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Short Communication

Backpropagation Artificial Neural Network To Detect Hyperthermic Seizures In Rats

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Abstract

A three-layered feed-forward back-propagation Artificial Neural Network was used to classify the seizure episodes in rats. Seizure patterns were induced by subjecting anesthetized rats to a Biological Oxygen Demand incubator at 45-47ºC for 30 to 60 minutes. Selected fast Fourier transform data of one second epochs of electroencephalogram were used to train and test the network for the classification of seizure and normal patterns. The results indicate that the present network with the architecture of 40-12-1 (input-hidden-output nodes) agrees with manual scoring of seizure and normal patterns with a high recognition rate of 98.6%.

Keywords: Artificial Neural Network, fast Fourier transform, electroencephalogram, Hyperthermic seizures

Introduction

Heat stroke or hyperthermia is one of the most serious of the disorders that may cause seizures. Literatures suggest that continuous exposure to high environmental heat as well as by hot water pour over the head generate seizures in both man and animals.(1,2) Several computer algorithms and programs for automatic detection of epileptic transients were developed but these methods were found unable to recognize the exceptions and minimize the number of false detections. Alternatively, Artificial Neural Network (ANN) has been successfully implemented for many pattern classification problems including detection of epileptic seizures.(3-5) However, most of the previous ANN based methods use measures of the electroencephalogram (EEG) such as amplitude, width, slope and sharpness of series of consecutive waves, measures thought to reflect in a general sense what expert clinicians attempt during EEG interpretation. In the present work, instead of using the physical characteristics of EEG signals, fast Fourier transform (FFT) has been used for the training and testing of the ANN as it conveys more information with respect to conventional analog EEG records.(6)

The experiment was carried out on male Charles Foster rats weighing 200-250 grams. Rats were housed in the animal room that was artificially illuminated with a 12 light cycle (7.00 A.M. to 7.00 P. M.) and the ambient room temperature maintained at 24± 1ºC. Rats were anaesthetized with Urethane anaesthesia (1.6gm/kg, I.P.) and three stainless steel screw electrodes were aseptically fixed on the rat's head under stereotaxic guidance. Two electrodes were placed on bilateral fronto-parietal region and one grounding electrode at the anterior most region of the skull to record the differential EEG patterns. Anaesthetized rats after electrode implantation were subjected to the thermal environment in the Biological Oxygen Demand (BOD) incubator with preset temperature at 45-47ºC.(1)

Seizure patterns in EEG recording were observed after 30 to 60 minutes on start of incubation.

Single channel analog EEG was recorded with the standard amplifier setting.(7) Signals were simultaneously recorded in the computer hard disk following digitization of the traces at 256 Hz with help of an analog to digital converter (ADLiNK, 8112HG, NuDAQ, Taiwan) and its supporting software (VISUAL LAB-M, Version 2.0c, Blue Pearl laboratory, USA). The digitized data were fragmented in 1 second epochs (256 data points) and stored in separate files. Each epoch was pre-processed for noise reduction before final FFT or power spectrum analysis. At first, the DC value was subtracted from the data and then the base line movement was reduced. In the final step of pre-processing, the data were band pass filtered with cutoff frequencies of 0.25 and 30 Hz, as the maximum frequency component of interest in anesthetized animal is less than 25 Hz.(8) These filtered data epochs were processed for FFT or power spectrum calculation before being used as input for ANN.

Three layered feed-forward back-propagation network was used for detecting the seizures. The network was implemented via software by using C++ programming language on a computer.(9) The individual computational elements that make up most artificial neural systems models are more often referred to as processing elements (PEs). Like a neuron, a PE has many inputs but only single output, which can fan out to many other PEs in the network. The input ith receives from the jth PE is indicated as xj. Each connection to the ith PE has associated with a quantity called weight or connection strength. The weight on the connection from the node jth to ith node is denoted as wij. Each PE determines a net input value based on all it's input connection.(10) The net input is calculated by summing the input values, gated (multiplied) by their corresponding weights. In other words, the net input to the ith unit can be written as:

