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Automated Feature Extraction of Epileptic EEG Using Discrete Wavelet Transform and Approximate Entropy

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***Abstract*—The disease epilepsy is characterized by a sudden and recurrent malfunction of the brain that is termed seizer. The electroencephalogram (EEG) signals play an important role in the diagnosis of epilepsy. Nonlinear analysis quantifies the EEG signal to address randomness and predictability of brain activity. In this study, the wavelet subband decomposition and Approximate Entropy (ApEn) is used for epilepsy detection from EEG signals. In first stage, EEG signals are decomposed into five EEG subbands viz. delta, theta, alpha beta and gamma, using Discrete wavelet transform (DWT). The second stage consists of the feature extraction of EEG using ApEn. The methodology is applied to two different EEG signals: 1) Normal 2) Epileptic. For each subband ApEn is calculated and it is observed that the each EEG subband value of ApEn drops during an epileptic seizures. Accuracy is calculated by using thresholding. Classification accuracy is determined by applying thresholding. The overall accuracy as high as 96% is achieved for EEG subbands as compared to the without wavelet decomposition accuracy value is 86%.**

***Keywords*- Electroencephalogram (EEG), discrete wavelet transform (DWT), approximate entropy (ApEn), epilepsy**

I. INTRODUCTION

Electroencephalography is the neurophysiologic measurement of the electrical activity of the brain using electrodes placed on the scalp. The resulting traces are known as electroencephalogram (EEG) and they represent electrical signals from a brain. Physiological information in the brain is carried by patterns of neural activity that are manifested in electrical fields of potential known as action potential and in EEG waves [1], [2]. The disease epilepsy is characterized by a sudden and recurrent malfunction of brain that termed "seizure". A seizure is the event and epilepsy is the disorder. The seizures must be spontaneous and recurrent to represent epilepsy. Epileptic seizures reflect the clinical signals of an excessive and hyper synchronous activity of neurons in the brain [3]. Neurons normally generated electrochemical impulses that act on other neurons, glands and muscles to produce human thoughts, feelings and actions. In epilepsy the normal patterns of neuronal activity becomes disturbed [4].

Long term electroencephalogram (EEG) recording is a widely used clinical procedure for the diagnosis of epilepsy because it is more likely to capture epileptiform abnormalities, both ictal and interictal, than short-term recording [5]. In majority of the cases, the onset of the seizures cannot be predicted in a short period, a continuous recording of the EEG is required to detect epilepsy. A common form of recording used for this purpose is an ambulatory recording that contains EEG data for a very long duration of even up to one week. It involves an expert's efforts in analyzing the entire length of the EEG recordings to detect traces of epilepsy. As the traditional methods of analysis are tedious and time-consuming, many automated epileptic EEG detection systems have been developed in recent years [6][7]. With the advent of technology, it is possible to store and process the EEG data digitally. The digital EEG data can be fed to an automated seizure detection system in order to detect the seizures present in the EEG data. Hence, the neurologist can treat more patients in a given time as the time taken to review the EEG data is reduced considerably due to automation [8], [9].

The electrical waves of brain basically have small amplitude (approximately 100μV) and the frequency range from 0.4 Hz to 80 Hz. Each EEG is commonly decomposed into five subbands: delta (0-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (13-30 Hz), and gamma (30-60 Hz) [9][10]. In order to extract EEG subbands wavelet transform is more advantageous instead of traditional Fourier transform. The wavelet transform has the advantages of time frequency localization, multirate filtering, and scale-space analysis [11].

Research on seizure detection began in the 1970s and various methods addressing this problem have been resented. The authors analyzed the autocorrelation of EEG to provide a measure for rhythmicity [12]. In the frequency domain, seizure detection relies on the differences in the

frequency domain characteristics of the normal and epileptic EEG [13]. Since the EEG is non-stationary in general, it is most appropriate to use the time-frequency domain methods like the wavelet transforms (WT) [14], [15] which do not impose the quasi-stationary assumption on the data like the time and frequency domain methods do. WT provides both time and frequency views of a signal simultaneously which makes it possible to accurately capture and localize transient features in the data like the epileptic spikes [16].

Artificial neural networks (ANN) have widely been applied to classify EKG and EEG signals over the last two decades [17], [18], [19]. A variety of different ANN based approaches were reported in the literature for epileptic seizure detection [16], [20]. Neural network based approaches are mainly based on building models of epileptic and normal EEG and then using these models to classify EEG as either epileptic or normal. The authors presented a comprehensive analysis for the performance of post classifiers such as Hierarchical Soft Decision Trees, Singular value decomposition (SVD), k-means clustering, Principal Component Analysis (PCA) and Rule based AI techniques in optimization of fuzzy outputs for the classification of epilepsy risk levels from EEG signals [27].

The electrical activity of a brain measured by EEG exhibits complex behavior with non linear dynamic properties [9]. There are many methods available for analysis of EEG. Epileptic seizer detection techniques can be divided into five categories: time domain based, frequency domain based, time-frequency domain based, artificial neural network based and nonlinear methods [8].

Nonlinear measures like correlation dimension (CD), largest Lyapunov exponent (LLE) and approximate entropy (ApEn) quantify the degree of complexity in a time series. When used with EEG, these measures help understand EEG dynamics and underlying chaos in the brain [21]. The study demonstrated that entropy values computed for the epileptic EEG were lower compared to the values computed for the normal.

