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NEURAL NETWORK CLASSIFIER FOR THE DETECTION OF EPILEPSY/SEIZURE BASED ON BISPECTRUM FEATURES

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ABSTRACT

Electroencephalogram (EEG) is widely used for the clinical investigation of epilepsy. Epilepsy is a brain disorder normally characterized by repeated seizures. This paper presents a method to detect epilepsy/seizure based on bispectrum features. For signals that are non-Gaussian and which are generated by nonlinear mechanisms, higher order spectra are useful in quantifying the nonlinearity. Bispectrum which is a second order spectrum is used to compute the features. The proposed method is tested on three datasets for detecting ictal / inter ictal EEG from normal EEGs and also classifying ictal and inter ictal EEGs and is giving a classification accuracy of 70% to 100% for various classes.

Key words: Electroencephalogram (EEG), ictal and interictal EEG, Higher order spectrum, Bispectrum.

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1. INTRODUCTION

Epilepsy is a brain disorder normally characterized by repeated seizures. Epilepsy affects more than 1% of the world population. It is commonly observed among both adults and children [1]. Epileptic seizures occur due to sudden excessive electrical discharge in a group of neurons. The occurrence of epileptic seizure is unpredictable and it affects the normal functioning of the brain. EEG is the commonly used and cost effective modality for the detection and study of epilepsy. The general procedure for the diagnosis of epilepsy involves visual inspection of the recorded EEG by a neurologist. This is difficult for long term recordings and subjective. Automatic detection is very helpful for the neurologists for quick and easy diagnosis and also to understand the causes and sources of seizure activity in a better way. The EEG recordings of patients suffering from epilepsy are grouped into inter ictal and ictal. Signal recorded between epileptic seizures is called inter ictal EEG and the signal recorded during an epileptic seizure is called ictal EEG [1].

Functioning of brain is non-linear. Non-linearity in the brain is introduced even at the cellular level [2]. EEG is nonlinear and non-stationary. Spectral estimation of a non-stationary signal is a challenging task. Several processing techniques proposed and available in the literature assume that the EEG is generated by a highly complex linear system. But nonlinear processing techniques which can detect the nonlinearities in the signal would be more suitable for processing EEG [2].

Since early days Fourier transform based methods and parametric methods have been applied to analyze the frequency changes in EEG [3]. Fourier Transform based methods of spectral estimation requires long segments of data for the estimation and also suffer from large noise sensitivity. Even though parametric power spectrum estimation methods reduce the spectral loss problem and give better frequency resolution, but they are not suitable for the analysis of EEG signals which are non- stationary [4].

Time –frequency methods are proved better than the conventional methods of frequency analysis[5]. Wavelet Transform (WT), which provides time–scale analysis and is more appropriate for non-stationary signals. Discrete Wavelet Transform (DWT) is used to recognize and quantify epileptic spikes, sharp waves and spike waves [8]. Empirical mode decomposition (EMD) has been used for nonlinear signal analysis without any assumption on linearity and stationarity. Empirical mode decomposition (EMD) has been used for nonlinear signal analysis without any assumption on linearity and stationarity. Several methods have been proposed to detect seizure based on features measured in EMD domain.Higher order moments extracted from the intermediate frequencies (IMFs) with ANN classifier are useful in detecting epilepsy [9]. Auto-regressive (AR) modeling has been used successfully for EEG because of its superior resolution for short data segments. AR modeling is preferred for real-time processing and analysis. Power spectrum obtained by applying AR-Burg method is used to extract EEG features. Features from Auto regressive (AR) model are combined with SVM [10] and relevance vector machine [11] classifiers are used to detect epileptic EEG.A number of nonlinear statistics are used to characterize EEG. Attempts were made to quantify characteristics of the underlying nonlinear system that generate EEG. The underlying dynamics is quantified using correlation dimension (CD) and the Largest Lyapunov Exponents (LLE). A comparative study of neural network approaches used in seizure detection are discussed in [12][13][14].