$$\text{net}_i = \sum x_j w_{ij}$$

Backpropagation network: The back-propagation learning involves propagation of the error backwards from the output layer to the hidden layers in order to determine the update for the weights leading to the units in a hidden layer. It does not have feedback connections, but errors are back propagated during training by using least mean square (LMS) error. Error in the output determines measures of hidden layer output errors, which are used as a bias for adjustment of connection weights between the input and hidden layers. Adjusting the two sets of weights between the pair of layers and recalculating the outputs is an iterative process that is carried on until the error falls below a tolerance level. Learning rate parameters scale the adjustments to the weights. The input of a particular element was calculated as the sum of the input values multiplied by connection strength (synaptic weight).(11) ANN was trained by FFT data of selected EEG data files. During training, the network was provided the inputs and the desired outputs, and the weights were adjusted accordingly so as to minimize the error between expected and desired outputs. After the training, the network was tested with unknown input patterns that were not present in the training set.

Results

The parameters of the ANN were set to get optimized performance of the network program over the entire set of EEG data. The training of the ANN was tried with variable number of hidden neurons as well as by assigning different learning rates parameters between the ranges of 0.01 to 0.5. The optimized performance of the ANN was found with structures of 40-12-1 (nodes of input, hidden and output) and with the learning rate of 0.1. The schematic diagram of the neural network used in the present study is shown in Fig.-1.

