# Brain Computer Interface Control of a Virtual Robotic System based on SSVEP and EEG Signal

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***Abstract*—In brain computer interface (BCI) systems the brain patterns for a certain type of behavior is extracted and the corresponding control commands are produced in order to control an external apparatus. SSVEP is a specific type of such control signal which is produced at the occipital lobe of the brain in response to an external oscillating stimulus. As the brain signals in SSVEP based BCI are the neurological reaction of the individuals to the presented stimulus, it is crucial to design a suitable stimulus system as well as investigation of its effectiveness. In this paper a suitable visual stimulus is designed and implemented, and its effectiveness to control the motion of a robot on a virtual robotic system is verified based on experiments. An online integrated system comprising of a virtual industrial robotic manipulator, an EEG deployment and statistical feature extraction method is developed and real time experiments to verify its accuracy and effectiveness is experimented on different subjects. The experiments shows the promising features of the developed systems for further applications.**

***Keywords*— Brain computer interface (BCI), steady state visual evoked potential (SSVEP), likelihood ratio test (LRT), Electroencephalogram (EEG), robotic manipulators***

## I. Introduction

Brain computer interface (BCI) establishes a direct connection between the brain activities and robotic system. The brain electrical activity contains a wide variety of phenomena and patterns that can be recognized and used in BCI system. These features are used as control commands that allow persons to control devices directly by their brain activity [1]. Such system has been a specific area of interest in order to provide interaction for people with disabilities with the surrounding environment.

Many EEG signals could be served as control signals in BCI systems; examples of these signals include slow cortical potentials, sensorimotor rhythms, P300 evoked potentials and steady state visual evoked potentials(SSVEPs) [2]. SSVEPs are elicited at the occipital lobe of the brain in response to external flickering stimulus that subject selectively focus attention on specific targets.The frequency of this signal is matched with the frequency of the input stimuli target. SSVEP are usually detectable when a person gaze at a specific visual stimuli flickering with constant frequency above 4Hz [3]. Recent studies indicate that SSVEPs need less training time and also higher classification accuracy than other EEG patterns [4]. The common structure of SSVEP BCI system has been illustrated in Fig.1.

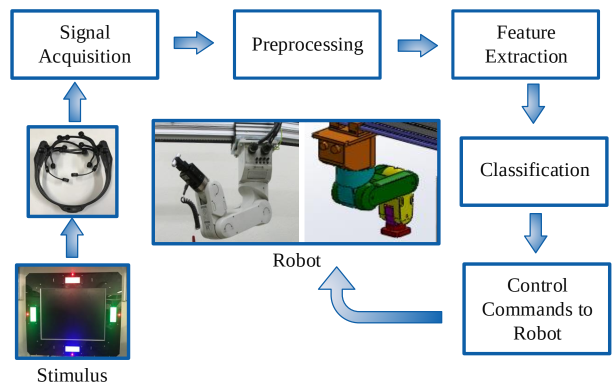


Fig. 1: SSVEP based BCI system structure

The SSVEP can be evoked by different flickering stimulus designed by Liquid Crystal Display (LCD) and Light Emitting Diode (LED). LCD is easily available in various patterns, but the flickering frequency is not adjustable, since the frequency is limited by refresh rate of the monitor [5]. Whereas LED has many advantages over LCD; firstly, LED simulator could evoke strong SSVEP in parietal and occipital cortex. Secondly, LED flicker frequency is more flexible in both range and accuracy [6].

In an SSVEP based BCI system, the targets are encoded by frequency. The user's attention to different targets are translated to different control commands. Several approaches based on frequency recognition of EEG signals have been proposed in different references. Power spectral density analysis (PSDA) is a traditional signal analysis method and can be estimated by fast Fourier transform (FFT) from the user's EEG signal within a time window [7]. The frequency corresponding to this maximum peak value is taken as the visual stimulus frequency. Fig.2 represents the PSDA of the SSVEP EEG signal at 17Hz frequency.

