A Novel Stimulation for Multi-Class SSVEP-Based Brain-Computer Interface using Patterns of Time-Varying Frequencies

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***Abstract*— Steady-state visual evoked potential (SSVEP) has become one of the most widely employed modalities in online brain computer interface (BCI) because of its high signal-to-noise ratio. However, due to the limitations of brain physiology and the refresh rate of the display devices, the available stimulation frequencies that evoke strong SSVEPs are generally limited for practical applications. In this paper, we introduce a novel stimulation method using patterns of time-varying frequencies that can increase the number of visual stimuli with a fixed number of stimulation frequencies for use in multi-class SSVEP-based BCI systems. We then propose a probabilistic framework and investigate three approaches to detect different patterns of time-varying frequencies. The results confirmed that our proposed stimulation is a promising method for multi-class SSVEP-based BCI tasks. Our pattern detection approaches improved the detection performance significantly by extracting higher quality discriminative information from the input signal.**

I. INTRODUCTION

Brain–computer interface (BCI) is a novel mode of communication in which the intention of the users is transmitted to the external world using only their brain signals [1]. While BCIs have been mostly employed to help users with reduced motor abilities, applications for wearable and portable BCIs are emerging in clinical, wellness, and entertainment domains [2, 3].

Various types of tasks and paradigms have been used for the realization of electroencephalography (EEG) based BCI systems such as event-related P300 [4], mu rhythm [5], and steady-state visual evoked potential (SSVEP) [6]. SSVEP-based BCI systems have advantages over the other paradigms in that they have a high signal-to-noise ratio, require relatively few electrodes in the occipital area, and generally do not need any training, compared to the requirements of other BCI systems [7].

SSVEP comprises a series of brain electrical responses elicited by repetitive visual stimuli flickering at a frequency ranging from 1Hz to 100Hz [8]. Conventionally, SSVEP-based BCI systems utilize a single frequency to encode each selection. Although SSVEP can be elicited by a broad range of frequencies, in practical BCI applications all available stimulation frequencies do not always evoke high SSVEP responses. Moreover, if the visual stimuli are displayed on a monitor screen the stimulus frequencies are limited by the refresh rate of the display devices. It has been shown that the highest gain of SSVEP is probably situated in the range of 6–20 Hz [9]. The harmonic signal of the SSVEP also limits this frequency range [10].

Considering the above limitations, in applications such as character spelling, the available frequencies for SSVEP-based BCIs are not enough to be assigned to every character for a speller paradigm [11]. Therefore, it is crucial to design a practical SSVEP-based BCI to create more target stimuli with limited available frequencies. Some previous studies have employed the phase information to design the targets in the SSVEP-BCI and showed the effectiveness of their approach [12]. In another effort [13], each target was simultaneously modulated by two different frequencies, which generated more flickering targets by combining the frequencies. In [14], the authors used a simple visual stimulus by flickering two different frequencies sequentially. They generated four target stimuli with two available frequencies. Despite the worthwhile initiating efforts, the proposed approach is very simple with only two frequencies and four target stimuli. Our work in this paper can be considered as a probabilistic generalization of the effort in [14].

In this paper, we propose a generalized multiple frequency stimulation method using patterns of time-varying frequencies. Our proposed method can produce more visual stimuli with a smaller number of stimulation frequencies for multi-class SSVEP-based BCI systems. We then present a probabilistic framework to recognize different patterns of time-varying frequencies by formulating it based on the number of patterns, the number of time-slots in each pattern, and the number of frequencies. Finally, we introduce three approaches to detect different patterns. Our novel method for stimulation and detection shows promising results for multi-class SSVEP-based BCI tasks.

