ISSN 2229-5518

CLASSIFICATION AND CLUSTERING OF BRAIN SEIZURE ACTIVITY USING WAVELET TRANSFORM AND RADIAL BASIS NEURAL NETWORK

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Abstract— Electroencephalogram (EEG) is the record of the brain electrical activity and it contains valuable information related to the different physiological and pathological states of the brain. Epilepsy is known to be the most prevalent neurological disorder in humans and seizure discharge is the main characteristics of the epilepsy. EEG is an important clinical tool for the diagnosis and monitoring of seizures. Epileptic seizure occurs irregularly and unpredictably manner due to temporary electrical disturbance of the brain. The aim of this project is Epileptic seizure detection in multichannel EEG. This paper presents a novel method for automatic epileptic seizure detection, useing recurrent rates derived from discrete wavelet transform in combination with a radial basis function neural network for classification and clustering of the pattern feature of EEG signals. The output of the neural network aids in finding existence or absence of seizures in the EEG data. We have used discrete wavelet transform (DWT) of Daubechie's wavelet order 4 to decompose the EEG signal at different levels in extracting approximation and detail coefficients. We have evaluated a unique dynamical parameter (recurrence rate) from the wavelet co-coefficients of EEG of different subjects (normal and epileptic). The recurrence rate has been used in a radial basis function neural network for seizure detection. The performance of the network has been evaluated in terms of the accuracy, specificity and sensitivity detecting in unknown EEG time series.

Index Terms— Discrete Wavelet Transform (DWT), EEG, Radial basis function Neural Network (RBFNN), Recurrence Quantification Analysis (RQA), Recurrent Rate

1 INTRODUCTION

An epileptic seizure ("a fit") is a common neurological disorder that has been with us ever since ancient times and approx 50 million people in the world badly affected by epilepsy. It may occur usually following physical or metabolic insult resulting in sudden surge of electrical activity in the brain [1]. Clinically an epileptic seizure is an intermittent, usually unprovoked, stereotypical, disturbance of consciousness, behavoiur, emotion, motor function or sensation that is result of cortical neuronal discharge [7].

Patient experience different types of symptom during seizures and it's depends on the location and extend of the affected brain tissue. The classification of seizure has been standardized by the International League Against Epilepsy (ILAE). Partial seizures affects small part of the brain and generalized seizures affects all parts of the brain [2].

Electroencephalograph (EEG) is the recording of brain activity and its signals contains valuable information for understanding of epileptic seizures. In recent years, classification of EEG signals increases based on the machine learning techniques applications, which assist physicians to diagnose the epileptic seizure. Although the epileptic seizures are unpredictable, so for automatic detection of epileptic discharges, this can be used to predict the onset of seizure [6].

Discrete wavelet transforms (DWT) is a versatile signal processing tool which helps to decompose the EEG signals in different levels of approximation and detailed coefficient based on frequency sub bands, which produces information about the brain activities [4]. Here, we have used DWT because wavelet transform has mother wavelets with a finite start and finish as compare to fourier transform with sines and cosines function, which have infinite in mathematical terms to generate the coefficients. We can say that mother wavelet has "compact support". The importance of having compact support is that when you fit it to the signal you get a localized result rather than generalized [6]. There are hundreds of mother wavelets available but Daubechies wavelet level 4 (db4) is more appropriate to detect changes in EEG signals.

Recurrence analysis is a method to measure the Recurrent Rate (RR) which is the density of recurrence points on a Recurrence Plot (RP). It is a fundamental property of dynamical systems, which can be exploited to characterize the system's behaviour in phase space [8].

Recurrence quantification analysis is a sensitive tool for detecting any dynamic changes, and it can be easily affected by settings like embedding dimension, time delay and mainly affected by threshold values. These measures are mostly based on the recurrence point density and the diagonal line structures of the RPs. It is a simplest application to measure the recurrent rate or per cent recurrences [13].