Frequency domain processing helps in understanding the information conveyed by EEG patterns. Power spectral density gives estimation of power among its frequency components. But phase relations between frequency components are suppressed. Power spectrum is considered as the second order spectrum [3]. But for signals which are generated by nonlinear mechanisms, higher order spectra are useful in quantifying the nonlinearity. Bispectrum is one of the higher order spectrums which can be used to process EEG signal [15] [16]. Bispectrum is defined as the Fourier transform of third order moment. Bispectrum has been used to derive EEG features by some researchers [18]. Earlier attempts of seizure detection used band limited EEG for the computation of bispectrum. Mean value and Phase entropy of the bispectrum are used as features. Classification with bispectrum features showed improved performance as compared to that of power spectrum features .Motivated by our earlier work

[19], we have made an attempt to reduce the number of features. The definition of bispectrum and features used in the present study are explained in section II.

We consider EEG analysis related to epilepsy under the following scenario.

- Detection of epilepsy
- Detection of seizure

Detection of epilepsy involves given an EEG signal, one must be able to detect whether the person is suffering from epilepsy or not. This requires finding feature sets to discriminate between normal and inter ictal EEGs. The detection of seizure involves detection and classification of ictal EEG from normal and also from interictal EEGs. Ictal EEG characteristics, as compared to normal EEG is required to understand complex brain dynamics during seizure attack. Understanding the differences between interictal and ictal EEGs help to find sources of epileptic activity in brain and to predict seizure so that a warning can be given to the epileptic patient to face the seizure attack with precautions.

In this paper we have addressed both the problems; epilepsy detection and seizure detection. Bispectrum features are computed from EEG of normal healthy subjects, ictal and inter ictal EEGs of epileptic patients. Then the features are applied to train and test artificial neural network (ANN) classifier to evaluate the effectiveness of the features in discriminating different groups.

2. BISPECTRUM

Bispectrum is a second order spectrum. Bispectrum quantifies the relationship between the sinusoids at two primary frequencies ω_1 and ω_2 and the modulation component at frequency ($\omega_1+\omega_2$). Bispectrum incorporates both power and phase information [18]. Bispectrum computation from a single epoch is not sufficient to infer whether the signal is phase coupled or not. Therefore multiple epochs are required. Issues related to number of epochs and length and overlapping of the epochs are discussed in [15].

Let X (k) be a third order stationary process with zero mean.

Let R (m, n) be a third order moment sequence of X(k) which is defined as

$$R(m,n) \triangleq E\{X(k)X(k+m)X(k+n)\} \tag{1}$$

Where $E\{.\}$ denotes the Expectation.

The bispectrum of the of the process X(k) is defined as the Fourier transform of its third moment sequence

$$B(\omega_1,\omega_2) = \sum_{m=-\infty}^{+\infty} \sum_{n=-\infty}^{+\infty} R(m,n)\exp(-j(\omega_1 m + \omega_2 n)) \tag{2}$$

$$|\omega_1|, |\omega_2| \leq \pi$$

Generally the bispectrum is complex and has diagonal symmetry. It is periodic in frequencies ω_1 and ω_2, with period 2π. Therefore computation of the bispectrum in the triangular region $\omega_1 \geq 0$, $\omega_1 \geq \omega_2$, $\omega_1+\omega_2 \leq \pi$ (shown in Fig.1) is sufficient for the complete description of the bispectrum. The sides of the triangle in Fig.1 are corresponding to bispectrum values at $\omega_1 = \omega_2$ and $\omega_1 + \omega_2 = \pi$.

