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Automated Feature Extraction of Epileptic Seizures Using Wavelet Decomposition of EEG 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 electroencephogram (EEG) has a lot of information about brain and also used in several automated epilepsy detection systems. 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 using four levels Discrete Wavelet Transform (DWT). EEG signals were decomposed into five subbands delta, theta, alpha beta and gamma. Approximate Entropy is used for the feature extraction. For each subband ApEn is calculated and it is observed that the value of ApEn drops during an epileptic seizures.**

***Key Words* — Electroencephogram (EEG), Epilepsy, Discrete wavelet transform (DWT), Approximate Entropy (ApEn)**

I. INTRODUCTION

The electroencephogram (EEG) signal is the summation of brain electrical activities and has a lot of information about brain and also used for epilepsy detection [1]. Epilepsy is the neurological disorder which is characterized by a sudden and recurrent malfunction of the brain. Epilepsy seizers reflect the signals of an excessive and hyper synchronous of neurons in the brain [2]. Neurons normally generate electrochemical impulses that act on other neurons, glands and muscles to produce human thoughts, feelings and actions. In epilepsy the normal pattern of neuronal activity become disturbed.

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) [3]. Wavelet transforms are widely used in many engineering fields for solving many real life problems. 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 [3],[4].

Approximate Entropy (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 [5]. 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 [6].

Fig.1 shows the generalized block diagram of automated epilepsy detection system [6]. 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.

In this paper, we used discrete wavelet transform (DWT) for subband decomposition of EEG signal into five subbands namely gamma, beta, alpha, theta and delta. In our previous work [9], we use 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 result shows 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 it. Section III describes the subband decomposition using DWT. Section IV describes the feature extraction using ApEn algorithm. Results are discussed in the section V.

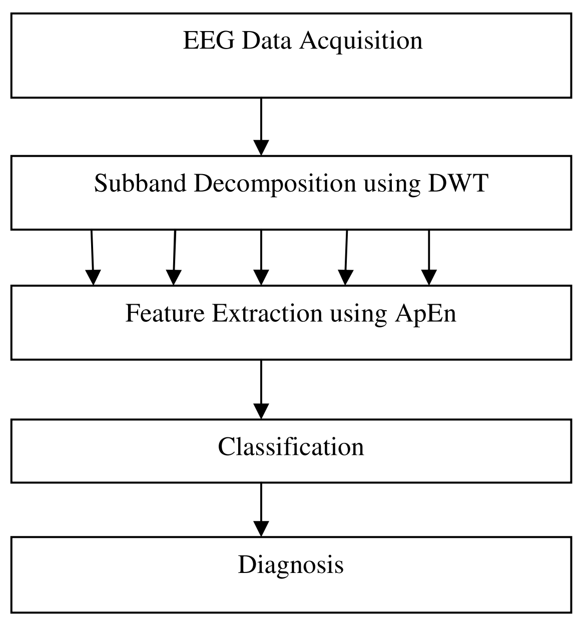

Fig.1. Block Diagram of Automated Epilepsy Detection System

II. 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). Set O contains normal EEG segments and set S is epileptic EEG segments recorded during seizures. Each set contains 100 single channel EEG segments of 23.6 sec duration each sampled at 173.61 Hz [3]. As such, each data segment contains N=4097 data points collected at intervals of 1/173.61th of 1s. Fig. 2 shows the sample EEG signals for epileptic EEG and normal EEG which are taken from above mentioned database [3].

III. EEG SUBBAND DECOMPOSITION USING DWT

Wavelet analysis can represent EEG subbands as a weighted sum of shifted and scaled version of the original wavelet without loss of information and energy. Wavelet transform (WT) 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 [3]. WT gives precise time information at low frequencies and precise time information at high frequencies. This makes the WT suitable for the analysis of irregular data patterns [4].

In DWT the scales and shifts are selected based on powers of two, then the wavelet analysis will be much more efficient. DWT is defined as

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

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 illustrates the four level wavelet decomposition of EEG signal [4].

Achieve better results in extraction with ApEn algorithm, with wavelet decomposition has been used as a preprocessing level for EEG segments to extract five physiological EEG bands, delta(0-4Hz), theta(4-8Hz), alpha(8-13Hz), beta(13-30Hz), and gamma(30-60Hz).For his four levels DWT with third order Daubechies (db3) wavelet function have been used.