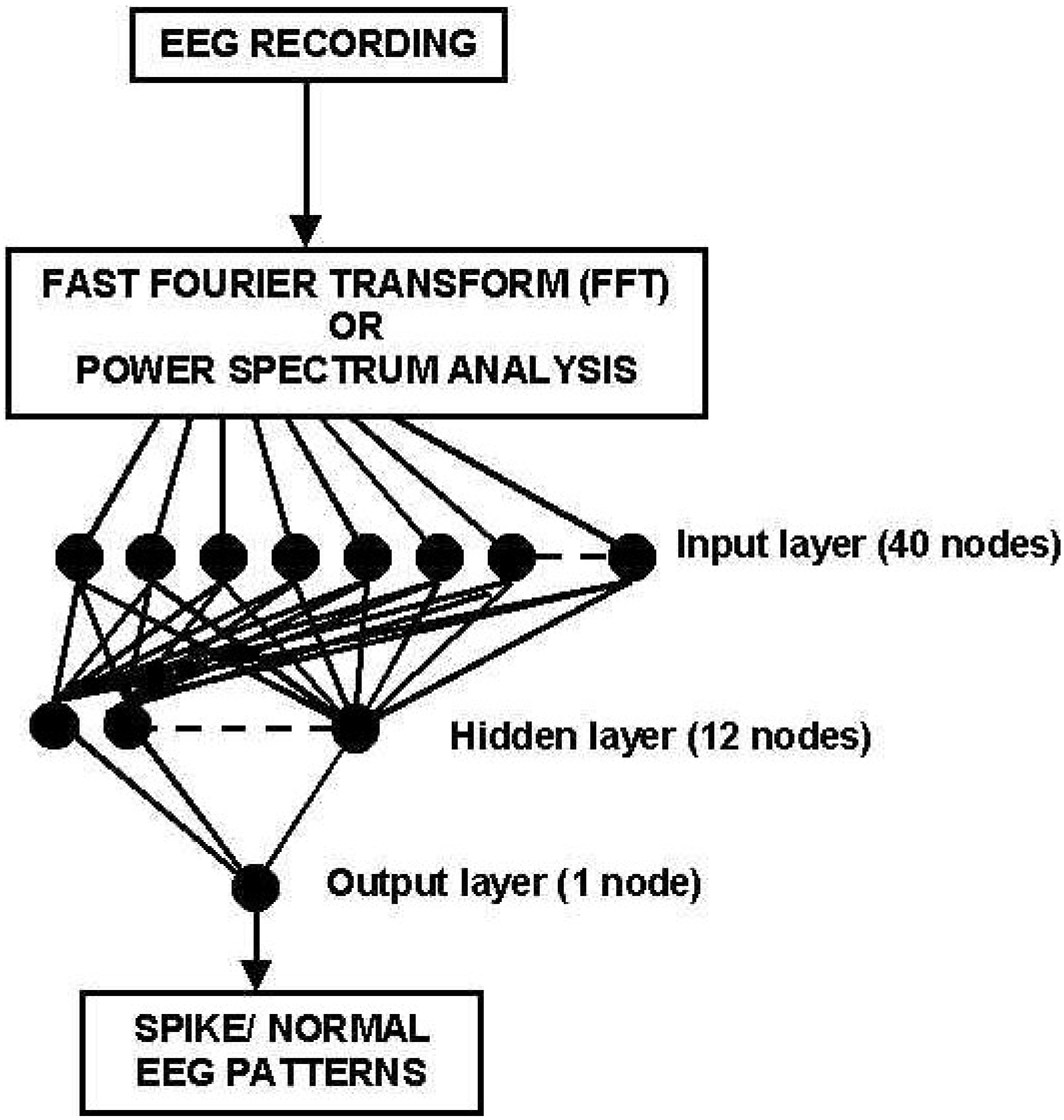

Figure-1: Schematic diagram of pattern recognition by ANN.

For the present work, the error tolerance was assigned as 0.001 to activate the network and the network was trained for 1 million of iterations with different training sets having variable number of training patterns. The ANN was trained with a training data file containing 100 training patterns (same number of seizures and normal patterns) arranged randomly. After training, the network was tested for other files having patterns which were not present during training session. The performance of the network in detecting these events (normal and seizure) was calculated with help of following formula.

$$\text{Performance of ANN(\%)} = \frac{\text{Number of correctly classified patterns}}{\text{Total number of patterns tested}} \times 100$$

The results of the seizure and normal events detected by the network compared with those detected manually are summarized in the Table-1. Manually detected events were taken as standard and agreement percentage represent the percentage of epochs in which ANN detected seizure or normal events agreed with manually detected ones.

Table 1: Percentage agreement of the ANN in the recognition of seizure and normal patterns in comparison with manual scoring.

File No.	No. of Test patterns	Number of correctly detected patterns		
		Seizure	Normal	Total
1.	200	98	100	198
2.	200	98	99	197
3.	200	100	98	198
4.	200	99	98	197
5.	200	97	99	196
Total patterns tested	1000	492	494	986 (% agreement = 98.6)

Discussion

In the present work, an approach of detection of hyperthermia induced seizure and normal EEG patterns through ANN has been successfully implemented and experimentally tested. Features calculated from the FFT such as relative power in various frequency bands and then using an ANN to generate a single number that indicates the degree of which the event is a seizure (3, 12) was used previously to classify seizure patterns. Instead of the features from the FFT of the EEG signals, in the present work, the selected frequency band of digital values of the FFT from one second epochs of the EEG signals for the training and testing of the ANN were used. The EEG spike patterns represent very good agreement with the human manual scoring.(3) The performance of the detector was observed with moderately high recognition rate of 98.6% in recognizing normal and seizure patterns. The results suggest that ANN is capable of clustering the input information with greater reliability similar as shown by Hopfield and Tank (13) and these analyses can substantially increase the power of analysis. Once the ANN is trained, the converged weights were stored and re-used to obtain instantly the result of seizure detection. The accuracy of recognition however, was found sensitive to several parameters such as the recording environment, the type of signals used, sample size, training method, the choice of network model and preprocessing of signals. Although in this work, online seizure detection has not been done, which may be possible with the help of fast computer and dedicated software.

The advantages and disadvantages of ANN in the clinical diagnosis have not been extensively explored yet. However, by application of these results, the future scope can be outlined. The ANN can be useful in differential diagnosis because the network can be trained with large data sets derived from patients with clear-cut, but clinically different diseases. Since only 1-5% of long term recording of EEG signals are of interest in clinical diagnosis,(3) the ANN can become useful for online monitoring of pathological events. Furthermore, the technicians can easily be trained for the manual selection of the already detected events, whereas recognition of abnormal patterns in the background of ongoing EEG requires substantial experience.

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