



## Seizure detection in EEG using Biorthogonal wavelet and fuzzy KNN classifier

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### ABSTRACT

Most of the brain disorders are diagnosed by analyzing the EEG signals. In this paper an efficient approach for detecting the presence of epileptic seizures in EEG signals using fuzzy KNN classifier is presented. Epilepsy is a disease due to temporary alternation in brain functions due to abnormal electrical activity of a group of brain cells and is termed as seizure. The analysis is performed in three stages. In the first step the biorthogonal Discrete wavelet transform is used for decompose the EEG signal into delta, theta, alpha, beta and gamma subbands. In the second step the statistical features are extracted from each subband and finally classification of the EEG signal that is epileptic seizure exists or not has been done using fuzzy KNN classifier. This method is applied for two different groups of EEG signals: 1) healthy (Normal) EEG dataset; 2) epileptic dataset during a seizure interval. The experimental results show that the proposed method efficiently detects the presence of epileptic seizure in EEG signals and also showed a reasonable accuracy in detection.

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### Introduction

Brain is one of the most important organs of humans, for controlling the coordination of human muscles and nerves. The transient and unexpected electrical disturbances of the brain results in an acute disease called Epileptic seizures. Numbers of researchers have presented automated computational methods for detecting epileptic seizures from EEG signals. The word 'epilepsy' is derived from the Greek word epilambanein, which means 'to seize or attack'. Seizures are the result of sudden brief, excessive electrical discharges in a group of brain cells called neurons. Transient symptoms can occur, such as loss of awareness or consciousness and disturbances of movement, sensation (including vision, hearing, and taste), mood, or mental function. The seizures occur at random to impair the normal function of the brain. [1].

It is probably the most prevalent brain disorder among adults and children. Over 50 million people worldwide are diagnosed with epilepsy, whose hallmark is recurrent seizures [2]. The prevalence of epileptic seizures changes from one geographic area to another [3].

The seizures occur at random to impair the normal function of the brain. Seizures can be classified into two main categories depending on the extent of involvement of various brain regions focal (or partial) and generalized. Generalized seizures involve most areas of the brain where as focal seizures originate from a circumscribed region of the brain, often called epileptic foci [4].

In recent years, a few attempts have been reported on seizure detection and prediction from EEG analysis using two different approaches: 1) Examination of the waveforms in the preictal EEG to find events or changes in neuronal activity such as spikes [5], which may be precursors to seizures. 2) Analysis of the nonlinear spatio-temporal evolution of the EEG signals to find a governing rule as the system moves from a seizure-free to seizure state [6]. Some work has also been reported using artificial neural networks [7] for seizure prediction with wavelet pre-processing [8].

Automatic analysis of EEG recordings in the diagnosis of epilepsy was started in the early 1970s. Many algorithms for spike detection have been proposed, including mimetic- and rule-based approaches [9], frequency-domain methods [10], ANNs [11], independent component analysis [12], dataming template matching [13], and topographic classification [14].

For seizure detection, t-f distributions are widely used. Markos G. Tsipouras, and Dimitrios used various time frequency distributions for extracting the features from the EEG signals and classify the signals based on artificial neural network [15]. This method offers the ultimate classification of the EEG segments regarding the presence of seizures or not.

### Materials and methods used

#### Proposed Method

The flowchart of the proposed method is shown in Fig1. In this method each EEG segment is decomposed into five EEG subbands: delta (0–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (>30Hz) using discrete wavelet transform. The subbands yield more accurate information about the neuronal activities of brain. The statistical features are extracted from each subband and form a feature Vector. The fuzzy KNN classifier is used to classify whether seizure is existing or not in the given signal.

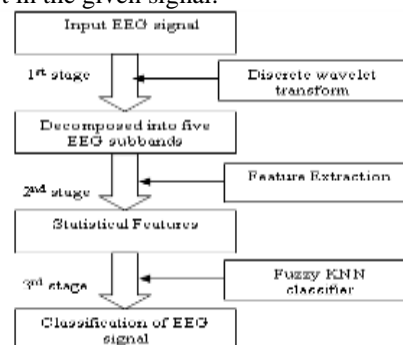


Figure 1: Flow chart of proposed metho

### Dataset Used

The data set used in the paper is publicly available online by Dr. Ralph Andrzejak of the Epilepsy Center at the University of Bonn, Germany .It includes both healthy and epileptic EEG dataset. The dataset includes two subsets (denoted as Z and S) each containing 100 single-channel EEG segments, each one having 23.6-second duration. The EEG signal available in the subset Z has been measured in seizure-free intervals, from five patients in the opposite hemisphere of the brain. The Subset S contains the EEG signal during seizure activity period. The sample waveform of the EEG signal obtained from each dataset is shown in the Fig2.

