Spectrum and Phase Adaptive CCA for SSVEP-based Brain Computer Interface

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***Abstract*—Among various brain activity patterns, Steady State Visual Evoked Potential (SSVEP) based Brain Computer Interface (BCI) requires the least training time while carries the fastest information transfer rate, making it highly suitable for deploying efficient self-paced BCI systems. In this study, we propose a Spectrum and Phase Adaptive CCA (SPACCA) for subject- and device-specific SSVEP-based BCI. Cross subject heterogeneity of spectrum distribution is taken into consideration to improve the prediction accuracy. We design a library of phase shifting reference signals to accommodate subjective and device-related response time lag. With the flexible reference signal generating approach, the system can be optimized for any specific flickering source, include LED, computer screen and mobile devices. We evaluated the performance of SPACCA using three sets of data that use LED, computer screen and mobile device (tablet) as stimuli sources respectively. The first two data sets are publicly available whereas third data set is self-collected in our BCI lab. Across different data sets, SPACCA consistently performs better than the baseline, i.e. standard CCA approach. Statistic test to compare the overall results across three data sets yield a p-value of 1.66e-6, implying the improvement is significant.**

I. INTRODUCTION

EEG-based Brain Computer Interfaces (BCI) can be categorized approximately into four different modalities: ERD/ERS (eventrelated desynchronization/synchronization) [1], P300 [2], SSVEP (steady state visual evoke potentials) [3] and SCPs (slow cortical potentials) [4]. Among these brain activity patterns, SSVEP based BCI requires least training time, carries the fastest information transfer rate, and needs fewer EEG channels [5].

SSVEP signals can be observed when brain response to visual stimulation at a particular frequency, such as flashing LED or flickering on computer screen. The visual stimuli at a specific frequency trigger the visual neural pathway and further radiate throughout the brain, producing electrical signals in the brain at the base frequency and multiple frequencies. The detection of underlying signals corresponding to different source frequencies enables a self-paced BCI solution. The most notable use of SSVEP technology is the cases of a text-based spelling system for paralysis patients [6]–[8]. Other interesting cases of SSVEP being employed are games such as spacecraft [9] and maze [10]. Like other EEG modalities, the SSVEP can be contaminated by background noises and spontaneous EEG. Accurate detection of its frequency components in a short time window is challenging and critical to the effectiveness of SSVEP-based BCI.

Early approaches for SSVEP recognition calculated power spectral density (PSD) at different frequencies within a specific time window, and identify the target frequency by the one with the maximal PSD value. This approach works on a signal EEG channel thus is sensitive to noise and needs a relatively longer time window. Later on, canonical correlation analysis (CCA) based recognition method was proposed [11] and soon become widely adopted [12]–[14]. CCA maximizes the correlation between the reference signals of sine-cosine and multi-channel EEG signals. The maximum correlation coefficient (CC) among CCs of all stimuli frequencies is identified as the target. Compare with PSDA, CCA approach optimizes the recognition procedure because by nature it combines information from multiple channels to improve the signal to noise ratio (SNR).

Various methodologies have been proposed to improve the basic CCA method for SSVEP-based BCI. Chen et al. [13] developed filter-bank CCA (FBCCA), conducting correlation analysis on the reference signals and the spectrum sub bands of original EEG signals, and optimize the overall performance through fine tuning the weights of the group of sub bands. Another study introduces a L1-regularized multiway CCA for SSVEP-based BCI [14]. The optimization was implemented on constructing matrix of multi-trial multi-channel EEG to learn the reference signals in correlation analysis for SSVEP recognition, and imposing L1-regularization to optimize the trial-way array for effective trial selection. Both methods take tedious offline parameter tuning process to obtain the best set of parameters, either by grid search or by regularized optimization.

Above mentioned methods attempted to build a general module working across all subjects, which have some limitations because individuals react to visual stimulus vary from each other. Research has shown that it takes 600 to 800 ms for cortical facilitation by visual attention, and such time lags vary among different individuals [12]. Furthermore, each individual has different base spectrum distribution, which may deteriorate the discriminative feature of CCA-based correlation coefficient. Therefore, subject-specific information needs to be incorporated to optimize the SSVEP detection.

In this study, we proposed a subject specific self-paced BCI for gaming and control, which differs from the other existing methods in the following aspects: firstly, it tackles the cross-subject heterogeneity of spectrum distribution characters through a novel spectrum adaptation module; secondly, we propose a novel solution to fit subject-specific cortical response time lags by composing a library of phase shifting reference signals. By applying spectrum adaptation and subject-specific reference signals, our framework can be optimized for any subject with any stimuli source.

