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Automated Epileptic Seizure Detection in EEG Signals Using FastICA and Neural Network

Sivasankari. N and Dr. K. Thanushkodi

Senior Lecturer, Department of ECE, Akshaya College of Engineering & Technology, Coimbatore
e-mail:sivasankari_phd@yahoo.com
Principal, Akshaya College of Engineering & Technology, Coimbatore
e-mail:thanush12@gmail.com

Abstract

Brain is one of the most vital organs of humans, 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. Epileptic seizures typically lead to an assortment of temporal changes in perception and behavior. A significant way for identifying and analyzing epileptic seizure activity in humans is by using Electroencephalogram (EEG) signal. In a significant number of cases, detection of the epileptic EEG signal is carried out manually by skilled professionals, who are small in number. This necessitates automated epileptic seizure detection using EEG signals. To add with, a number of researchers have presented automated computational methods for detecting epileptic seizures from EEG signals. In this article, we propose a novel and efficient approach for automatically detecting the presence of epileptic seizures in EEG signals. First, the input EEG signals are analyzed with the aid of Fast Independent Component Analysis (FastICA), a Statistical Signal Processing Technique, to obtain the components related to the detection of epileptic seizures. The BackPropagation Neural Network is trained with the obtained components for effective detection of epileptic seizures. The experimental results portray that the proposed approach efficiently detects the presence of epileptic seizure in EEG signals and also showed a reasonable accuracy in detection.

Keywords: *Electroencephalogram (EEG) signals, Epilepsy, Seizures, Epileptic Seizures, Statistical Signal Processing, Fast Independent Component Analysis (FastICA), BackPropagation Neural Network (BPNN).*

1 Introduction

Epilepsy is a common term that incorporates different types of seizures. Epilepsy is characterized by unprovoked, recurring seizures that disturb the nervous system. Seizures or convulsions are temporary alterations in brain functions due to abnormal electrical activity of a group of brain cells that present with apparent clinical symptoms and findings [3]. Epilepsy may be caused by a number of unrelated conditions, including damage resulting from high fever, stroke, toxicity, or electrolyte imbalances [3]. The disease epilepsy is characterized by a sudden and recurrent malfunction of the brain that is termed “seizure.” Epileptic seizures reflect the clinical signs of an excessive and hyper synchronous activity of neurons in the brain [1]. Approximately one in every 100 persons will experience a seizure at some time in their life [2].Epilepsy and seizure are two dissimilar terms where in seizures are the symptoms of epilepsy and epilepsy is the causal propensity of the brain to create an unexpected rupture of electrical energy. Epilepsy can be segregated into two broad categories namely idiopathic epilepsy and symptomatic epilepsy. The former is a kind of epilepsy in which the cause for the epilepsy remains unmarked whereas in the latter case a concrete cause is identified. The symptomatic epilepsy is typically identified through any one of the subsequent symptoms: stroke, serious illness in the nervous system, severe damage to the skull and more. In general there are nearly twenty types of seizures. These types are again divided into two categories namely partial seizures and generalized seizures.

In partial seizures the electrical disturbances is restricted to a precise area of one cerebral hemisphere. Further down, the partial seizures are classified into simple partial seizures and complex partial seizures. The difference between the two seizures is, in simple partial seizures consciousness can be retained and in complex partial seizures consciousness is harmed or lost. Partial seizures might spread to cause a generalized seizure, where in the classification category is partial seizures secondarily generalized [15]. Generalized seizures distress both the cerebral hemispheres from the onset of the seizure. They generate failure of consciousness, either for a short time or for a longer period of time.