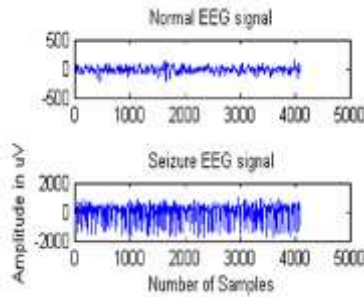


Figure 2 Sample EEG Data segments (Z001, S001)

### Subband decomposition of EEG based on wavelet

For extracting individual EEG subbands a wavelet filter (DWT) is used .The wavelet transform has the advantages of time-frequency localization, multirate filtering and scale space analysis. Wavelet transform 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 . The primary EEG signal contains five subbands: delta, theta, alpha, beta, and gamma. The sampling frequency of the EEG dataset obtained is 173.61 Hz. According to the Nyquist sampling theorem, the maximum useful frequency is half of the sampling frequency (ie 86.81 Hz).

Biorthogonal wavelet filter is used to decompose the EEG signal upto six levels to extract the five subbands delta, theta, alpha, beta, and gamma separately. The perfect reconstruction and symmetric wavelet property exists in biorthogonal wavelets because it has two sets of lowpass filters and high pass filters[16]. One set is the dual of the other. Two distinct scaling functions are used in biorthogonal wavelets for obtaining the decomposition and reconstruction filters. The biorthogonal wavelets have higher compression ratio than orthogonal wavelet. The biorthogonal wavelets have higher embedding capacity when they are used to decompose a signal or image [17]. This is a beneficial property of biorthogonal over orthogonal wavelet.

After the first level of decomposition, the EEG signal (0–86.81Hz), is decomposed into its lower resolution components, a1 (0–43.25) Hz and higher resolution components, d1 (43.25–86.81) Hz. Likewise six level of decomposition is done and then inverse discrete wavelet transform is used to recombine the various frequency band to form delta(0-4)Hz ,Theta(4-8)Hz ,Alpha(8-12)Hz ,Beta (12-30)Hz, and Gamma (>30)Hz. The low frequency decomposed band has less number of samples than higher frequency bands. The delta, theta, alpha band have 256 samples and beta have 1024 and gamma have 4096 samples.

### Feature Extraction

The purpose of feature extraction is to reduce the original data by measuring certain features that distinguish one input pattern from another. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input

data will be transformed into a reduced representation set of features (also named feature vector). Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

### Variance:

In this paper we have considered the statistical parameter variance as one feature. It describes how far the values lie from the mean. The Variance of each decomposed subband is estimated and form a feature Vector .The Variance of Seizure signal is higher than normal signals. Using this as one feature value the SVM is trained to classify the signal.

Let us assume a random variable X that have the sample values of each EEG subband signal .Let the sample value of X is  $X_i = \{x_1, x_2, \dots, x_n\}$  .Where i represent any one of the sample set from the subbands delta, theta, alpha, beta, and gamma.The corresponding variance can be expressed as

$$\sigma^2 = \frac{\sum (X - \mu)^2}{N} \quad (1)$$

Where  $\mu$  is the mean value of the set X and N is the number of samples. The range of variance value obtained from variance subband is given in table 1.

### Energy

The energy of the signal is defined as the sum of squared modulus of the sample values. The energy of various subbands such as delta, theta, alpha beta and gamma are calculated. The energy of the signal is expressed as

$$E = \sum_{n=0}^{N-1} |X_n|^2 \quad (2)$$

Where  $X_n$  is the samples values in each subbands and N is the total number of samples..

### Power Spectral Density (PSD)

The power spectral density (PSD) represents the distribution of the energy of the signal over the  $t$ - $f$  plane. It refers to the amount of power per unit (density) frequency (spectral) as a function of frequency. The integral of the PSD over a given frequency band computes the average power in the signal over that frequency band. Different algorithms are used for the estimation of PSD. Periodogram is the most popular method used for computing PSD. This is computed by squared modulus of the Fourier transform of the time series of the signal. The steps involved for computing the PSD is given below

- 1) Fast Fourier transform (FFT) is Computed on each EEG subband signal  $X(\omega_i)$
- 2) PSD is calculated by using expression

$$P(\omega_i) = |X(\omega_i)|^2 \quad (3)$$

The Maxima and minima values are estimated from the PSD of each EEG subbands are considered as feature and added to the feature vector

### Fuzzy KNN classifier

The K-Nearest Neighbor (KNN) is a non-parametric method which does not require tuning. The KNN classifier is easy to implement and does have a training phase. It simply stores all the training samples. When a new sample is put to test, it calculates the distances between the test sample and every training sample. The test sample is assigned to the class that has the least K aggregate distances. KNN has been widely used by

pattern recognition community. A good survey of KNN in pattern recognition is found in [18]. The KNN classifier has many advantage .It give competitive performance compared to other methods. KNN provides an easy and effective way to calculate the classification error rate.

