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Performance comparison of three artificial neural network methods for classification of electroencephalograph signals of five mental tasks

Vijay Khare[1], Jayashree Santhosh[2], Sneh Anand[3], Manvir Bhatia[4]

[1]Department of Electronics and Communication Engineering, Jaypee Institute of Information Technology, Noida, India;
[2]Computer Services Centre, Indian Institute of Technology, Delhi, India;
[3]Centre for Biomedical Engineering, Indian Institutes of Technology, Delhi, India;
[4]Department of Sleep Medicine, Sir Ganga Ram Hospital,New Delhi, India.
Email: vijay.khare@jiit.ac.in; jayashree@cc.iitd.ac.in; sneh@iitd.ernet.in; manvirbhatia1@yahoo.com

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ABSTRACT

In this paper, performance of three classifiers for classification of five mental tasks were investigated. Wavelet Packet Transform (WPT) was used for feature extraction of the relevant frequency bands from raw Electroencephalograph (EEG) signal. The three classifiers namely used were Multilayer Back propagation Neural Network, Support Vector Machine and Radial Basis Function Neural Network. In MLP-BP NN five training methods used were a) Gradient Descent Back Propagation b) Levenberg-Marquardt c) Resilient Back Propagation d) Conjugate Learning Gradient Back Propagation and e) Gradient Descent Back Propagation with movementum.

Keywords: Electroencephalogram (EEG); Wavelet Packet Transform (WPT); Support Vector Machine (SVM); Radial Basis Function Neural Network (RBFNN); Multilayer Back Propagation Neural Network (MLP-BPNN); Brain Computer Interface (BCI)

1. INTRODUCTION

Brain Computer Interface (BCI) system have the potential to offer a new nonmuscular communication channel, which enable severely handicapped persons to communicate with their external surroundings using the brain's electrical activity measured as electroencephalogram (EEG) [1,2,3,4,5]. There are various types of EEG based BCIs. Evoked potentials (EPs) based BCI depend on the brain's response to external events. Two types of evoked potentials have been widely explored in the field of BCI, namely P300 and Steady State Visual Evoked Potential (SSVEP). P300 is a electrical potential that appear 300 ms after task-related stimuli at Centro-Parietal location. The amplitude of the P300 depends on the frequency of stimuli occurrence like less frequent stimuli produce larger response (vice versa). P300 has been used to develop virtual keyboards and control of a wheelchair. Visual evoked potential (VEP) reflect electrophysiological mechanisms underlying the processing of visual information in the brain and change in response to visual stimuli. Flicker stimuli of variable frequency (2–90 Hz) elicit a Steady State Visual Evoked Potential (SSVEP) in the EEG which is characterized by an oscillation at the same frequency as the stimulus. Thus SSVEP can be detected by examining the spectral content of the signals recorded in the visual region, namely the occipital region. SSVEP were used to control flight simulator and functional Electrical stimulator (FES). Spontaneous BCIs are based on the analysis of the EEG phenomenon associated with various aspect of the brain function related to mental tasks carried out by the subject at his /her own will. EEG based of this kind BCI can use slow potential shifts and variation of rhythmic activity control. Slow cortical potentials (SCPs) are shifts in the depolarization level of upper cortical dendrites and reflect very low frequency, slow change in potential shifts, often developing over 0.5–10 seconds. A thought translation device was designed for cursor movement using SCP. Surface electrical potentials reflect electrical activity of large synchronous groups of neuron in the brain. This is recorded by electrodes placed in standard positions on the scalp and has amplitude between 2–100 microvolt with a frequency spectrum ranging from 0.1 to 100 Hz. The frequency bands of delta (0.5–4.0 Hz), theta (4.0–8.0 Hz), alpha (8.0–13.0 Hz), beta (13.0–22.0 Hz), gamma (30.0–40.0 Hz) and μ- rhythms (8.0-13.0 Hz) are examples of rhythmic activity. Most BCIs make use of spontaneous electroencephalogram (EEG) to distinguish between mental states. The past two decades have witnessed the importance of innovative BCI with voice, vision and a combination of these, as a communication platform [6,7,8,9]. Effective attempts have been made to achieve successful BCI systems based on bioelectric signals. They were mainly to help patients with various neuromuscular disorders by providing them a way of communication to the world, through extracting information about their intensions. So far the accuracy of the classification has been one of the main pitfalls of the existing BCI systems, since it directly affects the decision made as the BCI output. The speed &accuracy could be improved by implementing better methods for feature extraction and classification [10].