An Artificial Neural Network (ANN) is a powerful data-modeling tool that can capture and represent complex input/output relationships. The neural network technology materialized from the desire to develop an artificial system that could perform intelligent and complex tasks similar to those

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performed by the human brain. The main advantages of artificial neural network are adaptive learning and ability to learn how to do tasks based on initial experience or the data given for training. Self-organization in which an ANN can create its own organization and also represent the information it receives during learning time, real time operation which enables ANN computations to be carried out in parallel, fault tolerance due to which network capabilities may be retained even with major network damage [9]. There are many types of networks used, among which one is Radial Basis Function Neural Network (RBFNN). Its learning capacity is fast compare to other multilayer feed forward neural network. The Probabilistic Neural Network (PNN) classification comes under the RBNN, which we are implementing in our project. It is a form of multilayered feed forward network with four layers; input layer, pattern layer, summation layer, output layer. PNN is closely related to Parzen window Probability Density Function (PDF) estimator [12]. The main objective of this work is to diagnose the epileptic seizure using EEG signals. Discrete wavelet transform helps to decompose the signal in different levels of approximation and detail coefficients. Recurrence quantification analysis is used for measuring the recurrent rate of wavelet decomposition levels. The recurrence rate of each sub bands has been used as an input in PNN for seizure detection. The performance of the network has been evaluated in terms of the accuracy, specificity and sensitivity detecting in unknown EEG time series.

2 LITERATURE REVIEW

Many researchers have various techniques including unconventional approaches such as engineering diagnostic techniques, for determining patient‘s condition. A review of literature includes, automatic analysis of EEG waveforms for detecting the epileptic seizure began in 1970s. Since then many researches has been conducted on detection of epileptic seizure by EEG signal processing involving various methods and algorithms. Further on [1] Gotman in (1983) measured interchannel differences in onset times to study seizure propagation. In this work, he had analyzed a technique for automated seizures detection. [2] Osorio et al. (1998) have used a measure called seizure intensity they achieved perfect detection of seizure and the average detection latency was 2.1 seconds evaluated on a database of 125 patients, but they used same data for training and validation. [3] Nigam and Graupe (2004), described a method for automated non-linear detection of epileptic seizure from EEG signals using a multistage non-linear preprocessing filter for extracting two features namely, occurrence frequency and relative spike amplitude, then they feed those feature to diagnostic artificial neural network for classification. [4] Abdulhamit subasi et al (2005) have used fast Fourier transform and autoregressive model which have maximum likelihood estimation to optimize the epileptic and normal EEG signal which was used as an input of artificial neural network and accuracy rate was obtained grater then 92%. [5] Jahankhani et al. (2006) perform the wavelet transform decomposition of EEG signals into different sub-bands and some statistical information were extracted from the wavelet coefficient, which is used as a input of the radial basis function network and multilayer perceptron for the classification of epileptic seizure. [6] Ling Guo et al. (2010) have used a multiwavelet transform to decompose the EEG signals to several sub signals then the approximate entropy feature was extracted from each sub signals and finally extracted feature was classified with the help of artificial neural network. [7] Umut Orhan et al. (2011) implemented a new method for feature extraction called probability distribution based on Equal Frequency Discretization (EFD) to be used in the detection of epileptic seizure from EEG signals

3 PROCEDURE

A block diagram of the key stages of this work is shown in Figure 3.1. The methodology followed a traditional machine learning approach: (1) publically available data were used; (2) the data were appropriately preprocessed; (3) features were selected and extracted; (4) a classifier was trained; and (5) the performance of the system is evaluated. The entire process was iterated until acceptable performance results were achieved.

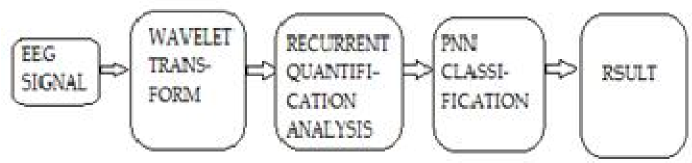

Fig. 1. Schematic illustration of the proposed method.

3.1 DATA SELECTION AND RECORDING

We have used the publicly available data described in Andrzejak et al. [7]. The complete data set consists of five sets denoted as A-E and each one containing 100 single-channel EEG segments of 23.6 s duration. The sets were selected from EEG records after purifying artifacts. These segments were selected and cut out from continuous multi-channel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements.

