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Classification of EEG Signal Using Wavelet Transform and Support Vector Machine for Epileptic Seizure Diction

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Abstract- **Feature extraction and classification of electroencephalogram (EEGs) signals for (normal and epileptic) is a challenge for engineers and scientists. Various signal processing techniques have already been proposed for classification of non-linear and non-stationary signals like EEG. In this work, SVM (support vector machine) based classifier was employed to detect epileptic seizure activity from background electro encephalographs (EEGs). Five types of EEG signals (healthy subject with eye open condition, eye close condition, epileptic, seizure signal from hippocampal region) were selected for the analysis. Signals were preprocessed, decomposed by using discrete wavelet transform DWT till 5th level of decomposition tree. Various features like energy, entropy and standard deviation were computed and consequently used for classification of signals. The results show the promising classification accuracy of nearly 91.2% in detection of abnormal from normal EEG signals. This proposed classifier can be used to design expert system for epilepsy diagnosis purpose in various hospitals.**

Keywords: Electroencephalogram (EEGs), Support Vector Machine (SVM), Discrete Wavelet Transform (DWT), Epileptic, Seizure.

I. INTRODUCTION

Epilepsy is the neurological disorder in which the abnormal firing activity of neurons can be seen which leads to the formation of seizure [1], [2]. It is mostly seen in the children and adults at the age 65-70 and at about 1% of worldwide population affected by this disease and it can be cured if it detected in initial stages .Eighty percent of the epileptic seizure activity can be controlled or can be treated effectively, if detected and diagnosed properly (Cited in WHO, http://www.who.intltopics/epilepsy/en/). In the developing countries like India percentage of epileptic patients are seen in more amount but there is lack of proper diagnosis technique. Traditionally, the EEG recordings were visually inspected by the trained neurophysiologist for detecting epileptic seizure or other abnormalities present. The visual scoring of the epileptic activity on the EEG background is very costly as well as time consuming task. More ever due to human error, leads to improper diagnosis of the diseases causing fatal to human life. Now a day's effort has been devoted by engineers and researchers to develop an automated expert system for the detection of seizure and epilepsy which might be helpful for speed up the detection and cure of epilepsy [1], [3], [11].

Various techniques were employed for the detection of seizures in the EEG using correlation function, time domain analysis, frequency domain analysis, time–frequency domain analysis, artificial neural network based analysis, fuzzy logic based analysis (Oeak,2008b; Iasemidis, Shiau,& Chaovalitwongsa, 2003; Khan & Gotman, 2003). Seizure detection in time domain analysis involve two stages; in first stage, features are extracted from EEG signals from both epileptic and normal subjects and in the second stage the expert system is created for detection of epileptic activity with high accuracy in less time. The features obtained from these stages were decomposed at each node of the tree. However, the EEG is non-stationary in nature, is most appropriate to use wavelet transform (time–frequency based) to get the time as well as the frequency information of the signal simultaneously [1],[2],[5]. It also helps to accurately capture and localize transient features of the epileptic signal on the EEG background.

In this work an algorithm based on Daubechies Discrete Wavelet Transform (DWT-db2) and Support Vector Machine (SVM) classifier is used to detect the epileptic signal from the EEG signature. The DWT is used for time frequency analysis giving quantitative evaluation of different frequency bands of clinical brain wave. The EEG epochs were decomposed into various frequency bands by using db2 mother wavelet up to 5th-level of the decomposition. The statistical parameter like energy, entropy and standard deviation were computed for feature extraction, the feature seats were used to train the machine using Support Vector Machine classifier to classify the normal and epileptic signal.

II. THE EEG DATA COLLECTION USED IN THE RESEARCH

500 epochs of EEG data from five different brain activities (Each group contains 100 signals) were obtained from the data base under the supervision of trained neurologist. The different human activities used for the measuring the brain activity were Eye close (0), Eye open (Z), Seizure (S), EEG from hippocampal region (N), EEG from opposite of epileptogenic zone (F). The data are collected according to international 10-20 system shown in figure.1 with sampling rate of 173Hz on 26.36sec time duration.

