BCI Based Wheelchair Control using Steady State Visual Evoked Potentials and Support Vector Machines

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Abstract— This paper presents a Steady State Visual Evoked Potential (SSVEP) based Brain Computer Interface (BCI) system to control a wheelchair in forward, backward, left, right and in stop positions. 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 by using Fast Fourier Transform (FFT). Three different classifiers, two based on Artificial Neural Network (ANN) and one based on Support Vector Machine (SVM) were designed and compared to yield better accuracy. Ten subjects were participated in the experiment and the accuracy was calculated by considering the number of correct detections produced while performing a predefined movement sequence. One-Against-All (OAA) based multiclass SVM classifier showed better accuracy than the ANN classifiers.

Index Terms—ANN; Brain Computer Interface; Steady State Visual Evoked Potential; Support Vector Machines

I. INTRODUCTION

Brain Computer Interface (BCI) is a system, that can acquire and translate the brain signals to provide a direct communication channel between the brain and a computer. For people suffering from severe neuromuscular disorders, such as spinal cord injury, brain stem stroke or Amyotrophic Lateral Sclerosis (ALS), a BCI system can provide an alternative, augmentative communication and control options to restore the interaction with their surrounding environment, without using peripheral nerves and muscles [1].

Electroencephalography (EEG) is a non-invasive way of acquiring brain signals from the surface of human scalp. It is widely accepted in the BCI systems due to its low cost, simple and safe approach. Some of the brain activities that can be effectively recorded from the scalp by using EEG are Event Related Potentials (ERPs), Slow Cortical Potentials (SCPs), P300 potentials and Steady-State Visual Evoked Potentials (SSVEPs) [3]. Among them SSVEPs are attracted due to its advantages of requiring less or no training, high Information Transfer Rate (ITR) and ease of use [4].

SSVEPs are the responses that are elicited in the brain when the person is visually focusing his/her attention on a Repetitive Visual Stimulus (RVS) 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.

Many research groups are developing SSVEP based BCI systems. Lalor et al. [5] developed the control for an immersive 3D game using SSVEP signal. Muller and Pfurtscheller [6] used SSVEPs to control two-axis electrical hand prosthesis. Cecotti [7] developed a self paced and calibration less BCI speller based on SSVEP detection. Recently, Lee et al. [8] proposed a SSVEP based BCI system to control a small robotic car in three directions.

Some of the main factors that can determine the performance of a BCI system include the type of the brain signal used to transfer the intentions, feature extraction methods, classification algorithms to get the control commands etc. In this study, we investigate the effect of three different classification methods in enhancing the performance of a SSVEP based wheelchair control system. This system can control a wheelchair in forward, right, left, backward and in stop positions. The classifiers, two based on Artificial Neural Network (ANN) and one based on Support Vector Machine (SVM) are compared with each other.

II. MATERIALS AND METHODS

A. System Configuration

Fig. 1 illustrates the block diagram of the proposed SSVEP based wheelchair control system, which includes visual stimuli developed using LabVIEW and displayed on a Liquid Crystal Display (LCD) monitor, EEG acquisition unit, signal processing unit with feature extraction and classification algorithms, hardware interface and a wheelchair prototype.

B. 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. None of them had previous BCI experience. Prior starting, subjects were informed about the procedure of the experiment and required to sign a consent form.

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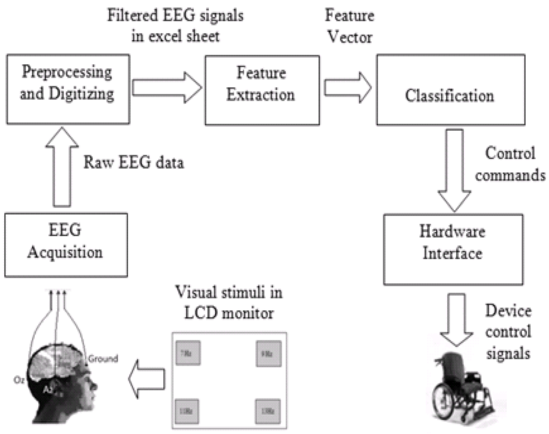


Fig.1. Conceptual block diagram of the proposed SSVEP based wheelchair control system.

Fig.2. Subject participating in SSVEP data acquisition (Courtesy- Department of Instrumentation and Control Engineering, National Institute of Technology, Jalandhar)

C. Visual 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 was designed by using LabVIEW software (National Instrument Inc., USA) and displayed using LCD monitor. The visual stimuli were square (4cm×4cm) in shape and were placed on four corners of the LCD screen. 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 [11].

