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Fusing Canonical Coefficients for Frequency Recognition in SSVEP-Based BCI

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ABSTRACT The canonical correlation analysis (CCA)-based frequency recognition method is one of the widely used methods in steady-state visual evoked potential (SSVEP)-based brain–computer interface (BCI), and several extended version were proposed in the past decade. However, these methods only adopt the maximal correlation coefficient provided by the CCA and discard other coefficients. This operation may lead to the loss of discriminative information that exists in the discarded coefficients. In the current study, we proposed to fuse all the correlation coefficients of the CCA with a nonlinear weighting function when performing frequency recognition with CCA method, termed as FoCCA. Evaluated on a benchmark dataset of thirty-five subjects, the experimental results demonstrated that the classification accuracy and information transfer rate (ITR) of FoCCA are significantly higher than those of the standard CCA at various time windows. Fusing correlation coefficients could be a new strategy to improve the performance of other extended CCA methods, which holds the potential to implement high-performance SSVEP-based BCI systems in the future.

INDEX TERMS Steady-state visual evoked potential, brain–computer interface, canonical correlation analysis, electroencephalogram.

I. INTRODUCTION

Brain-computer interface (BCI) provide an alternative channel for their users to communicate or control external devices, and it detects the intent of the user through the electrophysiological or other signals of the brain [1], [2]. These signals include sensorimotor rhythm [3]–[5], event-related potential [6]–[8], and steady-state visual evoked potential (SSVEP) [9]–[11], motion-onset visual evoked potential (mVEP) [12], [13], etc. Among them, the SSVEPs have been received increasing interests because of its robust characteristics. The SSVEP-based BCI achieved the highest information transfer rate (ITR) [14], [15].

In SSVEP-based BCI, the frequency recognition is one of challenging research topics [16]–[18]. Robust and effective methods are crucial for high-performance BCI applications. To date, many methods were proposed by different research groups. The canonical correlation analysis (CCA) based recognition method is one of the widely used methods to detect stimulus frequency of the flickering stimulus attended by the subject due to its efficiency [19]. The first study that used CCA for frequency recognition was presented by Lin et al. [20]. Later, various extended versions were proposed for frequency recognition. For instance, Pan et al. proposed a phase constrained CCA method [21]. In this method, the phases of reference signals designed with the sinusoidal functions were optimized according to the visual latency estimated from the calibration data. In another study [22], Chen et al. proposed a filter bank CCA method to incorporate fundamental and harmonic frequency components to enhance the frequency detection of standard CCA method, in which filter bank analysis was used to perform sub-band decomposition of SSVEP data. Beside, CCA was also used for reference signal optimization, such as multilayer correlation maximization [23], L1-regularized multiway CCA [24], sparse Bayesian multiway CCA [25], etc.

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CCA is a multivariate statistical method to measure the correlation between two multi-dimensional variables, and it can provide multiple canonical correlation coefficients [26]. Usually, only the largest coefficient which is considered to be the most discriminative feature was used for frequency recognition, the remaining coefficients were optionally discarded [20]–[23]. The scalp EEG data often contain noise and artifact. When CCA was used for frequency recognition method with EEG data, the noise and artifact could lead to discriminative information to span across all or parts of the canonical correlation coefficients [20], discarding other coefficients could lost useful information for frequency detection. This issue was not properly addressed in the past. It might be beneficial to exploit additional coefficients for frequency recognition with CCA method.

In current study, we fuse all the canonical correlation coefficients of CCA to enhance the performance of the standard CCA based frequency recognition method. The experimental results evaluated on the benchmark dataset indicate the promising potential of the proposed fusion strategy to enhance the performance of CCA based methods during frequency recognition.

The remainder of this paper is organized as follows. Section II presents the methods and the EEG dataset. In Section III provides the experimental results. The discussion and conclusion are provided in the last two sections.

