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SSVEP Based BCI for an Object Control in 2D Space

Niharika Thakur*

Department of Electronics & Communication, Manav Rachna College of Engineering, Faridabad, India

Abstract

The Brain-Computer Interfaces can successfully help the healthy and disabled users, in performing various activities in their day to day life. But still such high expectations are yet to be fulfilled by the existing BCI designs due to their restricted reliability and less understanding of the brain mechanisms used in it. Brain-computer interface (BCI) systems based on the steady-state visual evoked potential (SSVEP) provide higher information transfer rate and require lesser training time than BCI systems using other paradigms.

This work aimed to directly address the above problems by optimizing the BCI designs based on Steady-State Visual Evoked Potential (SSVEP) brain responses. The main goal of this work was to optimize the frequency to be used by the users and further enhance the information transfer rates and the reliability of multi-command SSVEP-based BCI systems.

The BCI system is designed to allow control of a virtual ball in 2D space with more than 97% of average accuracy with different users.

Keywords: Brain computer interface (BCI); SSVEP; SVM; Control

Introduction

A brain-computer interface (BCI) is a system that behaves as a communication pathway between the brain and an external device. The brain signals are translated into certain commands, thereby, making a BCI system as an alternative method of communication for people who have severe neuromuscular problems [1].

The brain signals can be obtained using invasive or noninvasive methods. Electroencephalography (EEG) is a noninvasive way of acquiring electrical potentials from the surface of human scalp, which is usually more favorable due to its simple and safe approach [1]. Different types of EEG input features can be used for BCI systems e.g. slow cortical potentials [2], oscillatory EEG activity [3], P300 potential [4] and visual evoked potential [5]. There are different factors that affect the selection of input feature for BCI's, such as the purpose of application, the influence of the input feature on information transfer rate of the BCI system, the signal processing methods used, training period required and adaptability for majority individuals. Steady-state visual evoked potential (SSVEP) is the response generated in the brain when a person is visually focusing his/her attention on a particular stimulus which is continuously flickering at frequency of 6 Hz and above [6]. SSVEP is being used as the input by many research groups for designing BCI systems. SSVEP is favourably used as an input signal as it is based on detection of increment in a specific power spectrum [7].

SSVEP is most prominent at the occipital region of the scalp [5,8]. Since the evoked response is focusing at specific frequencies, therefore by using simple frequency domain algorithms [8] the relative information between the stimulus and the triggered response can be determined. SSVEP-based system is usually less sensitive to artifacts, as long as the frequencies of the artifacts are not overlapping with the stimulus frequency [6,8]. Most of the SSVEP applications are for subjects who have the capability to control their eye movement [6]. In previous study [9], investigation has been done to evaluate the practicality and advantages of using SSVEP as input feature to a BCI system. SSVEP-BCI systems have different accuracy for different range of frequencies and different subjects respond differently to different frequencies leading to inter subject variability problem.

This paper presents a BCI system that is able to recognize the targeted stimulus the subject was focusing on. SSVEP is chosen as the input feature because it is a promising type of brain signals which can be triggered in most subjects when they are looking at a visual stimulus, without requiring special subject training. Optimal ranges of frequencies for which user responds accurately is found to remove the problem of inter subject variability. The system described in this paper is using SVM classification and is able to control an object in 2D space.

In future, the system may be integrated with more control commands, to control the movement of the wheelchair for the disabled persons.

Experimental Setup

To design a BCI system, RMS Super Spec 32 is used for the signal acquisition. It is fully computerised EEG machine with video and USB facilities it can record 32 channels of EEG data through electrodes placed according to the international 10-20 electrode system. It supports 24/32* Channel simultaneous acquisition of raw data.

The letters F, T, C, P, and O stand for Frontal, Temporal, Central, Parietal and Occipital sites. It allows fast exchange of data with MATLAB.

