MANTECH Publications

Journal of Artificial Intelligence, Machine Learning and Soft Computing
Volume 2, Issue 2, July-December 2017

Performance Comparison of two Classifiers for EEG Signals during Planning of Hand Movement

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Abstract

This Paper demonstrate the performance comparison of two artificial neural network (ANN) base techniques Levenberg-Marquardt and Radial basis function network for classification of planning of right hand movement with respect to an awake relax state. In this study data was collected from 10 healthy subjects. Wavelet packet transform (WPT) was used for Feature extraction of the relevant electroencephalogram (EEG) signals.

Keywords: *Electroencephalogram (EEG), Wavelet packet Transform (WPT), Levenberg_Marqurdt, Radial basis function network*

INTRODUCTION

Brain computer interface is a communication system, which does not require brain normal out pathway peripheral and nerves.

Electroencephalograph (EEG) signals are carry all the information needed for the design and development of any kind of brain computer interface (BCI) systems [1]. It is well documented that proper feature extraction and classification methods are the key features deciding the accuracy and speed of BCI systems. ANN has been more widely accepted as the best classification method to distinguish from various mental states of relevant EEG signals.

In this study a feature vector representing the unique EEG characteristics to differentiate the process of planning right hand movement with respect to an awake relax state. Frequency spectrum is analyzed by applying the FFT for each second of EEG recording for Event Related Desynchronization (ERD) feature. Wavelet packet transform was used for best fitting for classifiers. techniques Levenberg-Marquardt Radial basis function network classifier was used to compare the performance in classification of the two states namely planning of right hand movement and relax state[2 -3].

METHODOLOGY

A. EEG Data Acquisition

For the study, EEG data was collected from the 10 healthy right handed subjects. The Ag/AgCl scalp electrodes,placed 2.5 cm anterior and posterior toC3 to C4. Electrodes pair used are C4-F4,C4-T4,C4-P4 C4-Cz,C3-F3,C3-T3,C3-P3,C3-Cz as bipolar and F4-A2,C4-A2,T4-A2,P4-A2,F3-A1,C3-A1,T3- A1,P3-A1,as unipolar derivation according to the international standards 10-20 system of electrode placement .The reference electrode are placed on the left and right ears and ground electrode on the forehead. Electrocularגram was derived from two electrode placed on the outer canthi of left eyes in order to detect eye movement. These EOG signals are used to eliminate eye movement artifacts as shown in Figure1.

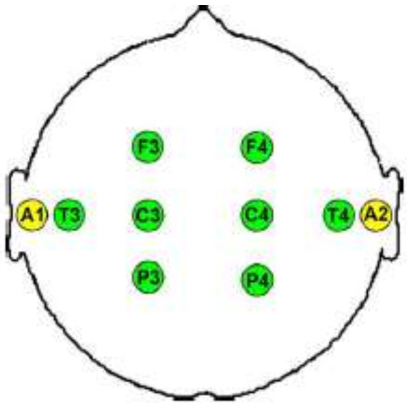

Fig. 1- Showing the electrode placement

An experiment paradigm was designed for the study and the protocol was explained to each participant before the experiment. In this, the subject was asked to comfortably lie down in a relaxed position with eyes closed. Initially the subject was asked to relax for 5 min. after assuring the normal relaxed state by checking the status of alpha waves the EEG was recorded for the 30 s and collecting the five session of 5 s epoch each for the relaxed . This is used as basic reference for further analysis of the planning data. the subject was asked to mentally plan to move the right hand ,on presentation of an audio cue, both at the start and end of a session .The duration of the sound cue was 1ms and at 60 dB .Five session of planning data were recorded each with a time gap of 180s . The whole experiment including preparation of the subjects last for 1 hr, collecting EEG data for the 10 sessions, five each for the relaxed and planning states. All data set were visually checked for the artifacts before the selection.

The 5s epochs related to the normal relaxed and planning period were first pruned for artifacts and then analyzed as the following setting high pass filter 5Hz and low pass filter 1.6 Hz, notch filter 50 Hz ,sensitivity 70 uv/mm and a sampling rate of 200Hz. As the first step, Frequency spectrum of the signal was analyzed with FFT plots in Mu rhythms (7-13 Hz).