A few multichannel detection methods such as minimum energy combination (MEC) [4], canonical correlation analysis (CCA) [7], multivariate synchronization index (MSI) [8], likelihood ratio test (LRT) [9], etc are used for target frequency detection in SSVEP based BCI. All of these methods are

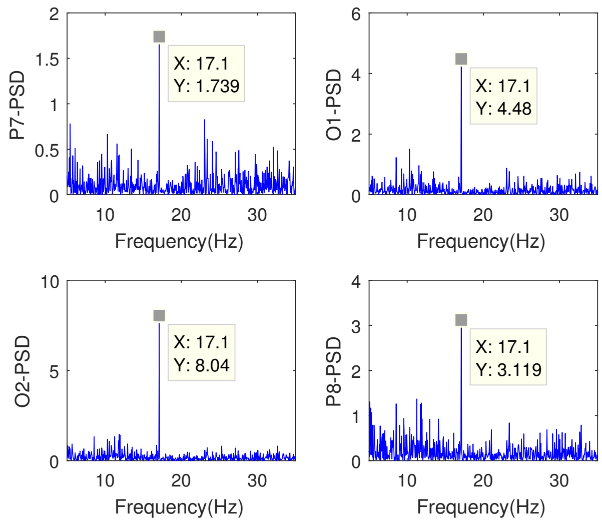


Fig. 2: The amplitude spectrum of the SSVEP EEG signal for $O_1, O_2, P7, P8$ electrodes in $17Hz$ stimulus frequency

based on the resemblance between the EEG signal and the reference signals. LRT method is used in this research for feature extraction, since it is more robust against the noise [9].

The goal of this study is to design and implement a complete wireless SSVEP based BCI system to control a robotic manipulator in an online manner. To accomplish this goal, all the BCI units are integrated in the Simulink environment. A SSVEP visual stimulus is designed as a smart multiple choice in the form of four LED modules flickering with different frequencies. Brain signals are recorded by Emotiv EPOC EEG system in the ARAS laboratory environment. Data is processed by LRT frequency detection algorithms and then the control commands are generated from the classification results and is sent to a stimulated robot in a virtual environment to control its position. This system is implemented to verify the performance before implementation on a real robotic manipulator.

## II. Materials and Methods

Generally, a SSVEP based BCI system consists of the following four parts: designing a proper visual stimulus module, EEG extraction system for data acquisition from occipital lobe, an analyzing model for extracting frequency feature and classification for coding the stimulus target as proper control commands for robot and designing user neuro–feedback and stimulation module to finally control the motion of a robot. In what follows, details of these subsystems are described in more detail.

### A. Visual Stimulus

It is proved that the SSVEP brain response elicited by a LED visual stimulus has larger signal to noise ratio (SNR) than that extracted by a stimulus designed on LCD screen [10]. Also visual brain response for light stimuli are larger than that of pattern reversal created on LCD [11]. Because of

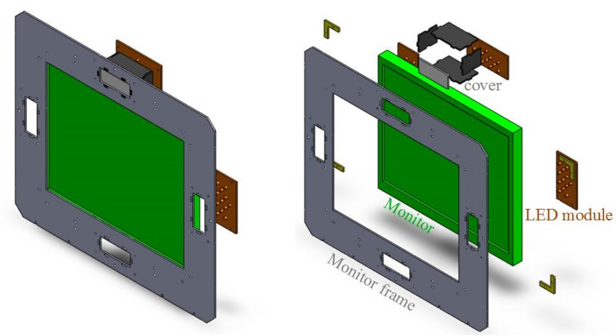


Fig. 3: Visual stimulus frame structure in Solidwork

the advantage of LED visual stimulus, this study is based on a stimulator composed of LEDs to generate SSVE potentials.

In this research the designed visual stimulus is comprised of four LED modules situated at the four sides of the monitor and flickering with different frequencies (11, 13, 15, 17 Hz). These frequencies are chosen as the medium frequencies for eye in order to give better responses [12]. Each one of the targets represents one intended movement in robot. Every LED module is $7.6 \times 3cm^2$ and contains 11 RGB LEDs. On top of any visual stimulus modules, a single red LED is placed and used as a guidance to improve the focusing of attention on selected target.

The MCU controller is the core of the system that accurately adjusts the frequency and color of the LED modules by PWM. Connection between the MCU and PC is established by USB and controlling the color and frequency of the stimulus is done directly in Simulink environment. There is a number dedicated to each color which controls each stimulus module color. Frequency of the LED modules is entered in Simulink and applied to them. The frame of the stimulus is designed in Solidworks and is made of plexy material. Its color is set as black and is well placed around the monitor. Positioning the monitor in the middle of stimulants, has the advantage of being able to be used as visual feedback. In order to uniform luminance and protect eye from direct light, LED modules are placed in correct distance from the monitor screen and a cover is placed against LED modules. One important aspect for design of a stimulus is the color. Colors were chosen depending on the following factors: Comfort of the subject, accuracy of classification and signal to noise ratio. In this study green color is selected for experiment [13].

### B. Data Acquisition

Brain signal acquisition in SSVEP experiment is performed using the Emotiv EPOC EEG system. Emotiv EPOC contains 14 measuring electrodes and 2 reference electrodes. Sampling rate of the system is 128Hz with 14bit resolution. All electrodes are arranged according to the international 10-20 system. The recorded EEG signal is transmitted to a computer by wireless communication channel [14].