Besides the existence of numerous technologies for diagnosing epileptic seizure, such as Electroencephalogram (EEG), Magnetic resonance imaging (MRI), Positron emission tomography (PET) etc., the EEG signals are widely used in the diagnosis and study of epileptic seizure. The reason for choosing the EEG over the other two is that the EEG signals record ample information regarding the function of the brain. Electroencephalogram (EEG) is illustrated as the representative signal containing information of the electrical activity generated by the cerebral cortex nerve cells. This has been the most utilized signal in clinical assessment of brain activities and the detection of epileptic form discharges in the EEG is an important component in the diagnosis of epilepsy [4].The Electroencephalograph (EEG) signals involve a great deal of information about the function of the brain. EEG obtained from scalp electrodes, is a superposition of a large number of electrical potentials arising from several sources (including brain cells i.e. neurons and artifacts) [13]. However the potentials arising from independent neurons inside the brain, not their superposition, are of main interest to the physicians and researchers to describe the cerebral activity. Direct measurements from the different centers in the brain require placing electrodes inside the head, which needs surgery. This is not acceptable because it causes pain and risk for the subject. A better solution would be to calculate the signals of interest from the EEG obtained on the scalp [14].

In general Signal processing is the analysis, interpretation, and manipulation of signals [9]. The secondary fields of signal processing are Analog signal processing and Digital signal processing. The essence of this work is Digital Signal Processing. DSP includes the representation of signals as a series of numbers or symbols and the processing of these symbols with the assistance of various digital techniques. DSP includes several sub fields like: audio and speech signal processing, sonar and radar signal processing, sensor array processing, spectral estimation, statistical signal processing, digital image processing, signal processing for communications, biomedical signal processing, seismic data processing, etc [10].Many approaches have been proposed to extract information from EEG signals that can be used to develop algorithms to predict or detect epileptic seizures such as Wavelet transform [5], Recurrent Neural network [6], nonlinear systems [7], logistic regression [8], spectral densities of DWT coefficients [16], etc. Here, the epileptic seizure in an EEG signal is discovered by utilizing the Fast ICA i.e. Fast Independent Component Analysis, a prominent statistical signal processing technique.

2 Related Works

Literature presents a number of researches that deal with detection of epileptic seizure detection from EEG signals. Of them, a handful of researches make use of the Statistical Signal Processing and Artificial Intelligence (AI) to achieve epileptic seizure detection from EEG signals. A few selected important contributions are presented below.

A.T. Tzallas *et al.* [22] have proposed a time-frequency analysis based method for EEG signal analysis. Firstly, chosen segments of the EEG signals are examined by making use of time-frequency methods and a number of features, representing the energy distribution in the time-frequency plane are extracted from every segment. Subsequently, the features extracted are fed as input to an artificial neural network (ANN), which offers the ultimate classification of the EEG segments regarding the presence of seizures or not. They made use of an openly available dataset so as to assess the method. The assessment results were very promising portraying an overall accuracy from 97.72% to 100%.

Andrew B. Gardner *et al.* [23] have presented an application of one-class Support Vector Machine (SVM) for accomplishing seizure detection in humans. The proposed technique mapped intracranial electroencephalogram (EEG) time series into equivalent novelty sequences by classifying short-time, energy-based statistics calculated from one-second windows of data. A classifier was trained on epochs of interictal (normal) EEG. In addition, a hypothesis test was used to determine when the parameter change differs considerably from its nominal value, signaling a seizure detection event. With the purpose of reducing the false alarm rate of the system, outputs were gated in a one -shot manner using persistence. The novelty detection paradigm overcame three important setbacks of its contenders: 1) the need for collection of seizure data, exactly mark seizure onset and offset times, and achieve patient-specific parameter tuning for detector training.

Srinath Vukkadala *et al.* [24] have presented an automated epileptic EEG detection system based on Elman neural network that makes use of approximate entropy (ApEn) as the input feature. ApEn is a statistical parameter that determines the predictability of the current amplitude values of a physiological signal on the basis of its previous amplitude values. Their system made use of the fact that the value of the ApEn drops sharply during an epileptic seizure. The accuracy of the overall system was evaluated based on recordings from only 21 patients but it had capability of being an efficient and accurate system for an automated Epileptic EEG detection, because of the robustness of ApEn and the high overall detection accuracies usually observed in ANNs.

