Comparison of SSVEP Signal Classification Techniques Using SVM and ANN Models for BCI Applications

Rajesh Singla and Haseena B. A.

***Abstract*—In recent years, Brain Computer Interface (BCI) systems based on Steady-State Visual Evoked Potential (SSVEP) have received much attentions. This study tries to develop a classifier, which can provide higher classification accuracy for multiclass SSVEP data. Four different flickering frequencies in low frequency region were used to elicit the SSVEPs and were displayed on a Liquid Crystal Display (LCD) monitor using LabVIEW. The Electroencephalogram (EEG) signals recorded from the occipital region were first segmented into 1 second window and features were extracted using Fast Fourier Transform (FFT). One-Against-All (OAA), a popular strategy for multiclass Support Vector Machines (SVM) is compared with Artificial Neural Network (ANN) models on the basis of SSVEP classifier accuracies. OAA SVM classifier had got an average accuracy of 88.55% for SSVEP classification over 10 subjects. Based on this study, it is found that for SSVEP classification OAA -SVM classifier can provide better results than ANN.**

***Index Terms*—Steady-state visual evoked potential, brain computer interface, artificial neural network, supprot vector machine.**

I. Introduction

Brain Computer Interface (BCI) is one of the fastest growing fields of research and development in recent years. The BCI system provides a direct communication channel between human brain and the computer without using brain's normal output pathways of peripheral nerves and muscles [1]. By acquiring and translating the brain signals that are modified according to the intentions, a BCI system can provide an alternative, augmentative communication and control options for individuals with severe neuromuscular disorders, such as spinal cord injury, brain stem stroke and Amyotrophic Lateral Sclerosis (ALS).

The brain activity for BCI system can be acquired via invasive or non-invasive methods. Electroencephalography (EEG) is a non-invasive way of acquiring brain signals from the surface of human scalp, which is widely accepted due to its simple and safe approach [2]. The brain activities commonly utilized by EEG based BCI systems including Event Related Potentials (ERPs), Slow Cortical Potentials (SCPs), P300 potentials, Steady-State Visual Evoked Potentials (SSVEPs) etc. Among them SSVEPs are attracted due to its advantages of requiring less or no training, high Information Transfer Rate (ITR) and ease of use [1], [3].

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SSVEPs are oscillatory electrical potential that are elicited in the brain when the person is visually focusing his/her attention on a stimulus that is flickering at frequency 6Hz or above [4]. These signals are strong in occipital region (visual cortex) of the brain and are nearly sinusoidal waveform having the same fundamental frequency as the stimulus and including some of its harmonics. Considering the amplitudes of SSVEPs induced, the stimuli frequencies are categorized into three ranges, centered at 15 Hz low frequency, 31 Hz medium frequency and 41 Hz high frequency respectively [5].

There are many research groups that are designing SSVEP based BCI systems. Lalor *et al*. [6] developed the control for an immersive 3D game using SSVEP signal and used Linear Discriminants as the classifier model. Muller and Pfurtscheller [7] used SSVEPs as the control mechanism for two-axis electrical hand prosthesis using Harmonic Sum Decision (HSD) method. Recently, Lee *et al*. [8] presented a BCI system based on SSVEP to control a small robotic car and the gazed target related component was detected by a Matched Filter Detector (MFD).

Some of the main factors that can determine the performance of a BCI system includes the type of the brain signal used to transfer the intentions, feature extraction methods used, classification algorithms to get the control commands etc. In this one of the main consideration is the classification of different brain activities, as the classifiers accuracy can affect the overall system accuracy and thus the ITR. In this research work, comparative study of Artificial Neural Network (ANN) and Support Vector Machine (SVM) have been carried out based on the classification accuracy of a multiclass SSVEP signal.

II. Materials and Methods

A. Subject

A total of ten healthy subjects (aged 22-27 years), seven males and three females, participated in the experiment. All had normal or corrected to normal vision and are right handed. None of the subjects had previous BCI experience. Prior to the recording all subjects were informed about the procedure of the experiment and required to sign a consent form.

B. Visual Stimuli

Visual stimuli for generating an SSVEP response can be presented on a set of Light Emitting Diodes (LEDs) or on a Liquid Crystal Display (LCD) monitor [9]. This study uses an LCD monitor to implement the stimuli because of its

flexibility. The visual stimulator was programmed by using LabVIEW and the flickering bars were square (4cm × 4cm) in shape. Four frequencies 7, 9, 11 and 13 Hz, in the low frequency range were selected, as the refreshing rate of LCD monitor is 60 Hz and the high amplitude SSVEPs are obtained at lower frequencies.

