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Simultaneous classification of motor imagery and SSVEP EEG signals

Omid Dehzangi, *Member*, Yuan Zou, *Student Member*, and Roozbeh Jafari, *Senior Member, IEEE*

***Abstract*— increased demands for applications of brain computer interface (BCI) have led to growing attention towards their more practical paradigm design. BCIs can provide motor control for spinal cord injured patients. BCIs based on motor imagery (MI) and steady-state visual evoked potentials (SSVEP) tasks are two well-established tasks that have been studied extensively. These two tasks can be combined in order for the users to realize more sophisticated paradigms. In this paper, a novel system is introduced for simultaneous classification of the MI and SSVEP tasks. It is an effort to inspire BCI systems that are more practical, especially for effective communication during more complex tasks. In this study, subjects performed MI and SSVEP tasks both individually and simultaneously (combining both tasks) and the electroencephalographic (EEG) data were recorded across three conditions. Subjects focused on one of the three flickering visual stimuli (SSVEP), imagined moving the left or right hand (MI), or performed neither of the tasks. Accuracy and subjective measures were assessed to investigate the capability of the system to detect the correct task, and subsequently perform the corresponding classification method. The results suggested that with the proposed methodology, the user may control the combination of the two tasks while the accuracy of task recognition and signal processing is minimally impacted.**

I. INTRODUCTION

Brain-computer interface (BCI) technology is gaining popularity due to recent developments of inexpensive, easy-to-wear, low profile and low power electroencephalography (EEG) acquisition systems. The applications of BCI are diverse with potential for large economic impact. For instance, monitoring brain activities with EEG sensory systems can be employed to help handicapped patients to move independently, or to develop entertainment and gaming applications, and also to design improved treatments for many disorders including neuro-degenerative, depression, obesity, and drug addiction [1, 2, 3].

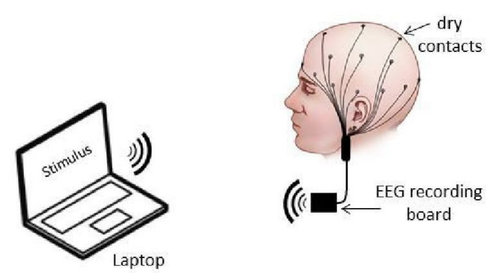
Recent developments in BCI have inspired investigations towards more practical BCI architectures, especially effective communication during complex tasks. We developed an integrated system featuring low cost, low power wireless data acquisition capability which is capable of interfacing with mobile devices. We particularly focused on creating BCI-enabled systems for smart phones and tablets for application selection and menu navigation. In this paper, an application selection task is defined which can be accomplished via combining two different BCI tasks, based on steady-state visual evoked potential (SSVEP) [4] and motor imagery (MI) [5]. These two BCI tasks have been studied extensively and their combination can help enable a large number of applications in gaming, entertainment, navigation and rehabilitation with significant commercial relevance. The major challenge is the requirement for simultaneous classification of MI and SSVEP EEG signals. Therefore, we propose a mechanism to simultaneously classify the MI and SSVEP tasks. The subjects participated in this study perform the MI and SSVEP tasks and their corresponding EEG data is recorded. We develop a task detection system to choose between the tasks and then feed the EEG signals to the detected target BCI task. To do so, we design discriminative measures based on CCA correlation values and support vector machine (SVM) classifier to accurately discriminate SSVEP/no SSVEP and MI/no MI, respectively.

The organization of this paper is as follows. In section II, we describe the low-power Bluetooth EEG acquisition system, and also the SSVEP-based and the MI-based systems. In section III, the combined task is explained and the proposed strategy for simultaneous classification of MI and SSVEP EEG signals is presented. In section IV, the experimental results are illustrated and analyzed. Finally, section V concludes the paper.

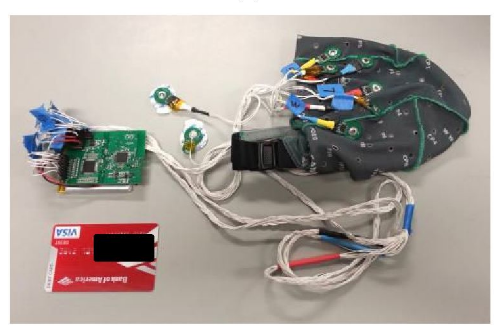
II. METHOD AND ARCHITECTURE

A. Signal acquisition system

The data acquisition system, designed and developed in our lab, comprises a set of active dry-contact electrodes, a low-noise recording electronics including Texas Instruments ADS1299 and Bluetooth low energy (BLE) communication module. The overall system design features low cost, low power consumption, with low component count, and is capable of interfacing with mobile devices.



