

Automated Electroencephalogram Based Advanced Diagnosis of Diseases

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Abstract: Automatic disease detection is important in relieving the heavy workload of examining prolonged electroencephalogram (EEG). Manually Diagnosing disease in EEG is a tedious process and it consumes tens of hours of EEG recording. Early diagnosis and classification of diseases is very important in clinical practice. With recent development in the biomedical engineering and instruments, EEG recording instruments are able to record the electric activities of brain with high accuracy, which founds EEG as a most important tool for diagnosing the abnormalities of brain. This paper represents automated electroencephalogram based advanced diagnosis of diseases using FastICA (fast independent component analysis) and artificial neural networks (ANNs). FastICA is an efficient method to identify artifact and actual EEG from their mixtures. EEG signals carry the information of human brain with artifacts. These artifacts are removed by FastICA algorithm. Further, an ANN is designed to achieve process like a brain. The clean EEG is fed to feed forward back propagation neural network to diagnosis disease. Training parameters and type of neural networks are decided by operators on the interface. Performance of this model is evaluated using overall accuracy.

Keywords: EEG Signals; Artificial Neural Network; Epilepsy; FastICA; electroencephalograph; ANN; feed forward back propagation.

I. INTRODUCTION

Encephalogram (EEG) is a method to record electro activity of the human brain. Normally electrodes placed along the scalp are non-invasive. Sometimes invasive electrodes are used in certain specific applications. It is recorded from many electrodes placed in a certain pattern (montage), widely accepted pattern standard is international 10/20 System standard. Generally these methods are inexpensive and give a continuous record with better than millisecond resolution. EEG measures voltage variations resulting from ionic current within the neurons of the human brain. Normal voltage range of the EEG is lying between 10 and 100 μ V, and in adults more frequently in the range of 10 and 50 μ V. In the EEG frequency spectrum, range lengthens from ultraslow to ultrafast. The extreme frequency ranges don't have any important role in the EEG. The general frequency range is between 0.1Hz and 100Hz. It is generally categorized into numerous frequency components. There are four frequency bands are relevant: (i) delta, (ii) alpha, (iii) beta and (iv) theta [1].

Delta wave is slowest wave having maximum amplitude. Its frequency range lies in between 0.5 and 4 Hz and is main in adults in deep sleep and kids up to one year. Theta wave is a slow wave, frequency range lies in between from 4 Hz to 7 Hz. It occurs with closing eyes and with relaxation in both kids and adults. Alpha waves have frequency range in between 7 Hz to 12 Hz. It is most common for adults. It occurs rhythmically on both sides of the human head. Alpha wave occurs with closing of eyes (indicate relaxation) and disappears normally with opening of eyes (indicates stress) and treated as a usual waveform. Beta waves have fast activity and amplitude is less than 30 μ V. Its frequency range lies in between 14 Hz to 30 Hz. It is actually present in those patients who are aware or anxious or have stressor their eyes open. Normally it is seen on both sides of head in symmetrical distribution and observed in all ages. It has a normal rhythm and mostly occurs in central region of the human brain.

There are several research endeavour on EEG signals shows an efficient way to diagnosis brain diseases such as epilepsy. Salai Selvam, V. and S. Shenbaga devi [2] proposed quadratic phase coupling phenomenon to detect brain tumor. Andrzej Cichocki, Sergei L., Shishkina, et.al [3] proposed a methodology to improve the performance of the existing EEG approaches to early diagnosis of Alzheimer's disease. Muhammad Tariqus Salam et.al [4] proposed a procedure for epileptic seizure onset detection. Marjan Mirzaei and Muhammad Tariqus Salam [5] present a new asynchronous seizure detector that is part of an implantable integrated device intended to identify electrographic seizure onset and trigger a focal treatment to block the seizure progression. Wei-Ming Chen et.al [6] proposed a methodology for real-time epileptic seizure control. Aapo Hyvärinen [7] introduced new objective (contrast) functions and algorithms for ICA. Ronald Tetzlaff and Vanessa Senger [8] proposed methodology for seizure prediction problem in epilepsy.