Kifah Tout *et al.* [25] have proposed a scheme for epileptic seizure prediction based on neural networks. They have applied the parameters that most probable could symbolize the long term EEG signal as inputs of the multilayer neural network .They have trained the neural network to detect the ictal and non-ictal patterns, and then, tested the network for prediction. Moreover, they determined the sensitivity and specificity of the prediction. They have also concluded that with 5 parameters used as inputs of the MLP network, the prediction had a high sensitivity and a high specificity (88%).

M. Abdulhamit Subasi *et al*. [26] have examined the application of AutoRegressive (AR) model using maximum likelihood estimation (MLE) and also interpretation and performance of their method to extract classifiable features from human electroencephalogram (EEG) by making use of Artificial Neural Networks (ANNs). ANNs was tested for accuracy, specificity, and sensitivity on classification of every patient into the right two-group categorization: epileptic seizure or non-epileptic seizure. They have also studied that, ANN classification of EEG signals with AR produced better results and those results could be used for detecting epileptic seizure

Forrest Sheng Bao *et al.* [27] have developed a diagnostic system that can employ interictal EEG data to automatically diagnose epilepsy in humans. The system could also detect seizure activities for preceding examination by doctors and impending patient monitoring. The system was developed by extracting three classes of features from the EEG data. These features were fed up with to build a Probabilistic Neural Network (PNN). Leave-one-out cross-validation (LOO-CV) on an extensively used epileptic-normal data set reveals a striking 99.3% accuracy of the system on distinguishing normal people's EEG from patients' interictal EEG. Moreover, it was found that the system can be used in patient monitoring (seizure detection) and seizure focus localization, with 96.7% and 76.5% accuracy respectively on the data set.

For epileptic seizure detection, Gulay Tezel and Yuksel Ozbay [28] have presented neural network models with adaptive activation function (NNAAF). The presented NNAAF models composed of three types namely, NNAAF-1, NNAAF-2 and NNAAF-3. The activation function of the hidden neuron in the model of NNAAF-1 was a sigmoid function with free parameters. NNAAF-2, the second model had the activation function of hidden neuron was the sum of sigmoid functions with free parameters and sinusoidal functions with free parameters. Whereas, hidden neurons' activation function was Morlet Wavelet function with free parameters in the third model, NNAAF-3. Besides, they have applied traditional multilayer perceptron (MLP) neural network (NN) model with fixed sigmoid activation function in the hidden layer to evaluate NNAAF models. The robustness of these models was analyzed by means of training and testing using 5-fold cross-validation and also found the best model among them. They have achieved 100% average sensitivity, average specificity, and in the region of 100% average classification rate in all their models.

D. Najumnissa and S. Shenbaga Devi [29] have proposed a simple approach to classify different types of epileptic seizures. A set of feed forward neural network with wavelet feature extraction are used to process time, frequency to detect and classify the type of seizure like absence, Tonic-clonic, Febrile and Complex partial seizures. Tests of the system on EEG show a success rate of 94.3%. The method makes it potential as a real-time detector, which will enhance the clinical service of Electroencephalographic recording. Otis Smart *et al.* [30] have presented a Genetic Programming (GP) application to optimally choose and combine conventional features (C-features) for the detection of epileptic waveforms within intracranial electroencephalogram (IEEG) recordings that occur prior to the onset of seizures, known as seizure precursors. Evidences recommended that seizure precursors may localize regions significant to generation of seizure on the IEEG and epilepsy treatment. They have recommended GP as an optimal substitute to generate a single feature after examining the performance of a binary detector that makes use of: (1) genetically programmed features; (2) features selected by means of GP; (3) forward sequentially selected features; and (4) visually selected features. Their results have illustrated that a detector with a genetically programmed feature surpasses the other three approaches, accomplishing more than 78.5% positive predictive value, 83.5% sensitivity, and 93% specificity at the 95% level of confidence.