(a)



(b)

Figure 1. The proposed BCI system configuration: (a) is the conceptual diagram of the proposed system; (b) is the photograph of the EEG signal acquisition system.

O. Dehzangi is with the University of Texas at Dallas, Richardson, TX 75080 USA (e-mail: omid.dehzangi@utdallas.edu).

Y. Zou, is the University of Texas at Dallas, Richardson, TX 75080 USA (e-mail: zouy@utdallas.edu).

R. Jafari, is the University of Texas at Dallas, Richardson, TX 75080 USA (e-mail: rjafari@utdallas.edu).

Fig. 1 illustrates the system configurations: (a) is the conceptual diagram of our system, and (b) is the photograph of the EEG recording system. In the proposed BCI system, eight dry electrodes including C3, C4, FC3, FC4, PO7, PO8, Oz, and POz are placed as the EEG channels and Cz is used as the reference in the international 10-20 system. The EEG recording system transfers the collected EEG signals to the PC or the mobile handset, where the entire signal processing procedure is performed. The prototype EEG recording system shown in (b) is capable of recording 16 channels simultaneously, and is approximately 3x1.5 inches in size. The EEG signals were filtered between 0.5 and 30 Hz and recorded with a sample frequency of 250 Hz.

B. SSVEP-based BCI task

In the SSVEP-based system, an LCD display with a 60 Hz refresh rate was used as the stimulus source. There were four targets in the BCI system, with three flickering frequencies of 6 Hz, 7.5 Hz, and 8.6 Hz which correspond to ten, eight and seven frames in one flicking period. There was also a non- flickering target in order to collect no SSVEP data. Fig. 2 shows the distribution of the four targets on the screen. We designed our experiments using the Psychophysics Toolbox [6].

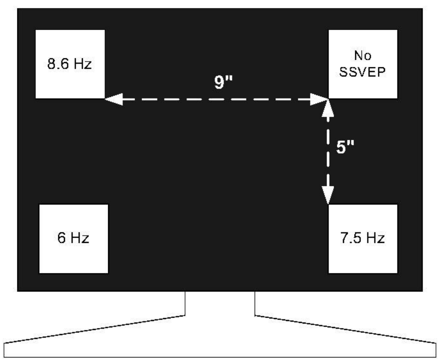


Figure 2. The distribution of four targets in the monitor

We employed the canonical correlation analysis (CCA) method for the SSVEP-based BCI. CCA is a multivariable statistical method used when there are two sets of data, which may have some underlying correlation [7]. It finds a pair of linear combinations, for two sets, such that the correlation between the two canonical variables is maximized. The use of the CCA method for multi-channel SSVEP detection was first proposed in [8]. Fig. 3 demonstrates the use of CCA to detect the frequency of the SSVEP-based BCI where there are K targets, with the stimulus frequencies being $f_1, f_2, \ldots, f_K$, respectively. X refers to the set of multi-channel EEG signals and Y_f refers to the set of reference signals which have the same length as X. The reference signals Y_f is,

$$Y_f = \begin{pmatrix} \sin(2\pi ft) & & \sin(2\pi Hft) \\ \cos(2\pi ft) & \cdots & \cos(2\pi Hft) \end{pmatrix} \quad (1)$$

where H is the number of harmonics (H = 3 in this study). The multi-channel EEG signals and each of the reference signals were used as an input of the CCA method. The output canonical correlation ρ can be used for frequency recognition. The user's command w is recognized as,

$$w = \arg\max_i \rho_i \quad , \qquad i = 1,2,\ldots,K \quad (2)$$

where ρ_i are the CCA coefficients obtained with the frequency of reference signals being $f_1, f_2, \ldots, f_K$.