II. METHOD AND MATERIALS

A. CCA-BASED FREQUENCY RECOGNITION

CCA is a statistical method to measure the underlying correlation between two multidimensional variables [26]. Given two multidimensional variables $X \in \mathbb{R}^{m\times k}$ and $Z \in \mathbb{R}^{n\times k}$, CCA seeks a pair of weight vectors $w \in \mathbb{R}^{m\times 1}$ and $v \in \mathbb{R}^{n\times 1}$, to maximize the correlation between $x = w^T X$ and $z = v^T Z$. The optimization problem can be expressed as in (1):

$$\begin{aligned}\rho &= \arg\max_{w,v} \frac{E\left[xz^T\right]}{\sqrt{E\left[xx^T\right]E\left[zz^T\right]}} \\ &= \arg\max_{w,v} \frac{w^T XZ^T v}{\sqrt{w^T XX^T w}\sqrt{v^T ZZ^T v}}. \end{aligned} \tag{1}$$

Maximizing formula (1) can be achieved by solving a generalized eigenvalue problem.

Suppose that $\bar{X} \in \mathbb{R}^{N1\times P}$ is a test sample of SSVEP data, $Y_i \in \mathbb{R}^{N2\times P}(i = 1, 2, \cdots, N_f)$ is a reference signal created with sine-cosine functions or individual template signal obtained by averaging SSVEP data across multiple trials at frequency $f_i(i = 1, 2, \cdots, N)$. Here, $N1$ and $N2$ are the numbers of EEG channels, P is the number of sample points, and N_f is the number of flickering stimuli. Let D be the minimal rank of $\bar{X}$ and Y_i. With (1), we can obtain D correlation coefficients, i.e., $\rho_1, \rho_2, \cdots, \rho_D$, for $\bar{X}$ and Y_i, $i = 1, 2, \cdots, N_f$. When CCA is used for frequency recognition, only the maximal correlation coefficients among $\rho_1, \rho_2, \cdots, \rho_D$ is adopted as the classification feature [20].

Denote maximal correlation coefficients for the $i-th$ stimulus as β_i, $i = 1, 2, \cdots, N_f$. Then, the frequency f of the test sample $\bar{X}$ is the that of the reference signal or individual template signal with the maximal coefficients, as shown in (2):

$$f_{test} = \max_f \beta_i(f), \quad i = 1, 2, \ldots, N_f \tag{2}$$

B. FUSING THE CANONICAL COEFFICIENTS OF CCA FOR FREQUENCY RECOGNITION

As mentioned above, when CCA is used for frequency recognition, only the maximal correlation coefficients among $\rho_1, \rho_2, \cdots, \rho_D$ is adopted as the classification feature, the remaining $D-1$ coefficients are discarded. To some content, the discarded coefficients can also provide useful information for frequency recognition, as shown in Fig.2. Therefore, it is beneficial to exploit all the coefficients to enhance the performance of CCA-based method for frequency recognition.

In current study, we proposed to fuse the D coefficients by a weighted summation method, termed as FoCCA. Denote the weights as $\phi = [\phi_1\ \phi_2\ \cdots\ \phi_D]^T$. The D coefficients were arranged in descending order and denoted as $\lambda = [\lambda_1\ \lambda_2\ \cdots\ \lambda_D]^T$. Then the new feature for classification becomes :

$$\eta = \sum_{k=0}^{D} \phi_k \cdot (\lambda_k)^2 \tag{3}$$

The weights ϕ can be obtained with the following nonlinear function [22]:

$$\phi_k = k^{-a} + b, \quad k = 1, 2, \cdots, D. \tag{4}$$

For the implementation of FoCCA method, we first adopted the standard CCA to obtain the canonical coefficients for a test sample and the reference signal (individual template signal) at each stimulus frequency. Then, we used formula (3) to calculate new feature for the test sample at each stimulus frequency, and used the formula (2) to implement frequency recognition. A schematic of the FoCCA method is presented in Fig.1

C. EEG DATASET

In order to evaluate the performance of the CCA and FoCCA, a publicly available benchmark dataset of 40-target speller was used [27]. The targets were coded by 8-15.8 Hz with an interval of 0.2 Hz. For this dataset, thirty-five healthy subjects participated in an offline experiment that included six blocks. In each block, 40 trials corresponding to all 40 flickering stimuli were presented to the subjects in a random order. Each trial lasted 6 s, which consisted of 0.5 s for the visual cue, 5 s for visual stimulation, and 0.5 s period during which the screen was blank (stimulus offset).