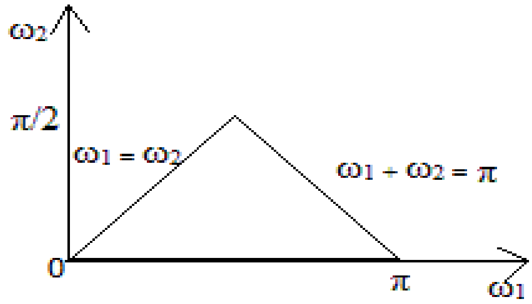

Figure 1 Non-redundant triangular region of bispectrum in the (ω1,ω2) plane

3. DATASET DESCRIPTION

Three groups of EEG data are used for testing the proposed method for epilepsy detection and seizure detection in the present study. i) normal EEG (EEG from healthy subjects); ii) interictal EEG (EEG recorded from epileptic patients during seizure-free interval) ; iii) ictal EEG (EEG recorded from epileptic patients during seizure). The EEG data is obtained from database available online. This dataset described by Andrzejak et al [22] consists of five subsets Z, O, N, F, and S. Each subset consists of 100 single-channel EEG segments of 23.6 s duration. The signals are recorded with sampling frequency 173.5 samples per second with 16-bit resolution. Sets Z and O are from five healthy volunteers, with eyes open and closed, respectively. Z and O have been recorded extracranially. Subsets N and F consists of Inter-ictal EEGs (seizure free interval). S contains ictal EEG (EEG recorded during seizure), sets N, F, and S have been recorded intracranially. This dataset is considered as benchmark data by many researchers for comparing the performance of different methods.

In this study main focus is on the detection of seizure. The analysis of interictal EEG and ictal EEGs of epileptic patients helps to track the changes in interictal EEG to predict seizure. But for comparison with methods developed by other researchers, proposed methodology is applied to classify the datasets as in the following groups.

- Classification between normal and ictal EEG (Z - S).
- Classification between normal and interictal EEG (Z - F)
- Classification between interictal and ictal EEG (F - S)

Time domain plots of normal EEG, inter ictal EEG and ictal EEG samples from the data base are shown in Fig.2.

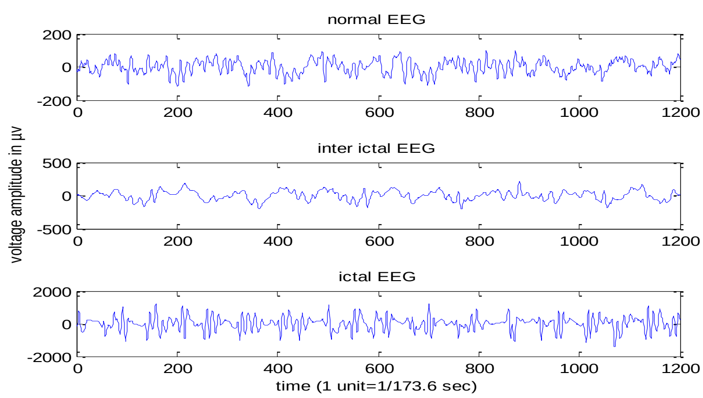

Figure 2 Plot of a sample normal, inter ictal and ictal EEGs in time domain

4. CLASSIFIER

Artificial Neural networks (ANN) are widely used tool for classification. The advantages of neural networks are that they are data driven and self-adaptive. They can approximate any function with an arbitrary accuracy [4]. In the present work, a three layer feed-forward back propagation neural network is trained with bispectrum features to detect and classify normal, inter-ictal and ictal EEGs. Schematic of a neural network classifier is shown in Fig.3.

Classification accuracy (CA) of a neural network classifier is defined as follows.

$$Classification\ Accuracy, CA(\%) = \frac{T_{CDP}}{T_{APP}} \times 100 \quad (3)$$

$T_{CDP} = total\ number\ of\ correctly\ detected\ patterns$

$T_{APP} = total\ number\ of\ applied\ patterns$

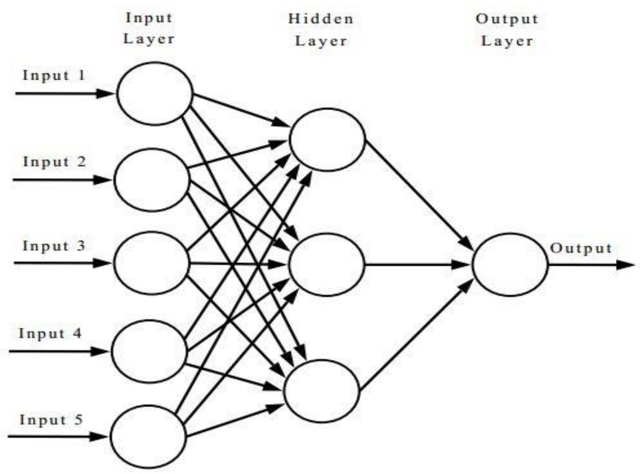

Figure 3 Schematic of a feed forward artificial neural network.

