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Neural Network based classification of EEG Signal in induced focal cerebral ischemic rat brain

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Abstract: **The brain exists in a number of attractors. In order to classify these attractors we have developed Matlab based Neural Network program. We have collected the EEG time series data of the fronto-parietal, occipital and temporal regions of the rat brain. Wavelet analysis was used to decompose the EEG into delta, theta, alpha, beta sub-bands. DWT (Discrete Wavelet Transform) coefficients of the EEG signals were used as input to the neural network. A mean square error of 10^{-20} was obtained in the training phase leading to accurate classification. This approach has a promise of becoming a useful diagnostic tool of cerebral stroke victims.**

Index terms - EEG; Focal Cerebral Ischemia; Discrete Wavelet transform; Neural Network.

I. Introduction

Worldwide, stroke is the second leading cause of death, responsible for 4.4 million (9 percent) of the total 50.5 million deaths each year [1]. A stroke is a condition in which the brain cells suddenly die because of a lack of oxygen. This can be caused by an obstruction in the blood flow, or the rupture of an artery that feeds the brain. Ischemic strokes are ultimately caused by a thrombus or embolus that blocks blood flow to the brain. Ischemic stroke accounts for about 87% of all strokes and occurs when a blood clot or thrombus forms that blocks blood flow to part of the brain. Accurate classification of the state of the patient is paramount in diagnosing the patient`s condition.

The Electroencephalography (EEG) recordings, which are aperiodic time series, are a result of the contributions of large number neuronal potentials. We have investigated induced focal cerebral ischemia and subsequent recovery by application of the Piroxicam drug. Piroxicam drug has been used earlier studies [2]. Ischemic model of rat brain has been extensively studied by [3]. We have therefore analyzed the focal ischemic rat brain EEG via neural networks. The neural networks developed here provide both rapid and accurate classification of the rat brain EEG signals.

II. Materials and Methods

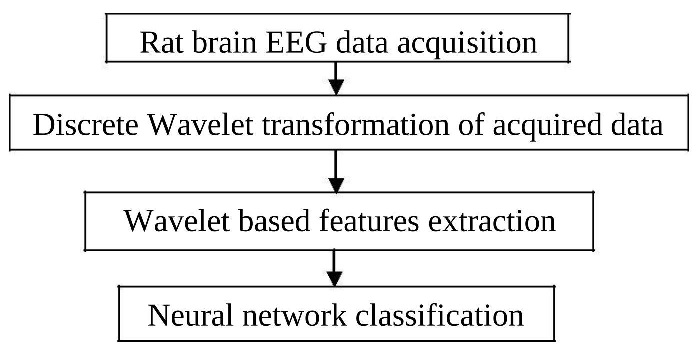

Figure 1. Flow Chart of EEG data analysis

Male Charles Foster rats (6 weeks, 270 ± 10 g) were in-bred at the Central Animal House, Banaras Hindu University were used for the experiments. Animals were kept under standard laboratory conditions maintained with animal care and housing. In our study, a total of 24 animals were divided in three groups consisting of control (n=8), induced stroke (n=8) and Piroxicam drug treated (n=8) for each group. Piroxicam and other chemicals were purchased from Sigma, USA. They were allowed free access to food and water and maintained at 12 h day/night cycle. Animals were anesthetized with ketamine and xylazine (75 mg/kg and 10 mg/kg i.p, respectively). EEG electrodes were implanted and placed to the skull at positions that were optimized following stereotactic coordinates (Paxinos) in pilot experiments.

Focal cerebral ischemia was induced by occlusion of the middle cerebral artery (MCA) using a modification of the intraluminal technique. Animals were anesthetized with ketamine and xylazine (75 mg/kg and 10 mg/kg i.p, respectively). The neck muscles were separated further to expose external carotid artery (ECA) and internal carotid artery (ICA). A 4.0 cm length 3-0 monofilament nylon suture (Ethicon) was introduced into the ECA lumen through a small nick and gently advanced from to the ICA lumen to block the origin of MCA.