ApEn is a recently formulated statistical parameter that describes the regularity of physiological signals in which larger values indicate a higher complexity in the phase space. Approximate Entropy (ApEn) is scale invariant and model independent [22]. It was first proposed by Pincus in 1991 and has been predominantly used in the analysis of heart rate variability and endocrine hormone release pulsatility, estimation of regularity in seizure time series data, and in the estimation of the depth anesthesia [5].

The nonlinear analysis quantifies the EEG to address randomness and predictability of the brain activities. The value of the ApEn drops abruptly due to the synchronous discharge of large groups of neurons during an epileptic activity . Hence it is a good feature to make use of in the automated detection of epilepsy [23].

Fig.1 shows the generalized block diagram of automated epileptic detection system. The EEG is recorded from 16 electrodes positioned according to the International 10–20 System of Electrode Placement. This is stored in digital form so one can easily compute any algorithm or process on it. At the second stage EEG is decomposed into its five subbands. Third stage is the feature extraction. Then classification and diagnosis by the doctors.

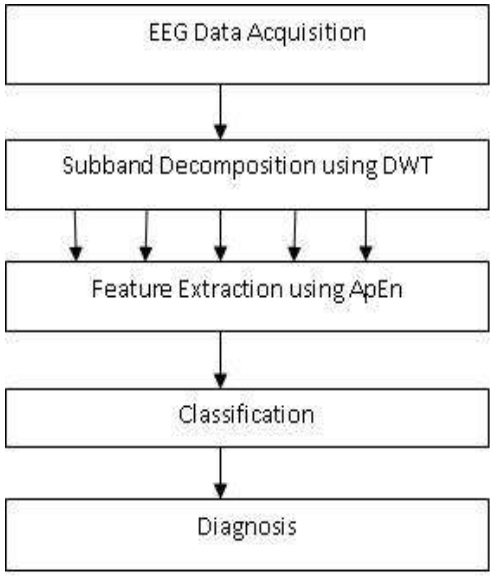

Fig 1 Block diagram of the EEG system.

In this paper, we used discrete wavelet transform (DWT) for subband decomposition of EEG signal into its five subbands namely gamma, beta, alpha, theta and delta. In our previous work [23], we used ApEn as a tool for the feature extraction of epileptic EEG.

The average ApEn is calculated for each subband of normal EEG and epileptic EEG. Our results show that the discrimination between normal EEG and epileptic EEG can be achieved with the help of ApEn. Rest of the paper is organized as follows Section II describes the data acquisition for normal and normal EEG and information related to dataset. Section III describes the subband decomposition using DWT. Section IV describes the feature extraction using ApEn algorithm. Results are discussed in the section V.

II. EEG DATA ACQUISITION

Data used in this work are a subset of the EEG data for both normal and epileptic subjects made available online by Dr. Ralph Andrzejak of the Epilepsy center at the University of Bonn, Germany (http://www.meb.uni-bonn.de/epileptologie/science/physik/eegdata.html). The whole dataset consists of five sets (denoted as Z, O, N, F and S), each containing 100 single-channel EEG segments of 23.6 s duration, with a sampling rate of 173.6 Hz. As such, each data segment contains N=4097 data points collected at intervals of 1/173.61th of 1s. These segments were selected and cut out from continuous multi-channel EEG recordings after visual inspection for artifacts (e.g., due to muscle activity or eye movements). Sets Z and O consisted of segments taken from surface EEG recordings

that were carried out on five healthy volunteers using a standardized electrode placement scheme. Volunteers were relaxed in an awake state with eyes open (Z) and eyes closed (O), respectively. Sets N, F and S originated from an EEG archive of presurgical diagnosis. Segments in set F were recorded from the epileptogenic zone, and those in set N from the hippocampal formation of the opposite hemisphere of the brain. While sets N and F contained only

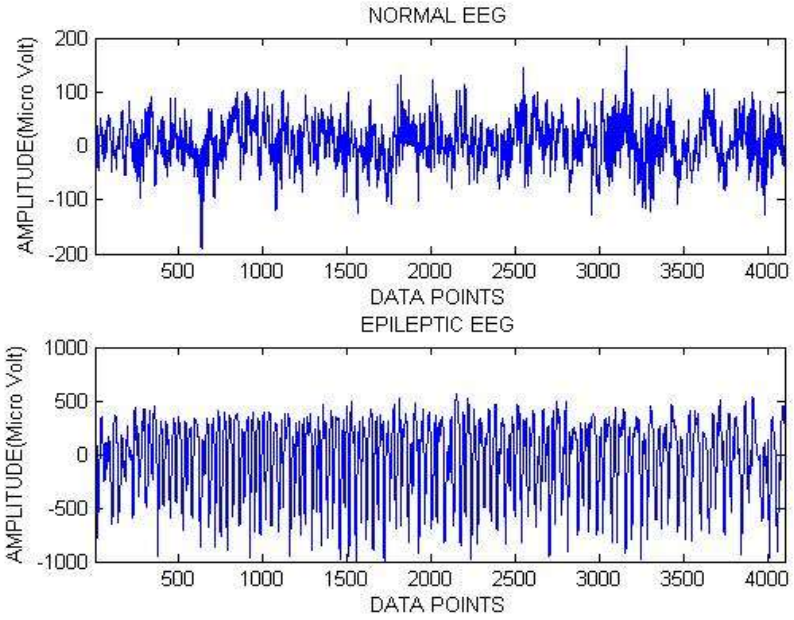

Fig. 2 Sample EEG signals for normal EEG and epileptic EEG.

activity measured during seizure free intervals, set S contained seizure activity. All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. The data were digitized at 173.61 samples per second using 12-bit resolution. Fig. 2 shows the sample EEG signals for epileptic EEG and normal EEG which are taken from above mentioned database [24].