II. AUTOMATED DETECTION

Automated diagnosis of abnormal EEG recordings gives two major problems: 1) detection of spike and 2) seizure analysis. Moreover, steps for automated diagnosis of seizure can be divided into two categories: (i), Artifacts removal [9] (ii) epileptic seizure detection

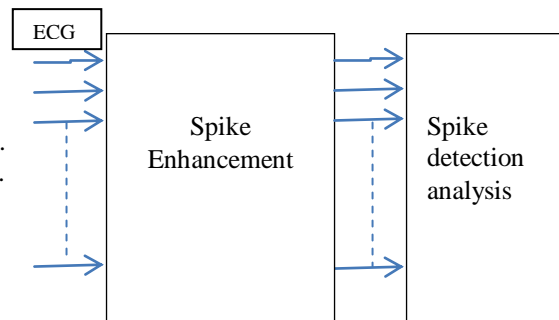


Fig1. Automated epileptic seizure analysis

A. FastICA

Independent Component Analysis (ICA) is a method for finding fundamental components or factors from multi-dimensional (multivariate) statistical data. ICA is different from other methods because it looks for components that are both non-Gaussian or nonlinear and statistically independent.

The model for ICA [10] is estimated by calculating function and then reducing or maximizing it. Such a type of function is known as objective function or cost function or contrast function. The optimization of the cost function enables the analysis of the independent components. The ICA method blends the optimization algorithm and a contrast function. The statistical parameter such as variance, robustness, and consistency of the ICA depend on memory requirements, numerical stability and convergence speed. The cost function is a calculation of independence.

An important calculation of non-gaussianity [11] is given by negentropy [11] (negative entropy). Negentropy is based on differential entropy. The entropy of a random variable (RV) can be taken as the degree of data that the observation of the variable gives. An essential result of information theory is that a Gaussian variable (GV) has the principal entropy among all RVs of same variance. This means that entropy could be used as a measure of non-gaussianity. The benefit of using negentropy as a calculation of nongaussianity is that it is well acceptable by statistical theory. When considering statistical property, negentropy is an ideal estimator of nongaussianity.

FastICA [10] is an efficient and accurate method to calculate independent component. It takes benefits of the approximation of negative entropy, which calculates the definite non-gaussianity of each IC, to reduce the computational or iteration time and complexity. This algorithm can be divided into two main stages: pre-processing stage and iterative stage.

The FastICA and the fundamental contrast functions have many important properties when compared with existing techniques for ICA.

- Cubic convergence (fast convergence)
- No step size features to choose. That is very easy to use
- The algorithm directly analysis independent components for any non-Gaussian.
- The characteristics of this algorithm can be improved by selecting a suitable nonlinearity. So it is very robust.
- The IC can be analysed one by one, which is unevenly comparable to doing projection pursuit. Can be used in exploratory data analysis, and decreases the iteration and computational time and load.
- Algorithm has all the merits of neural algorithms: It is distributed, computationally simple, needs little memory space and parallel. Stochastic gradient methods seem to be preferable only if fast adaptively in a changing environment is required.

B. Artificial Neural Network

The basic components of an Artificial Neural Network (ANN) are neurons, which are functions that calculate input data utilizing biases and weights to generate an output. These neurons can be made in clusters and cascaded, this forms a multi-layered networks. A feed-forward back propagating neural network includes managed learning, in which the processed outputs from each neuron move forward to different layers until final desired output is formed. The back propagation technique then modifies the weights and biases continually so that the computed output is near to the desired output as determined by the MSE (mean-squared error) value. The algorithms used for randomly adjusting

biases and weights changes are LM (Levenberg–Marquardt), the quasi-Newton algorithms and resilient back propagation (RP). These algorithms are different in their memory requirement, total time to train, and convergence speed. Although the LM is memory-intensive, converges fast, and hence generally chooses the feed forward back propagation algorithm for training. The training process stops when either the maximum number of epochs is reached or the desired performance is met.