The approximate length of filament inserted near the bifurcation point to the MCA blockade site was about 18-22mm. The ECA stump was tightened by thread around the intraluminal nylon suture to prevent bleeding. Reperfusion was allowed by gently removing the monofilament after 1 h of ischemia. In sham-operated animals, all the procedures except for the insertion of the nylon filament were carried out. Animals were allowed to recover from anesthesia and on regaining the righting reflex, were transferred to cages in the animal room, with temperature maintained at 26 ± 2.5^{o}C.
A bipolar electrode montage system was used for recording the rat brain EEG signal. Electrodes were placed bilaterally in the skull over the frontal-parietal, occipital and temporal regions of the rat brain. A reference electrode was placed posterior to lambda over the transverse sinus. In this study, we have selected the sampling rate 256 and the duration was 30 mins recording for each group signal.

A. Discrete Wavelet Transform:

In the procedure of multi-resolution decomposition of a signal s, each stage consists of two digital filters and two down samplers by 2. The first filter was the discrete mother wavelet, high pass in nature, and the second was its mirror version, low pass in nature. The down sampled outputs of the first high-pass and low-pass filters provided the details a1 and the approximation d1, respectively (Fig. 2). The first approximation was further decomposed and this process is continued [4]. The DWT coefficients were defined by the help of wavemenu toolbox in Matlab and the representative diagram is as follows:

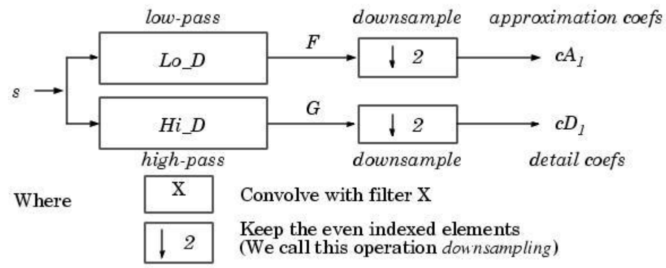

Figure 2. Diagrammatic representation of Wavelet transformation (source Matlab)

The EEG signals can be considered as a superposition of different structures occurring on different time scales at different times. Selection of appropriate wavelet and the number of decomposition levels is very important in the analysis of signals using the DWT with the help of haar wavelet function. The number of decomposition levels is chosen based on the dominant frequency components of the signal. In the present paper, the number of decomposition levels was chosen to be 4.Thus, the EEG signals were decomposed into the details d1– d4 (delta, theta, alpha, beta sub-bands) and one final approximation a4 [5].

Neural networks:

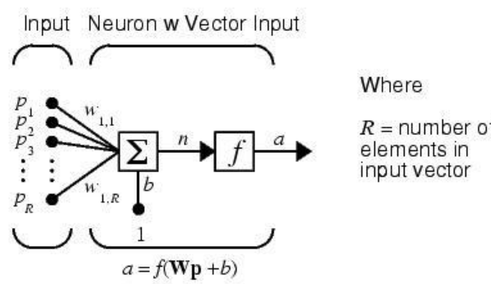

Figure 3. Structure of Neural Network (Source Matlab)

Feed forward neural networks (Fig. 3) have been used for analysis of EEG signals. The whole aim of the neural network [8, 9] was that it should be possible to train the neural network on a sample dataset and then identify a dataset from the training sample when its dataset is fed to the neural network. The neural network was set up in MATLAB 2010a. An input consisting of 4 neurons was followed by a hidden layer of 20, 000 neurons and then an output layer consisting of one neuron. The input layer was connected to the hidden layer via neurons with tansig activation function while the hidden layer was connected to the output layer via neurons with purelin activation functions. To train the neurons trainsig function was used. It was found by experimentation that the neural network gave optimum results if only 5 datasets were used to train the

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network. Using higher number of datasets in the training phase led to a dramatic increase in the mean square error (Fig. 13). Since a large number of datasets were involved (360) it was decided to put all the data in a text file. The algorithm implemented in Matlab (Fig. 4) would read 5 datasets train itself on the data and determine if the target data set was in the current set. If it was not found then the program continues to the set of next 5. The mean square error in the training phase was of the order of 10^{-20}. If a match was found the program identifies the match and exits.