In this study, wavelet packet transform method was used to capture the information of mental tasks from eight channel EEG signals of nine subjects. The coefficients of wavelet packet transform were used as the best fitting input vector for classifiers. The three classifiers (MLP-BP NN , SVM and RBFNN) were used to compare the performance in discrimination of five mental tasks.

2. METHODOLOGY

2.1. Subjects

Nine right-handed healthy male subjects of age (mean 23yr) having no sign of any motor- neuron diseases were selected for the study. A pro-forma was filled in with detail of their age & education level as shown in **Table 1** The participants were student volunteers for their availability and interest in the study. EEG data was collected after taking written consent for participation. Full explanation of the experiment was provided to each of the participants.

2.2. EEG Data Acquisition

EEG Data used in this study was recorded on a Grass Telefactor EEG Twin3 Machine available at Deptt. of Neurology, Sir Ganga Ram Hospital, New Delhi. EEG recording was done for five mental tasks for five days, from ten selected subjects. Data was recorded for 10 sec during each task and each task was repeated five times per session per day. Bipolar and Referential EEG was recorded using eight standard positions C3, C4, P3, P4, O1 O2, and F3, F4 by placing gold electrodes on scalp, as per the international 10–20 standard system of electrode placement as shown in **Figure 1** The settings used for data collection were: low pass filter1 Hz, high pass filter 35 Hz, sensitivity 150 micro volts/mm and sampling frequency fixed at 400 Hz. The reference electrodes were placed on ear lobes and ground electrode on the forehead. EOG (Electoculargram) being a noise artifact, was derived from two electrodes placed on outer canthus of left and right eye in order to detect and eliminate eye movement artifacts.

Table 1. clinical characteristics of subjects.

Subject No.	Subject Name	Age	Educational Status
1	Subject 1	22	BE
2	Subject 2	21	BE
3	Subject 3	23	BE
4	Subject 4	27	M.TECH
5	Subject 5	23	BE
6	Subject 6	22	BE
7	Subject 7	27	M.TECH
8	Subject 8	22	BE
9	Subject 9	22	BE

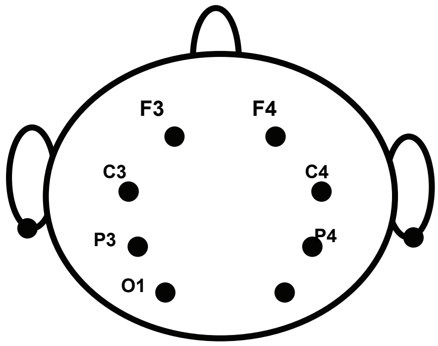

Figure 1. Montage for present study.

2.3. Experiment Paradigm

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. After assuring the normal relaxed state by checking the status of alpha waves, the EEG was recorded for 50 sec, collecting five session of 10sec epoch for the relaxed state. This was used as the baseline reference for further analysis of mental task. The subject was asked to perform a mental task on presentation of an audio cue. Five session of 10sec epoch for each mental task were recorded (as shown in **Figure 2**). The whole experimental lasted for about one hour including electrodes placement.

Data collected from nine subjects performing five mental tasks were analyzed. The following mental tasks were used.

Relaxed:The subject was asked to relax with their eyes closed. No mental or physical task to be performed at this stage.

