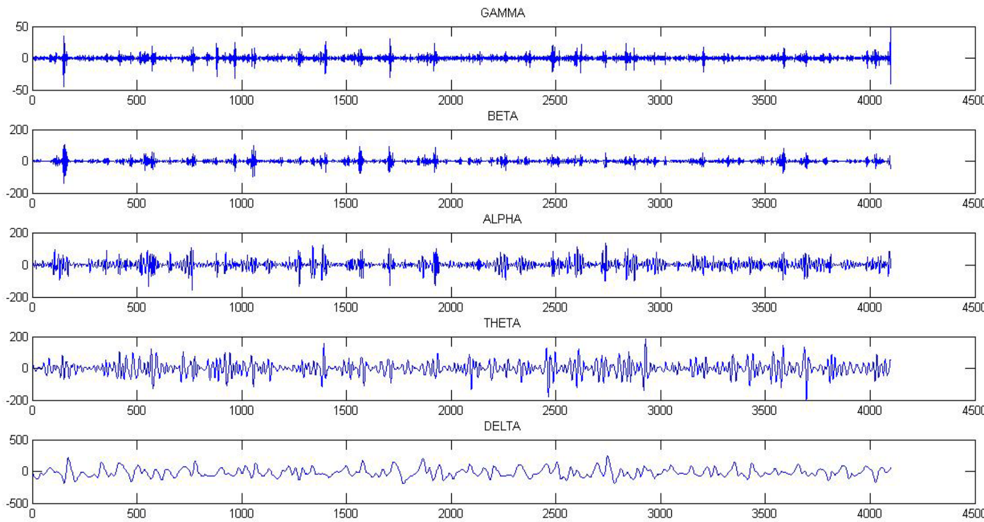
Fig. 2. Extracted Features using coiflet wavelet for (b) healthy state patient.



(i)

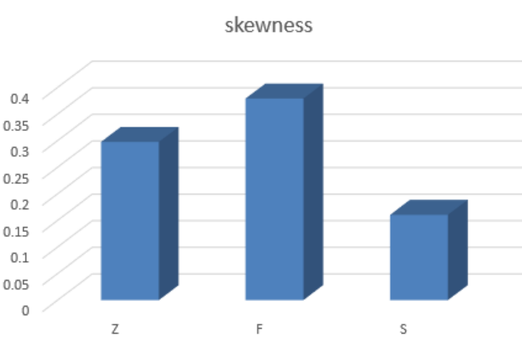


(ii)

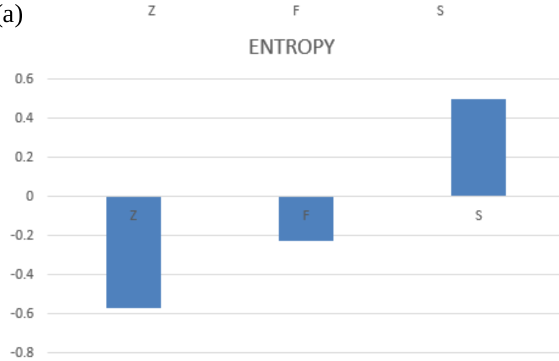


(iii)

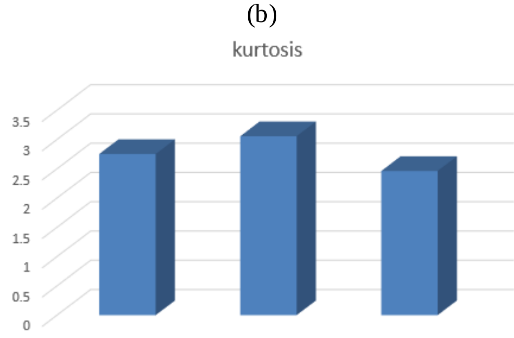
Fig. 3. Extracted wavelet coefficients of (i) ictal state (ii) normal state and (iii) inter-ictal state



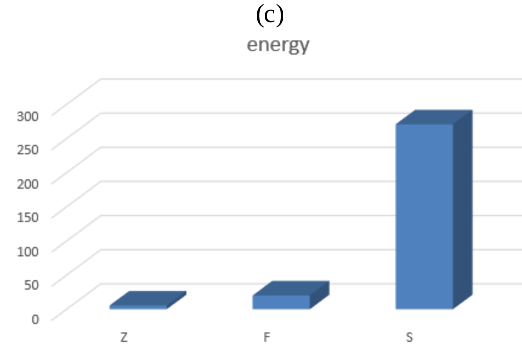
(a)



(b)



(c)



(d)

Fig. 4. Extracted features of ictal state –S, normal state-Z and inter-ictal state-F. (a) Skewness, (b) Kurtosis, (c) Energy (scaled to 10^6) and (d) Entropy.

CONCLUSION

The work performed results in a designed system of prognostication of the epileptic seizure from EEG signals with high accuracy and less computational complexity. Hence we concluded from the results demonstrated, that this technique can be used for efficient and precise epileptic seizure detection. We can observe that: Skewness and Kurtosis value is greatest in Inter-Ictal patient and least in Seizure patient. Energy value is greatest in Seizure patient and least in healthy individual. Entropy is positive in Seizure patient and negative in Healthy individual. Further, various classifiers give satisfactory results of classification of these signals using various attributes calculated from the wavelet coefficients.

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