III. EEG SUBBAND DECOMPOSITION USING DWT

Wavelet transforms are widely used in many engineering fields for solving many real life problems. A wavelet is a "short wave", which has its energy concentrated in time to give a tool for the analysis of transient, non-stationary, or time varying phenomena. In order to extract the individual EEG subbands a wavelet filter is employed instead of the traditional Fourier transform because the wavelet transform has the advantages of time-frequency localization, multirate filtering, and scale-space analysis. Wavelet transform uses a variable window size over the length of the signal, which allows the wavelet to be stretched or compressed depending on the frequency of the signal. This results in excellent feature extraction from non stationary signals such as EEGs. In this research, the discrete wavelet transform (DWT) based on dyadic (powers of 2) scales and positions are used to make the algorithm computationally very efficient without compromising accuracy.

In WT, long time windows are used to get a finer low frequency resolution and short time windows are used to get high frequency information. Thus, WT gives precise information at high frequencies. This makes the WT suitable for the analysis of irregular data patterns, such as impulses occurring at various time instances [10].

frequency information at low frequencies and precise time

A continuous wavelet transform (CWT) is used to divide a continuous time function into wavelets. Unlike Fourier transform, the continuous wavelet transform possesses the ability to construct a time frequency representation of a signal that offers very good time frequency localization. In mathematics, the continuous wavelet transform of a continuous, square integrable function x (t) at a scale a>0 expressed by a following integral

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right) dt \qquad (1)$$

Where a and b are so called the scaling (reciprocal of frequency) and time localization or shifting parameters, respectively. Calculating wavelet coefficients at every possible scale is computationally a very expensive task. Instead, if the scales and shifts are selected based on powers

of two, so-called dyadic scales and positions, then the wavelet analysis will be much more efficient. Such analysis is obtained from the DWT which is defined as,

$$DWT(j,k) = \frac{1}{\sqrt{|2^j|}} \int_{-\infty}^{\infty} x(t)\, \psi \frac{(t-2^j k)}{2^j} dt \qquad (2)$$

Where a and b are replaced by 2j and k2j, respectively. Mallat Mallat (1989) developed an efficient way for implementing this scheme by passing the signal through a series of low-pass (LP) and high-pass (HP) filter pairs named as quadrature mirror filters [25].

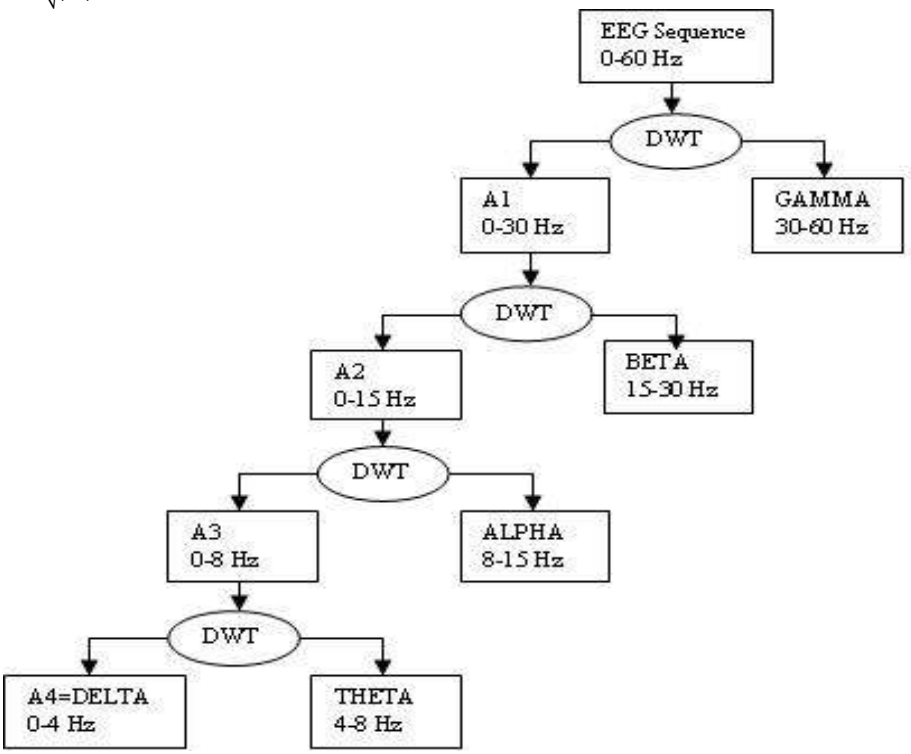

Fig. 3 Four Level Wavelet Decomposition of EEG.

In the first step of the DWT, the signal is simultaneously passed through a LP and HP filters. The outputs from low and high pass filters are referred to as approximation (A_1) and detailed (D_1) coefficients of the first level. The output signals having half the frequency bandwidth of the original signal can be downsampled by two according to Nyquist rule. The same procedure can be repeated for the first level approximation and the detail coefficients to get the second level coefficients. At each step of this decomposition process, the frequency resolution is doubled through filtering and the time resolution is halved through downsampling. Fig.3 shows the four level wavelet decomposition of EEG signal.