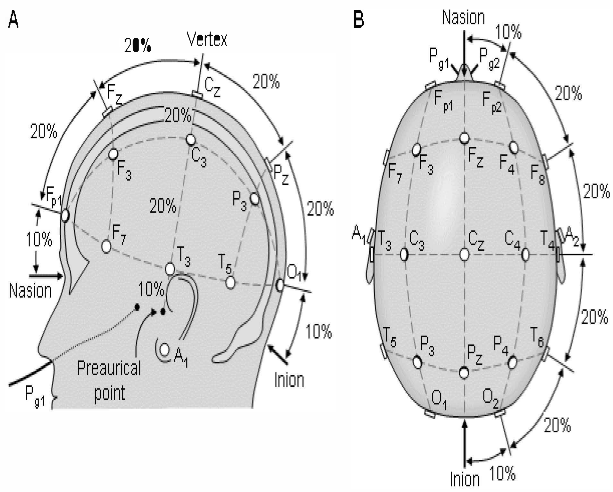

Fig.1. International system of electrode placement

III. METHODOLOGY

3.1. Wavelet Transform for Signal Analysis:

We used Wavelet transform method to decompose the signals and reconstruct the information accurately. Wavelet transform method is a suitable analytical tool for the Non-Stationary signals analysis such as EEG and it was proposed by Jean Morlet a French geophysicist in 1982[5]. It involves the breaking down of the brain signals into various shorter reads of bands as per requirement. In discrete wavelet analysis, a multi-resolution description is used to decompose a given signal f(t) into increasingly finer details based on two sets of basic functions [9], the wavelets and the scaling functions, as follows:

$$f(t) = \sum_{l \in Z} 2^{j/2} c_j(k)\varphi(2^j t - k) + \sum_{j=0}^{j-1}\sum_{k=0}^{\infty} 2^{j/2} d_j(k)\psi(2^j t - k) \quad (1)$$

where functions $\varphi(t)$ and $\psi(t)$ are the basic scaling and mother wavelet respectively. In the above expansion, the first summation presents an approximation of f(t) based on the scale index of j_0, while the second term adds more details using larger j (finer scales). The coefficients in this wavelet expansion are called the discrete wavelet transform (DWT) of the signal f(t). When the wavelets are orthogonal [9], these coefficients can be calculated by

$$c_j(k) = \int_{-\infty}^{\infty} f(t)\ \varphi(2^j t - k)dt \quad (2)$$

$$d_j(k) = \int_{-\infty}^{\infty} f(t)\psi(2^j t - k)dt \quad (3)$$

where cj(k) and dj(k) are, respectively, the scaling (approximation) and wavelet (detail) coefficients. In the DWT, the frequency axis is divided into dyadic intervals towards the lower frequencies while the bandwidth length decreases exponentially [13].

The WT can be implemented with a specially designed pair of FIR filters called a quadrature mirror filters (QMFs) pair which separate the high- and low-frequency components of the input signal. The dividing point is usually halfway between 0 Hz and half the data sampling rate (the Nyquist frequency) [10]. The outputs of the QMF filter pair are de-sampled by a factor of two. The original signal is passed to the pairs of QMF filter and emerges as two signals. The signal passed through the low-pass filter is called the approximation (A) and includes the high-scale (low-frequency) components. The signal passed through the high-pass filter is called the detail (D) and contains the low-scale (high-frequency) components [2], [3], [14]. The low-frequency (low-pass) filter output is fed into another identical QMF filter pair. This operation can be repeated recursively as a tree or pyramid algorithm, yielding a group of signals that divides the spectrum of the original signal into octave bands with successively coarser measurements in time as the width of each spectral band narrows and decreases in frequency [10].As per this matched the EEG signal is decomposed in to fifth level. After the first level of decomposition, the EEG signal, (0–86.5 Hz), is decomposed into its higher resolution components, (43.25–86.5 Hz) and lower resolution components, (0–43.25 Hz). In the second level of decomposition, the low-resolution component is further decomposed into higher resolution components, (21.62–43.25 Hz) and lower resolution components, (0–21.62 Hz). Following this process, after fifth levels of decomposition, the components obtained are (0–2.7 Hz), (2.7–5.4 Hz), (5.4–10.81 Hz), (10.81–21.62 Hz), and (21.62–43.25 Hz) [3].The entire quantitative analysis of EEG signals was coded using MATLAB and the Wavelet Toolbox (The Mathworks, Inc., Natick, MA).