To detect epileptic seizure segments in the neonatal electroencephalogram (EEG), Karayiannis N.B. *et al*. [31] have presented an approach by distinguishing the spectral features of the EEG waveform using a rule-based algorithm combined with a neural network. The rule-based algorithm employed screened-out short segments of pseudosinusoidal EEG patterns as epileptic based on features in the power spectrum. The conventional feed forward neural networks and quantum neural networks were trained with the output of the rule-based algorithm and their performance was also compared. The results denoted that the trained neural networks, cascaded with the rule-based algorithm, enhanced the performance of the rule-based algorithm working by own. The assessment of their cascaded scheme for the pseudosinusoidal seizure segment detection exposed its capability of being a building block of the automated seizure detection system under development.

3 Proposed Methodology

The proposed approach makes use of the Fast Independent Component Analysis (FastICA) and the Back Propagation Neural Network (BPNN) for achieving epileptic seizure detection from EEG signal. The proposed work is composed of two phases 1) Separation of EEG signals into independent subcomponents using FastICA and 2) Epileptic seizure detection using BPNN. In general, EEG signals recorded from scalp electrodes are found to have artifacts or simply, can be defined to consist of combination of few other signals. In the proposed approach, the input EEG signal is fed as input to the FastICA, which separates the inputted EEG signal into a number of additive subcomponents assuming the mutual statistical independence of the non-Gaussian source signals. The independent subcomponents thus separated are then provided as a training input to the BPNN. Afterwards, when an EEG signal is provided to the trained BPNN, it detects the presence of epileptic seizure based on the independent subcomponents obtained from a FastICA.

3.1 Epileptic Seizure Detection Using Fast Independent Component Analysis (FastICA)

The initial phase of our work is meant to separate the independent subcomponents from the recorded EEG signals, by employing FastICA. Signal processing has also been made use of to deal with miscellaneous issues in EEG analysis such as data compression, detection and classification, noise reduction, signal separation, and feature extraction. The analysis of these signals is vital for the research in medical diagnosis and treatment as well. A Statistical Signal Processing Technique has been employed, which considers signals as either stochastic processes or random processes [11]. The input EEG signals are to be interpreted before it is fed to the BPNN and, one of the best known ways to blindly separate the signals would be to make use of the Independent Component Analysis (ICA). In the proposed approach, we have utilized FastICA to separate the independent subcomponents from the recorded EEG signal. The primary reason behind the use of FastICA is that the algorithm directly identifies independent components of (practically) any non-Gaussian distribution using some nonlinearity. This is in contrast to many existing ICA algorithms, where some approximation of the probability distribution function has to be initially available, and the nonlinearity must be chosen accordingly. The section below presents the working of the FastICA.

3.2 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 (Hyvärinen and Oja (1997); Hyvärinen (1999)) is one of the most well- known and popular algorithms for both independent component analysis (ICA) and blind source separation. For an m- 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 behavior even when noise is present [21] .

Fast Independent Component Analysis (FastICA) algorithm separates the independent sources from their mixtures by measuring non-Gaussian. FastICA is a common offline method to identify artifact and interference from their mixtures such as Electroencephalogram (EEG), Magnetoencephalography (MEG), and Electrocardiogram (ECG). FastICA 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]. Other advantages of FastICA algorithm are: it can be used to perform projection pursuit and in addition it is used both in an exploratory fashion and also for estimating the independent components (or sources). FastICA maximizes the non-Guassianity mixtures of the detected signals at different frequencies and thereby tries to separate the different independent components under a number of assumptions.

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 BackPropagation Neural Network (BPNN).