C. Experimental Setup

The subjects were seated in a viewing distance of 60cm from the LCD monitor in which the visual stimulator is situated as shown in Fig. 1. EEG signals were recorded using RMS EEG-32 Super Spec system (Recorders and Medicare System, India). The brain signals recorded from the scalp by Ag/AgCl electrodes were amplified in head box and connected to the adaptor box. The Adaptor box consist the circuitry for signal conditioning and further connected to the computer via USB port. This system can record 32 channels of EEG data by placing electrodes on the scalp, as per the international 10-20 system of electrode placement. The electrodes were placed at the O1, O2 and Oz regions of the scalp. The reference electrodes were placed on the left and right earlobes (A1 and A2) and ground electrode on Fpz. The impedance between skin and electrode were maintained below 5KΩ. The signals were filtered by a 3-50 Hz band pass filter and a 50 Hz notch filter. The sensitivity of the system was selected as 7.5 μV/mm and the signals were sampled at 256 Hz.

Four continuously flickering frequencies were placed on the four corners of the LCD screen. Subjects were required to close their eyes for two minutes and recorded the base line signal. Then they were given 5 minutes to adapt to the flickering stimulus placed in front of them.

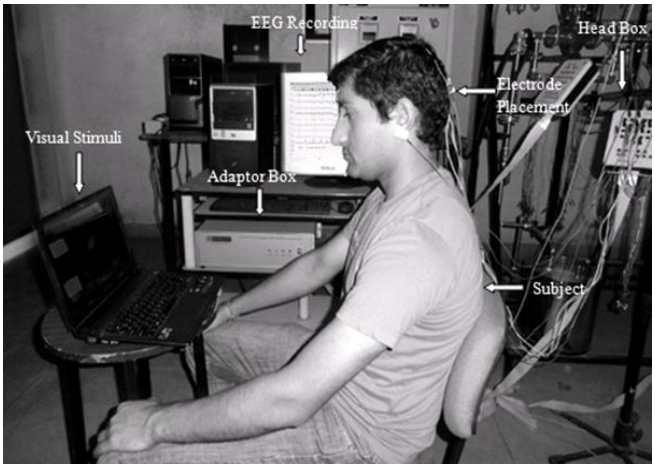

Fig. 1. Experimental set up for SSVEP data acquisition (Courtesy- Department of Instrumentation and Control Engineering, National Institute of Technology, Jalandhar).

The experiment paradigm included 5 second duration of gazing to a particular frequency following with a rest period of 5 second. At the focusing time subjects were instructed to avoid eye movements or blinking. Event markers were used to indicate the starting and ending time of each frequency. In a single run, each of the four frequencies performed three times and the same procedure repeated for another three more trials. Five minute break were given in between each trial. The time for completing the whole session was about 30 minutes.

D. Feature Extraction

The frequency features of SSVEPs can easily extracted by using Fast Fourier Transform (FFT) [10]. The EEG signals recorded from each channel were digitized and segmented into 1 second time window in every 0.25seconds. MATLAB was used for developing the FFT program. Fig. 2 shows the amplitude spectra of SSVEP induced by 13 Hz stimulation. From the FFT of all the connected channels, the data from Oz –A2 were selected for further system development as strongest SSVEP was observed at Oz. The coefficients at the fundamental and second harmonics of all the four target frequencies obtained from the amplitude spectra were considered as the feature vector for classification.

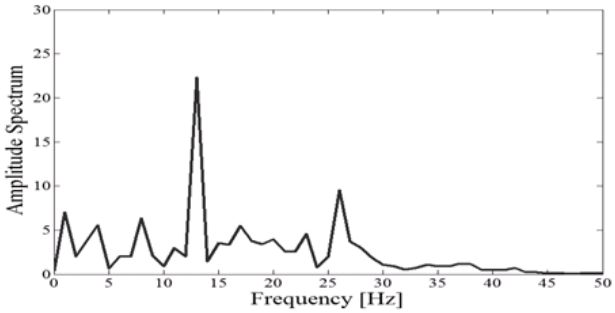

Fig. 2. Amplitude spectra of SSVEP in response to 13 Hz, recorded from Oz -A2 channel of subject S4. First and second harmonics can be found clearly.

