Development of a Steady State Visual Evoked Potential (SSVEP)-based Brain Computer Interface (BCI) System

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***Abstract*—This paper describes the development of a synchronous, online brain computer interface (BCI) system based on detecting the steady-state visual evoked potential (SSVEP). The system includes a programmable visual stimulator, EEG amplifier with filter system, data acquisition card, and signal processing and classification algorithms. Two types of experiments were carried out; training experiments were conducted to determine three optimal frequencies for each and every subject. For the testing experiments, three visual stimuli were presented simultaneously to the subject. Subject was required to focus his/her attention only on one of the target stimulus, and the system will detect the targeted stimulus the subject was focusing on. Five subjects have participated in the study with average detection accuracy of 83.10%.**

***Index Terms*— brain computer interface (BCI), electroencephalography (EEG), steady-state visual evoked potential (SSVEP).**

I. INTRODUCTION

A brain-computer interface (BCI) is a system that allows human to communicate with a computer by using brain signals. By acquiring and translating the brain signals into certain commands, a BCI system can serve as an alternative method of communication for individuals who have severe neuromuscular problems [1].

The brain signals can be obtained via invasive or non-invasive methods. Electroencephalography (EEG) is a non-invasive way of acquiring electrical potentials from the surface of human scalp, which is usually more favorable due to its simple and safe approach [1]. There are several types of EEG activities that can be utilized as input features for BCI systems, *e.g.* slow cortical potentials [2], oscillatory EEG activity [3], P300 potential [4] and visual evoked potential [5]. The selection of input feature is usually affected by several factors, 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, adaptability for majority individuals and training period required.

Steady-state visual evoked potential (SSVEP) is the periodic response elicited in the brain when a person is visually focusing his/her attention on a stimulus that is continuously flickering at frequency 6Hz and above [6]. There are many research groups [6] – [10] that are utilizing SSVEP as the input for their BCI systems. SSVEP is a favorable type of input signal because it is based on detection of increment in a specific power spectrum [11]. SSVEP signal is triggered when the subject is focusing their attention on a flickering visual stimulus, and is therefore less demanding as compared to mental strategies.

SSVEP is normally most prominent at the occipital region of the scalp [5], [12]. Since the evoked response is focusing at specific frequencies, therefore the relative information between the stimulus and the triggered response can be determined by using simple frequency domain algorithms [12]. 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], [12].

For SSVEP-based BCI system, a flickering apparatus is necessary to provide visual stimulus to the subject. Therefore, most of the applications are for subjects who have the capability to control their eye movement [6]. In previous study [13], investigation has been done to evaluate the practicality and advantages of using SSVEP as input feature to a BCI system.

This paper presents a synchronous online BCI prototype 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. The prototype system described in this paper is simple but is able to realize rapid detection of SSVEP signals. In future, the system may be integrated with more control options and can be used by neuromuscular disabled people to control external devices or express their thoughts.

II. METHODS

A. Subjects

A total of five voluntary healthy subjects consisted of three males and two females, aged between 24 and 63 have been recruited in the study. All of them have normal or corrected-to-

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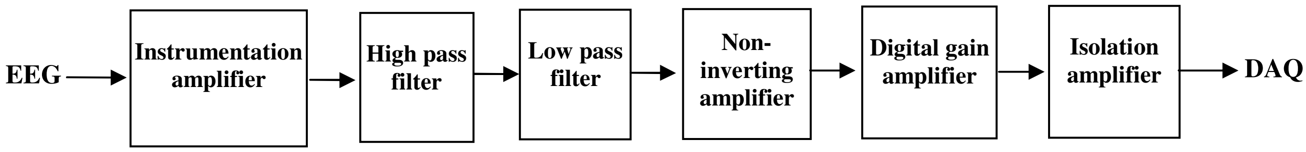

Fig. 1. Block diagram showing cascaded stages of the EEG signal acquisition system

normal vision. Subjects were briefed on the protocol of the experiment, and required to sign a consent form.

B. Development of SSVEP-based BCI System

The SSVEP-based BCI system is consisted of programmable visual stimulus, EEG amplifier with filter system, data acquisition card, and signal processing and classification algorithms. The visual stimulus is a 2cm diameter red color light emitting diode (LED) with wavelength of 660nm and luminous intensity of 70mcd. The frequency of the visual stimulus is controlled by programmable microcontroller chip.

The EEG signal acquisition system is composed of a two channel differential EEG amplifier with several cascaded stages which provides a total gain of 36396 and a data acquisition card. Fig. 1 shows the block diagram of the signal acquisition system.

