Classification of Epileptic EEG Signals Based on Spectral Features using k-NN

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***Abstract* -** In this paper, a method for classification of EEG signals based on k-NN classifier is discussed. This scheme provides an improved performance in terms of sensitivity, specificity and accuracy compared to existing methods. EEG signal is decomposed into sub bands using multi-wavelet transform and spectral features are extracted from each sub band which is classified using k-NN. The main challenge in this study is to extract features with high quality so as to achieve satisfactory performance for classification. Diagnostic applications mainly focus on spectral content of EEG signal. Spectral features such as mean spectral magnitude, spectral entropy, and spectral squared entropies are extracted from sub bands. The distributions of these features for normal and epileptic EEG signal are clustered in different regions which can be utilized to yield good classification result. The results show that classification of these features using k-NN achieved an accuracy of 97.5%.

***Keywords* -** Epilepsy, k-NN, multi-wavelet transform, mean spectral magnitude, spectral entropy.

I. INTRODUCTION

EEG is the recording of brain's electrical activity over a period of time usually 20-40 minutes. These long EEG recordings are visually inspected and marked by neurologists for identifying the disease condition of the brain such as epilepsy, stroke, Alzheimer's disease, Parkinson disease. EEG signals are generated by a complex non-linear system consisting of post synaptic neurons whose firing actions are based on whether their membranes exceed a certain threshold [1]. Epilepsy is characterized by the spontaneous and unforeseeable occurrence of seizures in which abnormal electrical activity in the brain causes disturbances in perception and behaviour of patients.

Research on seizure detection began many years ago and various methods addressing this problem have been presented. Fourier transform and fast Fourier transform are used for processing the EEG signal in earlier days of research, which have the disadvantage of being highly sensitive to noise. Yatindra Kumar et al. (2013) applied discrete time wavelet transform analysis of EEG signals and extracted wavelet entropy values as features [2]. Then those features were classified using t-test statistical method. Kalayci and Ozdamar (1995) used wavelet transform for extracting the features of EEG signal and then classified them using ANN to get satisfying result [3]. Subasi (2005, 2007) proposed a method for decomposing the EEG signals into time–frequency representations using discrete wavelet transform (DWT) [4, 5]. Qingfang Meng et al. (2010) proposed a feature extraction method based on the Volterra autoregressive model's prediction power and the data's predictability for the EEG signals to automatically detect the epileptic EEG signals from the EEG recording. Zisheng Zhang et al. (2014) presented a novel method in which the EEG signal is filtered by a prediction error filter (PEF) to compute a prediction error signal which is decomposed using wavelet transform to form feature vector. These features are classified using a linear support vector machine (SVM) classifier and an AdaBoost classifier [6]. Ling Guo et al. (2010) described a method for epileptic seizure detection using multi-wavelet transform. The features extracted are classified using ANN to achieve better result. Some features such as entropy, average power, standard deviation, mean value are derived from the wavelet coefficients were calculated and applied to different classifiers such as artificial neural network, dynamic wavelet network (DWN), dynamic fuzzy neural network for epileptic EEG classification [7].

In this work, a novel method for classification of epileptic EEG signals based on spectral features is proposed. The extracted features are classified using k-NN classifier. The results show that classification of features using k-NN yields better performance.

The paper is structured as follows: Section II presents the materials and methods used for the study. Proposed method is explained in section III. Results and discussions are covered in section IV. Paper concludes in section V.

II. MATERIALS AND METHODS

A. Source of data

The publicly available dataset described by Andrzejak et al. (2001) is used in the work [8]. The dataset consists of five sets (denoted as Z, O, N, F and S). Each dataset contains 100 EEG signals of 23.6 s duration with a sampling rate of 173.6 Hz using 12 bit resolution. Sets Z and O consists of segments taken from surface EEG recordings that were carried out on five healthy volunteers using 10-20 electrode placement schemes. Persons were relaxed in an awake state with eyes open (Z) and eyes closed (O), respectively. Sets N, Sets N, F and S originated from an EEG archive of pre-surgical diagnosis. Segments in set F were recorded from the epileptogenic zone. Segments in set N are recorded from the hippocampal formation of the opposite hemisphere of the brain. Sets N and F contains activities measured during seizure free intervals. Set S contains seizure activity. All

EEG signals were recorded using a 128-channel amplifier system. One EEG segment from each set of data is plotted in Fig.1.In this work two sets are examined, normal and seizure. Normal class includes only set Z and seizure class includes set S.