To achieve better results in feature extraction with ApEn algorithm, with wavelet decomposition has been used as a preprocessing level for EEG segments to ex-tract five physiological EEG bands, delta (0-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30), and gamma (30-60 Hz).

For this goal four levels discrete wavelet transform (DWT) with sixth-order Daubechies (db6) wavelet function have been used. Since our dataset is in range 0-60 Hz, coefficients D1, D2, D3, D4 and A4 corresponding to 30-60 Hz, 15-30 Hz, 8-15 Hz, 4-8 Hz and 0-4 Hz respectively that are almost standard physiological sub-bands.

IV. FEATURE EXTRACTION

The Approximate Entropy (ApEn) is one of the nonlinear dynamic parameters that measure complexity of the time series. ApEn assigns a non-negative number to a sequence or time series, with larger values corresponding to greater randomness or serial irregularity, and smaller values corresponding to more instances of recognizable features or patterns in the data. ApEn has advantages over other parameters as: a) it requires less data points (about from 100 to 5000), b) it is robust against noise and wild value points, c) it is appropriate for both deterministic chaotic and stochastic processes [3].

The system makes use of single feature called approximate entropy for the epileptic detection. The ApEn is a time domain feature that is capable of classifying complex system [22]. The values of ApEn determined by using following steps [23][26]

Step 1: The data sequence containing N data points be $X = [x(1), x(2), x(3), \ldots, x(N)]$

Step 2: $x(i)$ is a subsequence of X such that $x(i) = [x(i), x(i+1), x(i+2), \ldots, x(i+m-1)]$ for $1 \le i \le N-m$.

Step 3: *v represents* the noise filter level that is defined as

$$v = q * SD \qquad \text{for } q = 0.1,0.2,0.3, \ldots,0.9 \tag{1}$$

Where, SD is the standard deviation of the data sequence X:

$$SD = \sqrt{\frac{1}{N-1}\left[\sum_{i=1}^{N}\left[x(n) - \frac{1}{N}\sum_{i=1}^{N} x(i)\right]\right]} \tag{2}$$

Step 4: $\{x(j)\}$ represent a set of subsequences obtained from $x(j)$ by varying j from 1 to N. each sequence $x(j)$ in the set of $\{x(j)\}$ is compared with $x(i)$ and, in this process two parameters, namely $Ai(v)$ and $Aim(v)$ are defined as follows:

$$Ai(v) = \frac{\sum_{j=1}^{N-m} kj}{N-m} \tag{3}$$

Where,

$$k = \begin{cases} 1, & if\ |x(i) - x(j)|\ for\ 1 \le j \le N-m \\ 0, & otherwise \end{cases}$$

And

$$Aim(v) = \frac{\sum_{j=1}^{N-m} kj}{N-m} \tag{4}$$

with conditions

$$k = \begin{cases} 1, & if\ |x(i) - x(j)| \le v\ for\ 1 \le j \le N-m \\ 0, & otherwise \end{cases}$$

And

$$k = \begin{cases} 1, & if |x(i+1) - x(j+1)| \le v for\ 1 \le j \le N-m \\ 0, & otherwise \end{cases}$$

Step 5: Define $Ci(v)$ and $Cim(v)$ as follows:

$$Ci(v) = \frac{\sum_{i=1}^{N-m} ln\ (Ai(v))}{N-m} \tag{5}$$

$$Cim(v) = \frac{\sum_{i=1}^{N-m} \ln (Aim\ (v))}{N-m} \tag{6}$$

Step 6: ApEn(m,v,N) is calculated using $Ci(v)$ and $Cim(v)$

$$ApEn(m, v, N) = Ci(v) - Cim(v) \tag{7}$$

$$ApEn(m, v, N) = \frac{\sum_{i=1}^{N-m} \ln (Ai(v))}{N-m} - \frac{\sum_{i=1}^{N-m} \ln (Aim\ (v))}{N-m} \tag{8}$$

$$ApEn = \frac{1}{N-m}\left[\sum_{i=1}^{N-m} \ln\left(Ai(v)\right) - \sum_{i=1}^{N-m} \ln (Aim(v))\right] \tag{9}$$

$$ApEn = \frac{1}{N-m}\left[\sum_{i=1}^{N-m} ln\left(\frac{Ai(v)}{Aim\ (v)}\right)\right] \tag{10}$$

