

Epileptic Seizure Classification of EEG Image Using ANN

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Abstract : The Life of people is becoming complicated every day due to explosion of population leading to crises of land, employment, agricultural proceeds, price hikes etc. This is followed by crunch of resources on the one hand and drastic fall in per capita income of country man also educational improvement is followed by its fruitlessness except intellectual development, under this situation countryman is facing stress on mind. Also the insecurity of careers and mental tensions are growing exponentially in the life of people. This may take the youth either to the direction of becoming criminal or to direction of surrendering before the uncontrollable pressure of helplessness. Both the paths give rise to further insecurity and mental tensions. The ultimate part which is attacked is mental health of person due to overstressed conditions. It is therefore recovery of mental health has become an important challenging concern of the doctors. In recent years humans suffer from various neurological disorders such as headache, dementia, traumatic brain injuries, strokes and epilepsy. Nearly 50 million people of the world population in all ages suffer from epilepsy. To diagnose epilepsy an automatic seizure detection system is an important tool. In this paper we present a new approach for classification of Electroencephalogram (EEG) signals into two categories namely epilepsy and non epilepsy.

Keywords: EEG, ANN, EMG, BP, Electroencephalogram(EEG), SVM, Electroencephalogram Classification, Discrete Wavelet Transform (DWT)

I INTRODUCTION

Electroencephalogram (EEG) is a complex human brain signal consisting of high information about brain function and neurological disorders.

Epileptic seizures affect the daily life of the patient due to its unpredictable and abrupt nature. Particularly, for drug resistant epileptic patients, the possibility to predict forthcoming seizures could be very useful, not only for the patient's safety, but also to have the possibility to stop the unwanted event. Pharmacological or electrical treatment on demand could, in fact, be applied to stop an oncoming seizure (Gottingen et al., 2005), (Estelle et al., 2004).

Epilepsy is a seizure disorder that affects the nervous system. Seizure is caused if there is any disturbance in the normal pattern of neuron activity. Detection of epilepsy by visual scanning of EEG signal is very time consuming and may be inaccurate, particularly for long recordings. The detection of epileptic seizures in EEG signals is an important part in the diagnosis of epilepsy.

II Fast Independent Component Analysis (Fast ICA)

In this paper, the epileptic seizures from the EEG brain signal are diagnosed with the aid of FastICA. The FastICA algorithm is an extremely efficient method for performing the estimation of ICA. The FastICA (Hyvarinen and Oja (1997); Hyvarinen (1999) is one of the most well-known and popular algorithms for both independent component analysis (ICA) and blind source separation. For an element linear non- Gaussian signal mixture, the algorithm consists of a signal prewhitening stage followed by a set of m fixed- point iteration that extracts independent components using a non-Gaussianity signal measure. Coefficient vector orthogonality is used to guarantee uniqueness of the extracted components.

The algorithm possess a number of valuable properties, including fast convergence, guaranteed global convergence for certain mixing conditions and contrasts, and robust behaviour even when noise is present [21].

Fast ICA is a common offline method to identify artifact and interference from their mixtures such as electroencephalogram (EEG), Magneto encephalography (MEG), and Electrocardiogram (ECG). Fast ICA has been compared with neural-based adaptive algorithms and principal component analysis (PCA), and most ICA algorithms were found to outperform. Its popularity has been justified on the grounds of satisfactory performance offered by the method in several applications, as well as its simplicity [12]. By employing FastICA to the input signal (EEG), the proposed approach extracts the independent subcomponents corresponding to epileptic seizure from the mixture of EEG signals. This is followed by the training of the ascertained independent subcomponents, applying ANN (Artificial Neural Networks). Fig. 1 depicts the block diagram of epileptic seizure detection process from EEG signal using FastICA and Back Propagation Neural Network (BPNN).

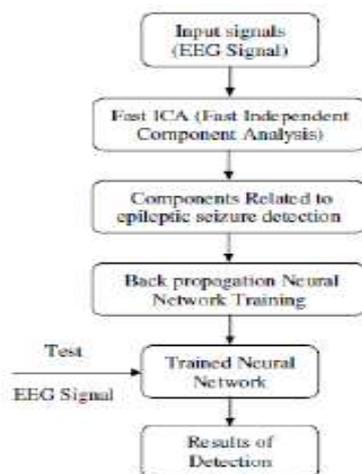


Fig. 1. Block diagram of the proposed epileptic seizure detection approach.

III Methodology

The proposed work aims at Classification of EEG signal as seizure and non-seizure, then do the frequency analysis of healthy and epileptic signal.