All data were recorded from 64 electrodes placed according to the international 10-20 system with a Synamps2 system (Neuroscan, Inc.). EEG data were recorded at 1000 Hz with a

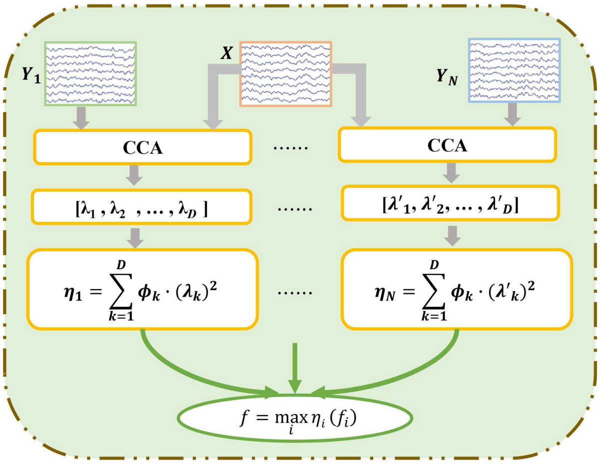

FIGURE 1. **The diagram of FoCCA. For a test sample $\bar{X} \in \mathbb{R}^{N1 \times P}$, and a reference signal or individual template $Y_i \in \mathbb{R}^{N2 \times P} (i = 1, 2, \cdots, N_f)$, we can obtain D canonical coefficients in descending order, e.g. $\lambda_1\ \lambda_2\ \cdots\ \lambda_D$. Then, we combine these D coefficients with formula (3) to obtain new features: $\eta_i (i = 1, 2, \cdots, N_f)$. Finally, the frequency of $\bar{X}$ is detected by formula (2).**

0.15 Hz to 200 Hz bandpass filter and a notch filter at 50 Hz. All the continuous EEG data have been segmented into epochs of 6 s. The epochs were subsequently downsampled to 250 Hz. More detailed information about this dataset can be found in [27].

In current study, all data epochs were band-pass filtered from 7 Hz to 90 Hz with an IIR filter. A delay of 140 ms in the visual system was considered during extracting data in each trial [14], [27]. In addition, only data from nine electrodes over the occipital and parietal areas (Pz, PO5, PO3, POz, PO4, PO6, O1, Oz, and O2) were adopted during following analysis.

D. PERFORMANCE EVALUATION

In current study, classification accuracy and ITR were used to evaluated the performance of CCA and FoCCA. ITR is the amount of information communicated per second, and can be calculated as follows [28]:

$$ITR = \frac{60}{T}\left[\log_2(N) + p\log_2(p) + (1-p)\log_2(\frac{1-p}{N-1})\right] \tag{5}$$

where N is the number of targets, p is the classification accuracy, and T is the required time for visual stimulation and gaze shifting in each operation period.

The accuracy and ITR were estimated using a leave-one-out cross validation. Specifically, the EEG samples from five blocks were used to calculate the individual template at each stimulus frequency while the reaming samples for validation. The procedure was repeated for six times for each subject. For the estimation of ITR, the 0.5 s gaze-shifting time was used when calculating the ITRs. We evaluated the performance of the two methods at different time windows, i.e., 0.5 s to 3 s (with a step of 0.5 s), and under different numbers of channels.