Sets A and B consisted of segments taken from surface EEG recordings that were carried out on five healthy volunteers. Volunteers were relaxed in awake state with eyes open (A) and eyes closed (B), respectively. Sets C–E originated from EEG archive of presurgical diagnosis. Segments in set D were recorded from within the epileptogenic zone, and those in set C from the hippocampal formation of the opposite hemisphere of the brain. While sets C and D contained only activity measured during seizure free intervals, set E only contained seizure activity. Here segments were selected from all recording sites exhibiting ictal activity. All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. The data were digitized at 173.61 samples per second using 12 bit resolution. Band-pass filter settings were 0.53–40 Hz (12 dB/oct). In this study, I used two dataset

(A and E) of the complete dataset.

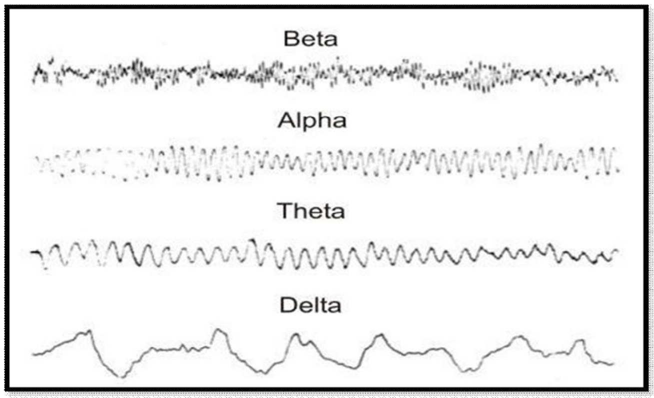

Fig.2. **EEG** wave at various frequencies

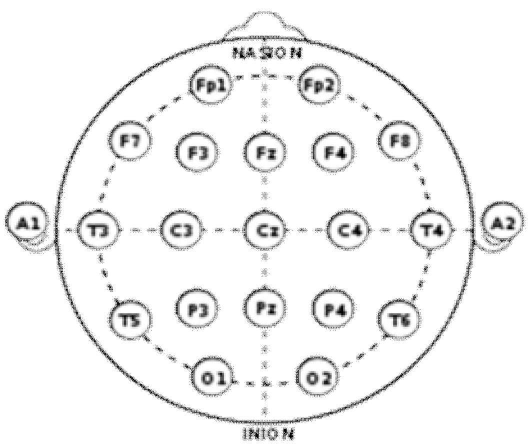

Fig.3. The 10-20 international system of electrode placement

2.2 Discrete wavelet transform

Here, we used multilevel one dimensional wavelet analysis using specific wavelet 'Daubechies'(db) to decompose the signal in different levels of approximation and detailed coefficients. The number of decomposition level was chosen to be 5. Thus, the EEG signals were decomposed into approximation (A1-A5) and detailed (D1-D5). We used Daubechies wavelet of order 4(db4) which helps to smooth the features, more appropriate to detect changes in EEG signals. The DWT decomposition can be described as;

$$a_{(i)}(l) = x(k)^{*} \varphi_{i,l}(k),$$
$$d_{(i)}(l) = x(k)^{*} \psi_{i,l}(k),$$

Where, $\alpha_{(i)}(l)$ and $d_{(i)}(l)$ are the approximation and detail coefficients of resolution i respectively.