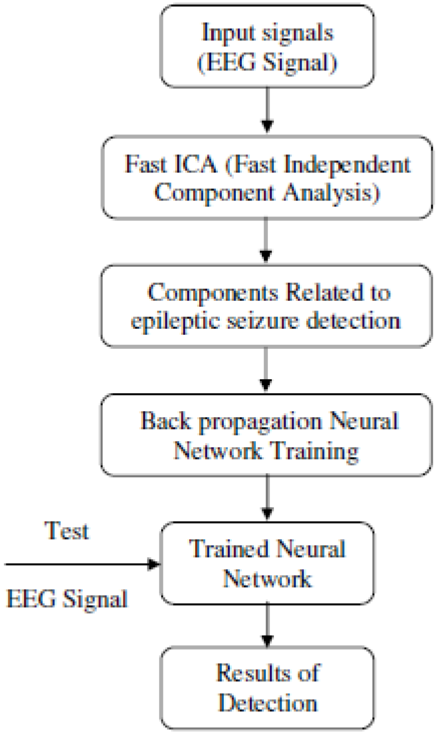

Fig. 1. Block diagram of the proposed epileptic seizure detection approach

4 Training of Backpropagation Neural Network

Once the epileptic seizure is separated from the EEG signals with the aid of Fast Independent Component Analysis, the training process will have to be carried out. Artificial Neural Networks (ANN) comes in handy for the training purposes and so it is utilized here. Literally speaking, the Artificial Neural Networks (ANN) is the elemental electronic delineation of the neural framework of the brain. An Artificial Neural Network is an adaptive, most often nonlinear system that learns to carry out a function (an input/output map) from data [16]. The effect of the transformation is determined by the characteristics of the elements and the weights associated with the interconnections among them. By modifying the connections between the nodes the network is able to adapt to the desired outputs, Fig. 2 [17] [18].

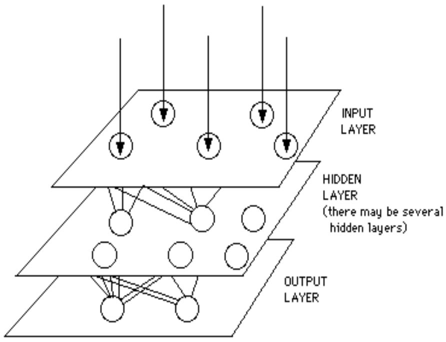

Fig. 2. Architecture of Artificial Neural Networks

The seizure affected parts of the brain can be identified once the Artificial Neural Networks are trained with the recorded EEG signals. In ANN, there are several techniques for training the input data. In the proposed approach, we use Back propagation algorithm for training the components obtained from the input (EEG) signals (Fig. 3).

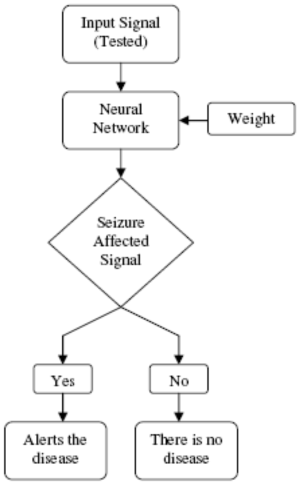

Fig. 3. Block diagram of Neural Network Detection

4.1 Back Propagation Algorithm

In this paper, for training the EEG signals we utilize Back propagation algorithm. One of the most commonly used supervised ANN model is back propagation network that uses back propagation learning algorithm [19]. Back propagation algorithm is appropriate for pattern recognition problems. The back propagation neural network is essentially a network of simple processing elements working together to produce a complex output. These elements or nodes are arranged into different layers: input, middle and output [20]. The advantages of Back propagation algorithm are, it is simple and its speed is also reasonable. The working procedure of back propagation algorithm is as follows (Fig. 4):

