Epileptic Seizure Detection Using Discrete Wavelet Transform and Support Vector Machines

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***Abstract* - The electroencephalogram (EEG) signal plays an important role in the detection of epilepsy. The EEG recordings of the ambulatory recording systems generate very lengthy data and the detection of the epileptic activity requires a time-consuming analysis of the entire length of the EEG data by an expert. The aim of this work is to develop a new method for automatic detection of EEG patterns using Discrete wavelet Transform (DWT) and Support Vector Machines (SVM). Our method consists of EEG data collection, feature extraction and classification stages. DWT is used for feature extraction in the principle of time – frequency domain analysis. In classification stage we implement SVM to detect epileptic seizure. SVM provides binary classification between preictal/ictal and interictal states. The study is carried out on EEG recordings of two epileptic patients; two classification models are derived from each patient. The models are then tested on the same patient and the other patient, comparing the specificity, sensitivity and accuracy of each of the models. This model provides high sensitivity compare other detection method.**

***Keywords* - Discrete Wavelet Transform (DWT), Support Vector Machines (SVM), Electroencephalogram (EEG)**

I. Introduction

Epilepsy is a chronic disorder characterized by recurrent seizures which may vary from muscle jerks to several convolutions. Estimated 1% of world population suffers from epilepsy [1], while 85% of them live in the developing countries. Epileptic detection is done from EEG signal as epilepsy is a condition related to the brain's electrical activity. EEG is routinely used clinically to diagnose, monitor and localize epileptogenic zone.

Occurrence of recurrent seizures in the EEG signal is characteristics of epilepsy. 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. The entire length of the EEG recordings is analyzed by expert to detect the traces of epilepsy.

Several approaches have been adopted for automatic detection of epileptiform activities [2]-[6]. A majority of these methods fail to take into account the morphological variability of the epileptiform activities and provide little information about the temporal and spatial distributions of the epileptiform activities [7]. And most of these researches focus on the detection of spike and spike-slow complex wave. Since the EEG is non-stationary in general, it is most appropriate to use the time-frequency domain methods.

Wavelet transform provides both time and frequency information of a signal which makes it possible to accurately get and localize features in the data like the epileptiform activities. This paper discusses an automated epileptic EEG detection system using Support Vector Machines (SNM) using a time-frequency domain feature of the EEG signal called Discrete Wavelet Transform (DWT). EEG data is first digitized. The digital EEG data is fed as an input to an automated seizure detection system in order to detect the seizures present in the EEG data.

II. Proposed Methodology

As in traditional pattern recognition systems, the epileptic seizure detection consists of main modules such as a feature extractor that generates a wavelet based feature from the EEG signals, feature selection that composes composite features, and a feature classifier (SVM) that outputs the class based on the composite features. The data flow of the proposed approach is illustrated in Fig. 1.