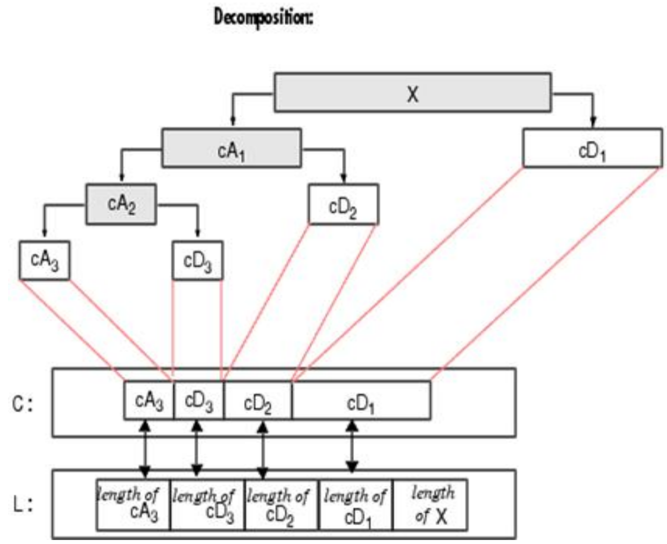

Fig.4. **multilevel one dimension decomposition**

2.3 Recurrence Quantification Analysis

It is a method of non linear data analysis. The RQA's parameter like embedding dimension (m), time delay (t), threshold, window size and window shift values are obtained to find recurrent rate. The m and t are found based on standard method like false nearest neighbour (for m) and average mutual information (for t), which avoid autocorrelation effects. Threshold value is one of the most critical parameter. Even a small change can dramatically affect the result of RQA. Threshold value is obtained with the help of Dr. Marwan recommended principle that is normalize the data and then use a fraction of the standard deviation as the value of threshold parameter. The window size (W) short windows focus on small-scale recurrences, whereas long windows focus on large-scale recurrences. The window shift value (WS) is the first five numbers after the data series. After finding all the parameter RR was measured;

$$RR(t) = \frac{1}{N-t} \sum_{l=1}^{N-t} l P_t(l),$$

Here, t-time delay, *Pt (l)* - diagonal line length

2.4 Radial Basis Function Neural Network

Probabilistic neural network (PNN) process is faster than backpropagation network and it is an inherently parallel structure. Training sample can be easily added and removed in this network without any extensive training. In this work, a four layer neural network is used to classify EEGs based on the previous obtained RR. The evaluation of this proposed method determined by computing the statistical parameters like specificity, sensitivity and classification of accuracy.

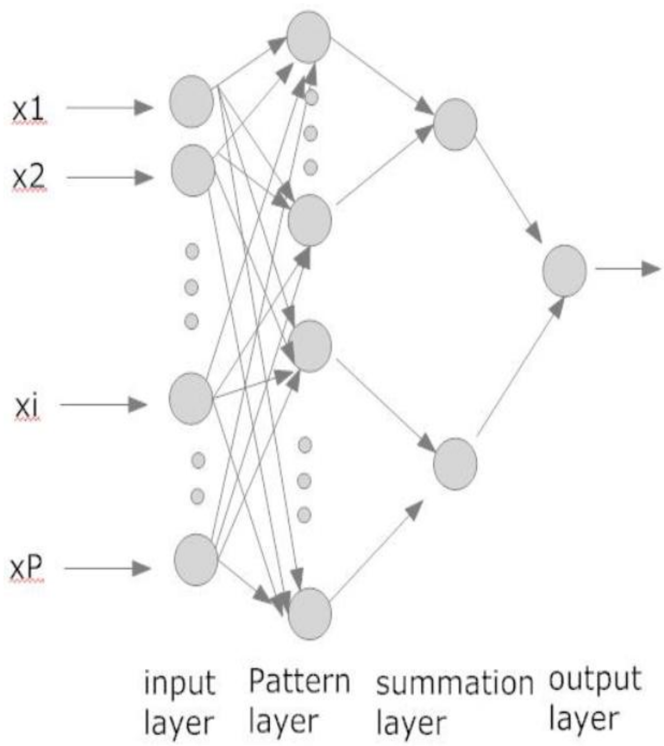

Fig.5. Architecture of Probabilistic Neural Network

3. Experiments

In order to apply the neural networks, we used Matlab R2010a with neural network program. In this project in Matlab platform we implemented several scripts that allowed us to run the experiments.