II. PROPOSED METHOD AND ARCHITECTURE

A. Signal acquisition system

Increased demands for applications of BCI have led to growing attention towards their low-power portable embedded design. We have previously designed and developed a dry-contact EEG data acquisition system [15] featuring low cost, low power, and wireless capabilities. For the experiments and data recording in this study, we used the

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above-mentioned system, which comprises a set of 16 active dry-contact electrodes, two low-noise EEG analog front end using the Texas Instruments ADS1299, and a Bluetooth low energy (BLE) communication module implemented in 3x1.5 inches in size as shown in Fig. 1.

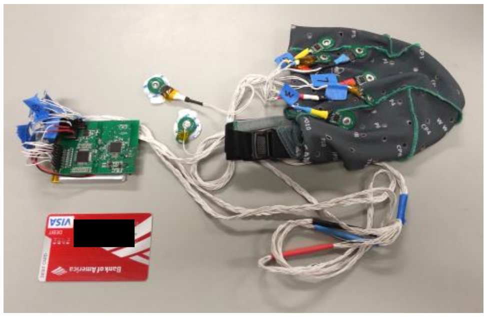

Figure 1. The EEG signal acquisition system

In our proposed SSVEP-based BCI system, eight dry electrodes are placed at O1, O2, PO3, PO4, PO7, PO8, Oz, and POz according to the international 10-20 system and all of them are referenced to the right mastoid. The EEG recording system transfers the collected EEG signals to a PC or mobile handset, where the entire signal processing procedure is performed, via Bluetooth. The sampling rate was 250 Hz, and the collected signals were filtered between 0.5 and 30 Hz.

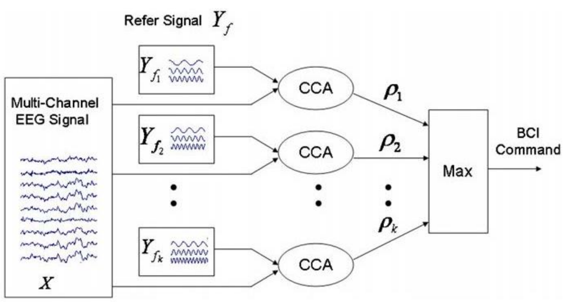

Figure 2. X is the multi-channel EEG signals. Y_f is a set of reference signals with f_i Hz stimulus frequency [18]

B. Canonical correlation analysis (CCA)

We aim to employ canonical correlation analysis (CCA) to extract and distinguish different patterns of time-varying frequencies. CCA is a multivariable statistical method used when there are two sets of data, which may have some underlying correlation [16]. The use of CCA for multi-channel SSVEP detection was first proposed in [17]. Fig. 2 demonstrates the use of CCA to detect brain responses to visual stimulations where there are K target stimuli, with the stimulus frequencies being $f_1, f_2, ..., f_K$, 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 set of reference signals Y_f is,

$$Y_f = \begin{pmatrix} \sin(2\pi ft) & \sin(2\pi H_1 ft) & \sin(2\pi H_2 ft) \\ \cos(2\pi ft) & \cos(2\pi H_1 ft) & \cos(2\pi H_2 ft) \end{pmatrix} \quad (1)$$

where H_1 and H_2 are the harmonics ($H_1 = 2$, $H_2 = 3$ 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 winner frequency w is recognized as,

$$w = \underset{i=1..K}{\arg\max}\ \rho_i \quad (2)$$

where ρ_i is the CCA coefficient obtained with the frequency of reference signals being $f_1, f_2, . . . , f_K$. We explored the CCA coefficient space for a robust discrimination between the patterns of frequencies.

C. Patterns of time-varying frequencies

The main purpose was to design a novel SSVEP paradigm using time-varying frequency patterns, in which we can increase the number of target LEDs without increasing the number of frequencies. We investigated six patterns generated from four different frequencies. Each pattern consisted of four time-spans of two second each. We formulated the problem based on the number of time-slots, T, the number of frequencies, K, and the number of patterns, Γ. We selected six patterns, as shown in Fig. 3(a), ranging from fixed frequency patterns in all their T=4 time-slots, such as {10.5Hz, 10.5Hz, 10.5Hz, 10.5Hz} to patterns with different frequency in every slot, such as {6.25Hz, 9.09Hz, 7.41Hz, 10.53Hz} to explore the impact of faster frequency changes.