5. METHODOLOGY

The approach used for the detection consists of the following stages.

- Preprocessing
- feature extraction and
- classification

5.1. Preprocessing

The sampling frequency of the EEG used in our work is 173.61 Hz. According to the Nyquist sampling theorem, the maximum frequency of the signal is half of the sampling frequency or 86.81 Hz. EEG subbands (delta, theta, alpha, beta, and gamma) span a frequency range which is 0-60Hz.This frequency range is also considered to be sufficient for the clinical diagnosis. Frequencies greater than 60 Hz are considered to be noise and are to be removed. Therefore EEG is band limited to frequency range 0.5-60 Hz using fourth order IIR filter.

5.2. Feature Extraction

Bispectrum is computed using direct (FFT) method. EEG signals of 4097 samples are used to compute the bispectrum. For each signal sub segments of EEG are used to compute FFT and averaged to estimate bispectrum.

Features are extracted in the non-redundant region of the bispectrum. The following features are computed from the bispectrum $B(\omega_1, \omega_2)$ [19].

- maximum value in the non-redundant region

$$B_{max} = max\{B(\omega_1, \omega_2)\} \ \ |\omega_1|, |\omega_2| \leq \pi \tag{8}$$

- minimum value in the non-redundant region

$$B_{min} = min\{B(\omega_1, \omega_2)\} \ \ |\omega_1|, |\omega_2| \leq \pi \tag{9}$$

- variance in the non-redundant region

$$var\big(B(\omega_1, \omega_2)\big) = E[(B(\omega_1, \omega_2) - \eta)^2] \ \ |\omega_1|, |\omega_2| \leq \pi \tag{10}$$

where $\eta = E\ [(B(\omega_1, \omega_2))]$ and E= expectation

These three features form the feature vector and applied to the classifier.

5.3. Classification

The two set of feature vectors are used to train and test the ANN separately. The number of training data and testing data used for each dataset are given in Table 1. Training data is not part of testing data.

Table 1 Number of data used to train and test the artificial neural network classifier

Total number of data used	data used for training	data used for testing
900	630	270

6. EXPERIMENT AND RESULTS

The bispectrum is computed for each data segment. Bispectrum plot is a 2D plot with frequencies f1 and f2 as independent variables. The bispectrum contour plots of a sample normal, inter ictal and ictal EEGs are shown in Fig.4.The differences in bispectrum of the three groups of EEGs are evident from the plots. The maximum, minimum and variance values in the non-redundant region are computed as features and combined as feature vectors.

The feature vectors are used to train and test neural network classifiers separately. The testing data is not part of training data. The classification accuracy obtained for each class is listed in table II. Classification accuracy of 70% to 100% is obtained for various classes.