D. Experimental setup

The subjects were seated 60cm in front of the visual stimulator as shown in Fig.2. 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 7.5µV/mm.

In training session the electrodes were placed at the O_1, O_2 and O_z regions of the scalp. The reference electrodes were placed on the right and left earlobes (A_1 and A_2) and ground electrode on F_{pz}. 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.

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 the whole session was about 30 minutes.

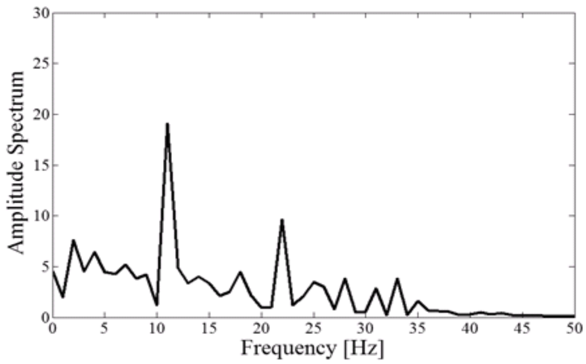


Fig.3. Amplitude spectra of SSVEP in response to 11 Hz, recorded from Oz -A2 channel of subject 4. First and second harmonics can be found clearly.

E. Feature Extraction

The frequency features of SSVEPs can be extracted using Fast Fourier Transform (FFT) [12]. The EEG signals recorded from each channel were digitized and segmented into 1 second time window in every 0.25 seconds. MATLAB was used for developing the FFT algorithm. Fig. 3 shows the amplitude spectra of SSVEP induced by 11 Hz stimulation. From the FFT of all the connected channels, the data from O_z –A_2 was selected for further system development as strongest SSVEP was observed at O_z. The coefficients of the fundamental and second harmonics of all the four target frequencies from the amplitude spectra were considered as the feature vector for classification.

F. Classification

ANN and SVM classifiers were implemented to classify the feature vectors. Two multilayer ANN models, Feed-forward Backpropagation (FFBP) and Cascade-forward Backpropagation (CFBP) were designed. Backpropagation [13] is a supervised learning algorithm which can be used in multilayer ANN.

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 backpropagation algorithm; with an exception that in CFBP each layer has a weight connection from the input and previous layers and thus each layer neuron relates all previous layer neurons including input layer neurons.

Modeling of the ANN was done by using MATLAB neural network training tool. Different combinations of internal parameters like number of hidden layers, number of neurons in each hidden layer, transfer function of hidden layers and output layer etc were tried. By considering the eight input parameters i.e. the first and second harmonics of each of the four frequencies, eight neurons were fixed in the input layer of the ANN models. Four neurons were fixed in the output layer to get a four digit data output for each class. Gradient descent with momentum weight and bias learning function was used in both ANN models. Different variants of the backpropagation algorithm were tried like Bayesian regularization, Levenberg-Marquardt backpropagation, Fletcher-Powell conjugate gradient backpropagation, and Gradient descent with momentum backpropagation.

Performance measure of the ANN models was done by Mean Square Error (MSE) function. The Cross Validation (CV) procedure [13] evaluates the training and learning of the ANN 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.

SVM introduced by Vapnik, [14] is basically a binary classifier that can separate two classes by using an optimal hyperplane. Kernel functions provide a convenient method for mapping the data space into a high-dimension feature space without computing the non-linear transformation [15]. Linear, quadratic, polynomial and radial basis function (rbf) kernels are some of the common kernel functions.

SVM training and classification was done by using Bioinformatics toolbox in MATLAB. As four visual stimuli were used, it was necessary to develop a multiclass SVM. One-Against-All (OAA) strategy [14], a multiclass SVM, was adopted in our experiment. 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, one for each frequency. After training, a structure was developed having the details of the SVM, indicating the number of support vectors, alpha, bias etc.

G. Hardware Implementation

The wheelchair prototype is shown in Fig. 4. Motor driver IC (IC L293D) was used to control two motors (M_1 and M_2) of the wheelchair. By changing the polarity of the signal given to the motors, through the motor driver IC, it is possible to move the motors in both forward and backward directions.

The parallel port of the computer was used to send out eight data bits. The first four data pins i.e. D_0, D_1, D_2, and D_3 were used to interface the control signal to the motor IC. Positive and negative of the right motor was given through D_0 and D_1 and that of left motor was by using D_2 and D_3. Rest of the data pins was not used. Interfacing program was developed using MATLAB.