B. Feature Extraction

As the first step, Frequency spectrum of the signal was analyzed with FFT plots. Mu rhythms (7-13 Hz) generated over sensorimotor cortex is the best features which would provide information about the intention for movement planning in the form of ERD. Mu rhythms are most pronounced when the subjects are relaxed and become desynchronized over the contralateral hemisphere to the region planning to move even when subjects think/plan about the movement. Hence EEG recorded during an awake relax state could be considered as the baseline task for the subsequent analysis. [4]. For relax, peaks for C3 & C4 almost coincide (or difference of 0-10 %) in Mu band (7-13 Hz) at a particular base frequency which varies from subject to subject and for planning a 50% decrease in magnitude of C3 w.r.t. C4 is observed at the same base frequency[5-6]. By observing the FFT plots for each second the valid data for further processing are sorted out.

At this stage, the FFT output could have also been used for feeding the ANN but the data size being too large and for ANN the input size decides the learning speed and the performance of the network. So the data is preprocessed using Wavelet packet transform to extract the most relevant information from the whole signal which could become a base for the classification of the two stages [7-8].

By applying the wavelet packet analysis on the original signal, wavelet coefficients in the 7-13 Hz frequency band at the 5th level node (5, 3) were obtained as shown in Figure2. For analysis, Daubechies (db5) wavelets were used as a mother wavelet because of its physiological shape, which closely resembles the EEG. These 21WPT coefficients are used as the best fitting input vector for Neural Network. **See Figure 2.**

C. Artificial Neural Network

A Neural Network (NN) being massively parallel, distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge. The main advantage of choosing artificial neural network for classification was due to the fact that NN could be used to solve problems, where description for the data is not computable. Hence NN has been widely accepted as one of the best classification method to discriminate mental states [9-11].

1. Levenberg_Marqurdt(tarinlm)

For classification of right hand movement tasks, a two layer feed forward neural network was used as classifier with topology of {10, 1}, indicate 10 neurons in hidden layer and one output layer as shown in **Figure 3.**

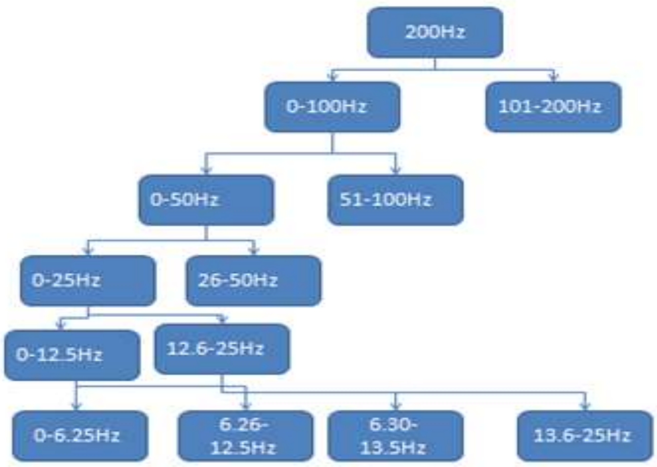

Figure 2: Wavelet packet decomposition tree for the present study

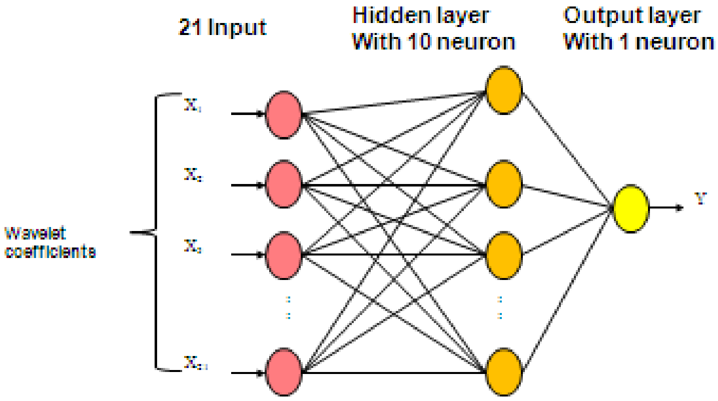

Figure 3: Architecture of multilayer feed forward network used for present study

The levenberg –Marquardt training algorithm was to tain the network with μ =.01, μ_dec=0.1and μ _inc =10 parameters. design to approach second order training speed without having to compute the Hessian matrix.when the performance function has the form of a sum of square(as is typical in training feed forward network) ,then the Hessian matrix can be approximate as H=JTJ and gradient can be computed as g=JTe. Were J is the jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$X_{k+1}=X_K - [J^TJ+\mu I]^{-1}J^Te$$

When the scalar μ is zero, this is just Newon's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

2. Radial basis function network classifier

A RBF networks may require more neurons than standard feed-forward backpropagation networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks as shown in Figure 4. They work best when many training vectors are available.