The Acquired signal is used with MATLAB for performing Feature Extraction and classification techniques. After the classification of the signal, the generated control signals are sent to LabVIEW for driving the application i.e. an object is moved in 2D space. These softwares served as the basis for the development of the BCI system. The system uses visual stimulation consisting of 4 flickering LED's, each of which produces different SSVEP over the visual cortex. These SSVEP's are analyzed and converted into 4 control signals to control the application. The design and implementation of this BCI is described in Figure 1.

Neurophysiological phenomena used to drive the BCI system

SSVEP's are elicited by a visual stimulus modulated at a certain frequency (above 6 Hz); this stimulus produces a response in the

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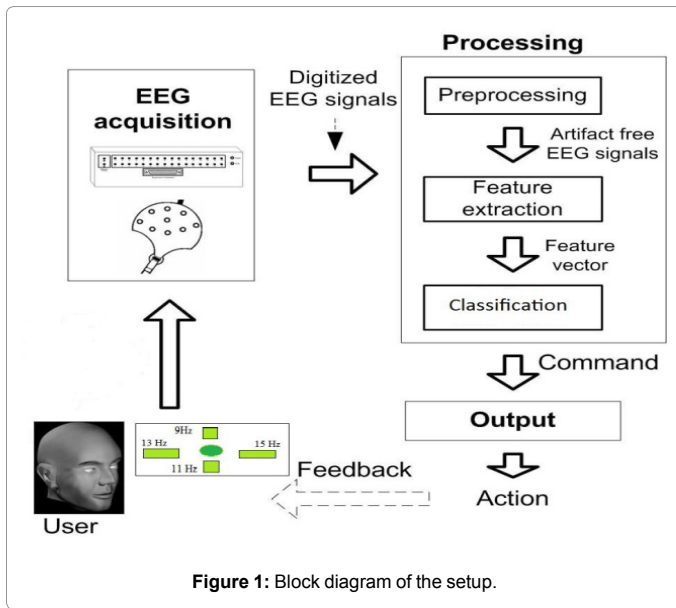
Figure 1: Block diagram of the setup.

EEG activity, which is characterized by oscillations at the stimulation frequency and sometimes at harmonics or sub-harmonics of it. SSVEP's are easily recognized by analyzing the frequency content of EEG signal recorded over the visual cortex. The neurophysiological phenomena used to drive the BCI system, studied in this study was chosen for the reason that SSVEP's are easily recognized by analyzing the frequency content of EEG signal. SSVEP require almost no training for its elicitation and have high communication bit rates but requires gaze control for practical applications.

Signal acquisition

The EEG signals were recorded in the process control laboratory of the university. The criteria for selection of a subject were a normal subject. The recording electrodes Fp1, Fp2, A1, A2, C4, Cz, C3, T4, T5, P3, Pz, P4, O1, Oz, O2, GND, REF were evenly distributed on the head surface according to the international 10-20 system and referenced to forehead [10]. Linked-earlobes are adopted as reference. During the EEG experiment, the subject was seated comfortably on a chair facing a LCD computer monitor. The LED stimulus was placed 50 cm in front of the subject. Subject was asked to close his eyes and two minutes of REST signals were recorded. After that, subject was given a few minutes to adapt to the flickering stimulus before the SSVEP sessions started. Twelve healthy male right-handed subjects participated in this study. All of them had normal or corrected to normal vision. The age of the ten subjects ranged from 21 years to 28 years. These subjects had no risk of epileptic seizure.

The parameters for the collection were: hardware filter between 1 and 48 Hz, sampling frequency 256 Hz, and a 50 Hz notch filter for the line frequency interference and impedance was kept below 5 kΩ. The sampling frequency was set based on the efficiency of the signals acquired from the patients head. Figure 2 shows the experimental settings.