This proposed work is implemented by dividing it into two phases: Train phase and Test phase as shown in below block diagram

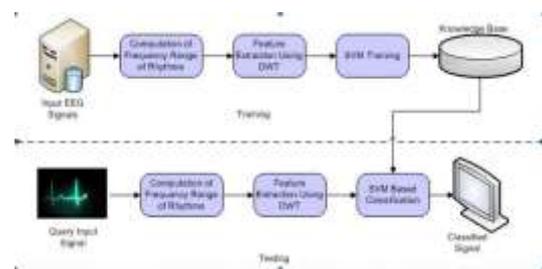


Fig.2. Block Diagram for Proposed work

A. Data Acquisition:

The EEG database for processing is extracted by the University of Bonn [8], [9]. This collection contains EEG information originating from different interval, to be specific, healthy subjects and epileptic subjects. The gathering these data contains five datasets recognized as: O, Z, F, N and S; each set have 100 sections of EEG signals of 23.6 seconds. Sets O and Z were gotten from healthy subjects with eyes open and shut individually; sets F and N were gotten among seizure free states in various zones of the mind and set S was gotten from a subject among seizure state [10]. Sets Z and S were utilized just for the outcomes reported here.

B. Generation of EEG signal using Dataset: We make use of the dataset to generate the EEG signal using MATLAB code. There are five sets of EEG dataset containing both healthy as well epileptic. We make use of both the signals to generate EEG signals. Each set have 100 signals, we take few in that and proceed for further process i.e. decomposition of these generated EEG signals.

C. Decomposition of EEG signals:

Now we make use of these generated EEG signals and decompose it using Daubechies Wavelet Transform db8, which decomposes EEG signal to 8 levels.

Based on the feature extraction, 8-dimensional feature sets (D1, D2, D3, D4, D5, D6 and D7 D8) for training and testing data were constructed.

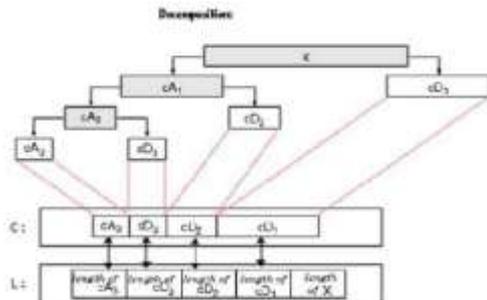


Fig.3. Decomposition of EEG signal

In above figure we see the decomposition using Daubechies, which decomposes the EEG signal into 8 levels as we are using db8. This decomposition of the signals gives us the co-efficient values and also the length of those co-efficient of different decomposed levels.

Disorder	A+ (Amplitude of Negative Spike)	A- (Amplitude of Negative Spike)	RMS Value of one cycle
Normal	+15	-15	15
Seizer	20	-10	22.36

Table -1 RMS value based Intelligent System development using ANN.

The above table-1 shows the wavelet coefficient frequency range and its signal information. After applying Daubechies Wavelet Transform db8 it decomposes EEG signal into 8 level i.e. 8 wavelet coefficient as shown in above table1-.As we are interested only in extracting the characteristics of EEG signal i.e. alpha, beta, gamma, delta and theta and we eliminate the higher frequencies which are basically noise.

D. Feature extraction: Feature Extraction is a sort of dimensionality diminishment to proficiently represent the significant attributes of a signal that are valuable for effective classification of EEG signal. The feature vectors are extracted by Discrete Wavelet Transform.

E. Support Vector Machine (SVM)

Training: The feature file created is given as input to the SVM toolbox for classification of EEG signal. SVM is chosen as a classifier because it is an efficient classifier for many real time applications. The goal is to correctly classify the given Data.

SVM is another sort of classifier that is inspired by two ideas. To start with, changing information into a high dimensional space can change complex issues (with complex choice surfaces) into less difficult issues that can utilize linear discriminant functions. Second, SVMs are inspired by the idea of training and utilizing just those inputs that are close to the choice surface since they give the most important data about the order. It is a sort of learning machine in view of statistical learning hypothesis.

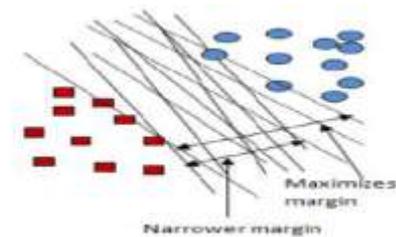


Fig.4.Support vector machine

IV.EXPERIMENTAL RESULTS

We have obtained EEG singals of various Brain disorders from Chilen Hospital Pitsburg Russia site and have processed them to maintain uniformity of presentation and for signal analysis . The EEG waveforms of various brain disorders is given as below.