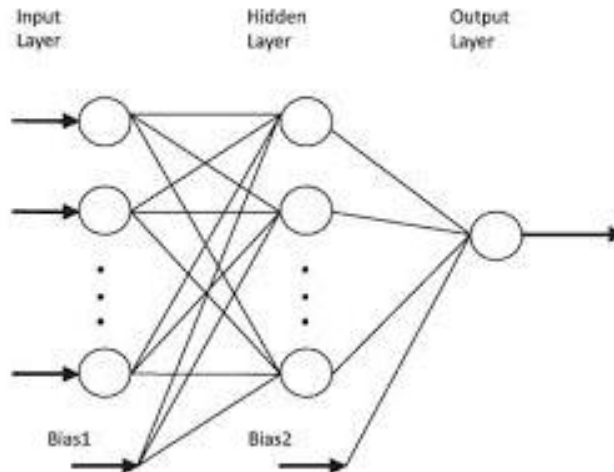


Fig 2. Neural network architecture

III. PROPOSED METHOD

Diagnosis of Epileptic seizure is important. This method will help Doctors especially neurologists in their diagnosis of disorders. Highly skilled neurologists and experts currently try to identify visual markers of EEGs. But, because of artifacts, EEG can include markers invisible to the eyes of them. Moreover, it can help them in identifying the source of the seizure activity or particular montage where seizure occurs.

Two main algorithms are used for automated diagnosis. First one is FastICA which is used to extract independent component from mixed 16 channels EEG. That is, this algorithm designed to separate artifacts and signal of interest. Second one is feed forward back propagation to detect abnormality in the cleaned EEG.

A. FastICA Algorithm

The FastICA algorithm can be partitioned into two main stages: pre-processing stage and iterative.

In pre-processing Stage Centering and whitening are used to reduce iteration time. i -th channel Centering function of the with length N is

$$\bar{x}_i(j) = x_i(j) - E\{x_i\} \quad (1)$$

Where $j=1,2,\dots,n$ sample length, $\bar{x}_i(j)$ and $E\{x\}$ are i -th channel centered data and the mean of the signal. Whitening can be described as follows:

$$C_x = E\{\bar{X}\bar{X}^T\} = EDE^T \quad (2)$$

Where C_x is an $n \times n$ symmetric matrix, D is a diagonal matrix formed and E is an orthogonal matrix
Then whitened data Z is

$$Z = D^{-1/2} E^T \bar{X} \quad (3)$$

Whitened data Z is used in the next stage (iterative stage). Approximated neg-entropy J is

$$J(w^T Z) \approx [E\{G(w^T Z)\} - E\{G(v)\}]^2 \quad (4)$$

Where

$$G(u) = \frac{1}{a} \log \cosh(au).$$

The operation of modified weight vector by Newton iteration and approximate negative entropy are represented.

$$w^+ = E\{Zg(w^T Z)\} - E\{g'(w^T Z)\}w \quad (5)$$

In order to prevent dependent component converges to maxima, de correlation is needed. For this deflationary or symmetrical orthogonalization method can be used.

$$w_{p+1}^+ = w_{p+1} - \sum_{K=1}^p (w_{p+1}^T w_K) w_K, \quad (6)$$

$$w_{p+1}^* = \frac{w_{p+1}^+}{\|w_{p+1}^+\|} \quad (7)$$

Where w_{p+1}^* is simplified by removing the projections on other orthogonal weight vectors and then being normalized. $p+1$ weight w_{p+1}^* vectors are orthonormal after the de-correlation and normalization. Iteration stops if they are in the same direction.

B. Artificial Neural Network

A feed-forward back propagating neural network includes managed learning, in which the processed outputs from each neuron move forward to different layers until final desired output is formed. The back propagation technique then modifies the weights and biases continually so that the computed output is near to the desired output as determined by the MSE (mean-squared error) value.

IV. EXPERIMENTAL RESULTS

In the simulation, initially EEG signals are in .EEG (Nihon Khoden) format which is converted to ASCII (.txt/.data) by using EDF browser.