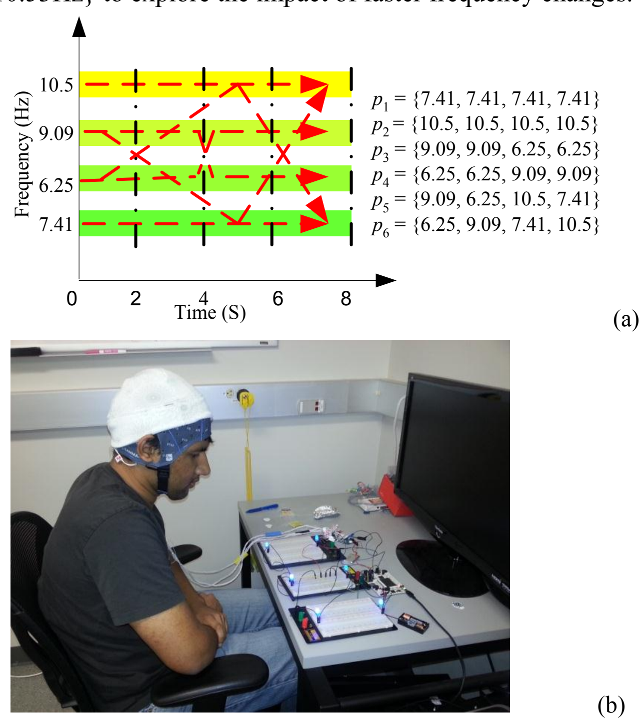

Figure 3. (a) Six selected patterns of time-varying frequencies, (b) a snapshot of the experimental setup and data acquisition

Several experiments were conducted to investigate different time-spans and frequency jumps to find a feasible operating point. In this paper, we used LEDs to accurately generate the target patterns. We set up the experiment as shown in Fig. 3(b) where six LEDs generated the selected patterns of frequencies, simultaneously. In order to generate the patterns, a microcontroller timer was configured to generate 100 clock ticks in one second. The toggling of the various LEDs was performed after an integer amount of clock ticks by the master timer. For example, the frequency of 7.14Hz is achieved by toggling the LED every 14 clock ticks and 9.09Hz constitutes toggling every 11 clock ticks.

D. Detection of the target patterns

We investigated the use of CCA correlation coefficients as a confidence measure in order to detect the target frequency at each time-span of the patterns. The index of the winner frequency pattern p_w, is calculated as below, given the EEG input signal X,

$$w = \underset{i=1..\ \Gamma}{\arg\max}\ \log P\left(p_i \mid X\right) \tag{3}$$

where Γ=6 is the number of patterns, P(p_i|X) is the posterior probability of the pattern p_i, given the input signal, X. Assuming that the probabilities of the time-slots in a pattern are independent,

$$\log P\left(p_i \mid X\right) = \sum_{t=1}^{T} \log P\left(p_{it} \mid x_t\right) \tag{4}$$

where T=4 is the number of time-slots, x_t is the input signal at the time-slot t, and p_{it} is the frequency of the pattern p_i at the time-slot t. Note that that p_{it} is a member of the target frequencies, $p_{it} \in \{f_1.f_K\}$. We know that log $P(p_{it} \mid x_t)$ = log $P(x_t \mid p_{it})$ + log $P(p_{it})$ – log $P(x_t)$ where log $P(x_t)$ can be ignored as a constant and log $P(p_{it})$, the log prior probability of the frequency at the slot t in pattern p_i, is known. For instance, from Fig. 3(a), the probability $P(p_{11}$ = 6.25Hz) = 1/6 and $P(p_{41}$ = 7.4Hz) = 1/3. In order to calculate $P(x_t \mid p_{it})$, we investigated three approaches: 1) Calculate the Hamming distance, 2) Calculate the summation of Normalized CCA coefficients, and 3) Train a log-likelihood ratio test for each of the target frequencies for different slots.