Arithmetic Task:The subject was asked to perform arithmetic simple (trivial multiplication) and arithmetics

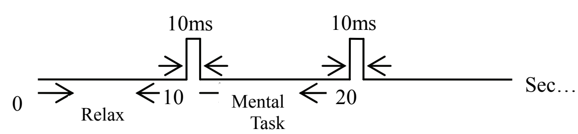

Figure 2. Timing of the protocol.

complex (nontrivial multiplication).An example of a trivial calculation is to multiply 2 by 3 and nontrivial task is to multiply 49 by 78. The subject was instructed not to vocalize or make movements while solving the problem. EEG signal were recorded corresponding.

Geometric figure Rotation:The subject was given 30 seconds to see complex three dimensional objects, after which the object was removed. The subject was instructed to visualize the object being rotated about an axis.The EEG signals were recorded during this period.

Movement Imagination: The subject was asked to plan movement of the right hand and corresponding EEG signals were recorded during this period.

2.4. Feature Extraction

The frequency spectrum of the signal was first analyzed through Fast Fourier Transform (FFT) method. The FFT plot of signals from the all electrode pairs were observed and maximum average change in EEG amplitude was noted as shown in **Figure 3.**

For relaxed, the peaks of power spectrum almost coincide for central area in the alpha frequency range (8–13 Hz) [11,12]. EEG recorded with relaxed state is considered to be the base line for the subsequent analysis. Mu rhythms are generated over sensorimotor cortex during planning a movement. For movement imagery of right hand, maximum upto 50% band power attenuation was observed in contralateral (C3 w.r.t C4) hemisphere in the alpha frequency range (8–13 Hz) [13]. For geometrical figure rotation, the peak of the power spectrum was increased (upto 100%) in right hemisphere rather than left in the occipital area for the alpha frequency range (8–13 Hz) [22]. For trivial multiplication, the peak of the power spectrum was increased (75%) in left hemisphere rather than right hemisphere in the frontal area for the alpha frequency range (8–13 Hz) [23]. For non trivial multiplication, the peak of the power spectrum was increased (120%) in left hemisphere rather than right hemisphere in the parietal area for the alpha frequency range (8–13 Hz).

The data was preprocessed using Wavelet packet transform to extract the most relevant information from the EEG signal [14]. By applying Wavelet packet trans

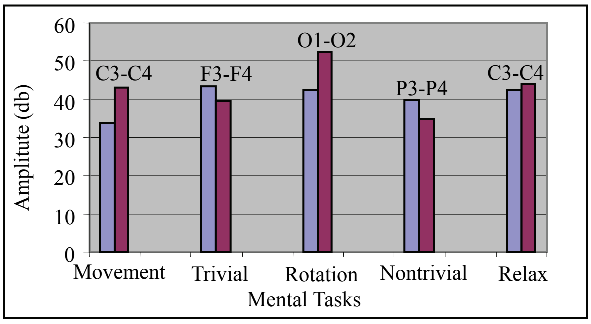

Figure 3. Maximum average change in amplitude of PSD.

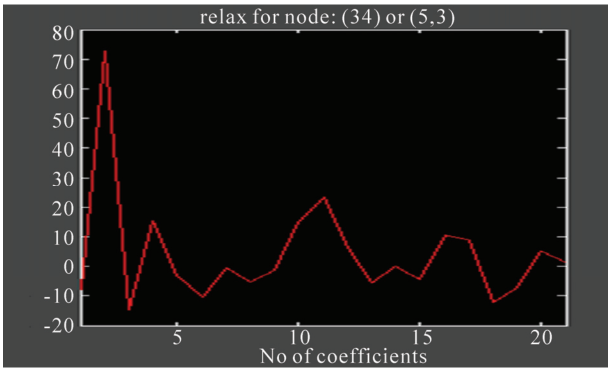

Figure 4. Wavelet coefficient for relax task.

