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On the Enhancement of Training Session Performance via Attention for Single-frequency/Multi-commands based Steady State Auditory Evoked Potential BCI

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Abstract— **To solve the eye fatigue problem on using the well known steady state visual evoked potential (SSVEP)-based brain-computer interface (BCI) system, the steady state auditory evoked potential (SSAEP) becomes one of the promising BCI modalities. However, SSAEP-based BCI system still suffers from the low accuracy. To increase the accuracy, in this paper, we propose the new training method to enhance the SSAEP training session. The training process is enhanced by making the users control their attention levels simultaneously with the detected auditory stimulus frequency. Furthermore, with the proposed training method, we also propose the corresponding single-frequency/multi-commands BCI paradigm. With the proposed paradigm, four commands can be detected by using only one auditory stimulus frequency. The proposed training system yields approximately 81% accuracy compared with 66% of the session without performing the proposed training.**

Keywords-electroencephalogrm; steady state auditory evoked potential; auditory attention; brain-computer interface.

I. Introduction

TOTALLY dependent or assisted living is the level of severe disabilities which usually happens with the spinal cord injury (SCI), stroke, or amyotrophic lateral sclerosis (ALS) patients who lose their abilities of movement. One of the key to enhance their living quality is by using the brain-computer interface (BCI) system. In [1] , spontaneous electroencephalogram (EEG) is employed to restore the communications and movement skill. Besides the spontaneous EEG, the evoked potential (EP)-based BCIs are also widely used due to theirs high accuracy. Among all of the EP-based BCIs [2-4], steady state visual evoked potential (SSVEP) is one of the BCI modalities that give a high accuracy while taking less time for training [3-4]. However, SSVEP-based BCIs also have drawback when the user enter the highly luminance condition. Furthermore, the users those cannot control their eyes movement also have difficulty focusing on a visual stimulator. Nowadays, an alternative EP-based BCI methods are being proposed via the use of the combination between auditory and visual evoked potentials [5, 6], or auditory evoked potential alone [7-11].

In [11], the active auditory stimulation paradigm is employed. The time dependent N2 signal is employed via the use of the support vector machine (SVM) and the probabilistic model to enhance the number of trial averaging. In [12], auditory spatial attention is employed to successfully modulate the event-related potentials (ERPs). By the use of the virtual sound field, promising BCI performance can be obtained.

Furthermore, to avoid the problems of time synchronization and time dependent artifacts, in [8], frequency dependent based BCI via auditory steady state responses (ASSR) approaches is employed. By simply using the bandpass filtering and AR spectrum estimation, the classification accuracy can be improved based on the two-class classification. Even though the ASSR-based BCI yields a promising result, it still requires the high experience users to maintain the high level of attention to obtain the high BCI accuracy. To enhance this training process, in this paper, we propose the new training paradigm that takes into consideration the attention index via the EEG signal from the frontal lobe together with the traditional training system. Furthermore, to increase the number of commands to four by using only one stimulus frequency, the new cue-based paradigm is also designed. The proposed training system with our proposed paradigm leads to approximately 15% improvement in the inexperienced subjects.

II. Proposed Paradigm and Training System

The proposed method can be divided into two parts, *A*. Proposed single-frequency/multi-commands paradigm and *B*. Proposed training system.

A. Proposed single-frequency/multi-commands Paradigm

The proposed paradigm for single-frequency/multi-commands is shown in Fig. 1. The paradigm contains four periods of auditory stimulus, 5 seconds for each stimulus and 1 second resting period between each stimulus. 7 Hz frequency is modulated with the 1 kHz carrier signal to generate the auditory stimulus implemented via the programmable integrated circuit (PIC) 16F627A microcontroller and the 0.25 watts (8 ohms) speaker. One speaker is used. The speaker is placed in front and 40 cm. away from the subject's ears.

For example, if the subject would like to select the third command, the subject must ignore the sound in the first and

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second periods of the stimulus and listen only to the third period. Hence, the response of the SSAEP would occur in the third period.

B. The proposed training system

Instead of training to only achieve the frequency of interest for auditory stimulus, we also create software that can simultaneously indicate the level of attention (Fig.2):

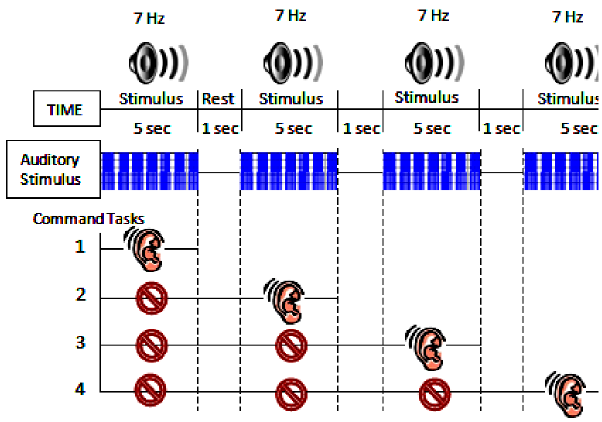

Fig. 1 The proposed single-frequency/multi-command paradigm using auditory stimulus.