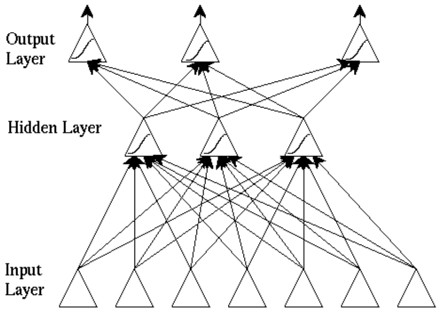

Fig.4. Architecture of Back Propagation Neural Network

In a backpropagation neural network, the learning algorithm has two stages. Initially, a training input pattern is presented to the network input layer. The network propagates the input pattern from layer to layer until the output pattern is produced by the output layer. If this pattern is dissimilar from the preferred output, an error is intended and then propagated backward through the network from the output layer to the input layer. The weights are customized as the error is propagated. In the proposed approach, we primarily present the test input signal i.e. EEG signals to the neural network, which in turn compares the input signal with the trained signal, on the basis of the weight factor. If the input signals (EEG signal) contain epileptic seizure, then the trained network notifies the occurrence of the disease. The utilization of Back propagation shows better results in the detection of seizure from EEG signal.

5 Experimental Results

The experimental results of the proposed approach for automatically detecting epileptic seizures in EEG signals using FastICA and back propagation neural network is detailed in this section. The presented approach is programmed in Matlab 7.8. The EEG signals experimented in the proposed approach was collected from [32]. Initially, the components corresponding to epileptic seizure detection are separated from the input EEG signals using FastICA. Afterwards, the BPNN was trained with the separated components from 400 EEG signals, of which 200 were seizure affected EEG signals and others were normal EEG signals. In the testing phase, an EEG signal is provided as test input for epileptic seizure detection. The accuracy results of the proposed approach are given in Table 1. Fig. 5 shows the results obtained using the experimentation on the proposed approach.

Table 1: Accuracy results of the proposed approach

Detection Accuracy		
Category	Detection Results	Overall accuracy in %
Seizure affected (200)	153 signals	76.5
Normal EEG Signals (200)	132 signals	66

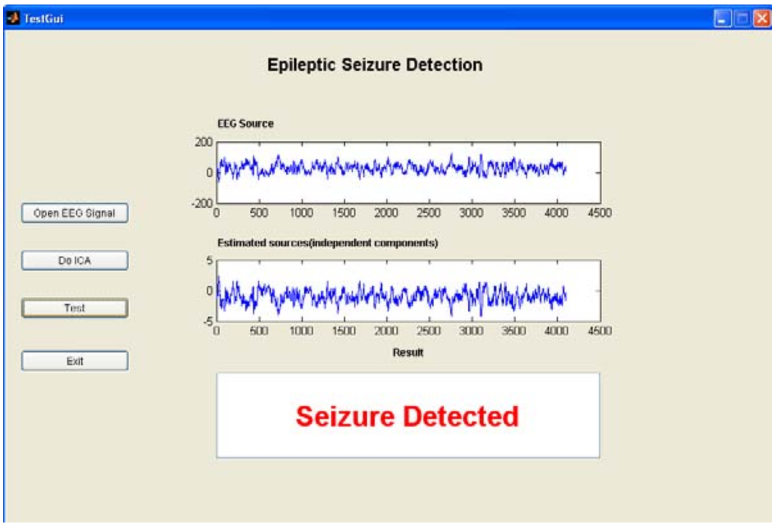

Fig.5. Detection of Epileptic Seizures

6 Conclusion

The predominant purpose of this research is to achieve epileptic seizure detection from the recorded EEG brain signals. To begin with, independent subcomponents are separated from the recorded signals with the aid of Fast Independent Component Analysis. Further, the signals are trained using ANN (Artificial Neural Networks) technique namely Back propagation algorithm. For testing, the EEG signals acquired from the brain are separated into independent subcomponents employing the Fast Independent component analysis and then, those independent subcomponents separated are fed to trained Back Propagation algorithm for epileptic seizure detection. The exertion of FastICA and ANN proffered encouraging results in the detection of epileptic seizure from the recorded EEG signals.

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