Standard gold-plated electrodes are used to acquire EEG signals. The magnitude of EEG signals picked up from EEG electrodes is very small, usually ranging from 1-100µV. Besides, the signals are usually riding on other larger common mode noise, such as the 50 Hz line noise. The first stage of the EEG amplifier is designed using an instrumentation amplifier to ensure good common mode rejection ratio (CMRR) and high input impedance. Three op-amp based INA121 is used to amplify the input signal to 100 times. The CMRR measured is 117dB at 15 Hz input sine wave. Subsequent high pass and low pass active filters are constructed using op-amp which provides the remaining gain and a bandwidth (-3dB) of 0.94 – 70.3 Hz. After being filtered, the desired signal is amplified by a non-inverting amplifier for 20 times. A digital adjustable gain amplifier and isolation amplifier is included in the latter stage to allow the output gain to be adjusted when necessary, and to isolate the noise. In order to reduce the 50 Hz interference, a Driven Right Leg (DRL) circuit is added to reduce the common mode noise.

The entire circuit is constructed on a printed circuit board (PCB). A voltage power supply unit is currently used to provide ±5V direct current (DC) to the amplifier system. However, the system has an option of using 9V batteries and voltage regulators when necessary. Total current consumption of the amplifier system is approximately 67 mA.

After being amplified and filtered, the EEG signal is sampled at 1024 samples per second by a 16-bit data acquisition card (ADLINK PCI9111HR) installed in computer.

C. Experimental Procedure

EEG signals were recorded from positions O1 and O2 according to the international 10-20 system and referenced to forehead [14]. DRL electrode was placed on the left arm of the subject. The signals were acquired using the EEG signal acquisition system mentioned in previous section.

During the EEG experiment, the subject was seated comfortably on a chair facing a 17 inches CRT computer monitor. The LED stimulus was placed 50cm in front of the subject. Subject was required to close their 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. Subjects were required to participate in two types of experiments, which is training and testing experiment, carried out on two different days. The experimental flow chart is shown in fig. 2.

The training experiment was carried out to determine three 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 [10], [13]. During the training experiment, only one visual stimulus was presented. For each trial, the LED stimulus was programmed to blink for 7 seconds at a selected frequency and OFF for 10 seconds. The signals recorded when the subject was focusing at the blinking stimulus is termed SSVEP signals. Subjects were required to maintain full visual concentration on the stimulus device when it is blinking. Frequencies ranging from 7Hz to 31Hz were tested, and each frequency was tested for at least 5 times.

After determining the three optimal frequencies, testing experiment was carried out on another day. Fig. 3 shows a subject taking part in an EEG testing experiment. Three LED stimuli placed at the left, bottom and right edge of the computer screen was presented 50 cm in front of the subject, each flickering at a particular frequency respectively. For each trial, the LED stimulus will blink for 7 seconds and dim for 10 seconds. 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. An audio feedback was given to inform the subject the predicted target. Subject was required to report verbally if the detected target was incorrect. In average, each target was tested for at least 20 trials.

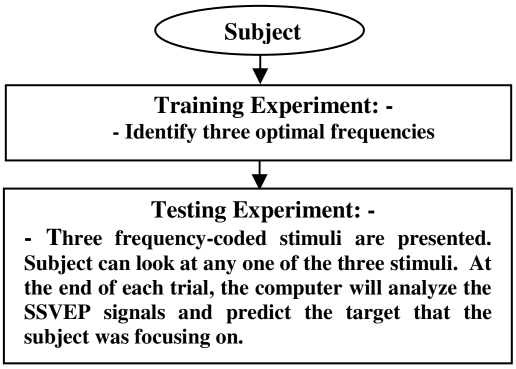

Fig. 2 Experimental flow chart.

Fig. 3 Subject taking part in a testing experiment.