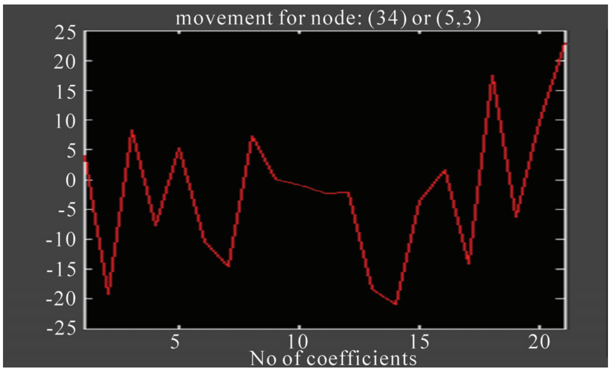

Figure 5. Wavelets coefficient for right hand movement task.

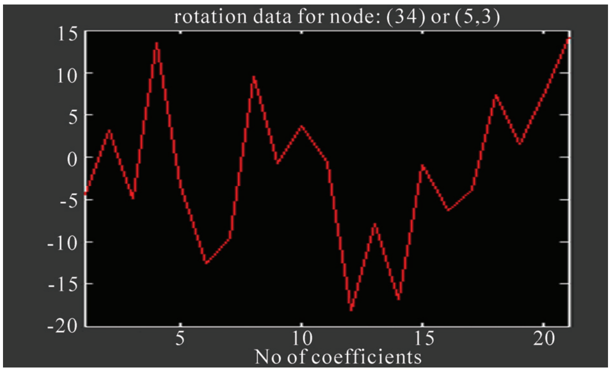

Figure 6. Wavelets coefficient for geometrical figure rotation task.

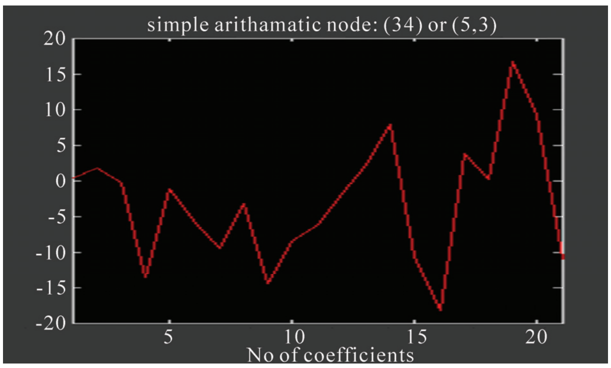

Figure 7. Wavelets coefficient for simple arithmetic task.

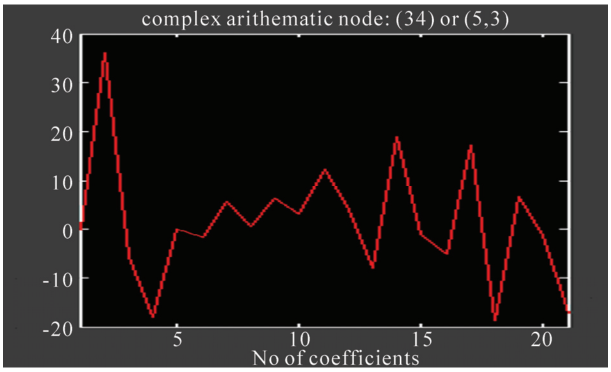

Figure 8. Wavelets coefficient for complex arithmetic task.

form on the original signal wavelet coefficients in the (8–13 Hz) frequency band at the 5th level node (5, 3) were obtained as shown in **Figures 4-8** We were able to reduce 1 second of EEG data to 21 coefficients. The signal was reconstructed at node (5, 3). These coefficients are scaled and used as the best fitting input vector for classifiers.

2.5. Classifiers

We have compared three classifiers: Multilayer Back propagation Neural Network (MLP-BPNN), Support Vector Machine and Radial Basis Function Neural Network to discriminate various mental activities. All three classifier were fed with the same dimensional feature data under identical conditions.