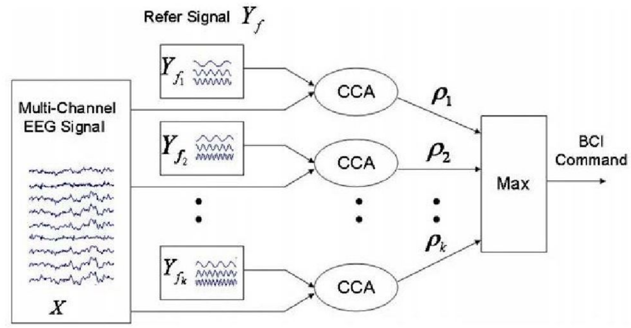


Figure 3. Employing CCA in EEG signals analysis. X is the multi-channel EEG signals. Y_f is the reference signals with f_i Hz stimulus frequency [9].

C. MI task

In the MI-based system, each subject sat about one meter distance in front of the computer screen. The MI training paradigm consists of a repetitive process of triggered movement imagery trials. Each trial lasted 10 seconds and started with the presentation of a blank screen. At the 2nd second, a fixation cross appeared in the middle of the screen and lasted for two seconds. This period is considered for no MI data collection. From the fourth second to the seventh second, the subjects performed left or right-hand motor imagery according to an arrow (cue) on the screen. An arrow pointing either to the left or to the right indicated the imagination of a left hand or right hand movement. The order of appearance of the arrows was randomized and at the seventh second, the screen content was erased. The trial finished with a three second inter-trial period beginning at the seventh second. Each recording session consisted of 80 trials. Fig. 4 shows the timing scheme.

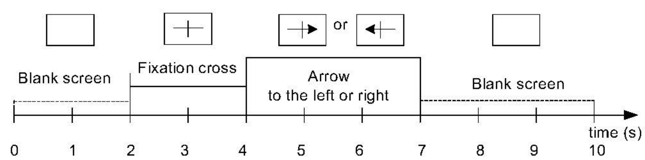


Figure 4. Training paradigm and time scheme for each recording

In this section, we present a lightweight classification method for single trial EEG. First, the baseline was removed, that is, the average of baseline segment (0-500ms) was subtracted from all samples of each trial. Then, the data were re-referenced to the average potential over the entire head. In the next step, we applied a band-pass filter (0.5 – 30 Hz) to eliminate high frequency and very low frequency noise. Then, we used band power (BP) [10], fractal dimension (FD) [11], and wavelet packet tree [12] to extract features. Extracted feature vectors are fed to the SVM classifier to distinguish the imaginary right and left hand movements. Fig. 5 shows the signal processing flow of the system.

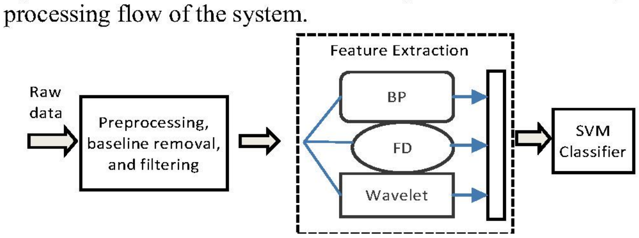


Figure 5. Signal Processing Architecture

III. COMBINING THE SSVEP AND MI BASED SYSTEMS

Recent successful development of BCI systems has inspired studies and efforts towards more practical BCI architectures, especially effective communication during more complex tasks. For example, Fig. 6 shows the Tetris game application. As shown in Fig. 6, the task can be accomplished via combining the SSVEP task (left/right rotation and pause), and MI task (left/right movement).

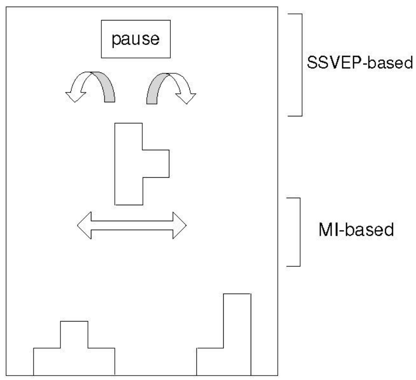


Figure 6. An application using SSVEP-based and MI-based BCI

The major challenge in the application shown in Fig. 6 is the requirement of simultaneous classification of MI and SSVEP tasks with common EEG input signals. We design a task detector to simultaneously classify the MI and SSVEP tasks. The subjects in this study performed MI and SSVEP tasks and the corresponding EEG data were recorded and used for training. Then, the proposed task detector feeds the input EEG signal to the detected target BCI task, as shown in Fig. 7. The SSVEP detector in Fig. 7 is designed based on the CCA classifier explained in section II.B. First, the CCA correlation values are filtered to keep only the frequencies between 5-10 Hz to ignore unwanted frequencies. Then, the discriminative measure Δ_i is calculated as follows,