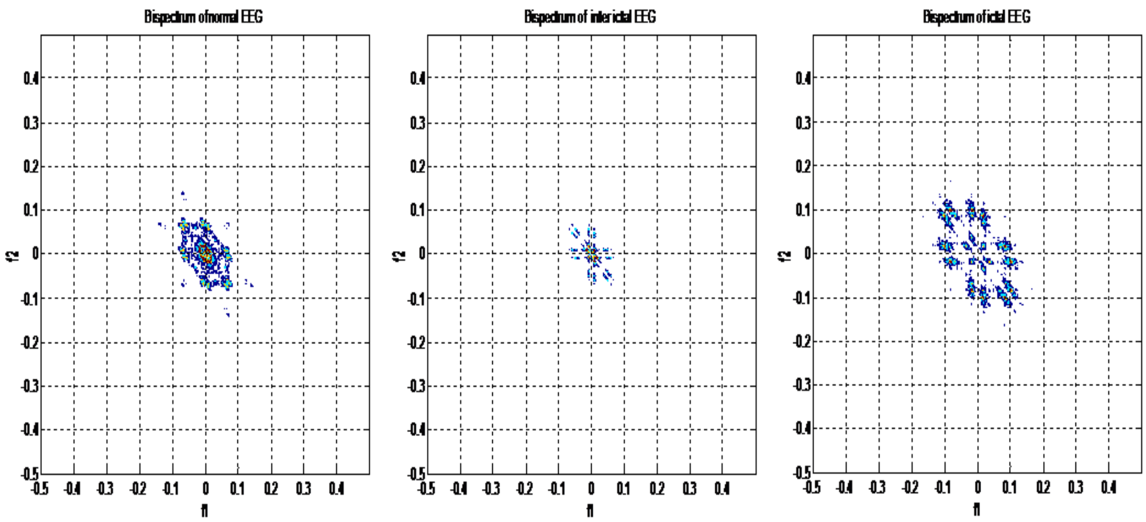

Figure 4 Bispectrum plots of the normal, inter ictal and ictal EEGs

Table 2 Performance of the proposed method.

Class	**Classification Accuracy (with 512 sample per epoch)**
Normal- ictal (Z,S)	100
Normal- interictal (Z,F)	70
Interictal –ictal (FS)	96.33

7. DISCUSSION

Bispectrum is a second order spectrum which quantifies the non linearitites in a signal. It indicates the phase coupling among the frequency components in a signal. It supresses any gaussian noise in a signal that means the bispectrum coefficients are zero for gaussian signal and can be used to detect any deviation from gaussianity. The present analysis proves that bispectrum is suitable for processing and analysing EEG signals.

Many researchers proposed methods which can classify normal and ictal EEG classification accuracy 100%. Our method is also giving 100% accuracy. The EEG pattern change significantly during seizure interval. It becomes more rhythmic and consists of spike and wave discharges with increased amplitude and change in frequency. During seizure the amplitude the bispectrum coefficients increase. The proposed method is giving 96.33 accuracy in classifying ictal EEG from interictal EEG. But the method is giving only 70% accuracy in classifying the interictal EEG from normal EEG. This is because the interictal EEG characteristics are similar to normal EEG in most of the cases. The result indicate that the proposed feature set do not show much difference in descriminating normal and interictal EEGs. Further investigation is required to improve the accuracy for this case.

Table VI Comparison of the performance of the methods proposed by other researchers

Authors	Dataset	Classification Accuracy %
Methods proposed by other researchers		
Nigam et al [23]	Z, S	97.2
Srinivasan et al [24]	Z, S	99.6
Kannathal et al.[25]	Z, S	92.22
Polat et al [26]	Z, S	98.72
Subasi [27]	Z, S	95
A.T. Tzallas et al[28]	Z, S	100
Srinivasan et al [22]	Z, S	99.35–100
Kiranmayi , Udayashankara[30]	Z, S Z, F	100 98.9
Proposed method	Z, S Z, F F,S	100 70 96.33

Table VI presents a comparison of the proposed method and the methods proposed by other researchers and our earlier methods. For comparison, the methods that are evaluated using the same data set are included. The proposed methodology achieves 100 % classification accuracy in detecting ictal EEG from normal EEG. The method proposed can also detect inter ictal EEGs from normal EEG. Accuracy of 96.33% is obtained in classifying normal and inter ictal EEGs.

8. CONCLUSIONS

EEG signals are characterized by low signal-to-noise ratio and non-stationary characteristics, which make the processing of such signals for the extraction of useful information a challenging task. The main focus of this work is to study the effectiveness of bispectrum features of EEG for seizure detection. The results indicate that the proposed bispectrum features are effective in the detection of seizure. The bispectrum which indicate non-linear interactions among frequency components in a signal is suitable for the analysis of EEG which is nonlinear and non-stationary. The bispectrum is proved to be an effective tool for the detection of seizure But the proposed method fails to detect epilepsy. Further investigation is required to find new features from bispectrum to detect epilepsy i.e to improve the accuracy for the classification of normal-inter ictal EEGs. In this study the proposed method is optimized for the detection of seizure and epilepsy from EEG, but bispectrum can be used as a general tool for the analysis of biomedical signals.

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