E. Classification

ANN and SVM classifiers were implemented to classify the feature vectors and compared with respect to the classification accuracy. The classifiers were designed using MATLAB.

Multilayer ANN architecture consists of an input layer, number of hidden layers and an output layer. Backpropagation [11] is a supervised learning algorithm which can be used in multilayer ANN. This algorithm involves a forward propagation of input data through the network for calculating output values. Then the error obtained from the comparison between the output and target values are backpropagated to adjust the weights of the neurons in each layer.

Two ANN models, Feed-forward Backpropagation (FFBP) and Cascade-forward Backpropagation (CFBP) were designed. In FFBP neurons are connected in feed forward fashion from the input layer to the output layer through the hidden layers according to backpropagation algorithm. CFBP is similar to FFBP in using backpropagation algorithm, with an exception that they have a weight connection from the input and every previous layer to the following layer and thus each layer neuron relates all previous layer neurons including input layer.

Modeling of the ANN was done by using MATLAB neural network training tool. The input and output data were normalized in the range of [-1, +1]. Different combinations of internal parameters, such as number of hidden layers, number of neurons in each hidden layer, transfer function of hidden layers and output layer etc were tried. The input layer requires eight neurons by considering the first and second harmonics of each of the four frequencies. The output layer

has four neurons corresponding to four frequencies. Gradient descent with momentum weight and bias learning function was used in both FFBP and CFBP models. Different variants of the backpropagation algorithm were explored like Bayesian regularization, Fletcher-Powell conjugate gradient backpropagation, Levenberg-Marquardt backpropagation, and Gradient descent with momentum backpropagation.

Performance of the ANN model was measured by Mean Square Error (MSE) function. The Cross Validation (CV) procedure [11] evaluates the training and learning of the NN model. The CV is executed at the end of training epoch and uses two independent data sets: the training set and the validation set for evaluating the training and learning errors.

The SVM technique introduced by Vapnik [12] is basically a binary classifier which can discriminate between two classes by using an optimal hyperplane which maximize the margin between the two classes. Kernel functions provide a convenient method for mapping the data space into a high-dimension feature space without computing the non-linear transformation [13]. The common kernel functions are linear, quadratic, polynomial and radial basis function (rbf).

SVM training and classification was done by using MATLAB Bioinformatics toolbox. One-Against-All (OAA) method [12] was adopted for getting a multiclass SVM. The formulation of this mode states that a data point would be classified under a certain class if that class's SVM accepted it while rejected by all other classes SVMs. In this mode four binary SVMs were trained, each for one of the four frequencies. After training, there develop a structure having the details of the SVM like the number of support vectors, alpha, bias etc.

III. Results and Discussions

The dataset per subject consists of 250 samples (50 samples of each of the four frequencies and 50 for rest signal) of feature vectors. After preprocessing 150 samples from each subject (30 samples from each class) that is a total of 1500 samples were separately selected for training. A network configuration having one hidden layer with 10 neurons was selected after dozens of training sessions. Levenberg-Marquardt backpropagation algorithm gave better results compared to other training algorithms. For better results pure linear functions for hidden layer neurons and tangent sigmoid functions for output layer neurons were selected.

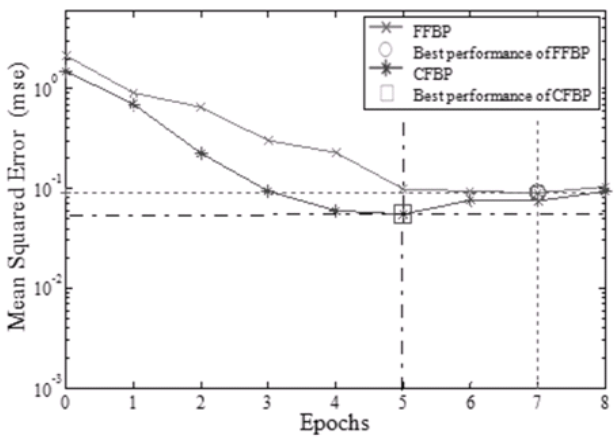

Fig. 3. MSE performance measure of FFBP and CFBP during training. CFBP got better result than FFBP.