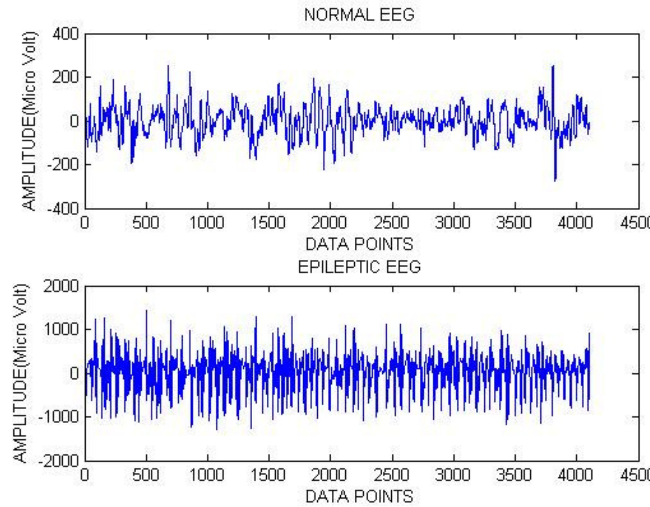

Fig. 2 Sample EEG signals for normal EEG and epileptic EEG

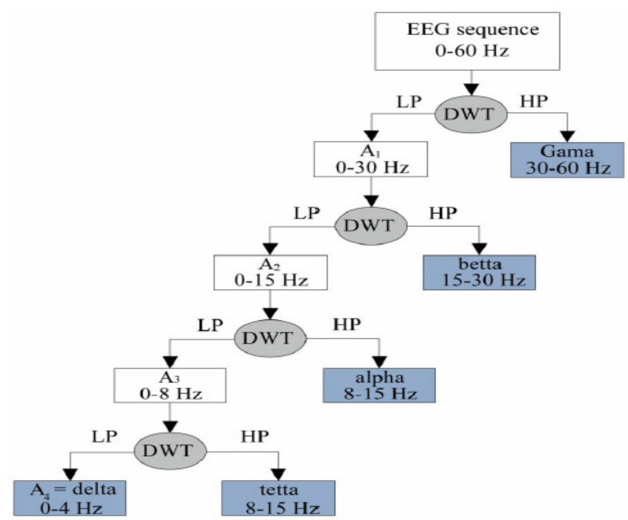

Fig. 3 Four Level Wavelet Decomposition of EEG

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 [5].

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 [6]. The values of ApEn determined by using following steps [6][8].

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

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

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 $Qi(v)$ and $Qim(v)$ are defined as follows:

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

Where,

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

And

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

with conditions

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

And

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

Step 6: ApEn(m,v,N) is calculated

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

From above equations it is quite clear that the values of ApEn depend on three parameters m, v and N.

V. Results

For subband decomposition four levels DWT with third order Daubechies (db3) 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 4 shows the wavelet decomposition of a normal EEG.