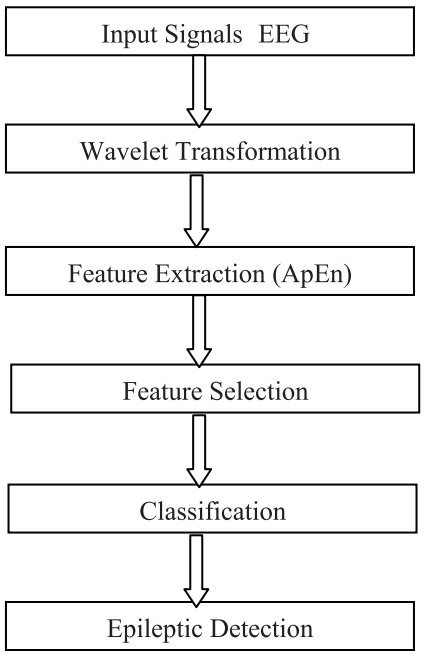

Fig. 1 Data flow diagram of the proposed system

A. Dataset Description

The data used in this research are a subset of the EEG data for both healthy and epileptic subjects made available online by Dr. Ralph Andrzejak of the Epilepsy Centre at the University of Bonn, Germany (http:// www. meb. unibonn.de/ epileptologie/science/physik/eeg data.html) [1]. EEGs from two different groups: group H (healthy subjects) and group S (epileptic subjects during seizure) are analyzed. The type of epilepsy was diagnosed as temporal lobe epilepsy with the epileptogenic focus being the hippocampal formation. Each group contains 100 single channel EEG segments of 23.6 sec duration each sampled at 173.61 Hz. As such, each data segment contains N=4097 data points collected at intervals of 1/173.61th of 1s. Each EEG segment is considered as a separate EEG signal resulting in a total of 200 EEG signals or EEGs. As an example, the first 6s of two EEGs (signal numbers in parentheses) for groups H (H029) and S (S001) are magnified and displayed in Fig. 2.

B. Wavelet Transformation

Wavelet transform is a spectral estimation technique in which any general function can be expressed as an infinite series of wavelets.

The basic idea underlying wavelet analysis consists of expressing a signal as a linear combination of a particular set of functions (wavelet transform, WT), obtained by shifting and dilating one single function called a mother wavelet.

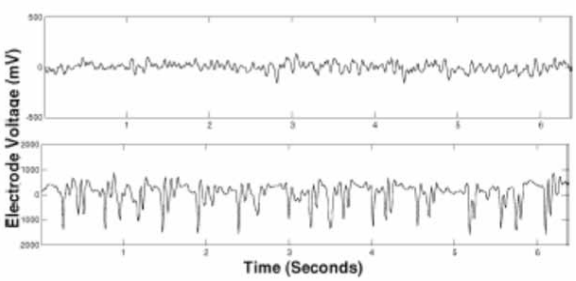

Fig. 2 Sample unfiltered EEGs (0–6 s) for (from top to bottom) Group H (H029) and Group S (S001)

The decomposition of the signal leads to a set of coefficients called wavelet coefficients. Therefore the signal can be reconstructed as a linear combination of the wavelet functions weighted by the wavelet coefficients. The key feature of wavelets is the time-frequency localization. It means that most of the energy of the wavelet is restricted to a finite time interval.

The wavelet technique applied to the EEG signal will reveal features related to the transient nature of the signal, which is not made obvious by the Fourier transform. Adeli et al. [7] gave an overview of the discrete wavelet transform (DWT) developed for recognizing and quantifying spikes, sharp waves and spike-waves. In general, it must be said that no time-frequency regions but rather time-scale regions are defined. All wavelet transforms can be specified in terms of a low-pass filter, which satisfies the standard quadrature mirror filter condition. One area in which the wavelet transformation has been particularly successful is the epileptic seizure detection because it captures transient features and localizes them in both time and frequency content accurately.

The wavelet transformation analyses the signal at different frequency bands, with different resolutions by decomposing the signal into a coarse approximation and detail information [8]. The decomposition of the signal into the different frequency bands is merely obtained by consecutive high-pass and low-pass filtering of the time domain signal.

The procedure of multi-resolution decomposition of a signal x[n] is schematically shown in Fig. 3. Each stage of this scheme consists of two digital filters and two down-samplers by 2. The first filter, h[n] is the discrete mother wavelet, high pass in nature, and the second, g[n] is its mirror version, low-pass in nature. The down-sampled 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 as shown in Fig. 3. The EEG sub bands of a2, d2 and d1are shown in fig. 4