EEG signals are recorded unipolarly by four electrodes placed on O1, O2, P7 and P8. The reference electrodes are

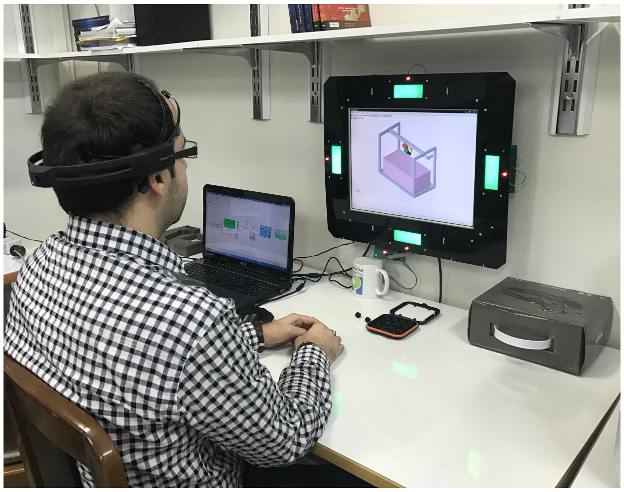

Fig. 4: SSVEP based BCI arm robot control with the participated subject, visual stimulus and EMOTIV EEG data acqusition

placed behind the ears. As shown in the Fig.4 during the EEG recording, subjects are seated in front of the stimulants that simultaneously flicker with different frequencies while gazing at the selected target. Subjects are free to blink during the experiment but they are not allowed to have any movement to prevent interaction of the EEG signal with other noise. The distance between the subject's eyes and the monitor is approximately 80 cm. On the computer screen a robotic arm with two degrees of freedom is shown which uses as visual feedback. The participants are asked to control the simulated robotic arm in computer by watching stimulates. If the target that the user attends and the result detected by EEG processing, are not matched user tries to increase his/her gaze to the selected target to compensate the result.

### C. Data Processing

We used likelihood ratio test (LRT) frequency recognition method for feature extraction in SSVEP BCI. This method is introduced in [9]. It is based on correlation of the two sets of variables. One set is EEG signal and the other set is reference signal that comprises Fourier series of stimulus frequency and its harmonics.

$$X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad m = \begin{bmatrix} m_1 \\ m_2 \end{bmatrix} \quad C = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} \tag{1}$$

in which, $m$ denotes the mean value and $C$ denotes the covariance matrix, while, $x_1$ is SSVEP data and $x_2$ is the reference signal. The likelihood ratio for static signals are as follows:

$$\lambda = \frac{|C|^{(1/2)N}}{|C_{11}|^{(1/2)N}|C_{22}|^{(1/2)N}} \tag{2}$$

in which, $V = \lambda^{(1/2)N}$ or

$$V = \frac{|C|}{|C_{11}| \quad |C_{22}|} = \frac{|C_{11} - C_{12}.C_{22}^{-1}.C_{21}|}{|C_{11}|} \tag{3}$$

The measure of association is given as follows:

$$L = 1 - \left( \frac{|C|}{|C_{11}| \quad |C_{22}|} \right)^{1/P} \tag{4}$$

$$P = number\ of\ channels + 2 \times number\ of\ harmonics$$

where, $L$ ranges from 0 to 1. If the two sets are uncorrelated, $L$ is zero and if the two sets of data are perfectly correlated, $L$ is valued 1. SSVEP signal correlation to every one of the reference signals is calculated and the value for $L$ is obtained. Maximum value for $L$ represents the maximum SSVEP signal similarity of frequency content with reference signal, which may be selected as the target signal.

The reference signal for each stimulus frequency is as follows:

$$x_2 = \begin{pmatrix} \sin(2\pi f_i t) \\ \cos(2\pi f_i t) \\ \vdots \\ \sin(2\pi N_h f_i t) \\ \cos(2\pi N_h f_i t) \end{pmatrix} \tag{5}$$

in which, $t = \frac{1}{F_s}, \frac{2}{F_s} ... \frac{M}{F_s}$, $F_s$ is the sampling rate, $f_i$ is stimulus frequency and $N_h$ is the number of harmonics. In this study, the number of harmonics($N_h$) is set to two.

Before the BCI data acquisition , baseline (BL) data had to be recorded. For this reason, the flickering lights were switched off, and the participants were asked to focus on the center of the monitor for 30 s. The BL data used for normalizing each subject EEG data to him/herself. Four seconds of EEG signal that overlaps with the %50 of the old data, is analyzed and processed to recognize the target that subject gazed before the new time window achieved. The resulting real time classification is used as a control command to the robotic system.