A RBF network can be described as a linear combination of basis function i.e.,

$$y = f(x) = \sum \theta_i \Phi_i (x)$$

Where

$y \varepsilon R$ the output variable;
$\boldsymbol{x} \varepsilon R''$ the input variable;
θ_i the optimal weights;
$\Phi(x)$ the radial basis function

There are many choices for the radial basis function. We selected the Gaussian function defined as

$$\phi_i(x) = exp\left(\frac{-\|x-x_i\|}{2\sigma^2}\right)$$

The parameter σ controls the radius of influence of each basis function, and x_i represents its center.

In this study, a two-layer RBF network was designed. The training vectors were selected as the centers of radial basis function. The output layer had only one unit. The parameter σ can be estimated by cross validation on the training data.

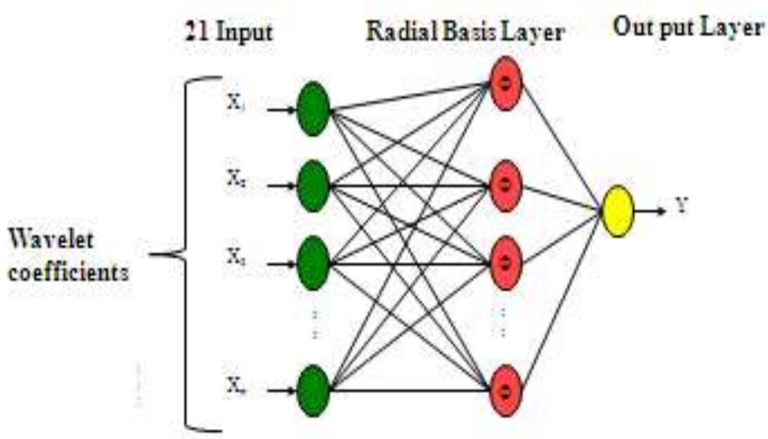

Figure 4: Architecture of Radial basis neural network used for present study

RESULT AND DISCUSSION

Comparison of the performance of neural network (NN) method Levenberg-Marquardt and Radial basis function network classifier in classification of planning of right hand movement and relaxes state. In all cases a two layer neural networks is used for the instance a topology of {10-1}indicate a 21input ,10 hidden layer neurons and one output architecture. The mean square error (MSE) is the condition to terminate training of all method's is originally set at exp(-5), how ever, these Method can also stop once the training exceeds the number of epoch set. Epoch is set at 5000 originally. By using The levenberg –Marquardt training 92% accuracy was obtained. As compare to The levenberg –Marquardt training method Radial basis function was better accuracy (95.00%).

For the application to the BCI system, it is necessary that EEG Feature related to the human intent were analyzed with EEG signals. The present study determines the feature that could reveal the intension and performance of the right hand movement and relax. Wavelet packet analysis results in signal decomposition with equal frequency bandwidth at each level of decomposition, which leads to an equal number of the approximation and detail coefficients. By applying Wavelet packet analysis on the original signal (for 200 samples at sampling frequency 200 Hz) we can obtain the wavelet coefficients in the 7-13 HZ frequency band at the 5th level node (5,3) . The signal is reconstructed at node (5,3).

We compare the performance of neural network (NN) method Levenberg-Marquardt and Radial basis function network classifier in classification of planning of right hand movement and relax state. Out of which Radial basis function network classifier method has highest performance (95.00%).it can be effectively used for classification of planning the right hand movement and relax state.

CONCLUSION

After the successfully discriminating the two cognitive states as awake relaxed and a right hand side movement planning from raw EEG recording. Using wavelet packet transform the authors intended to estimate feature coefficients and performance comparison of two neural network based classifier through various indigenously designed neural network architectures. It is observed that the performance given by Radial basis function network classifier method is significantly better.

ACKNOWLEDGMENT

The authors acknowledge their gratitude towards faculty of JIIT for their support and help to carried out the analysis and study.

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