The training experiment was carried out to determine four optimal frequencies for each subject, as the SSVEP frequencies need to be optimized for each and every subject in order to facilitate a higher detection rate [9,11]. During the training experiment, four visual stimulus was presented. For each trial, the LED stimulus were programmed to at a selected frequency following MATLAB Algorithm, and epoch duration of 2 s. The signals recorded when the subject was gazing at the blinking stimulus is termed as SSVEP signals. Subjects

were required to maintain full visual concentration on the stimulus when it is blinking. Frequencies ranging from 5 Hz to 59 Hz were tested, and each frequency was tested for at least 5 times.

After determining the four optimal frequencies, testing experiment was carried out. Figure 3 shows a subject taking part in an EEG testing experiment. Four LED stimuli placed at the left, bottom, up and right edge of the computer screen was presented 50 cm in front of the subject, each flickering at a particular frequency respectively. The experiment runs two sessions with each session containing 10 trails for each of the four stimuli, resulting in 40 trials for each session. During each trial, subject was given the freedom to decide which stimulus they want to focus on as the desired target. They were required to focus their attention on the target when the stimulus is blinking while ignoring the other two flickering LEDs. At the end of each trial, the computer will process the recorded EEG signals and predict which target the subject was looking at. Subjects have a 2-3 minutes break between each session to relax. The experiment lasted for about 1 hour.

The EEG signals were stored and further processed with the self-developed programme in MATLAB. O1, O2, and Oz electrodes are reported to usually have strong SSVEP waveforms. But only Oz is used in developing the PSD based frequency recognition as it has the best response. All the raw EEG signals were recorded for further offline analyses.

Signal processing and feature extration

As the EEG signals have small amplitude they are very sensitive to external interferences such as power line. The active electrodes are able
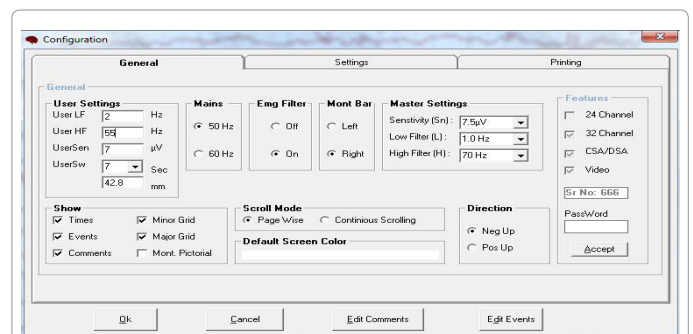

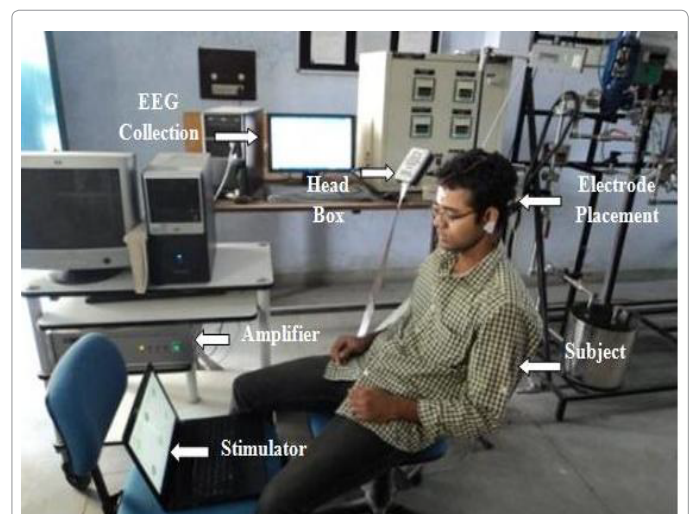**Figure 2:** Experimental settings for RMS-32.

