An Improved Method for 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 epileptic EEG signals based on k-NN classifier is discussed. This scheme provides an improved performance in terms of sensitivity, specificity and accuracy. EEG signal is decomposed into sub bands using multi-wavelet transform and spectral features such as mean spectral magnitude, spectral entropy, and spectral squared entropies are extracted. 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 98.585%. In order to evaluate the efficiency of the proposed method, classification is also done using ANN and SVM which yielded an accuracy of 98.415% and 87.5% respectively.*

Keywords —*Epilepsy, Spectral Features, k-NN classifier, Artificial Neural Network, Support Vector Machine*

I. INTRODUCTION

Epilepsy is one of the common neurological disorders which are characterized by a sudden and recurrent malfunction of the brain, called "seizure" [1]. An electroencephalogram (EEG) is the recording of electrical potentials generated by the cerebral cortex's nerve cells, and is a valuable clinical tool for the evaluation and treatment of epilepsy [2]. Examining this long term EEG recording is both tedious and time consuming. Different methods have been proposed for the automated detection of epileptic seizures by analyzing EEG data. Seizures are synchronized EEG waveforms which are characterized by high-amplitude.

In time-frequency analysis approach fundamental frequency and harmonic frequency of seizure events are analyzed. In earlier days of research Fourier transform and fast Fourier transform are used for analyzing the EEG signals. Yatindra Kumar et al. (2013) proposed a method in which discrete time wavelet transform analysis of EEG signals is done. The extracted feature includes wavelet entropy value which is classified using t-test statistical method [3]. A method for decomposing the EEG signals into time–frequency representations using discrete wavelet transform (DWT) [4, 5] was proposed by Subasi (2005, 2007). Kalayci and Ozdamar (1995) applied wavelet transform to extract features from EEG signals and then classified them using ANN to get satisfying result [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 [7]. 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 [8].Some features such as entropy, average power, standard deviation, mean value, approximate entropy, sample entropy 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]. The self-training capability of neural networks [9, 10, 11–14] and adaptive neuro fuzzy inference systems has been utilized for classification of normal events and seizure events by analyzing the spectra and/or the complexity of the EEG recordings.

In this work, a novel method for classification of epileptic EEG signals based on spectral features is proposed. EEG signal is decomposed into sub signals using multi wavelet transform (MWT).The extracted features are classified using k-NN, ANN and SVM. The results show that classification of features using k-NN yields better performance.

II. MATERIALS AND METHODS

A. Source of data

The publicly available dataset described by Andrzejak et al. (2001) is used in the work [15]. 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. SetS 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 Z-S classification problem is addressed.

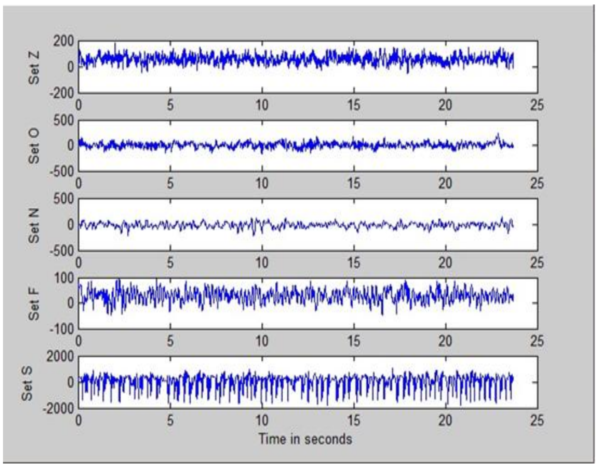

Fig.1.One EEG segment from each of the five sets.

B. Proposed Method

In this paper, a novel method for epileptic seizure detection is proposed.Using multi-wavelet transform EEG segment is decomposed into sub signals. Three spectral features namely mean spectral magnitude (M_{ave}), spectral entropy (P_1) and spectral squared entropy (P_2) are extracted from each sub signal. These features are used as input to k-NN, ANN and SVM separately to classify the EEG data into normal and seizure ones. The block diagram of proposed method is shown in Fig. 2.

1) Multi-wavelet Decomposition

Gernoimo-Hardin Massopust (GHM) multi-wavelet is used in this study. It has two scaling functions and two wavelet functions. Sets S and Z (200 EEG segments in total) are used in the analysis. After single level decomposition, the EEG segment gets decomposed into two high pass sub bands and two low pass sub bands. Then spectral features (M_{ave}, P_1 and P_2) are extracted from each sub band.

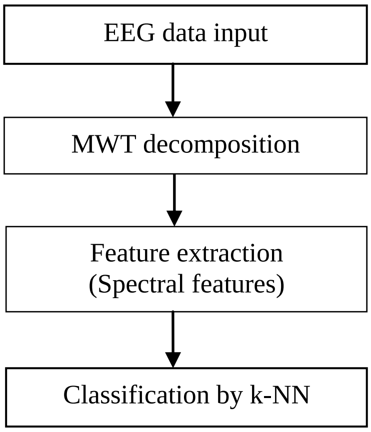

Fig.2. Block diagram of proposed method

2) EEG feature extraction

Mean spectral magnitude [16] is defined as

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

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

Spectral entropy [16] is defined as

$$P_1 = -\sum_k q_k \log q_k \quad (2)$$

$$q_k = \frac{|X_k|}{\sum_{k=0}^{N-1}|X_k|} \quad (3)$$

Spectral squared entropy [16] is defined as

$$P_2 = -\sum_i r_i \log r_i \quad (4)$$

where

$$r_i = \frac{|X_k|^2}{\sum_k |X_k|^2} \quad (5)$$

A typical distribution of M_{ave} for sets S and Z is shown in Fig.3.