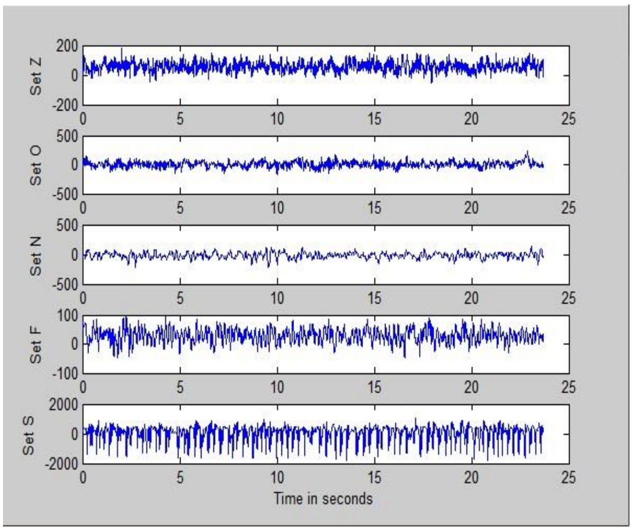

Fig.1: One EEG segment from each of the five sets (Z, O, N, F, and S).

B. Multi Wavelet Transform (MWT)

Multi-wavelets are the generalization of scalar wavelets. They have two or more scaling and wavelet functions. Scaling functions are denoted as $\Phi(t) = [\Phi_1(t), \Phi_2(t), \ldots, \Phi_r(t)]^T$ and wavelet functions are denoted as $\Psi(t) = [\Psi_1(t), \Psi_2(t), \ldots \Psi_r(t)]^T$. When r =1, $\Psi(t)$ is called a scalar wavelet. The dilation and wavelet equations for multi-wavelet have the following forms, respectively:

$$\phi(t) = \sqrt{2}\sum_k G_k \phi(2t-k) \qquad (1)$$

$$\psi(t) = \sqrt{2}\sum_k H_k \phi(2t-k) \qquad (2)$$

The pair $\{G_k, H_k\}$ is called a multiwavelet filter bank. MWT decomposition produces two low-pass sub-bands and two high-pass sub-bands for each level of decomposition which is shown in Fig.2. [7].

C. Spectral features

Blocks of 4096 samples of EEG signal corresponding to 23.1 seconds are used for computing the Fourier spectrum. From the spectrum three features are extracted for the analysis. The spectral based features are as follows [1]:

Mean of spectral magnitude:

$$M_{ave} = \frac{1}{N}\sum_{k=0}^{N-1}|X_k| \qquad (3)$$

where $|X_k|$ is DFT of the input signal.

Spectral entropy is defined as:

$$P_1 = -\sum_k q_k \log q_k \qquad (4)$$

where

$$q_k = \frac{|X_k|}{\sum_{k=0}^{N-1}|X_k|} \qquad (5)$$

Spectral squared entropy is defined as:

$$P_2 = -\sum_i r_i \log r_i \qquad (6)$$

where

$$r_i = \frac{|X_k|^2}{\sum_k |X_k|^2} \qquad (7)$$

D. EEG feature classification

1) k-NN classifier

k -Nearest Neighbors (k-NN) algorithm uses a database in which the data points are separated into several separate classes to predict the classification of a new sample point [9]. It computes a distance function between the features belonging to the EEG patterns in the test set and k neighboring EEG patterns of the training data from set S and Z. This algorithm is called k-nearest neighbor algorithm where the classification is based on the minimum distance of EEG data from the trained data.

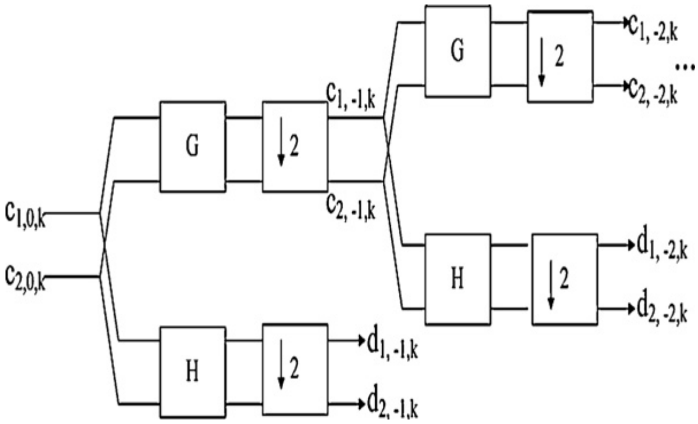

Fig.2: MWT Decomposition

2) Statistical Parameters

The performance of proposed method is evaluated in terms of statistical parameters such as sensitivity, specificity and accuracy [10]. Sensitivity is defined as the ratio of number of correctly detected seizure patterns to number of actual seizure patterns. Specificity is defined as the ratio of number of correctly detected normal patterns to number of actual normal patterns. Accuracy is defined as the ratio of correctly classified patterns to total number of patterns.