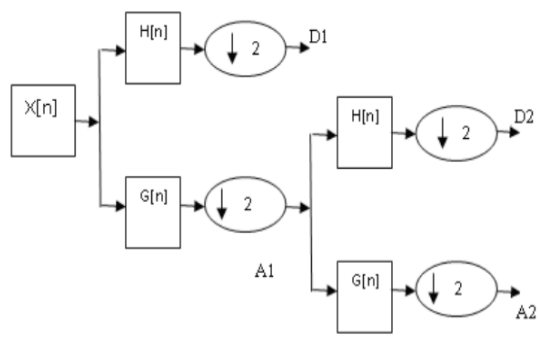

Fig. 3 Two level wavelet decomposition

Selection of suitable wavelet and the number of decomposition levels is very important in analysis of signals using the wavelet transformation. The number of decomposition levels is chosen based on the dominant frequency components of the signal. In the present study, since the EEG signals do not have any useful frequency components above 30 Hz, the number of decomposition levels was chosen to be 2. Thus, the EEG signals were decomposed into details D1–D2 and one final approximation, A2. Usually, tests are performed with different types of wavelets and the one, which gives maximum efficiency, is selected for the particular application. The smoothing feature of the Daubechies wavelet of order 4 (db4) made it more appropriate to detect changes of EEG signals. Hence, the wavelet coefficients were computed

using the db4 in the present study. The proposed method was applied on both data set of EEG data (Sets H and S).

In the discrete wavelet analysis, a signal can be represented by its approximations and details. The detail at level j is defined as

$$D_j = \sum_{k \in Z} a_{j,k}\, \psi_{j,k}(t) \qquad \text{..... (1)}$$

and the approximation at level J is defined as

$$A_j = \sum_{j>J} D_j \qquad \text{..... (2)}$$

It becomes obvious that

$$A_{j-1} = A_j + D_j \qquad \text{..... (3)}$$

And,

$$f(t) = A_j + \sum_{j \le J} D_j \qquad \text{..... (4)}$$

Wavelet has several advantages, which can simultaneously possess compact support, orthogonality, symmetry, and short support, and high order approximation. We experimentally found that time-frequency domain feature provides superior performance over time domain feature in the detection of epileptic EEG signals.

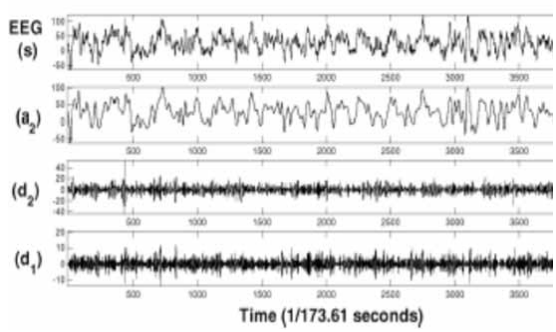

Fig. 4 Level 2 decomposition of the band-limited EEG into three EEG sub bands using fourth-order Daubechies wavelet (s=a2+d2+d1)

C. Feature Extraction

The proposed system makes use of a single feature called ApEn for the epileptic detection. The ApEn is a wavelet-domain feature that is capable of classifying complex systems. The value of the ApEn is determined as shown in the following steps [9], [10].

1) Let the data sequence containing N data points be X = [x(1), x(2), x(3), . . . , x(N)].

2) Let x(i) be a subsequence of X such that x(i) =[x(i), x(i + 1), .. …. , x(i + m − 1)] for $1 \le i \le N - m$, where m represents the number of samples used for the prediction.

3) Let r represent the noise filter level that is defined as

$$r = k \times SD \qquad \text{..... (5)}$$

for k = 0, 0.1, 0.2, 0.3,…, 0.9 where SD is the standard deviation of the data sequence X.

4) Let {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 $C_i^m(r)$ and $C_i^{m+1}(r)$ are defined as follows:

$$C_i^m(r) = \frac{\sum_{j=1}^{N-m} k}{N-m} \qquad \text{.....(6)}$$

where,

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

And

$$C_i^{m+1}(r) = \frac{\sum_{j=1}^{N-m} k}{N-m} \qquad \text{..... (7)}$$

with conditions depicted by (A) as shown at the bottom of the page.