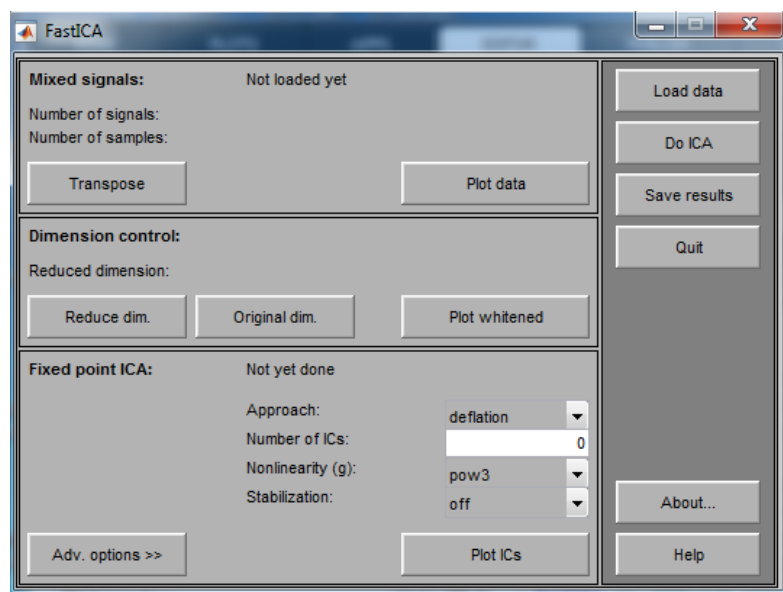


Fig 3 FastICA

Matlab based GUI have main two parts. In first part, 16 channel EEG signals are plotted with artifacts and without artifacts by using FastICA. Before this process, recorded EEG datasets are loaded to Matlab platform with Load data button as shown in Fig. 3.

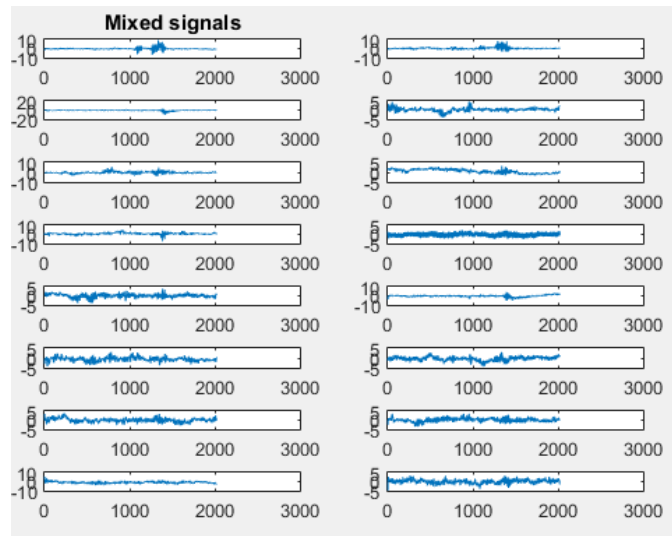


Fig.4 16 channel Mixed EEG signal

In Fig. 4 and Fig.5 are shows 16 channels EEG with artifacts and signals after preprocessing. In ICA processing, the artifacts from 16 channels EEG is extracted and separated into independent component, as shown in Fig. 6.