FFBP network was trained in just 18 seconds and CFBP was with 33 seconds. Fig. 3 presents the MSE performance measures during CV. The CFBP algorithm converges at a faster rate than FFBP. The best validation performance of FFBP is 0.08988 at epoch 7 and that of CFBP is 0.05514 at epoch 5. The result shows that the performance of CFBP is better than that of FFBP.

Individual SVMs were trained with different kernel functions and their accuracies and the number of support vectors used is shown in Table I. The kernels with maximum accuracies were selected for OAA-SVM formulation.

The Polynomial kernel with order 3 had got an accuracy of 100% for detecting 7 Hz from all other classes. For 9 Hz quadratic kernel provides an accuracy of 90.84%. Higher accuracy for 11 Hz and 13 Hz were provided by linear kernel and is 86.60% and 100% respectively. All these selected kernels used less number of support vectors for particular classes. SVM trained in a fraction of the second and thus much faster than the ANN models. The OAA-SVM designed with optimal kernels provides an overall accuracy of 94.36% for the training data set.

Fig. 4 presents the regression plots for FFBP, CFBP and OAA-SVM during classifier testing using a separate dataset with 100 samples (20 samples from each class) from subject S4. The regression value for CFBP is 0.9034 and that of FFBP is 0.84839. The OAA-SVM got a regression value of 0.9401. This proves the superior performance of OAA-SVM over FFBP and CFBP for SSVEP classification.

TABLE I: Comparison of Various Kernel Functions

	7 Hz		9 Hz		11 Hz		13 Hz	
Kernel Function	**Accuracy (%)**	**Support Vectors**	**Accuracy (%)**	**Support Vectors**	**Accuracy (%)**	**Support Vectors**	**Accuracy (%)**	**Support Vectors**
Linear	94.14	14	78.65	25	**86.60**	16	**100**	18
Quadratic	96.86	23	**90.84**	25	82.22	20	35.6	21
Polynomial (order 3)	**100**	23	69.66	37	80.17	22	66.16	22
Radial Basis Function	34.41	118	35.27	117	66.16	119	35.17	116

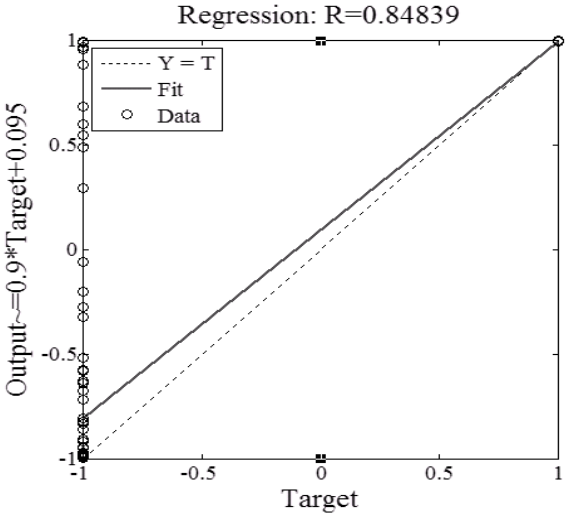

Fig. 4. (a) Regression plot of FFBP.

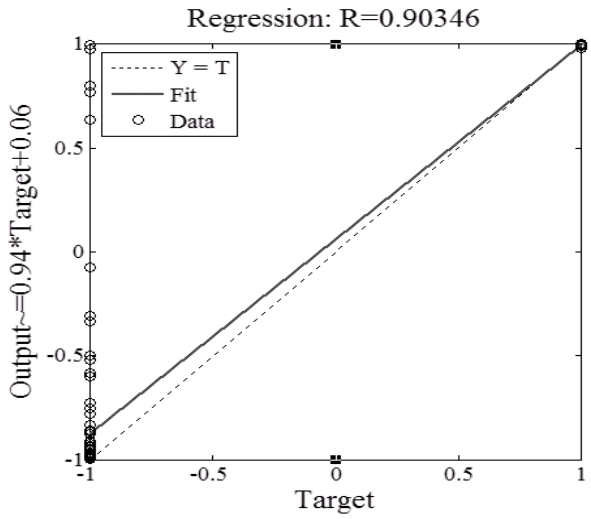

Fig. 4. (b) Regression plot of CFBP.