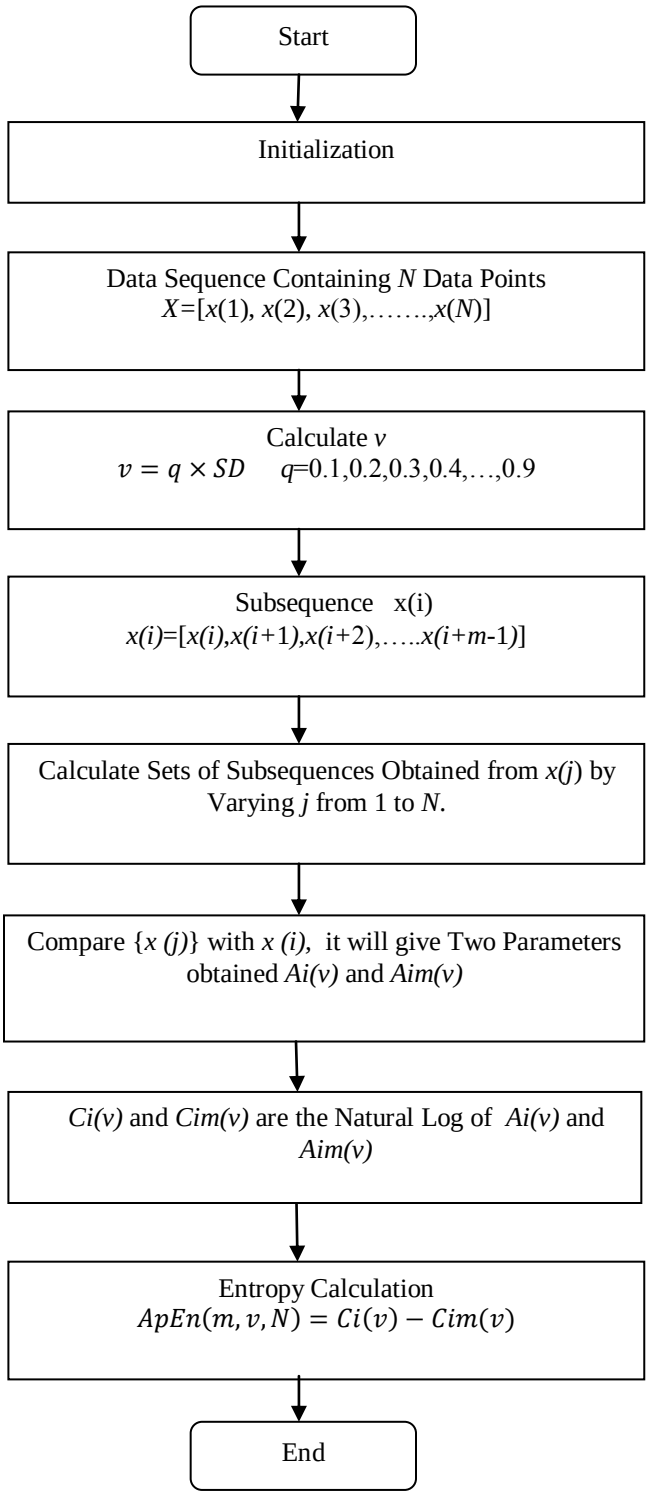

Fig. 4 Flow chart for ApEn (m, v, N).

From above equations it is quite clear that the values of ApEn depend on three parameters *m*, *v* and *N*. The flow chart for calculation of ApEn(*m* ,*v*, *N*) is shown in Fig 4.