The control commands used to change the polarity of the motors for each movement of the wheelchair were presented in Table I. Forward movement of both right (M_1) and left (M_2) motor results in the forward direction motion. Left motor forward and stop position of right motor will provide right movement of the wheelchair. Left motor stopped and a forward movement of right motor results left rotation of the wheelchair. The backward movement of both motor together provides the device to move backward. The stop positions of both the motor together results in the stopping of wheelchair.

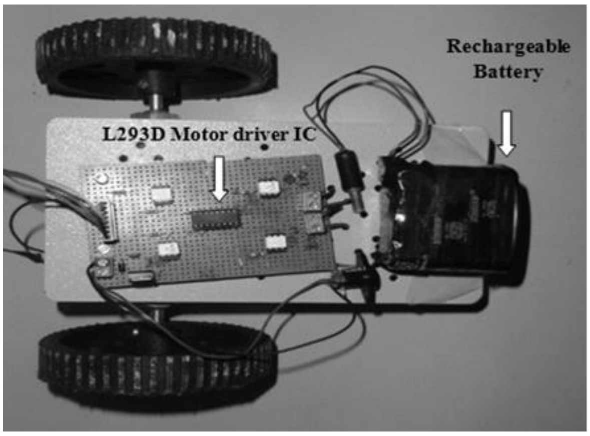


Fig.4. Wheelchair prototype for SSVEP based BCI control

Table I Control logic for Wheelchair movements

Right Motor (M_1)		Left Motor (M_2)		Movement Direction
+	-	+	-	
1	0	1	0	**Forward (F)**
0	1	0	1	**Backward (B)**
0	0	1	0	**Right (R)**
1	0	0	0	**Left (L)**
0	0	0	0	**Stop**

The classifier outputs for each of the four frequencies and relax state were assigned to the five different movements of the wheelchair. For 7 Hz detection, the output of the parallel port is [1 0 1 0] and will move the wheelchair in forward direction. 9 Hz would give [0 0 1 0] and will cause a right movement. 11 Hz detection delivers an output of [1 0 0 0] and will result in the left movement of the wheelchair. For 13 Hz the parallel port output is [0 1 0 1] which results in a backward movement of the wheelchair. The classifier result for the relax state of the user is [0 0 0 0] and it will stop the wheelchair.

III. RESULTS AND DISCUSSIONS

A. Classifier training

The training dataset consist 150 samples (30 samples for each of the four frequencies and 30 for rest signal) from each subject data. The data were normalized in the range of [-1, +1]. After dozens of training sessions, a 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. FFBP network was trained in 18 seconds and CFBP in 33 seconds. Fig. 5 presents the MSE performance measures for FFBP and CFBP 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. It is clear that the performance of CFBP is better than FFBP.

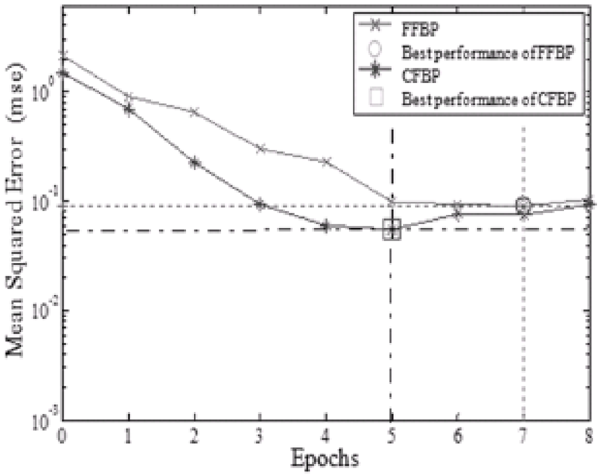
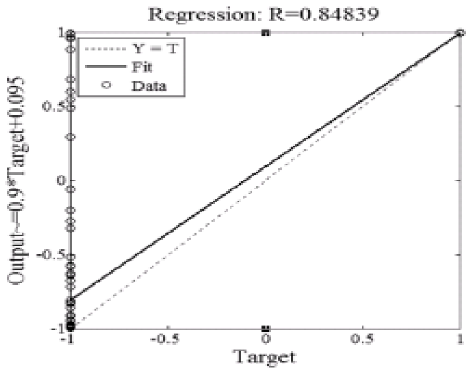