II. METHOD

A. SSVEP-BCI based on Basic CCA

CCA-based SSVEP BCI was first proposed by Lin *et al*. [11], we refer the method as *basic CCA* in this context. CCA is a method exploring the relationships between two multivariate sets of variables or vectors, to infer their similarity. In the SSVEP detection context, it is used to detect the similarity between stimuli frequency and the reference signal frequency. For two multivariate variables X and Y, CCA transforms them into 1D variable x and y, through a pair of vectors w_x and w_y, so that to maximize the correlation between x and y, where $x = w_x^T X$, $y = w_y^T Y$. The CCA problem can be considered as a generalized eigenvalue decomposition problem. It is realized by solving the optimization problem described in (1)

$$max_{w_x w_y}, \rho(x,y) = \frac{E[w_x^T X Y^T w_y]}{\sqrt{E[w_x^T X X^T w_y] E[w_x^T Y Y^T w_y]}} \tag{1}$$

In [11], reference signal Y is designed as a group of sine and cosine waveform with frequencies containing the frequency of stimuli f and its harmonics, as described in equation (2) as $Y(f)$.

$$Y(f) = \begin{bmatrix} sin(2\pi * f * n) \\ cos(2\pi * f * n) \\ sin(2\pi * 2 * f * n) \\ cos(2\pi * 2 * f * n) \\ \cdots \\ sin(2\pi * m * f * n) \\ cos(2\pi * m * f * n) \end{bmatrix}, n = \frac{1}{S}, \frac{2}{S}, ..., \frac{N}{S} \tag{2}$$

Where N is the number of samples in a EEG epoch, S is the sampling rate and f is the base frequency to be detected. To recognize the frequency f_{target} of the SSVEP-BCI system, CCA calculates the canonical correlation coefficient ρ between the multi-channel EEG signals and the reference signals at each stimulus frequency $f, (f = f_1, f_2, \ldots, f_K)$. The frequency of the reference signals with the maximal correlation is selected as the frequency of SSVEPs, as shown in (3). Let $w_x \in \mathbb{R}^{C \times 1}$ and $w_y \in \mathbb{R}^{2N_h \times 1}$ denote weighting vectors for X and $Y(f)$ respectively. C and N_h denote the number of EEG channels and the number of harmonics being considered respectively.

$$\left[f_{target} = argmax_f \; \rho(f), f = f_1, f_2, \ldots, f_K \right] \tag{3}$$

Where $f_{1,2..K}$ are different stimuli source frequencies.

The design of the reference signal $Y(f)$ as a group of sine and cosine waveforms works effectively to capture the frequency features of SSVEPs. This makes the template based CCA approach very successful in SSVEP BCIs. The first two coefficients in w_y that are correspond to $cos(2\pi * f * n)$ and $sin(2\pi * f * n)$ could reflect the phase information of the base signal. Thus CCA could address the phase shifting in SSVEPs by learning an effective weight vector w_y. However, it would requires a relatively lengthy base signal. CCA may not work well when the data length is short.

To address this problem, we design a algorithm called Spectrum and Phase Adaptive CCA (SPACCA), as describe in the following.

B. Spectrum and Phase Adaptive CCA

We proposed a Spectrum and Phase Adaptive CCA approch (SPACCA) to improve the SSVEP detection accuracy. The framework is illustrated in Figure 1. Visual stimuli (provided by LED lights, computer screen or mobile device) composes a group of flashing units, each flickers at a certain frequency implying a particular control command for gaming or other application. The subject provides desired command to interact with system by looking at the targeting flickering unit. EEG signals are acquired, processed and inferred by the system in order to detect the target unit and trigger the corresponding control command.

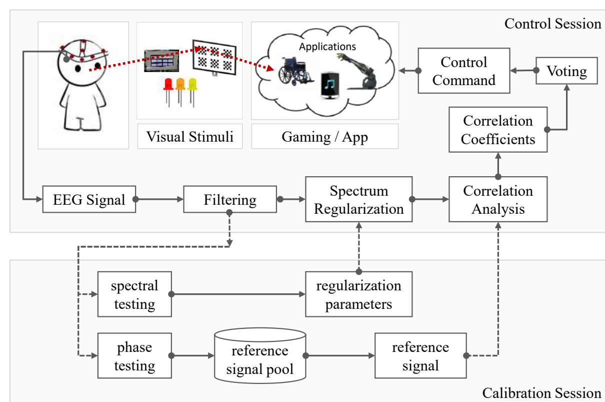

Fig. 1. Proposed SSVEP-BCI System Framework

The BCI system composes a *calibration session* and a *control session*. During calibration session, a set of regularization parameters are derived from spectrum distribution analysis; followed by a optimal reference signal selected to optimize CCA. The control session infers the targeting stimuli using SPACCA based on the parameters obtained in the calibration session.