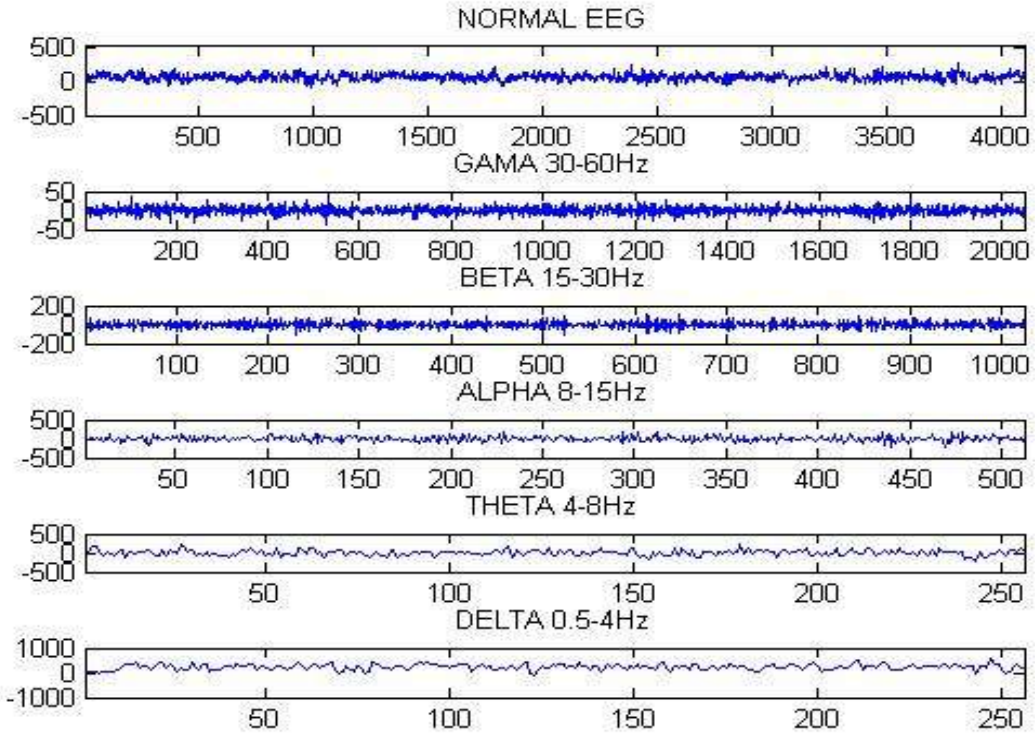

Fig 5. Wavelet decomposition of a sample normal EEG

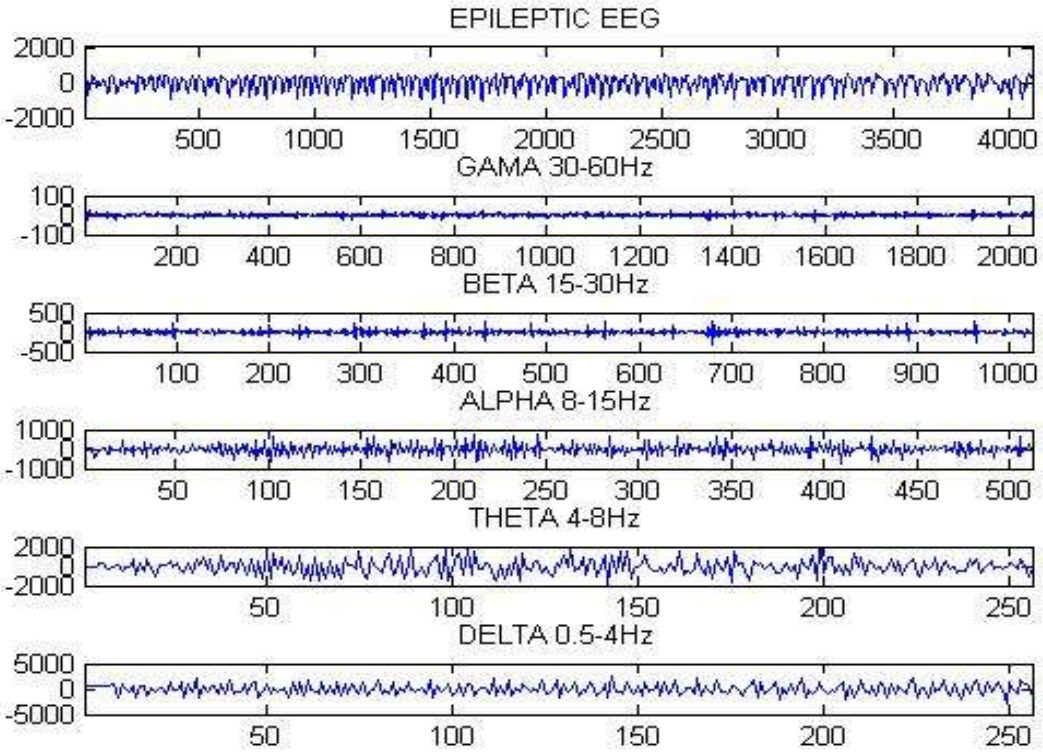

Fig 6. Wavelet decomposition of a sample epileptic EEG

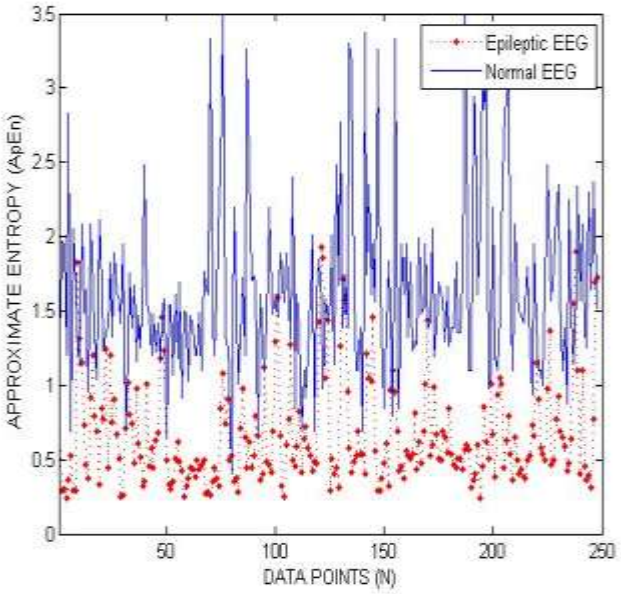

Fig. 7 ApEn of normal EEG and epileptic EEG.

V. RESULTS

A Subband Decomposition

For subband decomposition four levels DWT with sixth order Daubechies (db6) wavelet function have been used. Since EEG is in range 0-60 Hz, coefficient D1,D2,D3.D4 and A4 corresponding to 30-60Hz, 15-30Hz, 8-15Hz, 4-8Hz, and 0-4Hz respectively that are almost standard physiological subbands. Fig 5 shows the wavelet decomposition of a normal EEG and Fig 6 shows the wavelet decomposition of a epileptic EEG.

B. Approximate Entropy

ApEn values are computed for selected combination of *m*, *v* and *N*. The values of *m*, *v* and *N* that are used as follows:

1. $m = 2$
2. $N = 256$
3. $v = q \times SD$ Here v varies from 0 % to 90% of the data sequence in increments of 10%.

ApEn values are computed for both normal and epileptic EEG signals. The two signals namely, normal and epileptic EEG signals depends on the values of *m*, *v* and *N*. Fig 7 shows the plots of the ApEn that have cleared discriminations between the normal EEG and epileptic EEG signals.

Fig. 8 shows plot of the average ApEn values when percentage of SD varies from 10% to 90%. From above Table I, it is observed that maximum value of average ApEn is at 10% of SD and minimum at 90% of standard deviation.