1) Multilayer Back propagation Neural Network

For this classifier, a two layer feed forward neural network was used with topology of {10, 1} 10 neurons in hidden layer and 1 neuron in output layer. The neural network was designed to accept a 21 element input vector and give a single output. The output neuron was designed to give 0 for baseline (relax task) and 1 for mental task. The five different training methods used for this classifier were Gradient Descent, Levenberg-Marquardt, Resilient Back propagation, Conjugate Gradient Descent and Gradient Descent back propagation with movementum [15,16,17]. Parameter used for five training methods of neural network for classification of five mental tasks as shown in the **Table 2.**

2) Support Vector Machine

Input data as two sets of vectors in an n-dimensional space, an SVM will construct a separating hyperplane in that space, one which maximizes the margin between the two data sets.The solution of the SVM is based only on those data points that are at the margin and called support vectors [18].

A kernel is utilized to map the input data to a higher dimensional feature space so that the problem becomes linearly separable. The kernel plays a very important role in the performance of the SVM applications. In the present study linear and polynomial kernel functions have

Table 2. Parameter used for different algorithms with to pology {10, 1}.

Gradient descent method	
Topology {10,1}	A=.01
MSE=1exp-(5)	
Epoch=5000	
Levenberg-Marquardt	
Topology {10,1}	Mu=.01
MSE=1exp-(5)	
Epoch=5000	Mu_dec=0.1and Mu_inc =10
Resilient Back propagation	
Topology {10,1}	A=.01
MSE=1exp-(5)	
Epoch=5000	B=0.75 and β_1=1.05
Conjugate gradient descent	
Topology {10,1}	A=.01
MSE=1exp-(5)	
Epoch=5000	
Gradient descent with momentum	
Topology {10,1}	A=.01. Mu = 0.01
MSE= 1e-5	
Epoch=5000	

work (RBFNN) classifier was used. A two layer network was implemented with 21 input vectors, a hidden layer with Gaussian activation function consisting as many as hidden neurons as input vectors and one neuron in the output layer [19].The output layer has 1 neurons and neuron gives output as 1 for a particular task. In case of relax task, this value is 0.

2.6. Performance

The study evaluated the performance of three classifiers for classification of five mental tasks. 60% of entire EEG data (five sessions, five mental tasks with nine subjects) was taken as training data. Remaining 40% of EEG data was taken as test data and the performances were recorded. The entire analysis of the recorded data was carried out using Matlab® 7.0 from Mathworks Inc., USA.

Performance (RC) is calculated in percentage (%) as ratio between correctly classified patterns in the test set to the total number of patterns in the test set [20].

$$Rc = \frac{\text{Number of correctly classified test patterns}}{\text{Total number of patterns in the test set}}$$

3. RESULTS & DISCUSSION

Nine right-handed male subjects participated in the experiments. The subjects were asked to perform five mental tasks namely relaxed, movement imagery, geometrical figure rotation and arithmetic task (trivial and non trivial multiplication). Out of 50 sec data recorded data the most relevant one second epoch of signal were used for classification of each mental task. WPT is an excellent signal analysis tool, especially for non stationary signals. Hence in the present study, WPT was used for feature extraction [21].

As per literature [11,12,13,22,23] most prominent area of brain for domain of information during five mental tasks was shown in **Table 3** For relaxed, the peaks of power spectrum almost coincide in central area at a particular base frequency .For arithmetic simple (trivialmultiplication), it was observed that the amplitude of the power spectrum for alpha frequency range (8–13 Hz) increased left hemisphere rather than right hemisphere in frontal region.

For arithmetic complex (non trivialmultiplication), it was observed that the amplitude of the power spectrum for alpha frequency range (8–13 Hz) increased left hemisphere rather than right hemisphere in parietal region. For geometrical figure rotation, the peak of the power spectrum in the alpha frequency range (7–13 Hz) increased right occipital area. For movement imagery, the peak of the power spectrum in the alpha frequency range (7–13 Hz) had an attenuation central area.