B.1 Attention detection process

The process of attention detection can be summarized as follows:

1) Collect the baseline in relaxing state; the index for the relaxing state is calculated from the ratio of alpha (8-13 Hz) bandpower over beta (14-26 Hz) bandpower from the channel F3 (Frontal area that alpha activity can be clearly seen).

2) Start the training session.

3) During the training session, the index will be calculated in the same way as 1) The decision will be made as "attention" when the ratio of the relaxing index is less than the index during the training session.

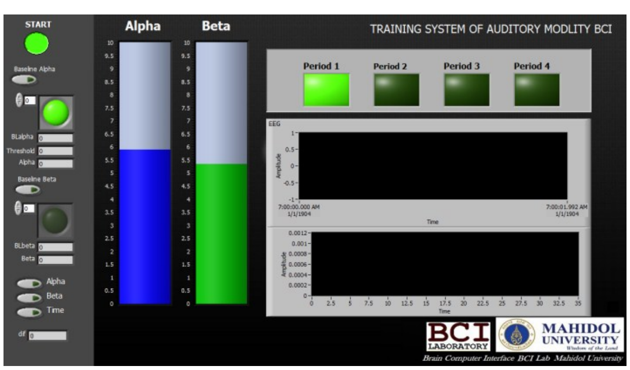

Fig. 2 GUI of the proposed training system.

B.2 SSAEP detection process

The SSAEP detection process can be separated into three parts, i.e. 1) Calibration process, 2) Feature extraction process, and 3) Decision making process. By recording the EEG from channel T4 (Temporal lobe for auditory evoked potentials), all three processes can be summarized as follows:

1) Calibrating process

Before using the proposed system, some baseline parameters need to be acquired as follows:

$$BL = max\ (BL_7, BL_{14}) \tag{1}$$

where BL_7 and BL_{14} are the baseline values of the fundamental frequency (7 Hz) and the first harmonics (14 Hz), respectively, which can be calculated as

$$BL_7 = mean\ (f_{7-r}, f_7, f_{7+r}) \tag{2}$$
$$BL_{14} = mean\ (f_{14-r}, f_{14}, f_{14+r}) \tag{3}$$

where f_i represents the amplitude of the power spectral density (using Welch periodogram method) at the frequency i. The neighboring frequency deviation (r) can be calculated as the ratio of maximum frequency over the number of sample to process in one window (e.g. in this paper, we acquire 5-second data to process each command, with sampling rate of 2000 Hz, r = 1000/2000 = 0.5)

2) Feature Extraction Process

The amplitude of the power spectral density F is extracted as our feature as the following process:

$$F = max\ (\hat{f}_7, \hat{f}_{14}) \tag{4}$$

where $\hat{f}_7$and $\hat{f}_{14}$, can be calculated as

$$\hat{f}_7 = mean\ (f_{7-r}, f_7, f_{7+r}) \tag{5}$$
$$\hat{f}_{14} = mean\ (f_{14-r}, f_{14}, f_{14+r}) \tag{6}$$

where f_i represents the amplitude of the power spectral density at the frequency i.

3) Decision Making Process

If F is 25% greater than BL, SSAEP is detected; otherwise it means that the subject ignores the stimulation.

B.3 Summary for the process of training

During the training process, there will be the random tasks assigned to the users to let them practice on using the SSAEP-based BCI system. The light will be illuminated in light green color once both decisions from *B.1* is "attention" and *B.2* is "SSAEP".

III. BCI SYSTEM USING PROPOSED PARADIGM AND TRAINING SYSTEM

By using the proposed training system together with the proposed single-frequency/multi-command paradigm, the corresponding BCI system can be designed as follows (See Fig. 3 for the real setup):

A. EEG acquisition

Since the temporal area of the brain relates to an auditory response, EEG from channel T4 is acquired. Furthermore, frontal lobe EEG at F3 is also acquired since it closely relates to human attention. Differential recording is used, i.e. Cz is used as the reference electrode and Fz is used as the ground electrode. The electrode positions are according to the international 10-20 electrode placement system. Analog 50 Hz notch filter is applied together with the analog bandpass filter from 5 to 35 Hz. The sampling rate is set to 2,000 Hz.