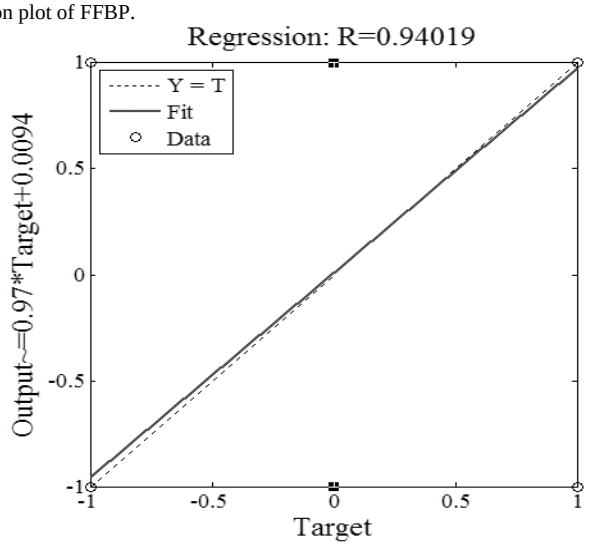

Fig. 4. (c) Regression plot of OAA-SVM.

TABLE II: COMPARATIVE RESULTS OF TESTING ACCURACY FOR 10 SUBJECTS BASED ON ANN AND SVM CLASSIFIERS

Subjects	Classifier Accuracy (%)		
	FFBP	**CFBP**	**OAA-SVM**
S1*	83.23	84.29	92.43
S2	80.04	82.19	91.76
S3	78.01	78.99	82.32
S4*	84.84	90.35	94.02
S5	79.26	81.34	89.98
S6	84.43	84.75	85.65
S7	75.54	77.93	86.87
S8	83.51	86.35	93.19
S9	69.54	71.77	80.28
S10*	77.42	81.35	89.04
Average	**79.58**	**81.93**	**88.55**

* Female Participants

Table II summarizes the classifiers accuracy for 10 subjects, by using a test data set of 100 samples. The average accuracy of OAA-SVM is 88.55%. The FFBP and CFBP got the average accuracies 79.58% and 81.93% respectively. By using OAA-SVM the classification accuracy is improved by an average value of 6.62% and 8.97% than by using CFBP and FFBP models respectively.

Experimental result suggested that, for a multiclass SSVEP data OAA-SVM can give better classification accuracy than that of FFBP and CFBP models.

It can be concluded from Table III that the SSVEP based BCI using OAA-SVM classifier with low frequency RVS can give a promising result. The wheelchair control developed by S. M. T. Muller et al. [14] provided an average classifier accuracy of 73% for four volunteers with hit rate of 60-100% during online experiment with visual feedback. A multi command SSVEP based BCI system using half-field stimulation method and thresholding algorithm for classification developed by Y. Punsawad, Y. Wongsawat [15] resulted with an average accuracy of 77% over four subjects. SSVEP based control with OAA-SVM developed in our study had got an average classification accuracy of 88.55% over 10 subjects.

IV. CONCLUSIONS

In this research three classifier models (FFBP, CFBP and OAA-SVM) were constructed for SSVEP data classification. The motivation of this work is to improve the accuracy of

SSVEP based BCI system by improving the classification accuracy. EEG signals were recorded by using RMS EEG-32 Super Spec system and SSVEP features extracted using FFT. The amplitudes of first and second harmonics of SSVEP data were successfully used as the feature vector to train the classifier models. The experimental result shows that OAA-SVM yields superior classification accuracy compared against FFBP and CFBP for SSVEP data. The average classification accuracy for 10 subjects provided by OAA-SVM is 88.55% while FFBP and CFBP provide 79.58% and 81.93% respectively. All the subjects participated in this study shows better accuracy by using OAA-SVM.

TABLE III: COMPARISON OF CLASSIFICATION ACCURACIES OF VARIOUS SSVEP BASED BCI SYSTEM

Classifier model	Stimuli	Average Accuracy
SSVEP with OAA- SVM classifier	RVS with four different flickering frequencies	88.55 % (10 subjects)
SSVEP with rule based decision for target discrimination [14].	Checkerboard stimuli with four different strips	73 % (4 subjects)
SSVEP Classification algorithm using maximum magnitudes of power spectrum as threshold values [15]	Half field stimulation method with four commands	77 % (4 subjects)

The future work may include the development of a SSVEP based BCI application system that can provide higher accuracy by using OAA-SVM classifier.

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