D. Signal Processing and Classification

The program for signal processing and classification is developed using Matlab 6.5.1. Fast Fourier Transform (FFT) is used to compute the power spectrum of the SSVEP and REST signals at the three stimulus frequencies. Each and every second of EEG data for a trial is windowed and zero padded to produce a frequency resolution of 0.5 Hz. Then, the mean power spectrum of the two channels is computed. Fisher's Linear Discriminant Analysis (LDA) is used to classify the computed power spectrum and find the boundary between SSVEP and REST classes for the three stimulus frequencies. Fisher's LDA is one of the linear classification methods that require less samples to produce a reliable classifier output [15]. It does not assume that the populations are from multivariate normal distribution. However, Fisher's LDA assume that the populations have common covariance matrix [16]. The pooled covariance matrix is given in equation below.

$$S_{pooled} = \frac{(n_1 - 1)S_1 + (n_2 - 1)S_2}{(n_1 + n_2 - 2)} \qquad (1)$$

Where

S_i = Sample covariance of groups *i, i*=1,2

n_i = Number of observations in the groups *i, i*=1,2

To achieve maximum separation of the samples from different groups, the solution is given below.

$$\max_{w} \frac{(w'(\overline{x_1} - \overline{x_2}))^2}{w' S_{pooled} w} = (\overline{x_1} - \overline{x_2})' S^{-1}{}_{pooled} (\overline{x_1} - \overline{x_2}) \qquad (2)$$

Where

x_i = Sample mean of groups *i, i*=1,2

w = LDA coefficients = $S^{-1}{}_{pooled} (\overline{x_1} - \overline{x_2})'$

The linear discriminant function *y(x)* is given in equation below.

$$y(x) = \log(\frac{n_1}{n_2}) - \frac{1}{2}(\overline{x_1} - \overline{x_2})' S^{-1}{}_{pooled} (\overline{x_1} + \overline{x_2}) \qquad (3)$$

For a new observation x, it will be allocated into group 1 if $y(x)>0$. Else, x will be allocated into group 2. By knowing the border between the two classes, the frequency population with the largest distance from the threshold is determined as the detected target, and will be reported to the subject at end of the trial.

III. RESULTS AND DISCUSSIONS

Fig. 4 shows an example of the graphic user interface (GUI) of the Matlab testing program. In this study, five subjects have used the real-time SSVEP-based BCI system to select the desired target from three frequency-coded visual stimulus. The results are shown in table 1.

From table 1, the results showed that the subjects are sensitive to frequencies ranging from 14 – 29 Hz. The highest detection accuracy achieved is 100%, while the lowest is 72%. The subject S3 with best detection accuracy shared her experience that while recording the REST signal and during the 10 seconds intermittent break between the trials, she kept her mind very calm and relax. During the SSVEP sessions, she maintained full visual fixation on the desired target, and avoided blinking or moving her eyes.

There are a few factors that may affect the detection accuracy of the system, including electrode locations, stimulus frequency, duration of selection in the experimental paradigm and others. In this experiment, the electrode locations were the same for every subject, taking the assumption that the SSVEP signals are most prominent at the central occipital region. The three optimal frequencies were selected based on the performance of the subject in training experiment. The operation duration is determined based on the experience from previous trial experiments. The 10 seconds rest allows the subjects to have an intermittent break between the trials, and can help to reduce visual fatigue.

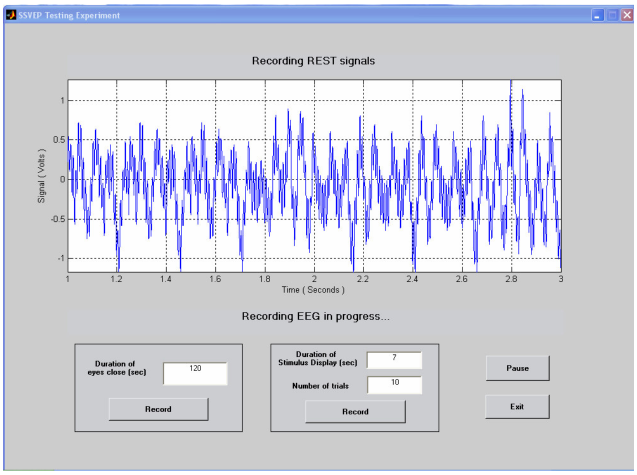

Fig. 4 GUI of the testing experiment.

Table 1 Results of the five subjects during the testing experiment.

Subjects	Frequencies (Hz)	Detection accuracy (%)
S1	14, 20.5, 23	90.14
S2	21, 24, 27.5	75.58
S3	20.5, 23, 25.5	100
S4	24, 26, 28	72
S5	24, 27.5, 29	77.78

IV. CONCLUSION

The existing system has been successfully tested on five subjects with average detection accuracy 83.10%. During the experiments, the subjects were able to adapt to the experimental paradigm rather quickly after undergoing a few trials without needing special subject training. The system may be improved in future by improving other system parameters such as increasing the number of target for selections, and optimizing the electrode positions and operating speed for each and every subject.

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