### D. Virtual Robotic Arm

The Mitsubishi RV2AJ robot is a series robot with five degree freedom and has been used in ARAS lab for different experimental verifications. This robot is simulated with real dimensions in Solidwork software and then transferred to the simmechancs of MATLAB for the experiments intended to be implemented in this paper, as depicted in Fig. 5. The number of the stimulus used in experiment is only four, and therefore, only two degree freedom of the simulated robot is controlled by EEG signals. By applying PID controller on the robot joints, suitable motion tracking of the joints is obtained. Two inputs are defined for the robot, first input refers to speed of the robot movement and the second one which is the output of classification methode represents the state of the robot.

## III. System Integration

For synchronization between all parts of the experiment, controlling and communication of all parts are created in Simulink environment Fig.6. First, the recorded data by EEG system is transmitted directly to the computer and the data is accessible online. Data is available in the form of vector. The four selected electrodes on the visual cortex of the brain are

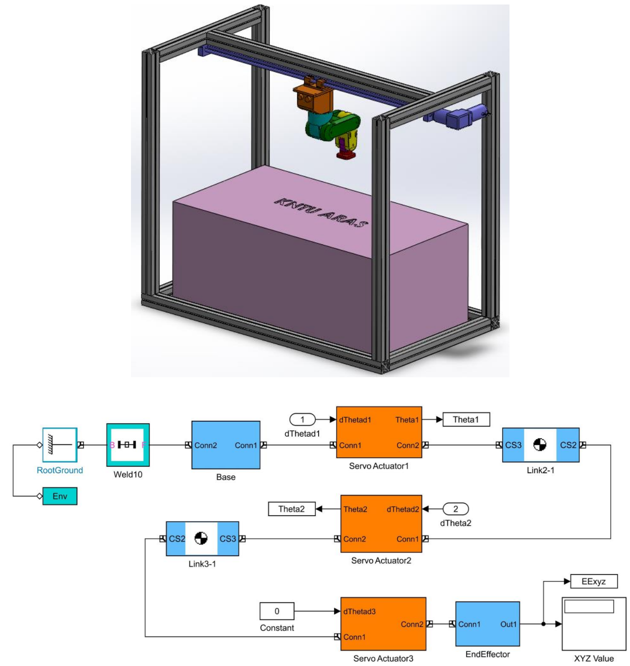


Fig. 5: Virtual model of RV2AJ robot and Solidwork-Simulink cosimulation

extracted from EEG recording signals and buffered in about four seconds. Then the buffered data is preprocessed, and high frequency noise is eliminated and the data is normalized. In the data processing section, the LRT algorithm is applied to the data, and the extracted features are entered into the classification section. Classification result can be one of the two states: a movement is detected, or none of the targets are gazed. For each classification outputs defines a control command for robot that indicates the state of the robot. The definition of each state for the robot is given in the table.I.

## IV. Experiment Results

In this research a series of experiments are performed and the performance of the offline and online BCI system

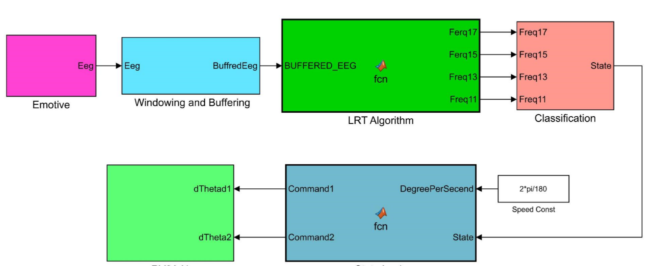


Fig. 6: Simulink block diagram of SSVEP based BCI system parts and their connection

TABLE I: State of the robot corresponding to stimulus frequency

| Frequency (Hz) | Class Number | Robot Command |
|---|---|---|
| 17 | 1 | Clockwise |
| 15 | 2 | Counter clockwise |
| 13 | 3 | Up |
| 11 | 4 | Down |

communication is evaluated.

### A. Offline result

Offline experimental data that was recorded in ARAS laboratory environment used to evaluate the LRT method performance. Four subjects is participated in offline experiment. All of them have normal vision. Each subjects instructed to gaze at each flickering stimuli for 20 seconds in four trial. The experiment was performed in dim room. Each time window data was processed and the maximum value saved as classification result. The accuracy is the ratio of the number of segments correctly classified to the number of total segments. Table II presented the accuracy of classification for four subjects in time length of four second. As can be seen, the accuracy of the chosen method is perfectly good and can be used for the implementation part.