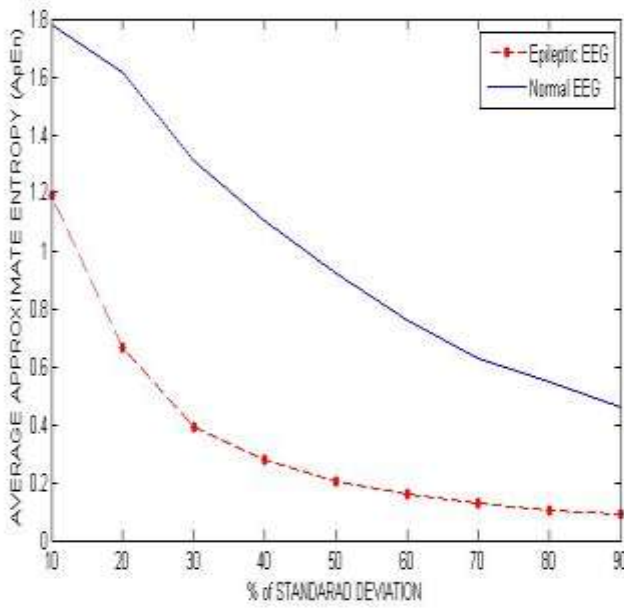

Fig. 8 Average ApEn values 10% to 90% SD variation.

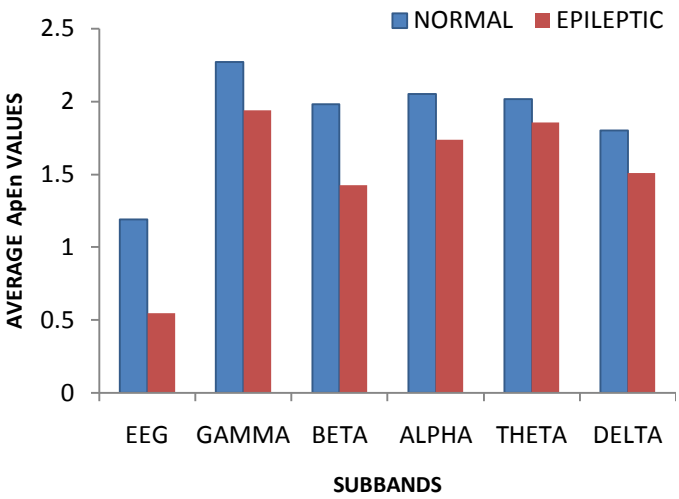

Fig 9 Average ApEn values for EEG signal and subbands.

Generally, *v* is set from 10 % to 25% of the SD. During this range it gives better results and it shows high sensitivity towards complexity of the signal. In this work we have considered 15% of standard deviation value for the purpose of computing. The value of average ApEn at 15% of standard deviation.

Fig. 9 shows the graph of average ApEn values for normal EEG and epileptic EEG and their subbands. From this graph it is observed that average ApEn values for epileptic EEG drops within subbands also.

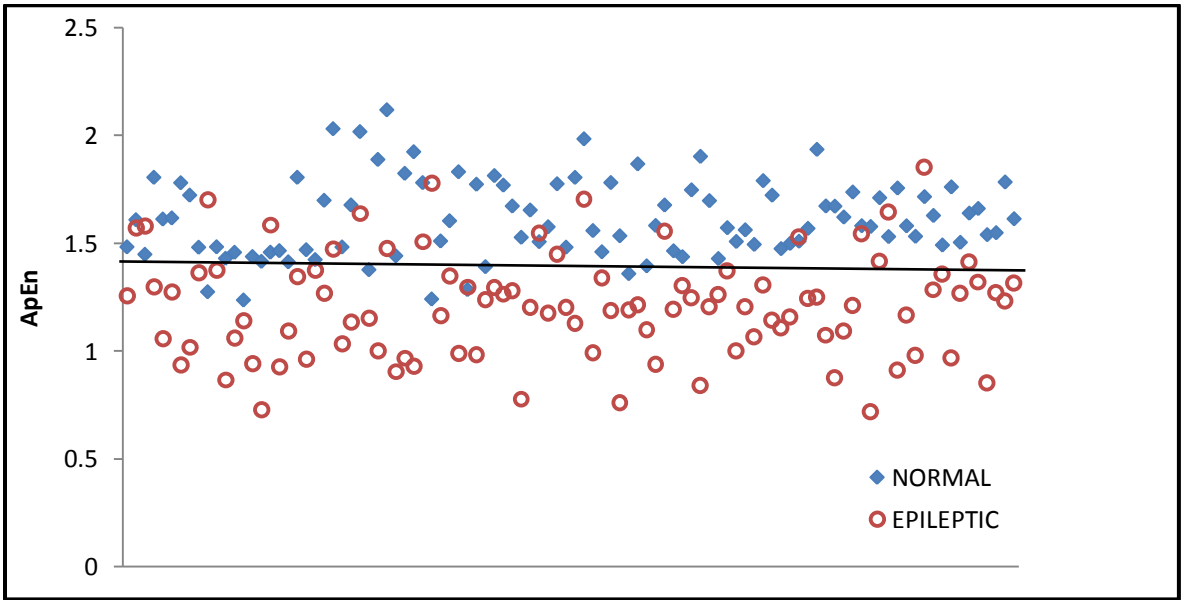

Fig 10. Thresholding for ApEn Values of Normal and Epileptic EEG.