$$\Delta_i = \rho^i_{w_1} - \rho^i_{w_2} \geq \theta^i \qquad (3)$$

where ρ is the output canonical correlation, w_1 and w_2 are the index of the first and second maximum CCA coefficients obtained with the frequency of the reference signals in Eq. (2), and θ^i is the threshold on the difference between the first and the second maximum CCA coefficient leading to the best accuracy to distinguish the SSVEP/no SSVEP data for the subject i. If the input EEG signal is SSVEP-based, the measure Δ_i tends to be higher, and vice versa.

The MI detector is designed based on a two-class SVM classifier which is trained using the collected MI and no MI data as described in section II.C.

$$f(\mathbf{x}) = \sum_{i=1}^{N} \alpha_i y_i \mathbf{x}_i \mathbf{x} + d \qquad (4)$$

where y_i ={1, -1} represents SSVEP and no SSVEP data respectively, the vectors $\mathbf{x}_i$ are the support vectors, N is the number of support vectors, α_i are adjustable weights, and d is the bias term. In the detection phase, if $f(\mathbf{x})$ is bigger than zero, the EEG signal is directed to the MI system. If the input EEG signal is MI-based, the SVM score tends to be positive towards 1, and if it is no MI, the score tends to be negative towards -1.

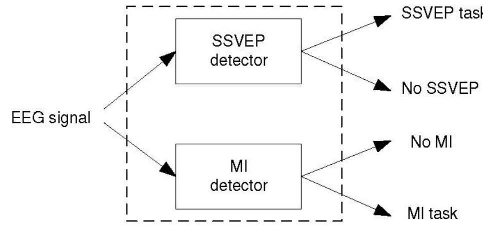


Figure 7. Detection of the target BCI task

There are 4 possible output combinations from the detector: 1) SSVEP, and no MI: The signal is detected as SSVEP and directed to the SSVEP-based system. 2) MI, and no SSVEP: The signal is detected as MI and directed to MI-based system. 3) no MI, and no SSVEP: The signal is considered as irrelevant and is skipped. 4) MI, and SSVEP: This is an invalid case in which the signal is directed to both systems and the right one is chosen based on the confidence level of the final decisions.

IV. EXPERIMENTS

Five healthy subjects participated in this study. Subjects ranged from 20 to 30 years old. We collected data from the subjects based on the methodology explained in section II.B and II.C for the SSVEP and MI BCI tasks. From the eight electrodes placed at C3, C4, FC3, FC4, PO7, PO8, Oz, and POz as the EEG channels, the first four were used as the input channels for the MI task and the remaining four were used for the SSVEP task.

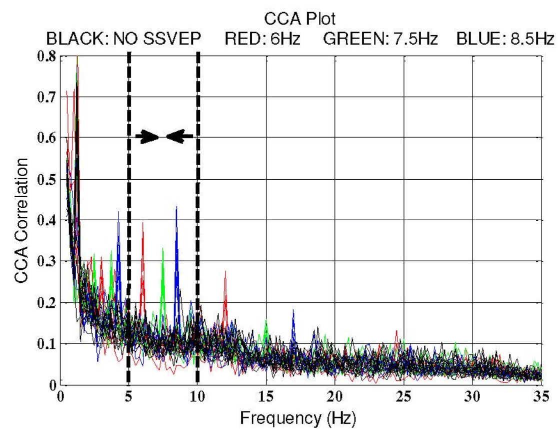


Figure 8. the CCA correlations for different target frequencies.