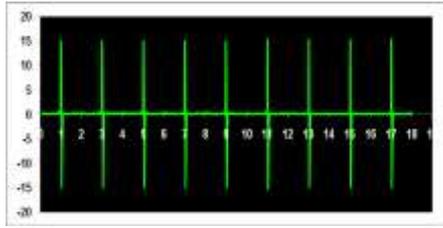


Fig.5 . EEG waveform of normal person

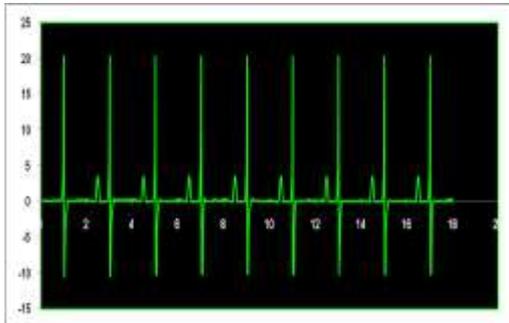


Fig. 6 EEG waveform of person suffering from Seizer disorder

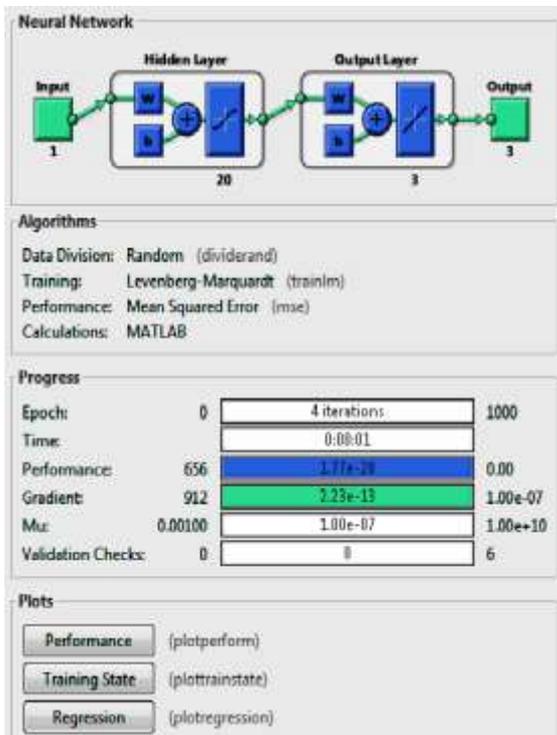


Fig.7 ANN – Training, Testing and Validation Process

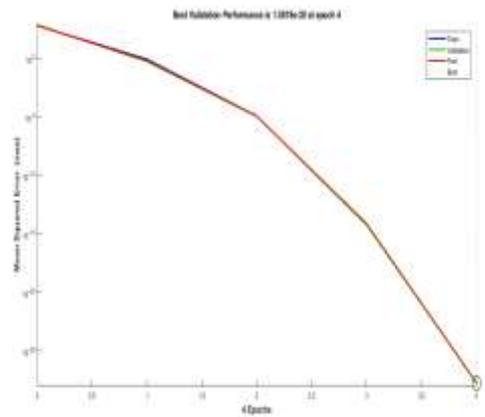


Fig. 8 Training results

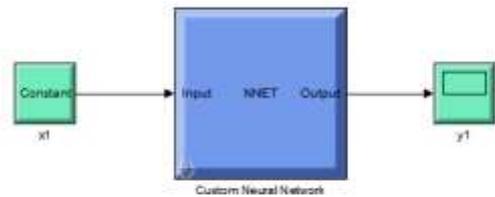


Fig 9 Simulink of ANN after training
Simulation Outputs



FIG. 10 Normal Human



Fig. 11 Epileptic seizures

V Conclusion

We Successfully trained the ANN with EBPN to efficiently classify the patterns of EEG Waveforms to respective Brain disorders. Thus we give an intelligent system which helps to classify the EEG record of patients using Soft computing approach. We have developed classification for seizure and non-seizure and frequency analysis for healthy and epileptic subject.

The proposed work uses SVM on signal processing for training of the system. A set of feature were chosen which were calculated using DWT during feature extraction phase and preserved in feature file which are used further for classification of signals as Seizure and Non-Seizure. This Computer-Aided technique is more reliable for classification of given EEG signal and also it helps to know the given signal is seizure or seizure free without the help of the neurologist. It is also time saving and efficient user friendly tool for the neurologist.

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