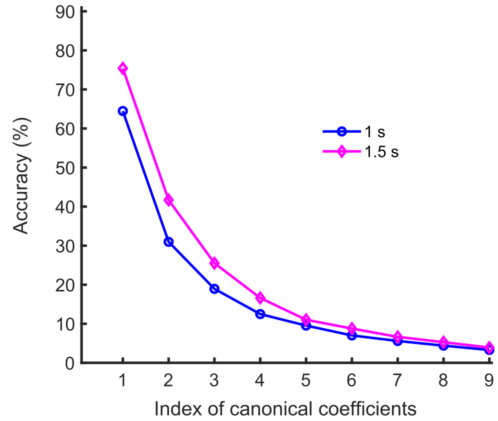

FIGURE 2. **The averaged classification accuracy of each canonical coefficient across subjects. The index numbers 1 and 9 correspond to the largest and smallest canonical coefficients, respectively.**

III. RESULTS

First, we investigated the classification performance of each canonical coefficient for standard CCA method as shown in Fig.2. We provide the averaged classification accuracy of each canonical coefficient across subjects at 1 s and 1.5 s time windows. We could find that almost all the coefficients could provide discriminative information to yield classification accuracy above chance level (1/40), and larger coefficients yield better performance. Therefore, during fusing these coefficients, larger ones should give larger weights. According to the style of the curve in Fig.2, we adopted formula (4) to calculate the weights for all the coefficients. Here, a and b were empirically set to 1.25 and 0, respectively. We believe that optimization of these two parameters may provide better results, but these settings have achieved the goal of current study. The curve of weights for FoCCA is depicted in Fig.3

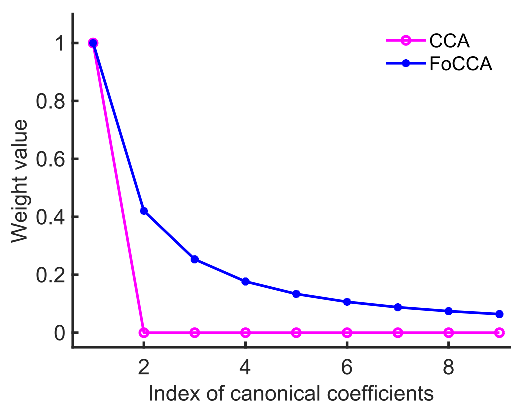

FIGURE 3. **The weights of CCA and FoCCA. The index numbers 1 and 9 correspond to the largest and smallest canonical coefficients, respectively.**

Fig.4 shows the averaged accuracies and simulated ITRs across all the subjects at various time windows, respectively. The number of training blocks and the number of electrodes were 5 and 9, respectively. The FoCCA yielded significantly better performance when combining all the coefficients at all time windows (paired t-tests, $p < 0.05$). The classification

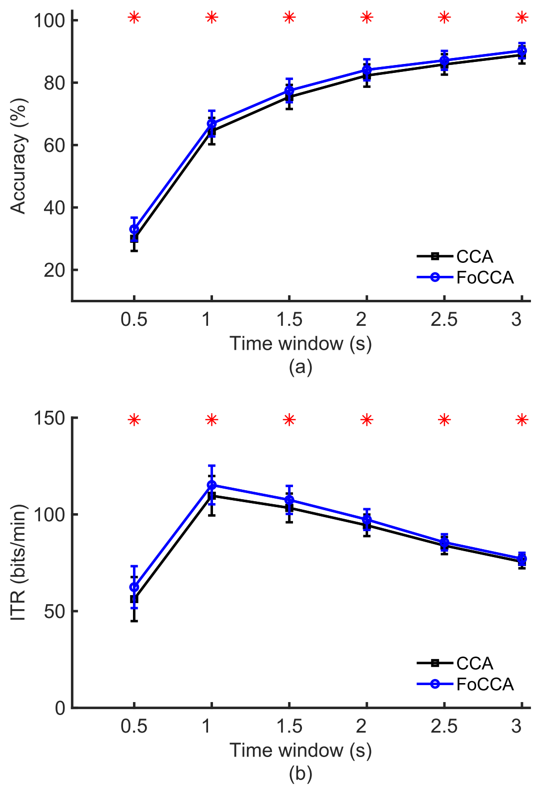

FIGURE 4. **Averaged results across subjects of the two methods using different time windows. (a) classification accuracy and (b) simulated ITRs. Error bars indicate standard errors. The asterisk indicates the statistically significant differences (paired *t*-test, $p < 0{:}05$).**