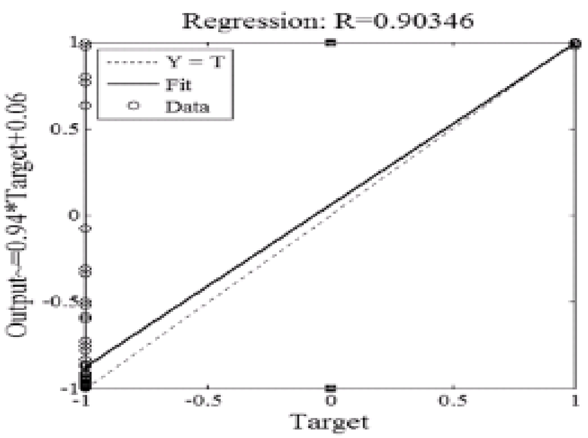
Fig.5. MSE performance measure of FFBP and CFBP during training. CFBP got better result than FFBP.

Individual SVMs were trained with different kernel functions and their accuracies and required numbers of support vectors are shown in Table II. For discriminating 7 Hz from other classes, both the 3rd and 4th order polynomial kernels are giving an accuracy of 100% with a requirement of 23 and 38 support vectors respectively. The polynomial kernel with less number of support vectors is selected to reduce the complexity of the SVM structure. For 9 Hz, quadratic kernel provides an accuracy of 90.84%. The accuracy for 11 Hz is 86.60% and that of 13 Hz is 100% by using linear kernel. SVM was trained in a fraction of the second and is 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.

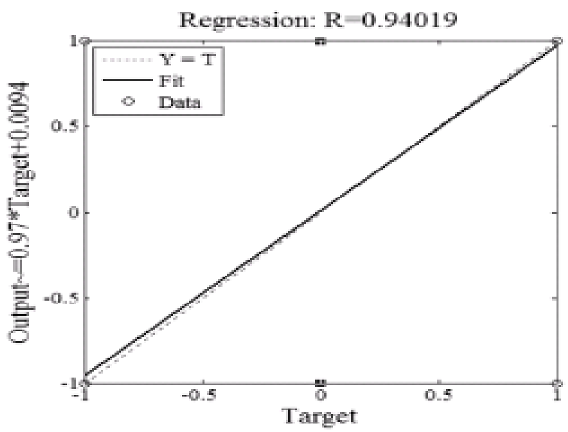
Fig. 6 presents the regression plots for FFBP, CFBP and OAA-SVM classifiers during classifier testing using a separate dataset with 50 samples from each subject. The regression value for CFBP is 0.90346 and that of FFBP is 0.84839. The OAA-SVM got a regression value of 0.94019. This proves the superior 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 OAA-SVM

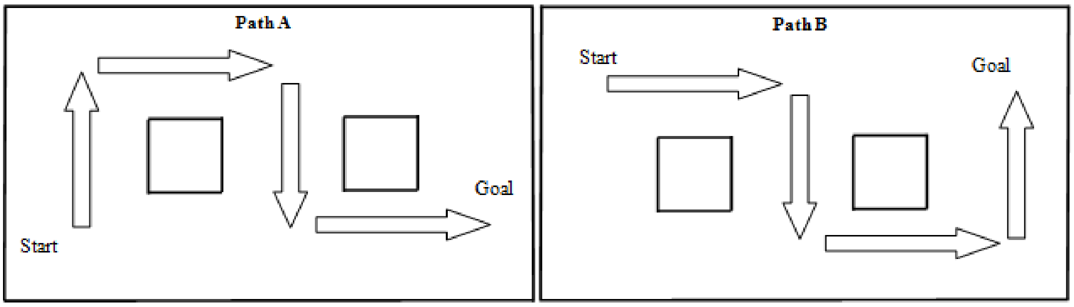
Fig.6. Comparison of regression plots of FFBP, CFBP and OAA-SVM models obtained during SSVEP data classification.
Plot shows the linear regression of Targets (T) relative to outputs (Y)

Table II Comparison of Various Kernel Functions

Kernel Function	7 Hz		9 Hz		11 Hz		13 Hz	
	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
Polynomial (order 4)	100	38	86.11	37	80.17	34	17.02	25
Radial Basis Function	34.41	118	35.27	117	66.16	119	35.17	116

