Influence of Stimuli Color and Comparison of SVM and ANN Classifier Models for Steady-State Visual Evoked Potentials

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***Abstract*—In recent years, Brain Computer Interface (BCI) systems based on Steady-State Visual Evoked Potential (SSVEP) have received much attentions. In this study 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. Two stimuli colors, green and violet were used in this study to investigate the color influence in SSVEPs. The Electroencephalogram (EEG) signals recorded from the occipital region were segmented into 1 second window and features were extracted by using Fast Fourier Transform (FFT). This study tries to develop a classifier, which can provide higher classification accuracy for multiclass SSVEP data. Support Vector Machines (SVM) is a powerful approach for classification and hence widely used in BCI applications. One-Against-All (OAA), a popular strategy for multiclass SVM is compared with Artificial Neural Network (ANN) models on the basis of SSVEP classifier accuracies. Based on this study, it is found that OAA based SVM classifier can provide a better results than ANN. In color comparison SSVEP with violet color showed higher accuracy than that with green stimuli.**

***Index Terms*—steady-state visual evoked potential, brain computer interface, support vector machines, ANN**

I. Introduction

The Brain Computer Interface (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).

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. 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], [2], [3].

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 of the brain and are nearly sinusoidal waveform having the same fundamental frequency as the stimulus and including some of its harmonics. By matching the fundamental frequency of the SSVEP to one of the stimulus frequencies presented, it is possible to detect the target selected by the user. 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. Muller and Pfurtscheller [7] used SSVEPs as the control mechanism for two-axis electrical hand prosthesis. Recently, Lee et al. [8] presented a BCI system based on SSVEP to control a small robotic car.

One of the main considerations during the development of a BCI system is to improve the classifiers accuracy, as that can affect the overall system accuracy and thus the ITR. In this research work, comparative study of Artificial Neural Network (ANN) and Support

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Vector Machine (SVM) have been carried out based on the classification accuracy of a multiclass SSVEP signal.

The retina of human eye contains rod and cone cells. The rod cells detect the amount of light and cone cells distinguish the color. There are three kinds of cone cells and are conventionally labeled as Short (S), Medium (M), and Long (L) cones according to the wavelengths of the peaks of their spectral sensitivities. S, M and L cone cells are therefore sensitive to blue (short-wavelength), green (medium-wavelength) and red (long-wavelength) light respectively. The brain combines the information from each cone cells to give different perceptions to different colors; as a result, the SSVEP strength elicited with different colors of the stimuli will different.

II. Materials And Methods

A. Subject

Ten right handed healthy subjects (seven males and three females, aged 22-27 years), with normal or corrected to normal vision participated in the experiment. All of them had normal color vision and not had any previous BCI experience. Prior starting, subjects were informed about the experimental procedure and required to sign a consent form.

B. Stimuli

The RVS for eliciting SSVEP responses can be presented on a set of Light Emitting Diodes (LEDs) or on a Liquid Crystal Display (LCD) monitor [9]. In this study RVS displayed using LCD monitor due to the flexibility in changing the color of flickering bars, and were designed using LabVIEW software (National Instrument Inc., USA). Two colors: green and violet were included in the experiment. Background color selected as black. 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 [10] and the high amplitude SSVEPs are obtained at lower frequencies. The visual stimuli were square (4cm×4cm) in shape and were placed on four corners of the LCD screen.

C. Experimental Setup

The subjects were seated 60cm in front of the visual stimulator as shown in Fig.1. EEG signals were recorded using RMS EEG-32 Super Spec system (Recorders and Medicare System, India). The SSVEP potential recorded from occipital region using Ag/AgCl electrodes were amplified and connected to the adaptor box through head box. 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. The electrodes were placed as per the international 10-20 system. The skin-electrode impedance was maintained below 5KΩ. The EEG signals were filtered by using a 3-50 Hz band pass filter and a 50 Hz notch filter. Signals were sampled at 256 Hz and the sensitivity of the system was selected as 7.5 μV/mm.

In training session the electrodes were placed at the O1, O2 and Oz regions of the scalp. The reference electrodes were placed on the right and left earlobes (A1 and A2) and ground electrode on Fpz. We first collected the SSVEP data for all the four frequencies with green color and then repeated the experiment for violet color in another session. The interval between the sessions was 10 minutes. Initially the subjects were required to close their eyes for recording 2 minutes of baseline signal and then given 5 minutes to adapt to the flickering stimulus placed in front of them.

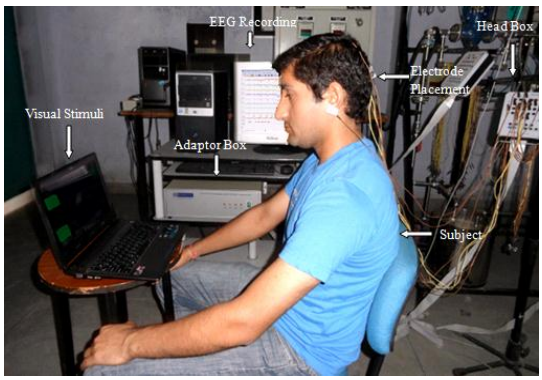


Figure 1. Experimental set up for SSVEP data acquisition (Courtesy-Department of Instrumentation and Control Engineering, National Institute of Technology, Jalandhar)

During experiments, the subjects were directed to focus on a particular frequency for 5 second duration followed by 5 second rest period. During focusing the subjects were instructed to avoid eye movements or blinking. The event markers were used to indicate the starting and ending time of each frequency. In a single trial, each of the four frequencies was performed three times and the same procedure was repeated for another three trials. 5 minutes break was given in between each trial. The time for completing one session was about 30 minutes.