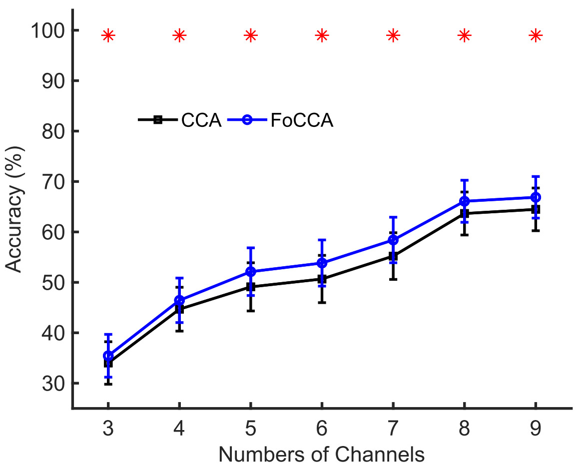

FIGURE 5. **Average accuracy across subjects for each method using different numbers of channels. Error bars indicate standard errors. Here, time window is 1 s. The asterisk indicates the statistically significant differences (paired *t*-test, $p < 0.05$).**

accuracy and the ITRs show consistent tendency. Furthermore, we investigated the influence of numbers of channels on these two methods. In Fig.5, we could find that the averaged classification accuracies of both methods at 1 s time window increase as the number of channels increased, and the FoCCA yield higher accuracy than CCA. Overall, the experimental results verify the effectiveness of the FoCCA in which the fusion strategy is used.

IV. DISCUSSION

CCA is a multivariate statistical method, and it has become a state-of-art method for frequency recognition in SSVEP-based BCI. To date, various sophisticated methods were proposed based on standard CCA [19], [23]. During measuring the correlation between two multidimensional variables, CCA could provide multiple canonical coefficients. Due to the simplicity and effectiveness, the classification features usually are designed based on the largest coefficients for SSVEP frequency recognition [29], [30]. Unfortunately, the remaining canonical coefficients are hardly exploited, which may discard the discriminative information. In Fig.2, we could find that most of the coefficients can provide discriminant information to classify SSVEP data above chance level.

EEG is nonstationary and nonlinear, and the scalp EEG often contains noise and artifact [31]. These factors can distort the components of interest and disperse some discriminative information across all or parts of the canonical coefficients when CCA is implemented on the EEG data [20]. Based on these considerations, it is beneficial to exploit all the coefficients for frequency recognition. In current study, we explore to combine all the correlation coefficients of CCA by a empirically-selected soft function in formula (4) to enhance the frequency recognition performance of the standard CCA based method. The performance evaluated by classification accuracy and ITR on the benchmark dataset demonstrate the proposed method with fusing strategy outperforms the standard CCA method, as shown in Fig.4 and 5. The proposed method could lead to better performance of SSVEP-based BCI. One limitation of current study is that only the offline experiment results were reported, the assessment of the method in an online SSVEP-based BCI system should be conducted in the future.