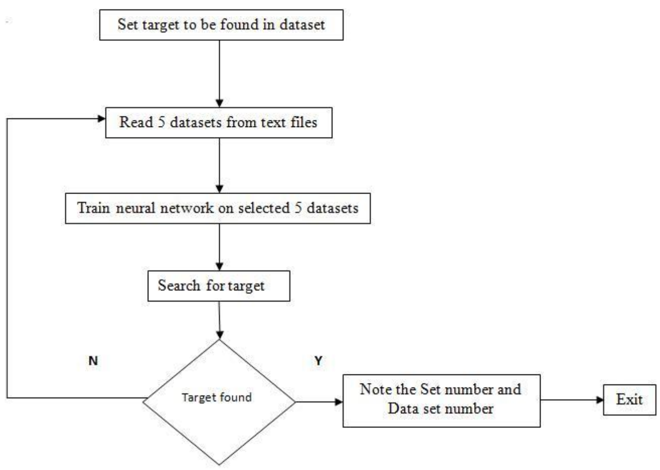


Figure 4. Algorithm of the neural network model

III. Results and Discussion:

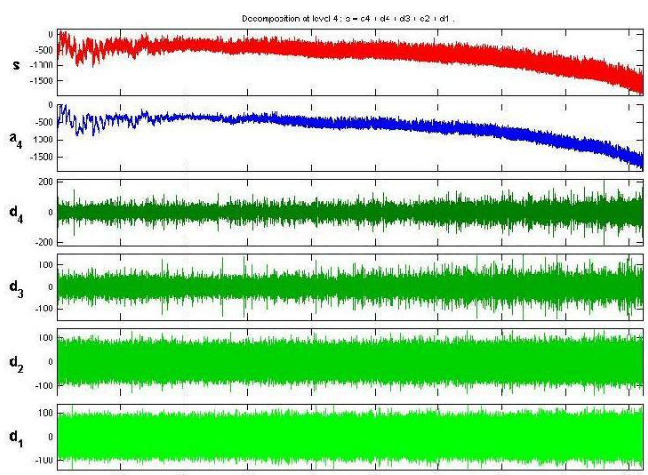


Figure 5. Wavelet Coefficients-Frontoparietal region control EEG Signal

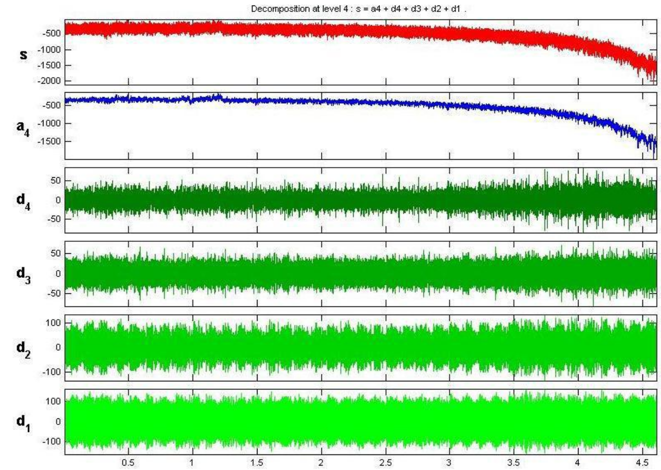


Figure 6. Wavelet Coefficients-Frontoparietal region stroke EEG Signal

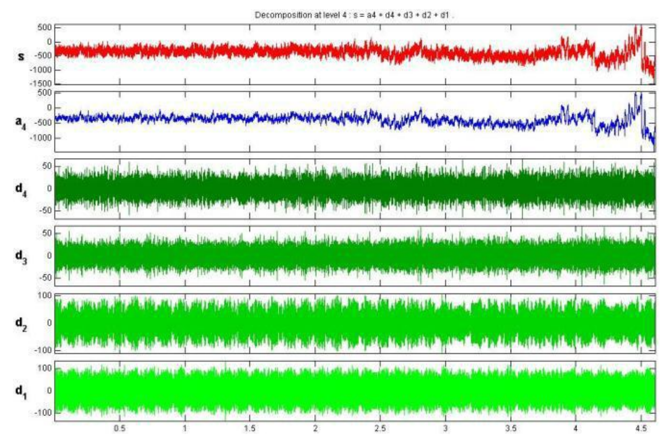