Table III Sequence of movements and corresponding frequencies

Path A	**Movement**	F	R	F	R	F	L	F	Stop
	Frequency (Hz)	7	9	7	9	7	11	7	Relax
Path B	**Movement**	F	R	F	L	F	L	F	Stop
	Frequency (Hz)	7	9	7	11	7	11	7	Relax



a. Path A **b. Path B**

Fig. 7 Shape of the paths used in testing session

A. Wheelchair Interface

In testing session the subjects were directed to perform two different sequences i.e. path A and path B, each one with 8 movements including stop command. Each of the sequence was performed three times, thus each subject performed a total of 48 movements. The shape of the paths is shown in Fig. 7. Table III presents the sequences required to complete the paths and corresponding frequencies. The SSVEP data recorded from O_z–A_2 channel was filtered, digitized and segmented into one second window in every 0.25 seconds and transformed into frequency domain using FFT. The predefined parameters obtained from the amplitude spectra of the SSVEP signal were classified using optimal FFBP, CFBP and OAA-SVM classifiers. To reduce the number of wrong selections, a requirement of three continuous detection of the same target was set to produce the particular command to the wheelchair.

Accuracy of the system is measured with the accurate detections made by the subject out of the total number of the detections. The number of correct detections and the accuracy of all the 10 subjects are presented in Table IV. Out of 10 subjects, eight got higher accuracy by using CFBP as compared to FFBP. One subject got equal number of correct detections by using both FFBP and CFBP. Only one subject shows a higher accuracy for FFBP than CFBP. These results show that for SSVEP classification, CFBP can provide a better accuracy than FFBP.

Compared to FFBP and CFBP, OAA-SVM shows a better result for all the 10 subjects. Subject S4 got 100% accuracy by using OAA-SVM classifier. The average detection rate during OAA-SVM classifier is 43.4 and it is higher than the detection rates

Table IV The number of correct detections and percentage accuracy in producing the sequences given for 10 subjects

Subjects	FFBP		CFBP		OAA-SVM	
	Correct Detections	Accuracy (%)	Correct Detections	Accuracy (%)	Correct Detections	Accuracy (%)
S1*	42	87.50	42	87.50	46	95.83
S2	41	85.42	43	89.58	45	93.75
S3	34	70.83	35	72.92	40	83.33
S4*	42	87.50	43	89.58	48	100
S5	39	81.25	42	87.50	44	91.67
S6	42	87.50	41	85.42	43	89.58
S7	37	77.08	39	81.25	42	87.50
S8	41	85.42	44	91.67	47	97.92
S9	30	62.50	31	64.58	34	70.83
S10*	39	81.25	40	83.33	45	93.75
Average	**38.7**	**80.63**	**40**	**83.33**	**43.4**	**90.42**

*Female participants

Table V Comparison of various BCI based Wheelchair Controls developed

Wheelchair controls	Possible movements	Range of Accuracy (%)
SSVEP with OAA- SVM classifier.	Forward, Left, right, Backward and stop	70.83-100 (10 subjects)
SSVEP with rule based decision target discrimination [16].	Forward, Left, right and stop	60.00-100 (4 subjects)
Sensorimotor Rhythm with Linear Discriminant Analysis (LDA) classifier [17].	Front and Right	63.30-70.00 (1 subject in 3 series of experiment)

obtained by using FFBP and CFBP methods.

It can be concluded from Table V that the SSVEP based wheelchair control using OAA-SVM classifier gives a promising result. The wheelchair control developed by S. M. T. Muller et al. [16] provided an average classifier accuracy of 73% for four volunteers with hit rate of 60-100% during online experiment with visual feedback. A Sensorimotor Rhythm based wheelchair control developed by Carra and Balbinot [17] resulted in an average hit rate of 65.7% in three series of experiments participated by a single subject. SSVEP based wheelchair control with OAA-SVM developed in this study is able to control in five different positions (forward, backward, left, right and stop) and this system has got an average accuracy of 90.42% for ten subjects.

IV. CONCLUSIONS

This work presented the development of a prototype of BCI based wheelchair control. The SSVEPs elicited by four different flickering frequencies were used to control a wheelchair prototype in four different directions. A total of ten subjects, seven males and three females participated in this study. EEG signals were recorded from O_z-A_2 channels by using RMS EEG-32 Super Spec system and SSVEP features were extracted using FFT. In this research three classifier models (FFBP, CFBP and OAA-SVM) were used for SSVEP feature classification. All the subjects participated in the experiment showed a better accuracy with OAA-SVM method. The results illustrated the superiority of OAA-SVM over FFBP and CFBP models for classifying SSVEP features. Also the results of the developed prototype indicate that the SSVEP based BCI with OAA-SVM classifier can give a promising way to develop a wheelchair control for disabled persons.

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