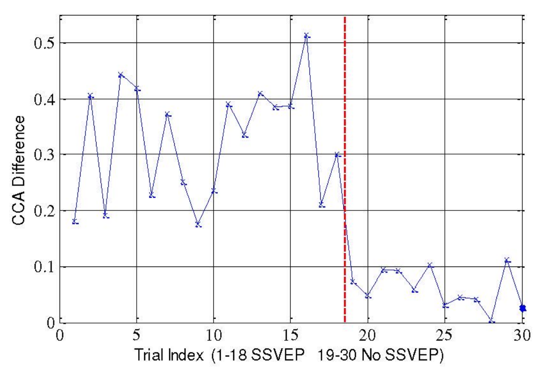


Figure 9. Comparison of the measure Δ_i for the SSVEP and no SSVEP trials

For the SSVEP task, there was no training required and for the testing, a set of 30 trials of eight seconds long was recorded per subject. Fig. 8 shows the CCA correlations of different frequencies for the SSVEP test data for subject 1. The target frequencies show clear peaks for their corresponding SSVEP data (Red, Green, and Blue curves) and demonstrated no significant peak for the no SSVEP data (Black curves). As illustrated in Fig. 8, the CCA correlation values for frequencies between 5-10 Hz are investigated using Eq. (3). Fig. 9 shows the measure Δ_i defined in Eq. (3) for the SSVEP/no SSVEP trials of subject 1. The trials 1-18 are associated with the SSVEP data, and the trials 19-30 represent the no SSVEP data. Fig. 9 shows that the measure Δ_i is consistently lower for the no SSVEP data compared to the SSVEP data which verifies its effectiveness to distinguish the two signals.

Table I reports the accuracy of classifying SSVEP/no SSVEP on the four different subjects. The accuracy is always higher than 93%. It also shows that there is no False Positive (FP) error. Please note that we forced the errors towards the False Negatives (FN) by highly waiting the FPs. Since, FP is the error that occurs by classifying a no SSVEP trial as the SSVEP trial and is a more crucial error to handle in the combined task compared to FN.

TABLE I. THE CLASSIFICATION ACCURACY: SSVEP/ NO SSVEP

Subject	Accuracy	False Positive	False Negative
Subject 1	100%	0	0
Subject 2	97%	0	1
Subject 3	100%	0	0
Subject 4	93%	0	2
Subject 5	97%	0	1

For the MI-based task, we collected 80 trials from each subject. Then, we trained the SVM classifier using the recorded training data. The radial basis kernel was used in the SVM classifier and the kernel parameters were optimized using cross validation on the training data. In the testing phase, a set of 40 eight seconds long trials was recorded per subject and the accuracy was calculated. Table II reports the classification accuracy of the MI/ no MI on our five subjects. It is observed that the detection accuracy is 95% and above. Similar to the SSVEP-based system, the FP error was forced to zero.

TABLE II. THE SVM CLASSIFICATION ACCURACY: MI/ NO MI

Subject	Accuracy	False Positive	False Negative
Subject 1	95%	0	2
Subject 2	97.5%	0	1
Subject 3	100%	0	0
Subject 4	95%	0	2
Subject 5	100%	0	0

We also investigated classification of the combined SSVEP and MI test data to assess the accuracy of the target system detector illustrated in Fig. 7. Table III reports the accuracy of different possible outputs. It is observed that combining the SSVEP and MI input data did not decrease the overall accuracy of the system. The results reported in Table III illustrate that the detector accurately discriminates the underlying information behind the two tasks. Note that the invalid case of an input being detected as SSVEP and MI at the same time did not occur on the combined data which shows the reliability of the system to pick the right target between the two BCI tasks.

TABLE III. THE ACCURACY OF THE TARGET SYSTEM DETECTION

Subjects	Accuracy		
	SSVEP & no MI	***no SSVEP & MI***	***no SSVEP & no MI***
Subject 1	98.2%	100%	98.2%
Subject 2	99.1%	99.1%	98.2%
Subject 3	100%	100%	100%
Subject 4	98.2%	98.2%	96.4%
Subject 5	100%	99.1%	99.1%

V. CONCLUSION

In this paper, a novel detection system for simultaneous classification of the MI and SSVEP tasks is introduced as an effort towards more practical and effective BCI during more complex tasks. In this study, subjects participated in performing MI and SSVEP tasks by focusing on one of the three flickering visual stimuli (SSVEP), or imagining the left or right hand movements (MI), or performed none of the tasks. The experimental results and analyses demonstrated that the proposed system successfully classifies the combined input data to choose the right BCI task with minimal changes in the overall accuracy of the system.

VI. ACKNOWLEDGEMENT

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