D. Feature Extraction

The frequency features of SSVEPs can easily extracted by using Fast Fourier Transform (FFT) [11]. The EEG signals recorded from Oz -A2 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 7 Hz stimulation. 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.

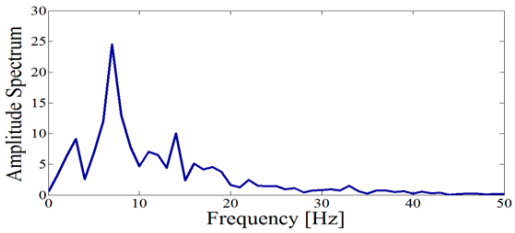


Figure 2. Amplitude spectra of SSVEP in response to 7 Hz, recorded from Oz -A2 channel of subject 4.

E. Classification

ANN and SVM classifiers were implemented to classify the feature vectors and compared with respect to the classification accuracy. Multilayer ANN architecture consists of an input layer, a number of hidden layers and an output layer. Backpropagation [12] 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 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 Levenberg-Marquardt backpropagation, Fletcher-Powell conjugate gradient backpropagation andBayesian regularization.

Performance of the ANN model was measured by Mean Square Error (MSE) function. The Cross Validation (CV) procedure [12] 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 in [13] 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 [14]. 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 [15] 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 feature vector extracted using FFT were used for classification. There have two separate data sets each for two different stimuli colors. The training dataset for each color consist 150 samples (30 samples for each of the four frequencies and 30 for rest signal) from each subject data i.e. a total of 1500 samples in a complete set. The data were normalized in the range of [-1, +1]. After dozens of training sessions, an ANN network configuration having one hidden layer with 10 neurons was selected. Levenberg-Marquardt backpropagation algorithm gave better results as compared to other training algorithms. For SSVEP classification, pure linear and tangent sigmoid functions were found better for hidden and output layer neurons respectively. Fig. 3 presents the MSE performance measures for FFBP and CFBP classifiers by using violet color data. The CFBP algorithm converges at a faster rate than FFBP. The best validation performance of FFBP is 0.068267 and that of CFBP is 0.049344 at epoch 5. It is clear that the performance of CFBP is better than FFBP.

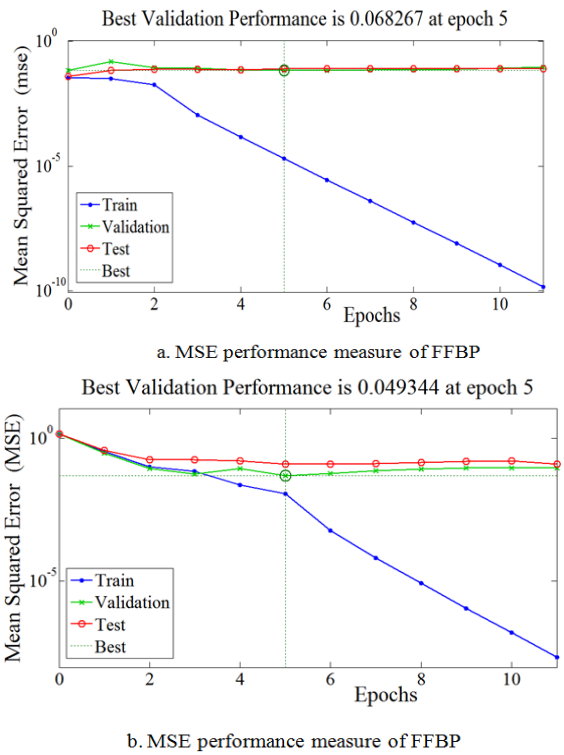
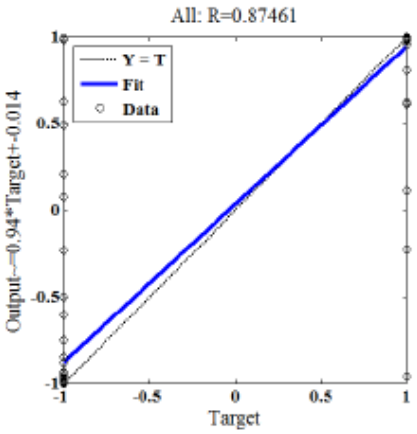