5) We define $\Phi_m(r)$ and $\Phi_{m+1}(r)$ as follows:

$$\Phi_m(r) = \frac{\sum_{i=1}^{N-m} \ln(C_i^m(r))}{N-m} \qquad \text{.....(8)}$$

$$\Phi_{m+1}(r) = \frac{\sum_{i=1}^{N-m} \ln(C_i^{m+1}(r))}{N-m} \qquad \text{.....(9)}$$

Small values of ApEn imply strong regularity in a data sequence and large values imply substantial fluctuations [11] In the proposed approach, ApEn is calculated for one approximation and for detailed information such as a2 and d2.

D. Feature Selection

As discussed in the above section, 30 ApEn features have been obtained from each sub band leading to a total of 60 ApEn features. As it consumes more time in processing these 60 ApEn features, there is a need to select the best thirty features. Table. 1 shows the extracted features (ApEn) for the sub bands for the sample set A. These best features are selected by our novel approach which involves choosing the feature having minimal variance within the class and maximum absolute difference between the classes.

Variance has been calculated for each class of sample set to find the minimal variance. And absolute difference between classes of sample set to find the maximal difference.

TABLE I FEATURE EXTRACTION SAMPLE DATA – SET A

Set	Sub-bands	ApEn
H	D1	-12513000
	D2	295
	A2	-101890
S	D1	-4391700000
	D2	47289
	A2	-16616000

E. Classification

The idea of using a hyper plane to separate the feature vectors into two groups works well when there are only two target categories, but how does SVM handle the case where the target variable has more than two categories? Several approaches have been suggested, but two are the most popular:

(1) "One against many" where each category is split out and all of the other categories are merged.

(2) "One against one" where k(k-1)/2 models are constructed where k is the number of categories.

The SVM classify function uses results from SVM train to classify vectors x according to the following equation:

$$c = \sum_i \alpha_i k(s_i, x) + b, \qquad \text{..... (10)}$$

Where s_i are the support vectors, α_i are the weights, b is the bias, and k is a kernel function. In the case of a linear kernel, k is the dot product. If $c \geq 0$, then x is classified as a member of the first group, otherwise it is classified as a member of the second group.

Where C is the capacity constant, w is the vector of coefficients, b a constant and ξ_i are parameters for handling non separable data (inputs). The index i labels the N training cases.

Note that $y \in \pm 1$ is the class labels and xi is the independent variables. The kernel ϕ is used to transform data from the input (independent) to the feature space.

It should be noted that the larger the C, the more the error is penalized. Thus, C should be chosen with care to avoid over fitting.

For classification tasks, most likely use C-classification with the RBF kernel(default), because of its good general performance and the few number of parameters (only two: C and γ). Libsvm suggest to try small and large values for C— like 1to1000— first, then to decide which are better for the data by cross validation, and finally to try several γ's for the better C's.

III. Results And Discussion

The test performance of the classifiers can be determined by the computation of specificity, sensitivity and total classification accuracy. The specificity, sensitivity and total classification accuracy are defined as:

$$Specificity = \frac{Number\ of\ true\ negative\ decisions}{Number\ of\ actually\ negative\ cases}$$

$$Sensitivity = \frac{Number\ of\ true\ positive\ decisions}{Number\ of\ actually\ positive\ cases}$$

$$Accuracy = \frac{Number\ of\ correct\ decisions}{Total\ number\ of\ cases}$$

Table II Parameters of DWT method

Parameters	Value
Specificity	99.2
Sensitivity	99.8
Accuracy	99.5

EEG Signals are obtained from the various hospitals such as Rubi Hall Pune, India as shown below. These signals are in .eeg format which are not supported by the MATLAB software. The original EEG signal is shown below. We have used EEG recording software provided by the doctors and widely used all over the India to convert EEG signal in .eeg format to .xls format supported by MATLAB.