#### Fuzzy KNN classifier

The KNN classifier is based on traditional (crsip) set theory. The Main disadvantage is that it implies an aura of precision and definiteness for a decision that may not be warranted. The samples that could be a member of more than once class may be classified differently depending on the distance measure used. Fuzzy KNN classifier overcomes the problem in the KNN classifier. Fuzzy KNN classifier assigns a membership value for each sample and it represents how closely for each given class. Fuzzy KNN algorithm has two main advantages over the traditional KNN algorithm [18]. While determining the class of test sample, fuzzy KNN algorithm is capable of considering the ambiguous nature of the neighbours. The second advantage is that the sample is assigned a membership value in each of the K-classes rather than binary decision of 'belongs to' or 'does not belongs to'. The membership functions in fuzzy KNN classifier provides strength and confidence with which the test sample belongs to a particular class.

#### Fuzzy KNN algorithm

Let us consider  $\{x_i, t_i\}$ , be the training feature set, where  $X_i$  is the feature values of the signal and  $t_i$  is the corresponding label class. The steps involved in the classification process is given below

Step 1: Compute the Euclidean distance between the testing signal feature and each feature in the training set of the signals and form a distance matrix.

Step 2: Find the summation value of the distance matrix

Step 3: Sort the distances in increasing numerical order and pick the first 'k' elements

Step 4: A fuzzy weight matrix is created for the K elements.

$$\text{Weight} = \text{distances}(\text{neighbor\_index})^{-(1/(m-1))};$$

where m is the scaling parameter for the classifier

step 5: Then the weight matrix is multiplied with the label values of the nearest neighbor values to obtain the output matrix of the classifier.

step 6: The output class label is computed by considering the maximum weight value position in the output matrix.

#### Experimental Results and Discussion

The proposed method is implemented in Matlab 7.8. In this paper 100 non-seizure and 100 seizures EEG signal is used to test the performance of the system. Each EEG signal is sampled at 173.6Hz. From each segment 4096 samples are used for evaluation. Because the wavelet transform (DWT) based on dyadic (powers of 2) scales is used to make the algorithm computationally very efficient with good accuracy.

EEG signal is decomposed using DWT upto six levels and from the decomposed signal delta, theta, alpha, beta, gamma subbands are constructed using Inverse discrete wavelet transform (IDWT). Fig.3 and Fig.4 shows the EEG signal/segment and the corresponding constructed subbands for normal and seizure subject respectively. The lower frequency decomposed band has less number of samples than higher frequency bands. The delta, theta, alpha band have 256 samples and beta have 1024 and gamma have 4096 samples.

The statistical features such as variance, energy and maximum value in the PSD is estimated by using equation (1),

(2) and (3). The feature values of seizure signal are much higher than that of non seizure signal in all the subbands. The obtained PSD of normal and seizure EEG signal of delta subband is shown in figure 6 and Fig.7.

When a test signal is given as input to the KNN classifier, it computes the distances between the test sample and every training sample and creates a distance value matrix. The distance values in the matrix are arranged in ascending order. The K value used in this paper is 4. So first four values in the ascending order matrix is considered as nearest distance values for the given test signal.