Figure 7. Wavelet Coefficients-Frontoparietal region drug induced EEG Signal

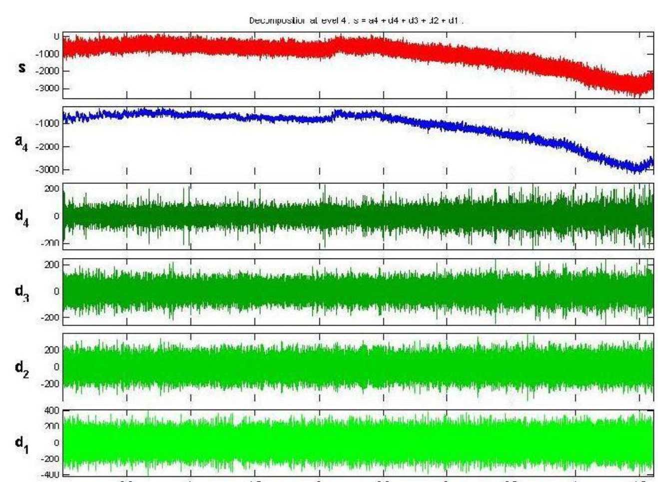
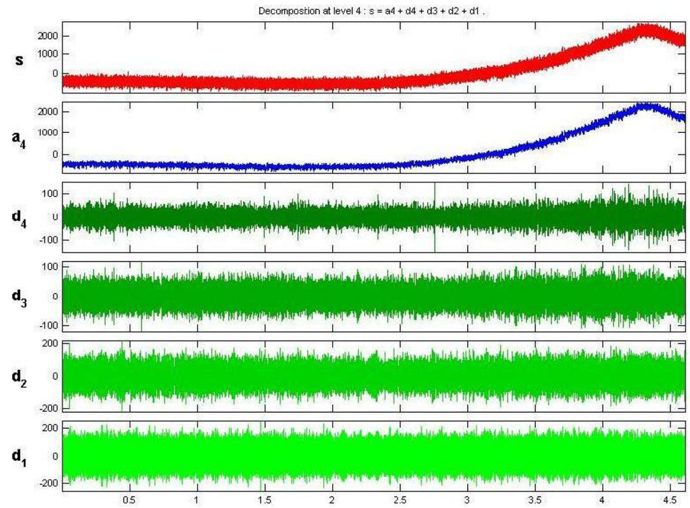


Figure 8. Wavelet Coefficients-Occipital region control EEG Signal



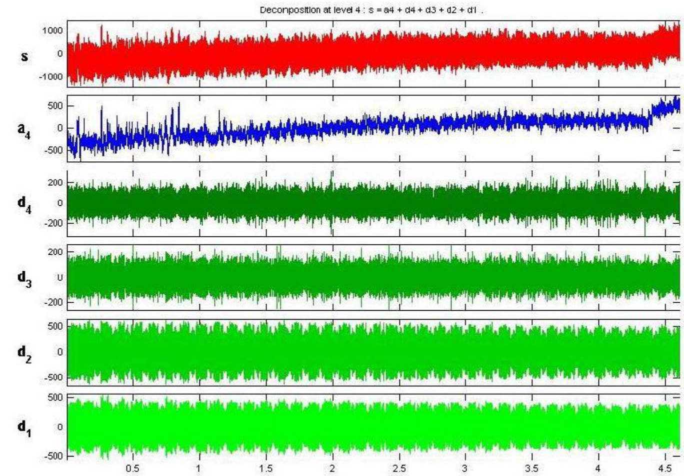


Figure 11. Wavelet Coefficients-Temporal

Figure 9. Wavelet Coefficients-Occipital region stroke region stroke EEG Signal EEG Signal