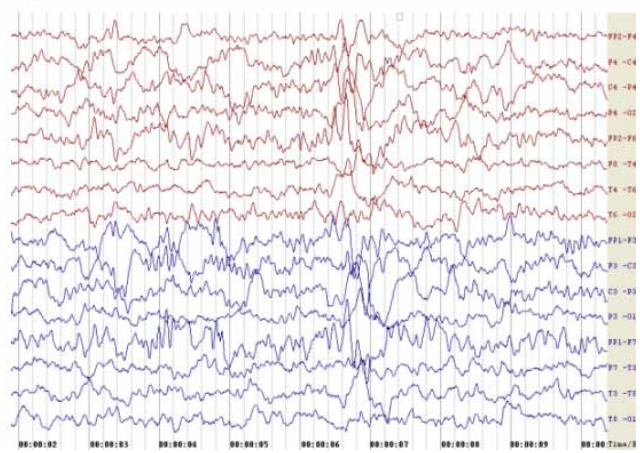

Fig. 5 Original EEG

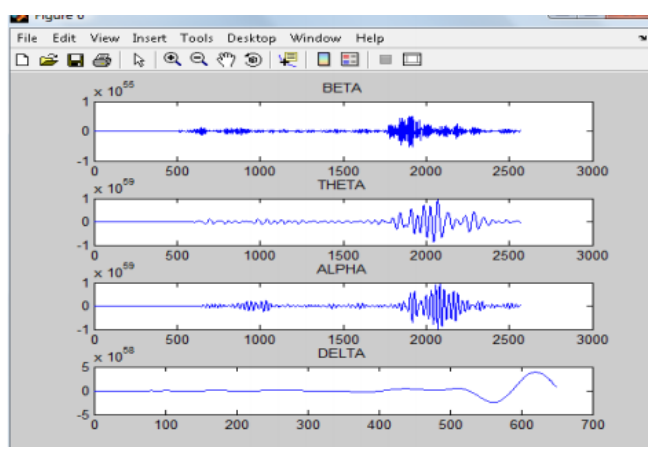

Fig. 6 Separated Wave

Fig. 6 shows the original EEG is separated by DWT.

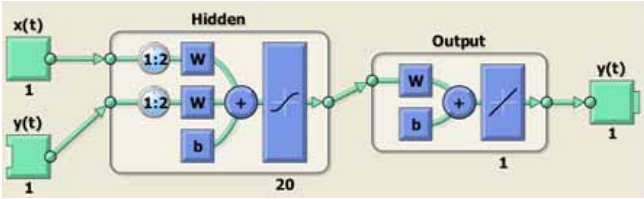

Fig. 7 Classifier

Fig.7 shows the classification between normal and ictal stages

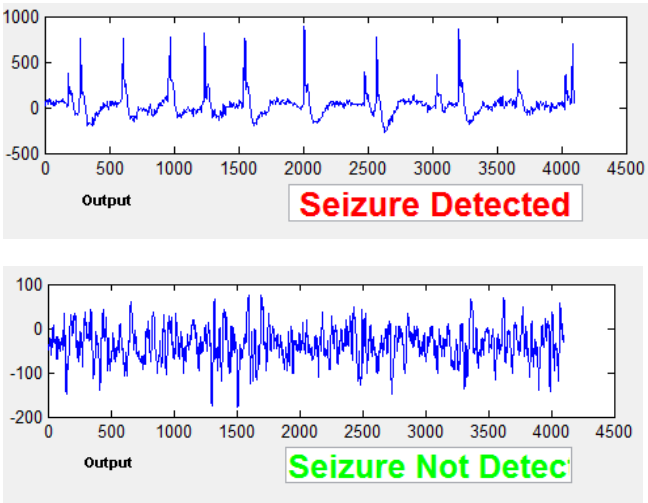

Fig. 8 Simulation output of Epileptic and Non Epileptic form

IV. Conclusion

A method for the analysis of EEG for seizure detection using wavelet based features has been presented here. As EEG is a non stationary signal the wavelet transform gives good results. After wavelet decomposition at level 4 using Daubechies wavelet of order 2, four statistical features minimum, maximum, mean and standard deviation were computed over the wavelet coefficients at each level. Classification was done using the simple linear classifier. By using the wavelet based features for classification between normal and seizure signals the accuracy obtained was 99.5%.

In future, apply this same dataset to other epileptic detection methods and compare all their performance.

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