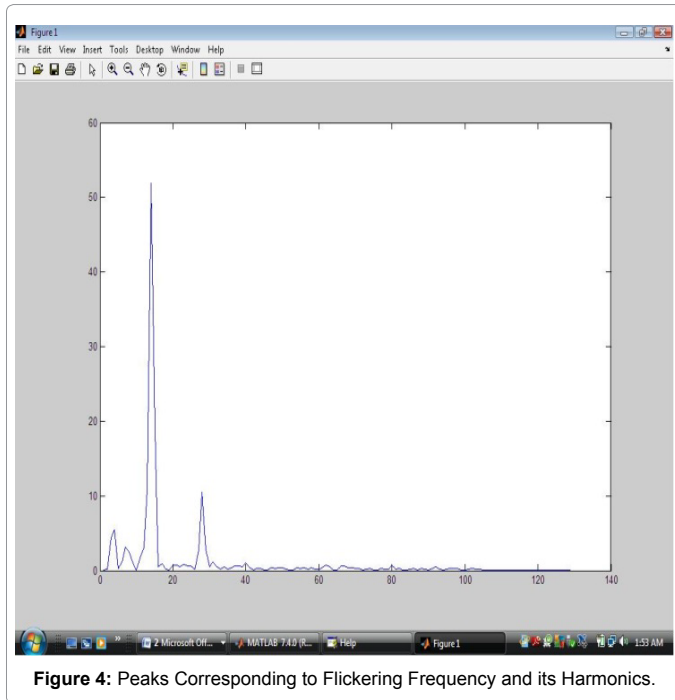**Figure 3:** Subject taking part in the experiment.

Figure 4: Peaks Corresponding to Flickering Frequency and its Harmonics.

to produce very low-noise measurements [12]. Ocular and muscular movements can induce large artifacts that distort the EEG signals. The EEG segments that contain such artifacts are identified, by means of their spectral content as explained in [13-15], and discarded.

The EEG signal is amplified, sampled and digitalized. Before performing feature extraction and classification techniques, this digital signal is normally pre-processed to eliminate artifacts and enhance the spatial resolution.

If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. Many feature extraction methods have been proposed for brain-computer communication. Some are known to be good and have been applied successfully depending on the experimental strategy used. An example of such a good method is band power, which extracts features for specific frequency ranges and is often used when there is change occur in frequency domain.

To achieve the goal of this work that is to use the SSVEP responses of BCI system to control an object (virtual ball). Therefore, to extract the SSVEP responses of the brain from the raw EEG data power spectral density with time window of 2 sec. with a fixed length. The main concept behind this method is that the frequency component with the highest spectral power corresponding exactly to one of the SSVEP stimulation frequencies will be considered as a BCI feature vector (Figure 4).

The amplitude of harmonic peaks keep decreasing and it's always less than the actual peak.

Classification into control signals

Classification methods are used to identify patterns of brain activity adopting techniques commonly used for pattern recognition and machine learning. Two classification techniques are used in this work:

Thresholding method: After the EEG for each subject was recorded, the peak values (after normalization) were computed corresponding to

each stimulus frequency and its harmonic for 2 s time. Then, average of peak powers for all the frequency was taken separately and these were the threshold for corresponding frequency. Then a simple algorithm was made to classify the signal using the concept that if power value corresponding to any frequency and its harmonic is more than this threshold then user was looking at that. This gives an output control signal corresponding to each selection which can be further used to control the application.

SVM classification: In order to understand whether a SSVEP pattern has been generated by the visual stimulus, a Support Vector Machine was developed. Generally speaking, the Support Vector Machine implements the following idea: it maps the input vector **x** into a high-dimensional feature space **Z** through some non-linear mapping **K**, chosen a priori. In this space, a hyper plane is constructed. This hyper plane, in our case, separates the SSVEP patterns from the non-SSVEP patterns. The core of a SVM classifier is the kernel function, as

$$K(x) => Z$$

One of the most used kernel functions, as in our experimental sessions, is the radial basis kernel. After the EEG for each subject is acquired and transformed into frequency domain, PSD of these signals was computed. They work as input matrix to train SVM after preprocessing. Then, the output matrix is created as per the instructions given to the subject for gazing. SVM is trained using the train signal. Classification of signal is performed to generate the control signal. Lastly, SVM performance is evaluated using regression plots.