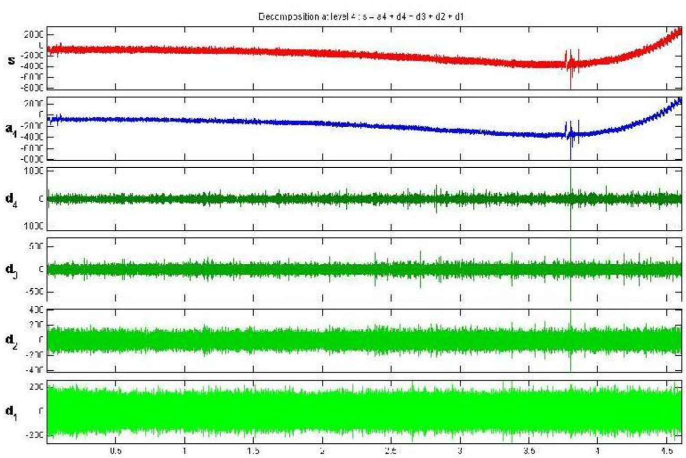


Figure 10. Wavelet Coefficients-Occipital region drug induced EEG Signal

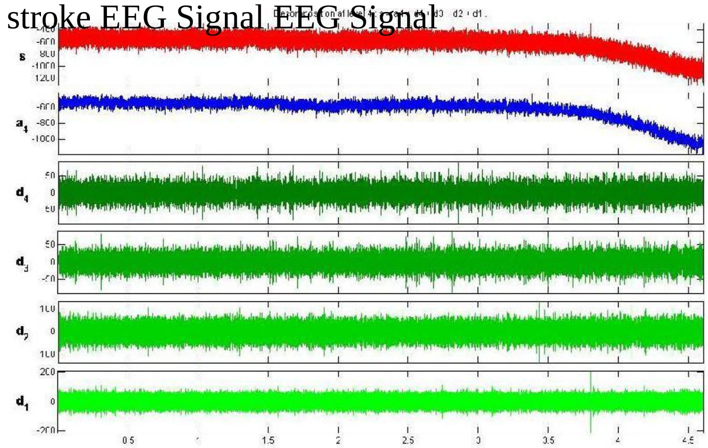


Figure 12. Wavelet Coefficients-Temporal region drug induced EEG Signal

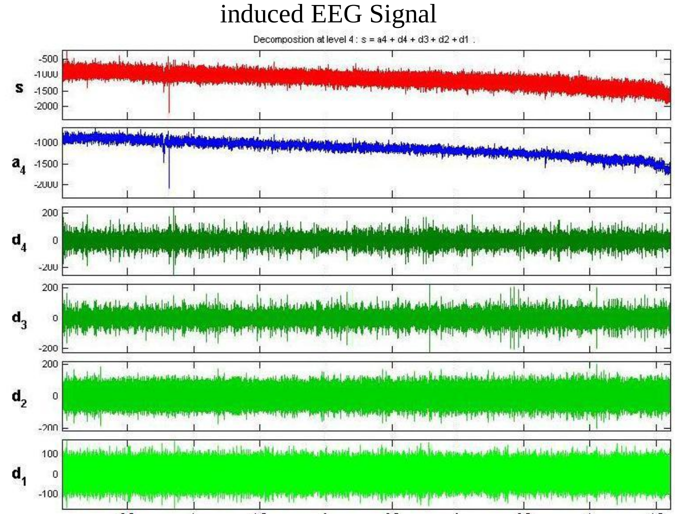


Figure 11. Wavelet Coefficients-Temporal region control EEG Signal

Neural Network analysis:

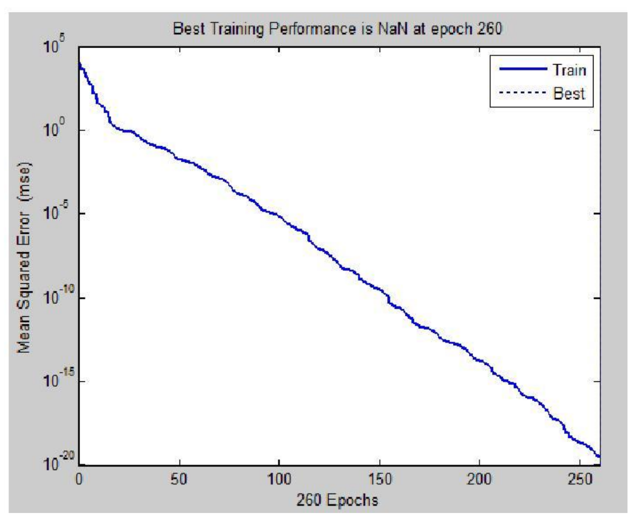


Figure 13. Neural Network- Performance plot

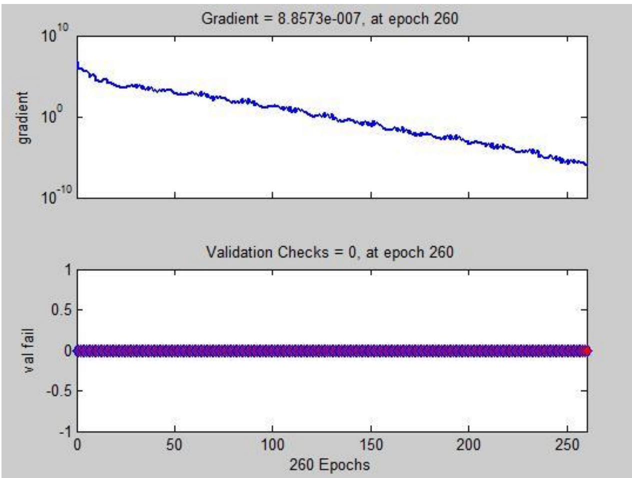


Figure 14. Neural Network- Training state plot

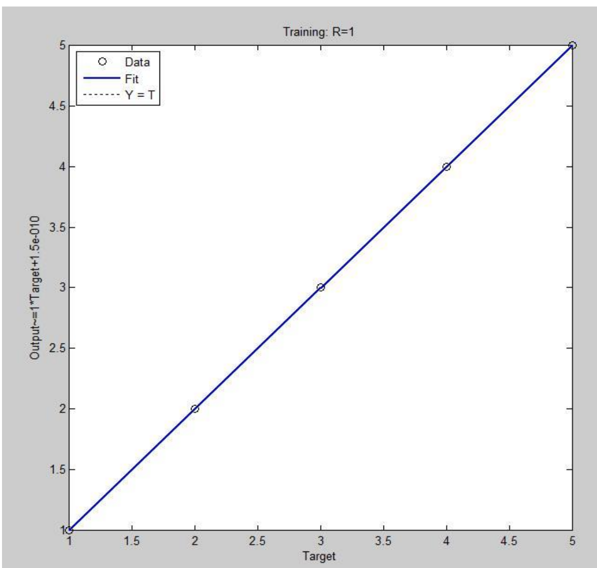


Figure 15. Neural Network- Regression plot

We have used discrete wavelet transformation to obtain the DWT coefficients (Fig. 5-12) of the rat brain EEG signals [7]. Table I represents the extracted wavelet statistical features for various sub bands of our experimental data. These coefficients were used as input to the neural network. We were able to obtain accurate classification of the EEG data. In the training phase (Fig. 14) the mean square error was found to be order of 10^{-20} (Fig. 13). The entire dataset was written on to a text file which was read 5 at time. The regression plot of the neural network was also found (Fig. 15). We found that by following these approach (namely training the neural network in entire datasets) results in very high mean square error in the training alone. Since accuracy of classification is of paramount important, we therefore adopted this approach.

Conclusion:

We find that highly accurate classification of EEG spectra is possible. Our results imply that neural network based software can be possibly used as a diagnostic tool for diagnosing the mental state of a patient.

Conflict of Interest

The authors declare that there is no conflict in interests and there are no ethical issues associated with this work.

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