It is seen that the features of set S and set Z are clustered in different regions. This validates the proposed classification scheme.

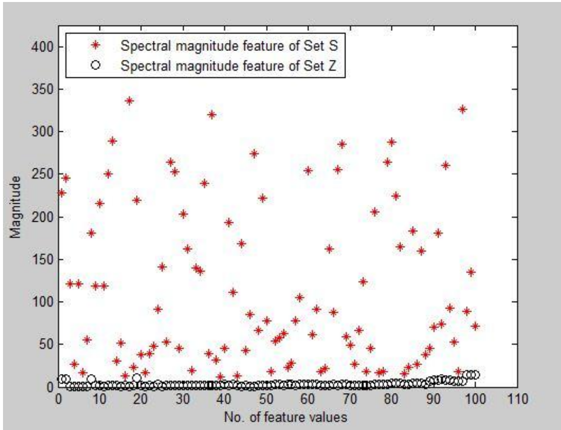

Fig.3. Typical distribution of M_{ave} for sets S and Z

3) *Selection of training data set*

The features extracted from low pass filter coefficients after level-1 decomposition of the signal contain most of the signal information. Hence these features are used for training. The training data for set S is selected as follows:

- Extract the features of 100 segments in set S. Compute mean of M_{ave} , P_1 and P_2.
- Compute the distance between mean value of $M_{ave}$and M_{ave} of each segment in Set S.
- Repeat the above step for the other two features P_1 and P_2.
- First 20% of the above values is used for training.

Above procedure is carried out on Set Z to obtain its training set.

4) *EEG feature classification*

20 segments each from sets S and Z are used for training. The extracted features are separately classified using k-NN, ANN and SVM.

- *k-Nearest Neighborhood classifier (k-NN)*

k-NN algorithm uses a database in which the data points are separated into classes to classify a new sample point [17]. 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 minimum distance of EEG data from the training data.

- *Artificial Neural Network (ANN)*

Multi-layer perceptron (MLP)is the most commonly used ANN structure for classification problems.. It has the ability tolearn themselves from written-in rules or has the ability tolearn from outside trainers.Smaller training data, faster operation & easier implementation are the advantages of ANN. In this study, a three-layer MLP Neural network is used to classify the EEG segments..

- *Support Vector Machine (SVM)*

SVM is a binary classifier which is a linear extension of perceptron based learning technique. Pre-classified signals belonging to the two classes of normal and seizure are used to train SVM. The features extracted from these signals are used to define the hyper plane separating the classes. The criterion for this classification is maximum Euclidean distance from hyper plane.

5) *Performance Evaluation*

Statistical parameters used for the evaluation of a classification method are sensitivity, specificity and accuracy [18]. 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.

$$Sensitivity = \frac{No\ of\ correctly\ \ detected\ \ normal\ \ patterns}{Total\ no\ of\ normal\ \ patterns} \tag{6}$$

$$Specificity = \frac{No\ of\ correctly\ \ detected\ \ seizure\ \ patterns}{Total\ no\ of\ seizure\ \ patterns} \tag{7}$$

$$Accuracy = \frac{Total\ no\ of\ correctly\ \ classified\ \ patterns}{Total\ no\ of\ patterns} \tag{8}$$

III.RESULTS AND DISCUSSION

Z-S classification problem is addressed in this study. The feature extraction is carried out with GHM wavelet andclassification by k-NN. The classification is also carried out with ANN and SVM and performance is compared with that of k-NN. 20% of data is used for training. The results are tabulated in Table 1.The results show that k-NN classifier is more accurate in detecting seizures when compared to ANN and SVM. Accuracy with k-NN classifier is 98.59%, whereas the accuracy with ANN and SVM is at 98.42% and 87.25% respectively.

TABLE I. PERFORMANCE COMPARISON (k-NN, ANN,SVM)

Method	Statistical Parameters		
	Accuracy (%)	Specificity (%)	Sensitivity (%)
k-NN	98.59	99.92	99.21
ANN	98.42	99.88	96.95
SVM	87.25	96.13	88.63

The performance obtained with multi wavelets is compared with that of scalar wavelets. Multi-wavelets GHM, Chui-Lian (CL) and the scalar wavelets Daub2 and Daub8 are used in this study. Feature extraction and classification are separately carried out with these wavelets. The classification is done using k-NN. The accuracy obtained with the different wavelets is shown in Fig. 4. Results show that multi-wavelets outperform scalar wavelets in classifying EEG signals.

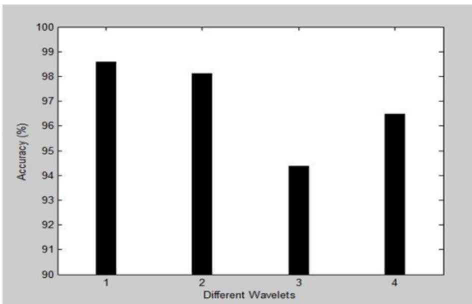

Fig.4. Accuracy of classification with different wavelets.

(1) GHM (2) CL (3) Daub 2 (4) Daub 8

IV. CONCLUSION

A scheme for classification of EEG signals based on MWT and k-NN is proposed. The set of spectral features extracted using MWT are M_{ave}, P_1 and P_2. These features are seen to provide sufficient information to the k-NN classifier to perform a reliable classification. In order to evaluate the efficiency of the proposed method, classification is done also using ANN and SVM. The classification performance is evaluated in terms of accuracy, sensitivity and specificity.

The performance with k-NN classifier is seen to outperform the other two classifiers. It is also seen that the performance with multi wavelets is far superior to that with scalar wavelets.

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