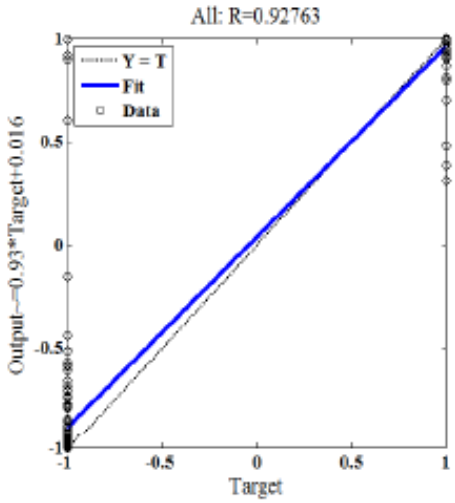
Figure 3. MSE performance measure of FFBP (a) and CFBP (b) during training using SSVEPs elicited by violet stimuli

Individual SVMs were trained with different kernel functions. The kernels with maximum accuracies were selected for OAA-SVM formulation. For 7 Hz the polynomial kernel with order 3 had got an accuracy of 100% for both violet and green color and for 9 Hz quadratic kernel provides an accuracy of 98.69% for violet and 90.84% for green. Higher accuracy for 11 Hz was provided by linear kernel and is 95.43% for violet and 86.60% for green. For 13 Hz both colors got an accuracy of 100% using linear kernel. 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 green and 98.53% for violet during training.

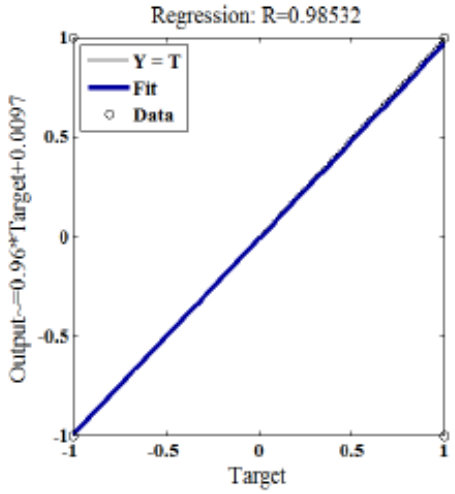
Fig. 4 presents the regression plots for FFBP, CFBP and OAA-SVM classifiers during training using violet data. The regression value for CFBP is 0.92763 and that of FFBP is 0.87461. The OAA-SVM got a regression value of 0.98532. The regression values obtained during training of green data is 0.8484, 0.9035 and 0.9402 for FFBP, CFBP and SVM classifiers respectively. This proves the superior performance of OAA-SVM over FFBP and CFBP for SSVEP classification.



a. Regression plot of FFBP



b. Regression plot of CFBP



c. Regression plot of SVM

Figure 4. Comparison of regression plots of FFBP, CFBP and OAA-SVM models obtained during SSVEP data classification

TABLE I. COMPARATIVE RESULTS OF TESTING ACCURACY OF SSVEPS ELICITED BY GREEN AND VIOLET COLOR STIMULI FOR 10 SUBJECTS BASED ON ANN AND SVM CLASSIFIERS

Subjects	Classifier Accuracy (%)					
	FFBP		CFBP		OAA- SVM	
	Green	Violet	Green	Violet	Green	Violet
S1*	83.23	86.50	84.29	86.93	92.43	94.57
S2	80.04	82.06	83.19	83.98	91.76	96.32
S3	78.01	80.31	78.99	81.23	82.32	86.64
S4*	84.84	84.99	86.46	88.78	94.02	94.95
S5	79.26	85.08	83.34	87.36	89.98	91.41
S6	84.43	86.42	84.75	87.07	85.65	90.23
S7	75.54	77.43	79.03	81.45	86.87	89.07
S8	83.51	88.18	86.35	92.73	93.19	97.48
S9	69.54	71.63	71.58	73.08	80.28	84.16
S10*	77.42	82.04	81.35	83.77	89.04	93.70
Average	**79.58**	**82.46**	**81.93**	**84.64**	**88.55**	**91.85**

The designed classifier models were tested using the data sets obtained from ten subjects. The accuracies obtained during testing of all the data sets using the same configurations of FFBP, CFBP and OAA-SVM classifiers are presented in Table I. Compared with FFBP and CFBP the OAA-SVM gave higher accuracy for both colors. Accuracy of CFBP is higher than the accuracy of FFBP but lower than that of OAA-SVM. Experimental result suggested that, for a multiclass SSVEP data OAA-SVM can give better classification accuracy than that of FFBP and CFBP models.

Test data result of violet stimuli shows higher accuracy than that of green color with all three classifiers. Violet color has an average accuracy of 91.85% with OAA-SVM classifier and is higher than the accuracy of green with the same classifier. The reason for this may be related to the principle of perception of light and color sensitivity of human eyes. As mentioned, the green color can only elicit medium cone cells. Violet color, a combination of blue and red can elicit the cones responsible for blue and red, i.e. both short and long cones. As a result, with violet color more intense SSVEP is appeared in visual cortex (occipital lobe) of the brain compared to green color.

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. SSVEPs were elicited using four different frequencies. Two different stimuli color, green and violet were compared to get better performance. 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 result also showed that SSVEPs with violet stimuli is better than that with green stimuli.

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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