Application Interface

For a quadriplegic patient, something as basic as controlling an object in 2-Dimension space would represent a revolutionary improvement in quality of life. In this work a virtual ball is controlled in 2D space using the SSVEP responses of the user towards different flickering frequency.

Object control in 2D space

This application allows the user to move the ball in different directions according to the following strategy:

- User gazing at LED flickering at 9 Hz: Ball will move in positive-y direction.

- User gazing at LED flickering at 11 Hz: Ball will move in negative-y direction.

- User gazing at LED flickering at 13 Hz: Ball will move in positive-x direction.

- User gazing at LED flickering at 15 Hz: Ball will move in negative-x direction (Figure 5).

Results and Discussions

All experimental data were re-sampled at 256 Hz and filtered with a band-pass of 1-48 Hz for off-line analysis in MATLAB. Signals from channels of Oz were used as its input for frequency detection using PSD analysis. Oz was in the occipital region, and the reason to involve Oz was because the occipital region (Oz) was the place where maximum response for SSVEP was observed 18 Healthy right handed male subjects participated for this study. 12 subjects were for optimizing the frequency for object control as well as testing it, whereas 6 subjects were made to test this optimized SSVEP based BCI for object control without any training (Table 1).
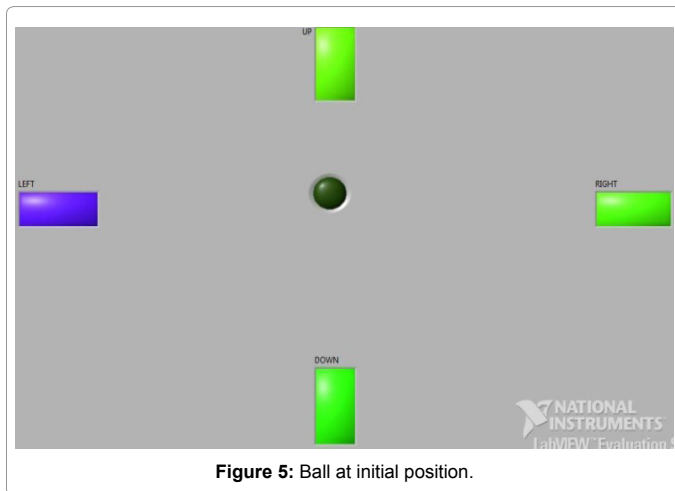
Figure 5: Ball at initial position.

Frequency(Hz)	Accuracy
7 Hz	91.50
10 Hz	96.75
13 Hz	97.25
16 Hz	94.25
19 Hz	92.00
22 Hz	92.25
25 Hz	90.50
28 Hz	89.00
31 Hz	86.25
34 Hz	84.25
37 Hz	82.00

Table 1: SSVEP Response Accuracy towards different frequencies.

Variation in accuracy with different frequencies

Above table shows that SSVEP's gives different accuracy for different range of frequencies. So, the ranges of frequencies are tested and it is observed that accuracy decreases with the increase in stimulus frequency. Therefore, low and medium ranges of frequencies are used for carrying out this work.

Optimal frequency for different users

As the flickering LED's are set at different frequencies for testing, the accuracy for different users gazing at different frequency varied. Experiment was performed for 12 Subjects of age group (21-30 yrs). As it is clear from the every user has their favorite frequency over which they give max accuracy (Table 2).

The problem of inter subject variability i.e. different subjects have different SSVEP response for different frequencies thereby, different accuracies. So, to remove this problem and develop a generalized system different users were checked with the frequency range of 5-59 Hz and found out that at these particular frequencies their performance gets enhanced. This can be used to design subject selective BCI control which uses only particular subject's favorite frequencies for flickering. This will lead to a better accuracy. Therefore, the most appropriate response is obtained in the range of 8-15 Hz. Most of the users have highest accuracy for the flickering frequency of 13 Hz.