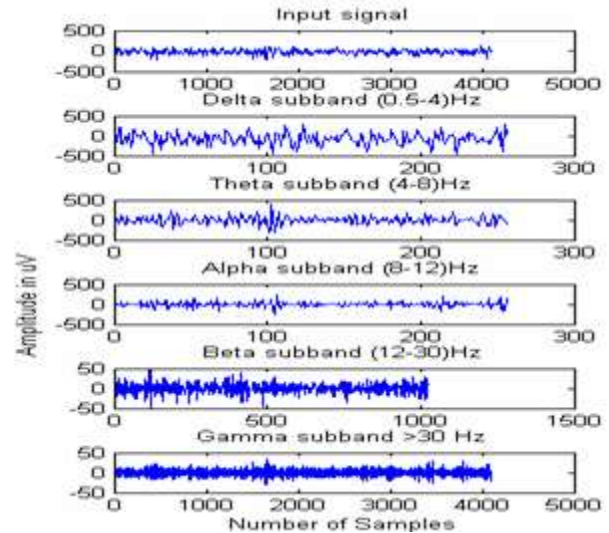


Figure 3: Normal EEG signal with delta, theta, alpha, beta and gamma subband

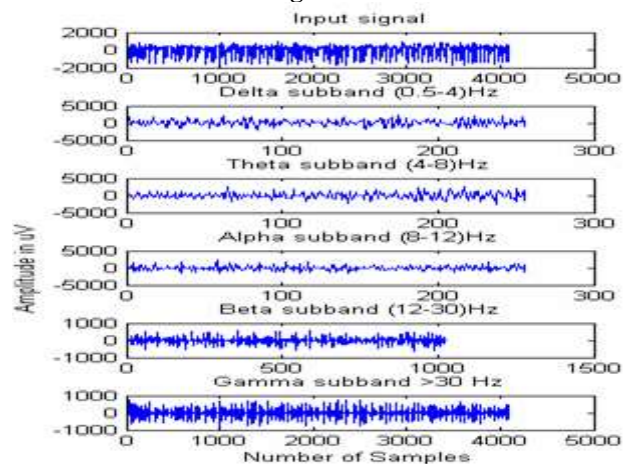


Figure 4: Seizure EEG signal with delta, theta, beta, alpha and gamma subband

Then a fuzzy weight matrix is created for the K values in the distance matrix. Then the label values of the K distance values are multiplied with fuzzy weight matrix to obtain the output matrix. The maximum weight value and its positions are computed from the output matrix. The position value gives the corresponding output class for the test signal. The accuracy obtained by the classifier for the normal and seizure signal is given in table 1.

The performance of the system is measured in terms of accuracy. The accuracy is given by

$$\text{Accuracy} = \frac{\text{correctly detected patterns/signals}}{\text{total number of patterns/signals}}$$

In the classification problem 160 signals feature values are considered as training features and 40 signals features are used

for testing the classifier. Out of 160 training signals 157 signals are correctly classified and the 40 testing signals used for testing are correctly classified without error. So the accuracy obtained by this method is 98.5%.

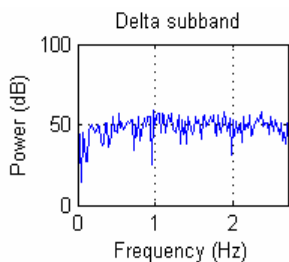


Figure 7 : PSD of Seizure signal

### Comparison with others works

There are many other methods proposed for the epileptic seizure detection. The comparison of results obtained from this method and other method in the described dataset is given in the Table 2.

### Conclusion

In this paper epileptic seizure detection in EEG signal is presented. EEG signal is first decomposed into delta, theta, alpha, beta, and gamma subbands. After decomposition the statistical feature such as variance, energy, maximum sample value in PSD is computed for each subband. Feature vector is generated based on the statistical features. The fuzzy KNN classifier is used to classify/detect seizure EEG signal and normal EEG signal. Accuracy of the classifier is computed. The accuracy obtained in this method is much better than other results available in the literature. Autoregressive model and various time-frequency distributions can also be used to extract the features for comparing the performance and accuracy for detecting Epileptic Seizure in EEG signals.

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Table 1 Classification accuracy of EEG signal using Fuzzy KNN classifier

Category	Number of trained signals	Number of tested signals	Correctly detected signals	Accuracy in percentage	Overall Accuracy
Training Phase (which include 80 seizure and non seizure signals)	160	160	157	98.125	98.5
Testing phase (Which include 20 seizure and non seizure signal)	-	40	40	100	

**Table 2 The comparison of the classification accuracy obtained by our method and others method**

Researchers	Methods used	Accuracy
Nigam and Graupe	Nonlinear pre-processing filter-Diagnostic neural network	97.2
Srinivasan et al.	Time & frequency domain features-Recurrent neural network	99.6
Kannathal et al.	Entropy measures-Adaptive neuro-fuzzy inference system	92.22
Kannathal et al	Chaotic measures-Surrogate data analysis	90
Polat and Gunes,	Fast Fourier transform-Decision tree	98.72
Alexandros T.Tzallas*	Time frequency analysis-Artificial neural network	100
This Work	Biorthogonal wavelet transform and Fuzzy KNN Classifier	98.5