B. BCI session

B.1 Training mode

For the inexperienced user, the training session for 20 minutes can be selected before using the real-time BCI system to simultaneously feel how to make the attention so that the real SSAEP can be easily and clearly detected. The process of the training system is described in Section II.B.

B.2 Real-time mode

For real-time mode, the user needs to follow the calibration process before start using the system. The process of the system is the same as Section II.B.2. The user can command up to four commands according to the proposed paradigm in Section II.A.

IV. RESULTS AND DISCUSSIONS

According to the proposed training system and stimulus paradigm, two experiments will be formulated to justify the performances of the proposed systems.

Experiment 1: Relationship between the SSAEP detection accuracy and attention detection via the proposed index

In this experiment, five normal subjects with no experience in BCI are selected. The baseline parameters of each EEG channel are collected before testing. Each subject needs to perform all 4 trials (in each trial, tasks are shown in Table I) for 5 times. Since close eyes and open eyes might affect the attention level, Table II illustrates both cases separately. Maximum average SSAEP detection of 86.7% can be achieved in eye closing session using channel T4. Meanwhile, maximum average attention detection of 92% can be also achieved in eye closing session using channel F3. According to Table II, we can further have three points of discussion:

1) Attention level can be more efficiently detected from the frontal lobe (F3) compared to the temporal lobe (T4)

2) Attention level can be efficiently detected when eyes are closing.

3) Increasing in accuracy of attention level detection in F3 directly leads to increasing in accuracy of SSAEP detection.

Experiment 2: Performance of the proposed SSAEP-based BCI system

Four normal subjects are selected in this experiment with the condition that they are new to BCI. According to the results from the Experiment 1, for our proposed SSAEP-based BCI system, SSAEP will be detected from channel T4 while the attention level will be detected from channel F3. Each subject will perform the 8-trial tasks to randomly select 4 commands according to Table III. We can clearly observe that maximum accuracy of 81.25% comes from letting the user train with the proposed system while the accuracy of 65.63% comes from traditional training system, and 62.5% is the accuracy of the user without having the training session.

TABLE I
STIMULUS TASKS FOR TESTING THE SYSTEM IN EXPERIMENT 1

Trial	Eyes	Stimulus period			
		1st	*2nd*	*3rd*	*4th*
1	Open eyes	Attention	ignore	Attention	ignore
2		ignore	Attention	ignore	Attention
3	Close eyes	Attention	ignore	Attention	ignore
4		ignore	Attention	ignore	Attention

TABLE II
RESULTS OF THE RELATIONSHIP BETWEEN THE SSAEP DETECTION ACCURACY AND ATTENTION DETECTION VIA THE PROPOSED INDEX

Subject	Eyes	% Accuracy			
		Temporal (T4-Cz)		*Frontal (F3-Cz)*	
		SSAEP	**Attention**	**SSAEP**	**Attention**
1	Open eyes	60	73.3	53.3	46.6
	Close eyes	80	60	60	100
2	Open eyes	73.3	33.3	53.3	100
	Close eyes	100	100	100	100
3	Open eyes	86.7	66.7	66.7	60
	Close eyes	80	100	100	100
4	Open eyes	73.3	73.3	53.3	80
	Close eyes	80	70	60	80
5	Open eyes	93.3	60	70	80
	Close eyes	93.3	100	60	80
Avg	Open eyes	77.3	61.3	59.3	73.32
	Close eyes	86.7	86	76	92
Total Accuracy		**81.9%**	**73.6%**	**67.6%**	**82.6%**

V. CONCLUSIONS

In this paper, we have proposed the cue-based paradigm of single-frequency/multi-commands SSAEP-based BCI system. In addition, we have also proposed the new SSAEP training system by making use of the proposed attention index. The additional attention index can be detected from frontal EEG channel. With four commands (using one frequency), we can obviously see the enhancement of the performance via our proposed training system. For future application, if we increase the number of stimulus frequencies, the number of commands can be easily increased by a factor of four.

Fig. 3 The proposed SSAEP-based BCI system.

TABLE III
TASKS FOR TESTING THE SYSTEM IN EXPERIMENT 2

Trial #	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***
# of commands	1	3	2	4	1	2	3	4

TABLE IV
PERFORMANCE OF THE PROPOSED SSAEP-BASED BCI SYSTEM.

Sub jects	***% Accuracy***		
	Without Training	***Training without Attention index***	***Training with Attention index (Proposed System)***
1	75	62.5	87.5
2	62.5	75	75
3	50	62.5	75
4	62.5	62.5	87.5
Avg	62.5	65.63	81.25

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