Hamming distance: In the first approach, we calculated the Hamming distance between the patterns. Based on CCA decision rule in Eq. (2), the probabilities of the frequencies at time-slot t of the pattern w will be measured as follows:

$$\log P\left(x_t \mid p_{it} = f_w\right) = \left| \begin{array}{ll} 1 & if \quad w = \underset{j=1..K}{\arg\max}\, \rho_{jt} \\ 0 & otherwise \end{array} \right. \tag{5}$$

where K is the number of target frequencies and ρ_{jt} is the CCA coefficient for the target frequency j at the time-slot t.

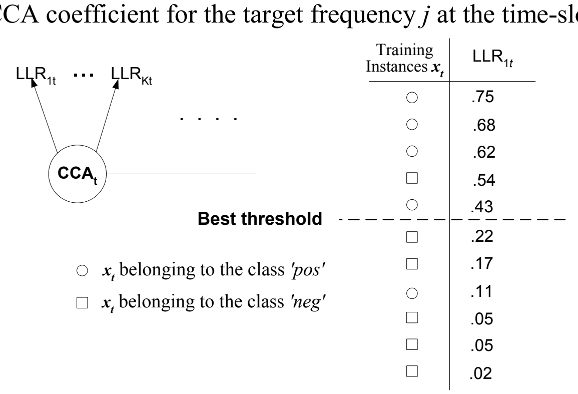

Figure 4. (a) Six selected patterns of time-varying frequencies, (b) A snapshot of the experimental setup and data acquisition

Normalized CCA correlation coefficients: In the second approach, we introduced a soft measure as opposed to Hamming distance $\in \{0,1\}$. In this way, we aimed to capture higher resolution of discriminative information to effectively distinguish different patterns. We employed the normalized CCA correlation coefficients as the probability, $P(x_t \mid p_{it}{=}f_w)$.

$$\log P\left(x_t \mid p_{it} = f_w\right) = \log \left\langle \rho_{wt} \Big/ \sum_{\forall j=1..K} \rho_{jt} \right\rangle \tag{6}$$

Log-likelihood ratio test: The frequencies that elicit strong SSVEP responses are highly dependent upon the participants. Therefore, different individuals respond differently to a specific frequency due to the still unclear physiological mechanisms. Consequently, a strong response to a particular frequency in a time-slot can introduce a bias in the overall likelihood of a pattern. The third approach in this paper aims to alleviate this effect. In this approach unlike the previous approaches, there were two phases: training and recognition. We trained a log-likelihood ratio (LLR) test for each of the target frequencies at each of the time-slots using a training data set. To do so, we collected 20 trials of 8 seconds (i.e. the length of each pattern) while the subjects were looking at each of the six LEDs. Therefore, we generated a training set comprising 120 trials of EEG signal. Then, we trained the best threshold on the LLR value per each target frequency, w, as the positive class, '*pos*', and the rest of the frequencies as the negative class, '*neg*' (Fig. 4).

$$\forall t = 1..T, w = 1..K,\ LLR_{wt} = \log \left\langle \rho_{wt} \Big/ \sum_{\forall j=1..K \,\&\, j \neq w} \rho_{jt} \right\rangle \tag{7}$$