C. Subject Specific Phase Regularization

In formula 2, f refers to the stimulation frequency and m is the number of harmonics. The basic CCA calculates the canonical correlation between multi-channel EEGs and $Y(f)$ corresponding to each stimulation frequency to recognize the stimuli. Such approach does not take into consideration the time lag variations among subjects' reaction to visual stimuli.

In this study, we propose a new way to compose reference signals, one example is $Y_2(f)$ shown in 4, where $s_i, c_i, i = 1..m$ are values in $[-1, 1]$, representing the shifting phase of delayed response.

$$Y_2(f) = \begin{bmatrix} sin(2\pi * f * n) \\ cos(2\pi * f * n) \\ sin(2\pi * f * n + s_i), i = 1, ..., m \\ cos(2\pi * f * n + c_1), i = 1, ...m \end{bmatrix}, n = \frac{1}{S}, \frac{2}{S}, ..., \frac{N}{S} \quad (4)$$

Figure 2 visualizes our library of different reference signal sets. In Figure 2 Y1 plots the original reference signals proposed in [11]. Y2 to Y4 plot the different reference signal sets we proposed, which are designed to cover various phase shifting range. The library provides multiple choices for CCA reference signals, ensuring the optimal detection accuracy for different subject. The selection of reference signal can be realized in a calibration session.

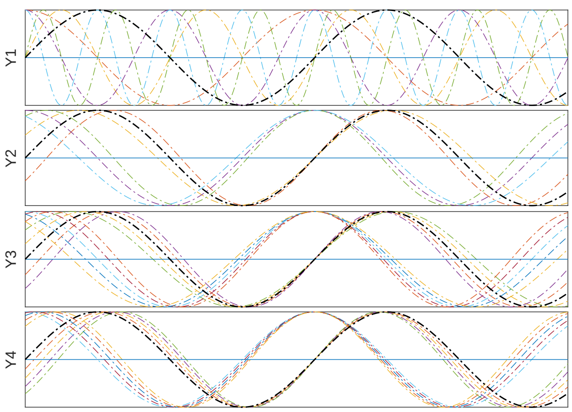

Fig. 2. Library of Reference signal sets for CCA. a. original reference signals proposed in [11] b,c,d. proposed reference signals.

D. Subject Specific Spectrum Regularization

Each individual's EEG signals, under different situations demonstrate different characteristics of spectrum distribution. Such variation would affect the subsequent analysis of CCA. To tackle this issue, we propose a subject specific spectrum regularization step. A subject's baseline spectrum distribution can be detected during idle epochs at the initial part of the calibration session. A simplified procedure to search for reguralization parameters is described as following:

- Calculate base correlation coefficients (CC) between EEG signal acquired from idle state and reference signal (see next subsection): $\hat{\rho}_i,\ i \in 1, 2, ...n$
- Infer a regularization parameter based on $\hat{\rho}$, $\lambda_i = \frac{\sum_{j=1}^{n} \hat{\rho}_i}{\hat{\rho}_i}$
- Calculate CC ρ_i , $i \in 1, 2, ...n$ between SSVEP EEG signal and reference signal, then normalize them by regularization parameter, $\widetilde{\rho_i} = \lambda_i \times \rho_i, i = 1, 2, ..n$

A set of subject specific parameters are obtained and will be used by control session. The correlation coefficients for each stimulus frequency then will be regularized accordingly.

III. Experiment and Result

We conduct experiment on three sets of SSVEP data, with visual stimuli generated from LED, computer screen and tablet respectively. The details of data is described in table I.

TABLE I
DATA SETS USED FOR EXPERIMENT

Data set	Flickering Device	Number of subjects	Number Sessions	Stimulus frequencies
1	LED	5	20	13,17,21Hz
2	monitor	4	20	8,14,28 Hz
3	tablet	5	20	8,9,10,...,15Hz

- Data set 1 [15] includes SSVEP recordings from 5 subjects focusing on LED blinking at three different frequencies. Each subject had 4 sessions of record, end up a total of 20 records.
- Data set 2 [16] contains 4 subjects' SSVEP data, each conducted 3 groups of trial for 3 stimuli frequencies. We combine every 3 stimuli sessions into 1 session and obtained 20 sessions for analysis. Since 14 Hz and 28Hz are harmonic frequencies, we treat this data as a bi-class problem.
- Data set 3, we design our own experiment to collect mobile device SSVEP data using a tablet as flickering stimulus. 5 Subjects each conducted 4 sessions: 2 for static stimuli (target is not moving) and 2 for dynamic stimuli (target is moving randomly around its position) of 8 flickering frequencies In total, 20 sessions were available for analysis.

A. Effect of Spectrum Regularization

Each individual's EEG signals, under different situations, will not have the same characteristics of spectrum distribution. We illustrate this by an example shown in figure 3.