4 Evaluation formulas

To evaluate our result we used three different formulas: specificity (the capacity of correctly identified negative cases), sensitivity (the capacity of correctly identified positive cases), and accuracy (the proportion of correct classified instances). These formulas are mainly used in this project, making easier to compare our results with other works.

$$Specificity(\%) = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \times 100$$

$$Sensitivity(\%) = \frac{True\ Positives}{True\ Positives + False\ Negatives} \times 100$$

$$Accuracy(\%) = \frac{Correct\ cases}{Total} \times 100$$

5 Result And Discussion

The phenomena of seizure activity can be physiologically understood as an enhanced coherence resulting from the simultaneous bursts of firing across a mass of neurons. The EEG shows a discharge of seizure. The EEG segment contains a seizure discharge and from the recurrent we classify the absence and presence of seizure activity. First part of the project shows the result of the decomposition of DWT in the levels of approximate and detail coefficient.

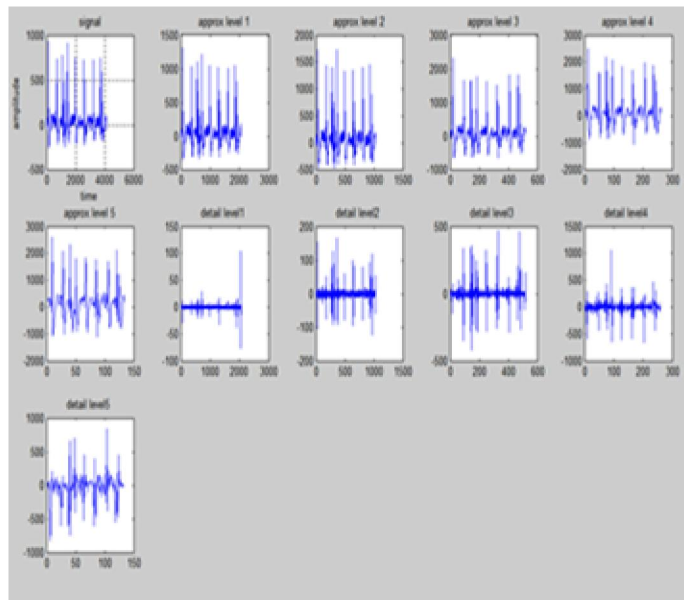

Fig.6. Original normal signal and wavelet decomposition approximated and detailed levels 1 to 5

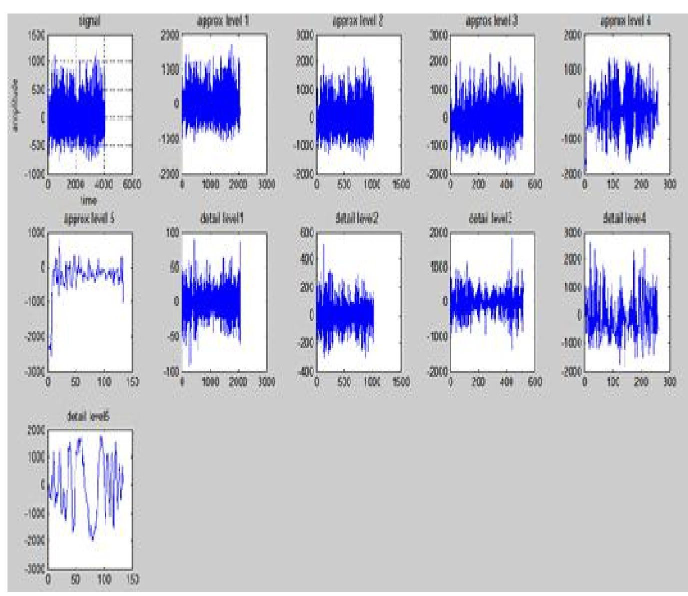

Fig.7. Original seizures signal and wavelet decomposition approximated and detailed levels 1 to 5

The recurrent rate is the unique dynamical parameter of recurrence plot. Recurrent rate of seizures and non- seizures data are different because seizures tend to be periodic that's because of periodic recurrent are small. The recurrent rate of each wavelet decomposition approximate coefficient (CA) and detailed coefficient (CD) levels are calculated and values are tabulated below:

Table 1. Seizure signal decomposed DWT coefficient recurrent rate.