Variation in accuracy with different kernel functions

The SVM kernel functions are used for nonlinear mapping into feature space, and different kernel function perform with different classification accuracy, so to get the maximum classification rate all

kernel functions were tested and Gaussian radial basis function have the maximum classification accuracy, so it was used for classification technique. The table shows the different accuracy achieved with different kernel functions used (Table 3).

The effect of classification

Table 4 shows that thresholding classification gives less accuracy. So, SVM classification technique was used for classification. Then to increase the classification no. of samples were increased which enhanced the accuracy and after 200 samples accuracy was the same. Therefore, 200 samples are optimal for training the SVM.

Introduction of new user for testing

Then 6 new right handed male users were introduced who and have never gone through such experiment before (Table 5). They were asked to gaze on the screen as per the instruction given. This time Oz, REF, A1, A2 and ground were used for recording. 2 second time window was used for all subjects and SVM classifier which is already trained from the previous 12 users with 200 samples. The average accuracy rates for

Users	Optimal Frequencies	Accuracy
User 1	13 Hz	96.00
User 2	8 Hz	96.25
User 3	10 Hz	97.75
User 4	11 Hz	95.00
User 5	11 Hz	98.50
User 6	13 Hz	99.00
User 7	12 Hz	97.50
User 8	14 Hz	99.50
User 9	9 Hz	96.50
User 10	13 Hz	97.50
User 11	13 Hz	98.50
User 12	13 Hz	97.50

Table 2: USERS Accuracy towards different frequencies.

SVM Kernel Functions	Accuracy(%)
Quadratic Kernel	87.25
Polynomial Kernel	90.45
Gaussian Radial Basis Function Kernel	98.25
Multilayer Perceptron Kernel	94.35

Table 3: SVM Classification Accuracy for Different Kernel Functions.

Method	Average Accuracy for 2 second duration
Simple Thresholding	87.75
SVM for 50 Sample training	91.25
SVM for 100 Sample training	94.75
SVM for 200 Sample training	98.25
SVM for 300 Sample training	98.25

Table 4: Effect of Classification Method.

Users	Average Accuracy
User 13	94.75
User 14	98.50
User 15	96.50
User 16	94.75
User 17	99.50
User 18	100.00
Overall Average	97.25

Table 5: Testing Accuracy on 6 New Subjects.

these new subjects are shown in above table as it can be seen clearly that the accuracy rate is quite good without any calibration and training. Therefore by optimizing the frequency parameter for the object control very good results are obtained.

Information transfer rate

The ITR of SSVEP-BCI mainly depends on three factors, i.e., the total number of targets in the system, the accuracy and the time needed to produce a selection. The ITR of the simulated application is 27-30 bits/minute, which is comparable to some of the existed systems with ITR 27.15 bits/min [6] (This system had thirteen targets) and 28.29 ± 12.19 bits/min (This system had eight targets). As mentioned above, with four frequencies, the SSVEP of 2 s time window can realize four targets.

Conclusion and Future Scope

A virtual ball control of SSVEP based BCI, which uses the PSD information of flickers to code targets has been tested. The test in this study confirmed its effectiveness as an adequate application of the frequencies to code targets for the SSVEP-based BCI with almost no interference with each other. The average accuracy for new users was 97% with ITR of 27-30 bits/min, which is better than the many existing BCI systems.

Some of the possible future directions for the SSVEP-based BCI designs presented in this thesis are:

1. Hybrid BCI systems using integration of 3 or more independent BCI types (such as SSVEP-BCI, motor-imagery BCI, P300-BCI and others). Easy switching between systems for users who have difficulties with a particular BCI type; Enhanced usage of commands when 2 or more BCI types are used simultaneously.

2. SSVEP-BCI systems with more than 20 independent commands, which would work reliably for most home users.

3. New error-resistant SSVEP-BCI designs to minimize false-ositive commands even outside the laboratory, as the brain may use the same frequencies as the SSVEP flicker for other activities

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