The present study was a comparison of three classifiers to discriminate five mental tasks effectively. **Tables 4-6** shows the performance of neural network with resilient back propagation training method, support vector machine and radial bases function Neural Network for classifying of mental tasks w.r.t baseline as shown in **Figure 9**.

From **Tables 4-6** we can say that RBF neural network method has best performance among all the classifiers for classification of mental tasks w.r.t baseline. By using RBF Neural Network 100% accuracy was obtained. While classification ,Resilient back propagation training method showed better performance than other (Gradient Descent method Levenberg-Marquardt, Conjugate Gradient Descent and Gradient Descent back propagation with movementum) back propagation training methods.

Table 3. Domain of information.

Tasks	Domain of information	(Contralateral/ Ipsilateral)	Type of change in amplitude of alpha rhythm(8-13
Movement Imagination	Central	Contralateral	Decreased
Arithmetic Simple	Frontal,	Ipsilateral	Increased
Geometrical figure rotational	Occipital	Ipsilateral	Increased
Arithmetic complex	parietal	Ipsilateral	Increased
Base line	Occipital, Central	Contralateral	Coincide

Table 4. Comparisons of different NN training methods.

Tasks / Method	Baseline and Arithmetic simple	Baseline and Arithmetic complex	Baseline and Rotation	Baseline and movement
Gradient Descent Back Propagation	95%	95%	87.5%	90%
Leveberg-Marquardt	95%	90%	90%	92.5%
Resilient Back Propagation	97.5%	95%	95%	95%
Conjugated Gradient BP	97.5%	92.5%	92.5%	92.5%
GD BP with Momentum	95%	95%	90%	90%

Table 5. Comparisons of different kernel function.

Tasks / Method	Baseline and Arithmetic simple	Baseline and Arithmetic complex	Baseline and Rotation	Baseline and movement
Linear Function	57.5%	55%	57.5%	57.5%
Polynomial Function	55%	57.5%	62.5%	62.5%

Table 6. Performance using radial basis function.

Tasks / Method	Baseline and Arithmetic simple	Baseline and Arithmetic complex	Baseline and Rotation	Baseline and movement
Radial bass Function network	100%	100%	100%	100%

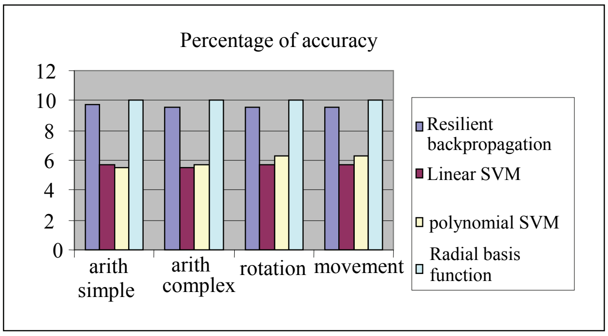

Figure 9. Performance of comparision using three classifiers.

4. CONCLUSIONS

This for various applications of BCI systems, it is necessary that EEG feature related to the human intentions were to be uniquely identified as accurate as possible. In this study, nine healthy male subjects were selected to investigate three classifiers of discriminating five mental tasks (relaxed state, movement imagery of right hand, geometrical figure rotation, arithmetic simple task, arithmetic complex task) effectively.

The result showed the performance of neural network with resilient back propagation training method, support vector machine and radial bases function Neural Network for classifying of mental tasks w.r.t baseline. RBF (Radial Basis Function) neural network method has best performance among all the classifiers for classification of mental tasks w.r.t baseline. By using RBF Neural Network 100% accuracy was obtained. While classification, Resilient Back Propagation training method showed better performance than other (Gradient Descent method, Levenberg-Marquardt, Conjugate Gradient Descent and Gradient Descent Back Propagation with movementum) back propagation training methods. The main conclusion is that the Radial baisis function network was found to be most suitable in various applications of BCI systems.

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