The training was based on the minimum classification error (MCE) criterion using 10-fold cross validation (10-CV). At the recognition phase, the test pattern $X=\{x_t \mid t=1..T\}$ was passed through the time slots and its scores for each frequency are compared with the trained threshold,

$$\begin{aligned} &\forall t = 1..T, w = 1..K, \\ &Sc_{p_{it}=f_w}(x_t) = \log \left\langle \rho_{wt} \Big/ \sum_{\forall j \in K \,\&\, j \neq w} \rho_{jt} \right\rangle - th_{wt} \end{aligned} \tag{8}$$

where $Sc_{p_{it}=f_w}(x_t)$ is the degree to which the input signal correlates with the frequency w at the time-slot t of the pattern i. It was compared to the minimum error estimate of the one-versus-rest discriminant threshold, th_{wt}, on LLR_{wt}. The overall score for the pattern i given the input X is,

$$Score_i(X) = \sum_{t=1}^{T} Sc_{p_{it}}(x_t) \tag{9}$$

The scores calculated in Eq. (9) are directly used in the decision rule instead of *a posteriori* probabilities in Eq. (3) without normalization as they reflect the contribution of each time-slot in the overall pattern detection. The index of the winner frequency pattern, p_w, given the input X is,

$$w = \underset{i=1..\Gamma}{\arg\max} \left\langle Score_i(X) \right\rangle \tag{10}$$

III. RESULTS

Five subjects participated in this study. Table 1 reports the results using our three proposed approaches to distinguish six selected patterns generated from four different frequencies shown in Fig. 3(a).

The results in Table 1 shows that using the time varying patterns of frequencies, we are able to generate more target patterns with a fixed number of available frequencies. Comparing the results of the Hamming distance with the normalized CCA coefficients, it can be observed that the CCA coefficients significantly improved the detection performance by capturing higher resolution information in the CCA output space. Table 1 also demonstrates that LLR thresholds led to the best results. This approach, described in section 2.4.3, aims to relieve the subject dependencies as well as to incorporate context dependencies into the recognition process. Overall, employing the normalized coefficients and the trained LLR thresholds leads to 39% and 53% relative improvements over the hamming distance.

TABLE I. THE FREQUENCY PATTERN RECOGNITION ACCURACIES (%)

Subject	Accuracy		
	Hamming	Normalized Coefficient	LLR threshold
Sbj1	73	84.7	88.3
Sbj2	70.5	82.2	87.5
Sbj3	65.6	78.7	84.2
Sbj4	68.3	80.8	85.8
Sbj5	66.2	78.2	82.6
AVE	**68.72**	**80.92**	**85.68**
STDEV	**±3.07**	**±2.67**	**±2.33**

TABLE II. THE AVERAGED CONFIDENCE OVER THE SUBJECTS FOR DIFFERENT PATTERNS OF FREQUENCIES

	p_1	p_2	p_3	p_4	p_5	p_6
Confidence	0.76	0.69	0.63	0.59	0.57	0.61
Accuracy (%)	87.55	84.75	85.03	86.31	84.27	86.17

We also calculated the average confidence for each of the selected patterns to investigate if there was any pattern related advantages in this task. p_1 and p_2 are target patterns with fixed frequencies while the rest of the patterns demonstrate time-varying frequencies. We calculated the confidence for different patterns in terms of averaged normalized CCA coefficients over the subjects, which is the sum of the target CCA correlation coefficients versus the sum of all the coefficients on the 20 target trials over the subjects. Table 2 reports the confidence and the target detection accuracy using the LLR test. The results show that patterns with fixed frequencies yield slightly higher confidence over the time-varying patterns. However, the differences do not translate into the detection accuracy which confirms that our novel stimulation method and detection approaches are effective for unified target pattern detection.

IV. CONCLUSION

The available stimulation frequencies that evoke strong SSVEPs are generally limited due to the nature of brain and display refresh rate. In this paper, we proposed a novel stimulation method of using patterns of time-varying frequencies that produced more visual stimuli with limited number of stimulation frequencies (6>4) for use in multi-class SSVEP-based BCI systems. The results confirmed that our proposed stimulation is a promising method for multi-class SSVEP-based BCI tasks. We also introduced a probabilistic framework and three approaches to recognize the patterns of time-varying frequencies. Our proposed approaches significantly improved the detection performance of the system by extracting higher quality discriminative information in the CCA space, subject dependent cues, and dependencies between the CCA scores.

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