Wavelet decomposed approximate and detailed levels	Seizure signal Recurrent rate (1)	Seizure signal Recurrent rate (2)	Seizure signal Recurrent rate (3)	Seizure signal Recurrent rate (4)	Seizure signal Recurrent rate (5)
CA1	0.3018	0.4333	0.4009	0.4670	0.0036
CA2	0.2111	0.3705	0.2713	0.4159	0.1517
CA3	0.0206	0.1381	0.0754	0.1245	0.2575
CA4	0.0654	0.0982	0.0597	0.0511	0.0036
CA5	0.1269	0.0330	0.0999	0.1377	0.0341
CD1	0.3754	0.3092	0.2778	0.8746	0.4208
CD2	0.1411	0.2327	0.0796	0.1857	0.2688
CD3	0.0939	0.1465	0.0381	0.0781	0.1667
CD4	0.0754	0.0405	0.1835	0.0910	0.0853
CD5	0.1309	0.1565	0.0084	0.1565	0.1687

Table 2. Normal signal decomposed DWT coefficient recurrent rate.

Wavelet decomposed approximate and detailed levels	Normal seizure Recurrent rate (1)	Normal seizure Recurrent rate (2)	Normal seizure Recurrent rate (3)	Normal seizure Recurrent rate (4)	Normal seizure Recurrent rate (5)
CA1	0.9683	0.9411	0.9976	0.9595	0.9432
CA2	0.6622	0.5886	0.3943	0.9841	0.9754
CA3	0.7568	0.6306	0.7652	0.8206	0.7864
CA4	0.2570	0.5816	0.2372	0.6302	0.7651
CA5	0.3131	0.3485	0.5641	0.4764	0.5433
CD1	1	1	1	1	1
CD2	0.9940	0.9940	0.7928	1	0.9988
CD3	0.8236	0.8694	0.6351	0.4790	0.5122
CD4	0.3033	0.4395	0.3357	0.3468	0.4322
CD5	0.6682	0.7906	0.7645	0.7117	0.7122

In this project, we used a DWT, RQA and PNN. The current work verifies that the discrete wavelet transform and recurrent quantification analysis are one of best method for extracting the epileptic seizure feature. Radial basis function neural network trained the network more robustly and tolerantly then traditional backpropagation neural network. Here, PNN shows the 100% classification result between seizure and non-seizure EEGs data. The classification of PNN values are tabulated below:

Table 3. The performance evaluation parameters of recurrent rate for A–E data set classification

ANN	SPECIFICITY	SENSITIVITY	ACCURACY	NO.v OF OUTPUT	DECOMPOSITION LEVEL
PNN	100%	100%	100%	15	5

5. Conclusion

In this project, a novel method for epileptic seizure detection in EEGs is proposed. Study explores the capacity of applying recurrent rate derived from discrete wavelet transform to classify EEG signals. The EEG signals are decomposed into 5 sub-signals through 5-level DWT. For each approximate and detailed coefficient recurrent rate feature obtained, which is used as an input of PNN classifier. We used data set A and E for the classification of healthy segments and epileptic seizure segments and the proposed method shows 100% classification accuracies result.

Acknowledgment

I would like to thank Dr. N. Pradhan, Senior Professor, Psychopharmacology department, National Institute of Mental Health and Neuro Sciences (NIMHANS), Bangalore, Karnataka, who has given me the much sought for opportunity to work in this prime research institute, and for guiding me with immense patience. And I am sincerely grateful to Prof. Chaitanya Srinivas L.V, Dept. of Biomedical Engineering, VIT University, Vellore, Tamil Nadu, India for his affectionate guidance and moral support throughout my project work.

Future scope

Seizure prediction with the help of EEG is however, still far from maturity and the uses of nonlinear techniques such as discrete wavelet transform and recurrent quantification analysis discussed in this paper should be considered exploratory. These explorations are essential, and they must continue to be pursed if there is eventually to evolve a body of techniques that can confidently be used to study signals from the brain. The methodology employed in this project is well defined for stationary time series generated by a low dimensional dynamical system moving around an attractor. Since the epileptic discharge is stationary for a brief period of time this technique is successful in estimating the onset of seizure discharge. But this methods fails in investing event related brain potential (ERP) because they are nonstationary by definition. Event related brain potential are characteristic changes in the EEG of a subject during and short after stimulus (surprising moment).

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