3.2. Feature extraction:

In this work we have chosen the statistical parameters like energy, entropy and standard deviation were calculated at each decomposition level starting from D2 to D5 for the all categories of signals. The energy indicates the strength of the signal as it gives the area under the curve of power at any interval of time. The energy of EEG signal of finite length is

given by:

$$[\![Energy(E]\!]_i) = \sum_{j=1}^{N} |D_{ij}|^2 \quad i = 1,2,3 \ldots\ldots l \quad \mathbf{(4)}$$

Entropy is numerical measure of uncertainty of outcome where signal contained thousands of bits of information. The mathematical representation is:

$$Entropy\ (EN) = \sum_{j=1}^{N} D_{ij}^2 \log\left(D_{ij}^2\right) \quad i = 1,2 \ldots l \quad (5)$$

Standard deviation in one word it is 'mean of mean' it is statistic that tell which tell how closely various features are near to mean.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \psi_i)^2} \qquad (6)$$

X is random variable with mean μ

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} D_{ij} \quad i = 1,2 \ldots\ldots l \qquad (7)$$

IV. CLASSIFICATION USING SVM TECHNIQUE

After feature extraction, feature matrix is normalized in order to have features in a same range. Simply, linear SVM classifier was trained by the train-train data and then used for classifying the train-test data. SVMStruct trains a SVM classifier using Training, a matrix of training data taken from two groups; test the classifier with other groups. Information about the trained SVM classifier is returned in SVMStruct, a structure with the Kernel Function fields [4],[6]. Kernel Function Value is Gaussian Radial Basis Function kernel ('rbf') function handle with a scaling factor, sigma, of 6. This kernel linearly maps samples into a higher dimensional space so it, unlike the linear kernel working in high dimensional feature spaces solves the problem of expressing complex function.the multidimensional linear classifier use for neural classification for better accuracy. This task was performed using MATLAB. For the purpose of training, MATLAB code "svmtrain" was used, while for classification, MATLAB code "svmclassify" was used.

V. RESULT AND DISCUSSION

In present work to find maximum accuracy we train and test the extracted features of the signal. we make the different combination of wavelets bands because while plotting the normal and epileptic signal it is seen that the signal accumulated in specific frequency band .in these combination of wavelets band we train and test signal with various feature like energy, entropy and standard deviation. We also make combination of feature of these signals as shown in table from these observation it is find that energy feature give the maximum accuracy 91.2% require just 0.5 second for processing also energy and standard deviation shows the better accuracy 83.34%.

Table of result:

In this work, using SVM classifier and different features of signal like energy, entropy & standard deviation in various combination, we found that the diagnosis of epilepsy is possible. We make the mean of our all combination which is show in following table 1 where

Table – 1

mean observation for all five types of singnal												
Sr.No.	USING DIFFERENT PROPERTIES	USING DIFFERENT ORDERS										
		1	2	3	4	5	6	7	8	9	10	mean
1	ENERGY	88	92	93	91	93	92	92	91	90	90	91.2
2	ENTROPY	78	84	86	85	85	85	85	85	85	85	84.3
3	STD. DEVIATION	74	75	75	74	75	77	79	82	82	82	77.5
4	ENERGY & ENTROPY	87	86	87	87	86	86	86	86	86	86	86.15
5	ENERGY & STD. DEVIATION	88	86	87	87	86	86	86	86	86	86	86.2
6	ENTROPY& STD. DEVIATION	74	74	75	76	74	75	76	79	81	82	76.6
7	ENERGY, ENTROPY& STD. DEVIATION	89	88	85	87	89	86	90	91	91	92	88.8

'En' stands for Energy, 'Ent' stands for entropy and 'Sd' stands for standard deviation.

VI. CONCLUSION

An expert model was developed for detection of epilepsy on the background of EEG by using discrete wavelet transform and support vector machine. The feature like energy, entropy & standard deviation were extracted from the EEG signal. From the training and testing on the proposed classifier it is finding that energy is the best feature among all which gives accuracy about 91.2% and time required is just 0.5 second. This expert model can be successfully mounted in real time diagnosis in hospitals of the developing countries like India where acute shortage of train neurologist and proper diagnostic technique for epilepsy detection.

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