III. PROPOSED METHOD

In this work, a novel method based on wavelet transform and spectral features is proposed for the classification of EEG signals into normal and epileptic seizures. The EEG data is decomposed into sub signals using MWT. Mean spectral magnitude (M_{ave}), spectral entropy (P_1) and spectral squared entropy (P_2) features are extracted for each sub band to form a feature vector. This feature vector is given as input to k-NN classifier. The block diagram of proposed method is shown in Fig. 3. Each segment of dataset is considered as an input vector. Using Gernoimo-Hardin-Massopust (GHM) wavelet, 4-level decomposition of input vector is done to obtain 10 sub bands. Performance of MWT with respect to feature extraction is superior to that of scalar wavelets. From the Fourier transform of each sub band the three spectral features are extracted.

A typical distribution of the three spectral features for set S and Set Z is shown in figure 4. It can be seen that features for set S and set Z are clustered in different regions. This validates the proposed classification scheme. The experiment is repeated many times by choosing different test and training data combinations. Combinations of training and test data were randomly chosen. The training dataset is used to train the k-NN classifier whereas testing data is used to verify the accuracy and effectiveness of trained k-NN classifier. The performance is evaluated in terms of standard parameters specificity, sensitivity and accuracy.

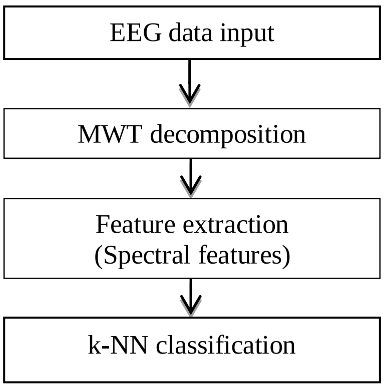

Fig. 3: Block diagram of proposed method

IV. RESULTS AND DISCUSSIONS

k-NN classifier was able classify normal and epileptic EEG segments with an improved accuracy. The performance of proposed method is tabulated in table 1. In k-NN classifier, in order to achieve better classification performance suitable k value is required. In this method the value of k is varied in a

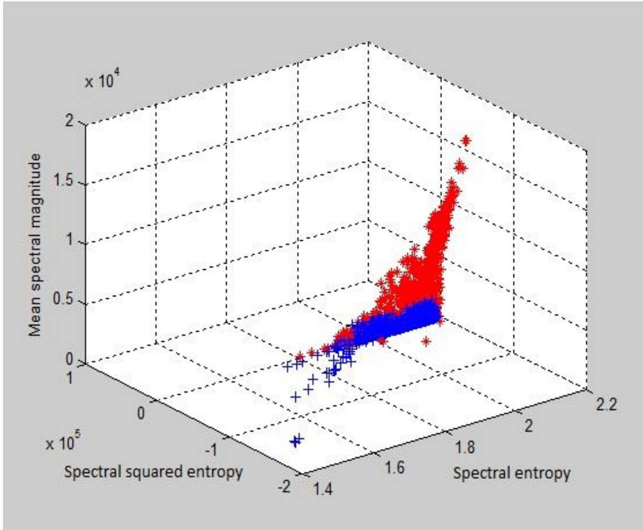

Fig.4: Distribution of spectral features.

large range and corresponding classification performance was analyzed. It is found that best performance is achieved when k value is 1. It was found that k–NN classifier obtained an accuracy of 97.5% by using 10% training data. This shows that better performance can be achieved by using lesser training data. In all combination of feature sets k-NN was able to obtain satisfactory performance in terms of specificity, sensitivity and accuracy.

TABLE I. CLASSIFICATION ACCURACY OF K-NN CLASSIFIER

Method	**Statistical Parameters**		
	Accuracy (%)	***Specificity (%)***	***Sensitivity (%)***
k-NN	97.5	98	97

V. CONCLUSION

In this paper feature extraction is based on MWT. The set of spectral features (M_{ave}, P_1 and P_2) extracted are seen to provide sufficient information to the k-NN classifier to do a reliable classification. The accuracy level obtained is at 97.5% which is much higher than the levels reported in literature so far.

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