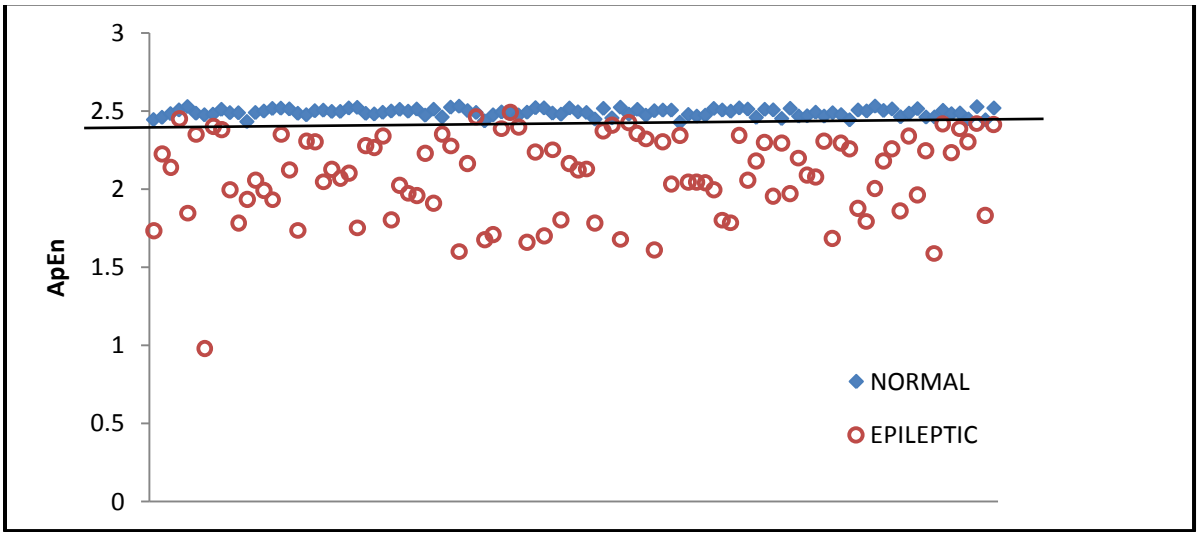

Fig 11. Thresholding for ApEn Values of D1 coefficient for Normal and Epileptic EEG

TABLE I
Classification accuracy results for different sub-bands of DWT for S-Z datasets

	ACCURACY
EEG	86%
D1 (30-60 Hz)	96%
D2 (15-30 Hz)	88%
D3 (8-15 Hz)	79%
D4 (4-8 Hz)	68%
A4 (0-4 Hz)	55%

C. Thresholding

ApEn values of the approximation and detail coefficients at five sub-bands were computed for the entire data sets described earlier. Epileptic EEG detection was based on applying a threshold to the ApEn values. EEG signals with ApEn less than the threshold were classified as epileptic and EEGs with ApEn greater than or equal to the threshold were classified as normal EEG.

From the observation TABLE I it is cleared that the accuracy is greater at D1 coefficient (96%) which is greater than the EEG signal (86%). Fig 10 shows the thresholding

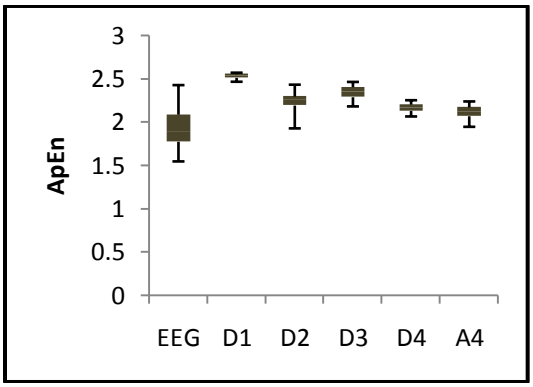

Fig 12. Box plot for the ApEn Values of S set (Epileptic).

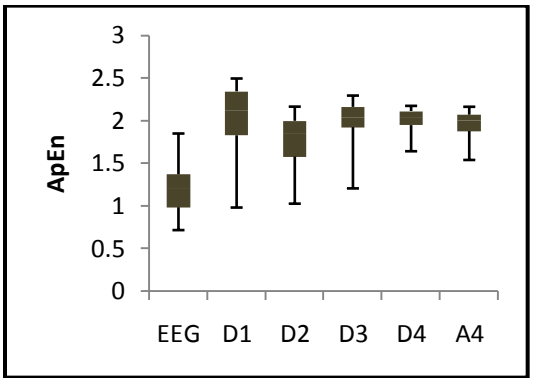

Fig 13. Box Plot for the ApEn Values of Z set (Normal).

coefficient. By observing these two plots we can conclude that the accuracy is increased during decomposition of the signal. From these two figures it is observed that the average

values of ApEn drop during the epileptic seizures. And the discrimination between these two values that is for normal and epileptic is more during the D1 coefficients that is during gamma (30 – 60 Hz) subband. Fig 12 shows the box plot of ApEn values with subbands for the S- set (Epileptic). Fig 13 shows the box plot for the ApEn Values with subbands for Z set (Normal).

VI. CONCLUSION

The discrete wavelet transform and ApEn based methodology is presented. Although it is observed that the ApEn of the EEG signals can discriminate the normal and epileptic EEGs, but it cannot be concluded with certainty. However, when the statistical analysis is performed on EEG subbands, it is observed that the ApEn is used within certain physiological subbands gives better results. In this paper, the discrete wavelet transform and ApEn are used for analysis of EEG and its subbands viz. delta (0-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30), and gamma (30-60 Hz) to detect seizures and epilepsy. The classification accuracy is computed for original EEG and EEG subbands for set S (epileptic) and set Z (normal) datasets. From results it is observed that the overall accuracy as high as 96% is obtained for gamma EEG subband (30 to 60 Hz). ApEn combined with wavelet decomposition analysis gives the features of epileptic activities in EEG signal. Hence it is best feature for the detection of epileptic seizures.

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