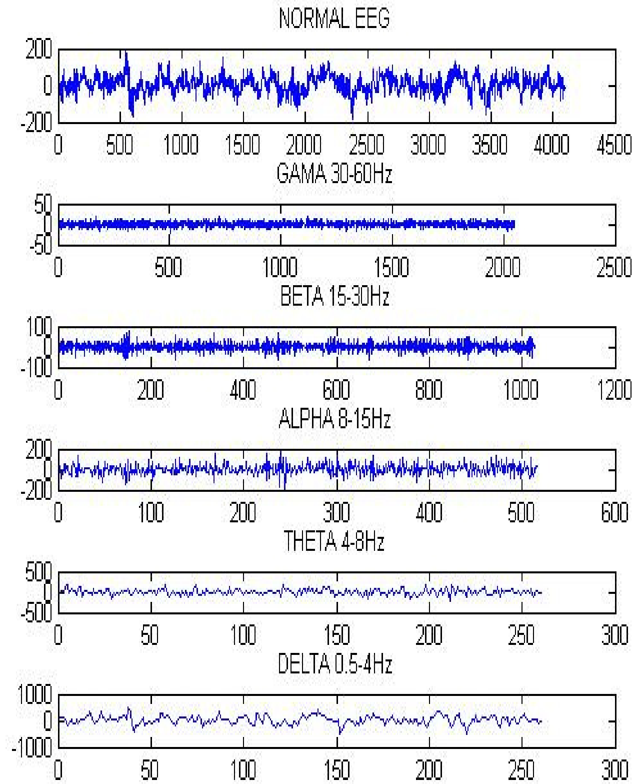

Fig. 4 Wavelet decomposition of a normal EEG

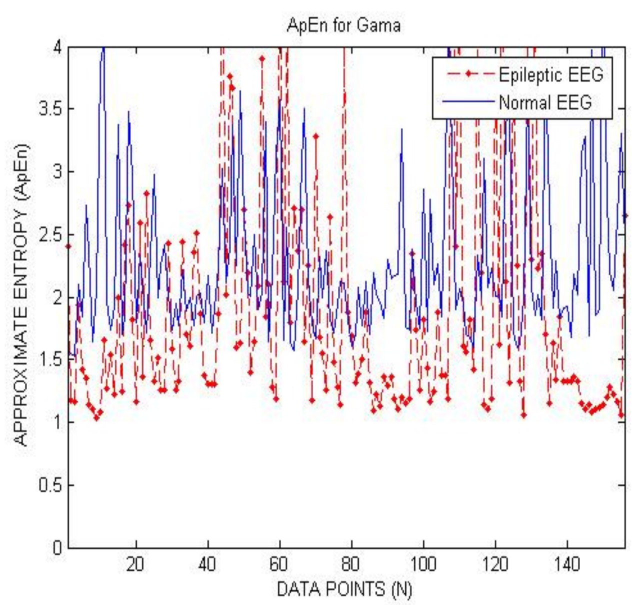

Fig. 5. ApEn Values for Gamma Subband

The subbands extracted from the wavelet decomposition as input for ApEn algorithm. We calculated ApEn values for each subband. Fig 5 shows the ApEn values for gamma (30-60Hz) subband for both normal and epileptic EEG.

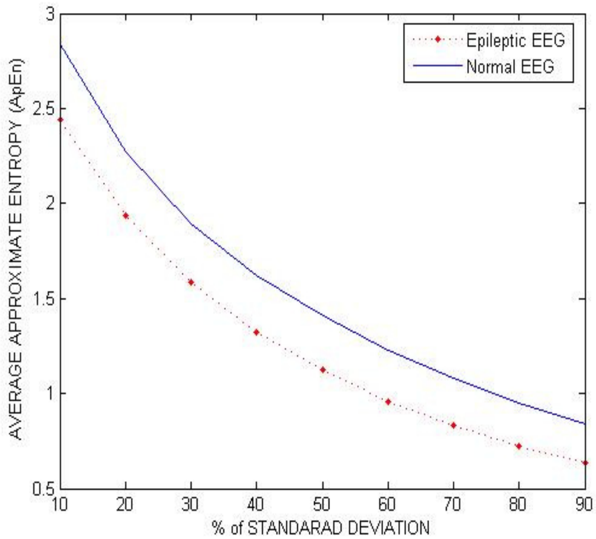

Fig. 6 Average ApEn values when % SD varies from 10% to 90% for gamma subband

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. $v = r \times SD$ Here v varies from 0 % to 90% of the data sequence in increments of 10%.

Fig. 6 shows plot of the average ApEn values when percentage of SD varies from 10% to 90% for normal and epileptic gamma subband of EEG.

From Fig. 6 it is observed that maximum value of average ApEn is at 10% of SD and minimum at 90% of standard deviation. In this work we have considered 20% of standard deviation value for the purpose of computing.

Fig. 7 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.

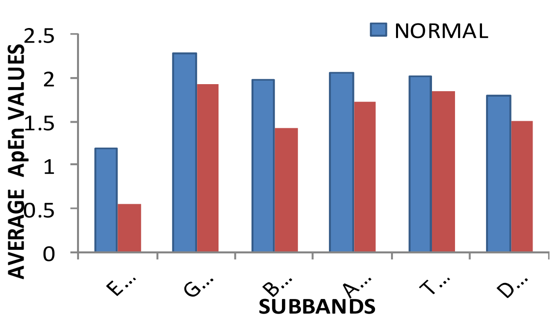

Fig 7 Average ApEn values for EEG signal and subbands

CONCLUSION

We used Discrete Wavelet Transform for four levels decomposition of normal and epileptic EEG. EEG is decomposed into five subbands delta, *theta*, *alpha*, *beta*, and *gamma* for detection of seizure and epilepsy. The discrimination between normal EEG and epileptic EEG can be achieved with the help of ApEn. According to results ApEn analysis features of EEG and their subbands shows acceptable difference between normal EEG and epileptic EEG. ApEn combined with wavelet decomposition analysis gives the features of epileptic activities in EEG signal.

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