For fusing canonical coefficients, a straightforward idea may be that summarizing the squared canonical coefficients of CCA, then the formula (3) becomes as follows:

$$\bar{\eta} = \sum_{k=0}^{D} (\lambda_k)^2 \tag{6}$$

In order to evaluate the method with strategy in (6) (termed as sCCA), we conducted the classification on the benchmark dataset. The results of the three method, i.e., FoCCA, standard CCA and sCCA are presented in Fig.6. We can find that sCCA yield worse performance than standard CCA and FoCCA outperform other methods. Accordingly, combing the coefficients with the same weights might confuse the importance of different coefficients, and then result in less discriminative features. These results further verify the effectiveness of FoCCA. For standard CCA, it can be considered to be a special case of FoCCA method, in which all the coefficients are combined by a hard function that has sharp transition from 1 to 0, as depicted in Fig.3. This hard function only keeps the largest canonical coefficient.

Furthermore, the computational efficiency evaluated by the computational time was compared between FoCCA method

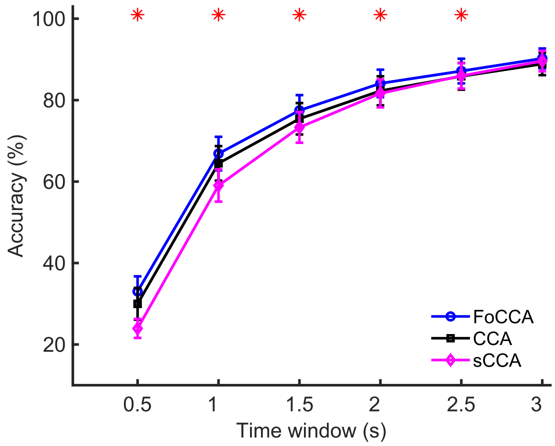

FIGURE 6. Performance comparison of three methods. Error bars indicate standard errors. The asterisk indicates the statistically significant differences between FoCCA and sCCA (paired t-test, $p < 0.01$).

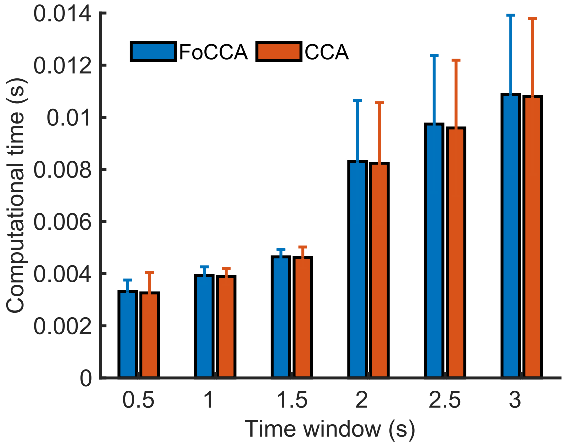

FIGURE 7. The average computational time taken for frequency recognition of one sample by FoCCA method and CCA method.

and CCA method. Here the computational time was that taken for frequency recognition of one sample. The experiments were conducted with MATLAB R2018b on a laptop computer with a 2.11 GH CPU (16 GB RAM) at six time windows. The results are presented in Fig.7. We can find that both methods can be implemented efficiently, and the differences of time spent by these two methods are very small.

In current study, the weighted function presented in formula (4) was chosen based on a previous study [22]. It can be replaced by other types of functions, such as exponential function, etc. Besides, the parameters in formula (4) were empirically specified, which can be optimized with extra training data. The optimization of the weighted function and parameters is worth further investigation in future study. Till now, various extended methods for frequency recognition based CCA have been proposed [19], [22], implementation of the proposed fusing strategy on these method will be an interesting direction in future study.

V. CONCLUSION

In current study, we proposed a fusion strategy that fuses all the canonical coefficients of CCA method to enhance its performance for frequency recognition. By the strategy, we can obtain more robust features for frequency recognition based on standard CCA method. The experimental results demonstrated that our method could yield better performance than standard CCA method. In future, fusing correlation coefficients might be a promising strategy to enhance the performance of other extended CCA methods, which can be used to implement high-performance SSVEP-based BCI systems.

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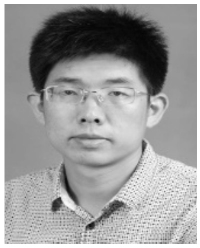

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