TABLE II: Classification accuracy by LRT method at four second time length for all subjects.

| Subject1 | Subject2 | Subject3 | Subject4 | Mean |
|---|---|---|---|---|
| 70.5% | 73% | 75% | 81.25% | **74.9%** |

### B. Online result

In online implementation all of the stimulus are flickering with different frequency and subjects are free to gaze their intended target. For illustrate the performance the online system, classification results of two different tests, is given in Fig.7 and Fig.8. In this experiment the subjects asked to control the robot for 20 seconds clockwise then 20 seconds counter clockwise. Therefore the subjects should gaze at the $17Hz$ flickering stimuli for 20 seconds and then $15Hz$ flickering stimuli. Switching between the stimulants is done by guidance LED for users. The figure contains four outputs. Each of them represents the LRT measurement value between the EEG signal and each stimulus reference signal. As shown in the figure 7, the data is being buffered for up to four seconds, and the time window refreshes every 2 seconds and is applied to the processing unit.

As shown in the two results the frequency of 17 Hz has obviously the maximum value for the first 22 seconds and the classification output indicates the first class as the output. while the subject is switching from $17Hz$ to $15Hz$ the maximum algorithm of output belongs to $11Hz$ and the classification result is the fourth class. This result is compensated by increasing the subject gaze attention to the stimulus target and then the result showes $15Hz$ as maximum value.

## V. Conclusions

In this paper an effective strategy is done for implementation of complete online BCI system by virtual robotic system. LRT frequency recognition method is evaluated in offline analysis and implemented for online detection. By refer to the results of analyzing the EEG signals of different subjects, it is improved that the four stimulus input frequency are perfectly distinguishable. As shown in online results, establishing visual feedback between the subjects gazed stimulus target and the signal processing unit results, compensation of the output error was made possible by the person's focus. These results can be used in various robotic applications. As future work implementation of the SSVEP based BCI by industrial robotic system and controlling the more degrees of freedom will be provided.

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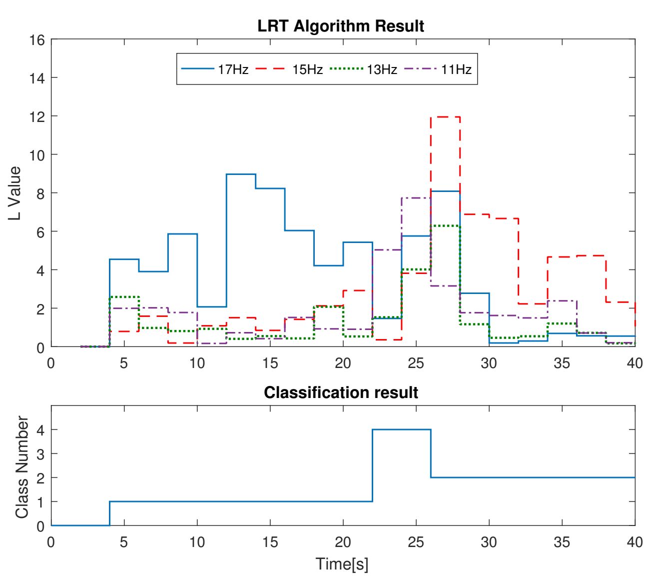


Fig. 7: Online result of LRT algorithm and Classification output in test1

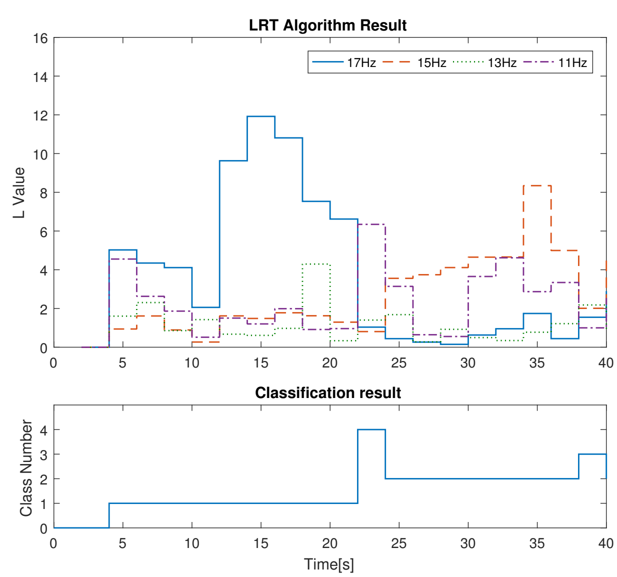


Fig. 8: Online result of LRT algorithm and Classification output in test2