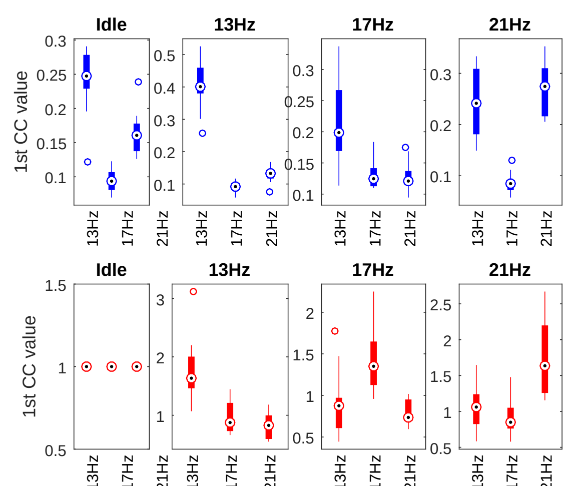

Fig. 3. Subjective Spectrum Adaptation improves discriminative power for SSVEP detection. (CC- correlation coefficients)

The plots were generated by averaging the ρ values across multiple trials of SSVEP experiment. The top subplots at left show the subject's ρ distribution during idle state. Apparently, the subject has a relatively higher $13Hz$ power ratio as compare to 17 and $21Hz$. This will affect the approach using CCA algorithm. The second to forth subplots shows the distributions of EEG power ratios during visual stimulation using $13, 17, 21Hz$ respectively. It is clear that the discriminative power decreases at $17Hz$, mainly because the subject's base $17Hz$ power is rather low. Results after adaptation are shown in the bottom plots. The regularized ρ values for both 17 and $21Hz$ are much more discriminative.

B. Comparison of the different approaches

We evaluated performance of SPACCA using three data sets comparing the three approaches: 1/ Baseline method using standard CCA approach as described in [11]; 2/ Spectrum Adaptive method, which applies subjective spectrum adaptive approach; and 3/ SPACCA, which , further to spectrum adaptation, applies phase adaptation through choosing the suitable reference signal from our signal pool.

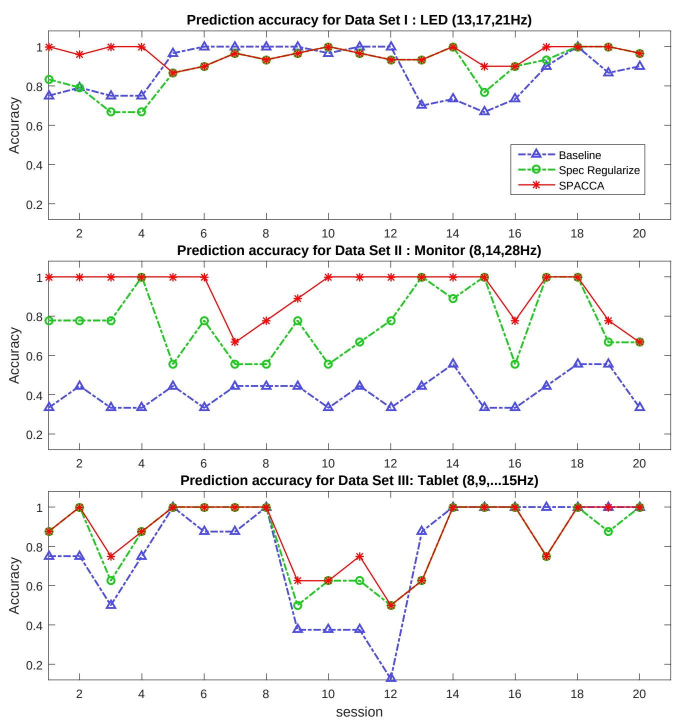

Fig. 4. Comparison of different methods across three data sets

Figure 4 shows the prediction result for all the sessions of three data sets. We observe that SPACCA may not always perform the best, however, across different data sets, SPACCA is the most stable method. The increase of accuracy for three data sets are 8.6%, 51.7% and 8.8% respectively. We conduct Wilcoxon rank sum test to assess the improvement of SPACCA versus baseline method, the p-value is 1.66e-6, inferring that the improvement is statistically significant.

IV. Conclusion

In this study, we proposed a subject specific and device specific SSVEP-based solution for self-paced gaming and control BCI. Cross-subject heterogeneity of spectrum distribution is incorporated into the system to improve the prediction accuracy. A library of phase shifting reference signals tackles the variations of subject-specific cortical response time lags. Such system can be optimized for any specific flickering source device, include LED, computer screen and mobile devices. With a simple calibration stage, optimized parameters can be obtained with ease for best modeling.

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