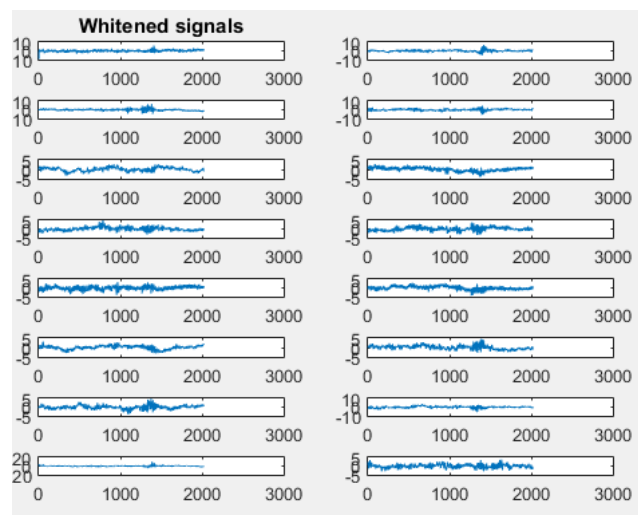


Fig.5. 16 channel whitened signal

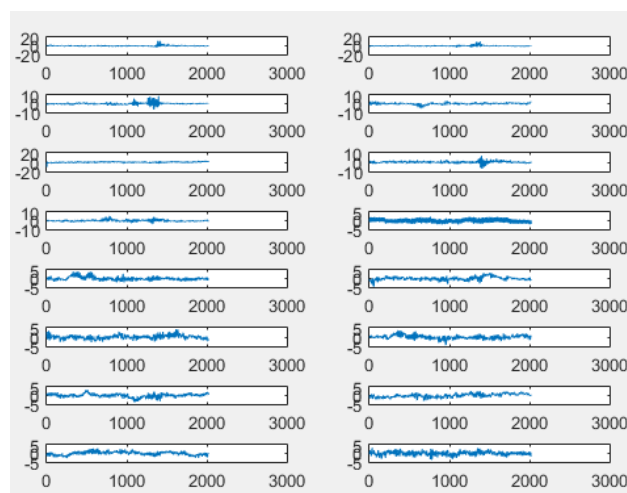


Fig.6. 16 channel independent component

Artificial neural network is used to analysis epilepsy from cleaned 16 channel EEG, in which used some EEG data to train network.

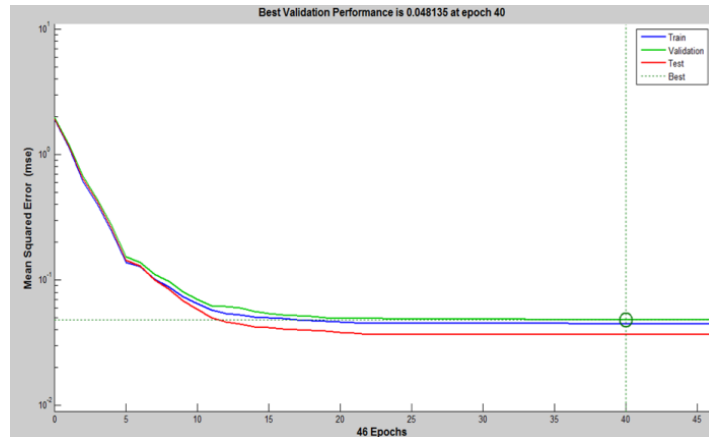


Fig. 7 Training performance

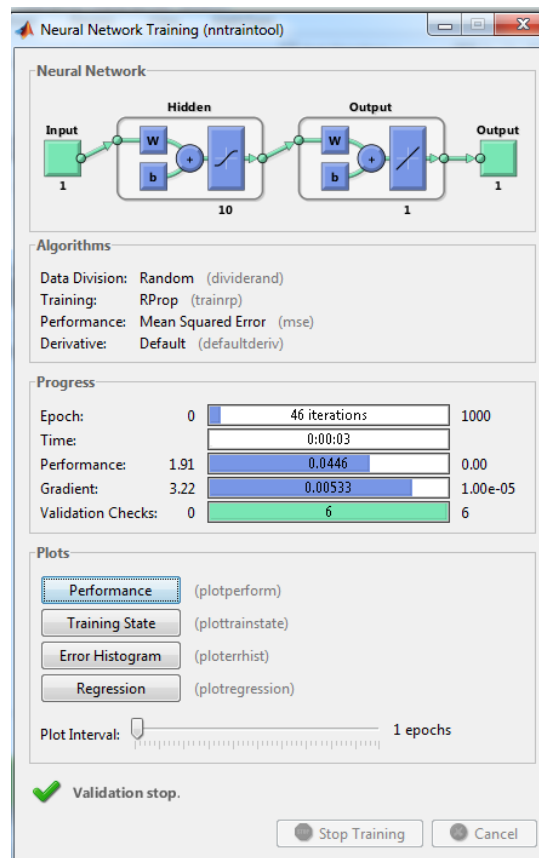


Fig. 8.ANN

Fig.8 shows the artificial neural network and Fig.7gives the training performance of ANN. Got the bestvalidation performance as 0.048135 at epoch 46.The trained neural network is simulated with normal and seizuredata.

V. CONCLUSION

Automated Electroencephalogram Based Advanced Diagnosis of Diseases is proposed. Artifacts can be removed efficiently by using FastICA and disease can be diagnosed using artificial neural network. The proposed method achieves a better evaluation and an automated diagnosis of possible neural disorders, than those obtained using existing detection techniques.

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