Common feature analysis for recognizing steady-state visual evoked potential in brain-computer interface

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Abstract

Canonical correlation analysis (CCA) has been successfully applied to steady-state visual evoked potential (SSVEP) recognition for brain-computer interface (BCI) application and outperforms the traditional power spectral density analysis through multichannel detection with resorting to the pre-constructed reference signals of sine-cosine waves. However, the CCA method is like to encounter overfitting in using a short time window length since the reference signals include no features from training data. We consider that a group of electroencephalogram (EEG) data trials recorded at a certain stimulus frequency on a same subject should share some common features that may bear the real SSVEP characteristics. This study therefore proposes a common feature analysis (CFA)-based method to exploit the latent common features as natural reference signals in using correlation analysis for SSVEP recognition. Effectiveness of the CFA method is validated with EEG data recorded from ten healthy subjects, in contrast to CCA and a multiway extension of CCA (MCCA). Experimental results indicate that the proposed CFA method significantly outperformed the CCA and the MCCA methods for SSVEP recognition in using a short time window length (i.e., less than 1 s). This superiority suggests that the CFA method is promising for the development of a high-speed SSVEP-based BCI.

Keywords: Brain-computer interface (BCI), Electroencephalogram (EEG),

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1. Introduction

As an advanced communication system, brain-computer interface (BCI) provides a direction connection between human brain and computer, thereby assisting to re-establish communicative and environmental control abilities for people with severe motor disabilities [1, 2, 3]. In the last couple of years, BCIs were mainly designed with steady-state visual evoked potential (SSVEP), event-related potential or sensorimotor rhythm recorded by electroencephalogram (EEG) [4, 5, 6, 7, 8, 9]. SSVEP-based BCI has been increasingly studied since it requires less training to the user and usually provides relatively higher information transfer rate (ITR) [10, 11].

SSVEP is a periodic brain activity elicited at the same frequency as flicker frequency and also at its harmonics over occipital scalp region, when subject focuses attention on a flickering stimulus [12, 13]. SSVEP-based BCI is developed to translate EEG signals recorded from the subject into computer commands through recognizing the SSVEP by typically using power spectral density analysis (PSDA) with fast Fourier transform (FFT) [13, 14, 15, 16]. However, the PSDA method is sensitive to noise with a single or bipolar channel and requires relatively long time window length (TW) to estimate the spectrum with sufficient frequency resolution. These drawbacks result in relatively low SSVEP recognition accuracy when the TW is not enough long (e.g., < 3 s) [17, 18]. Canonical correlation analysis (CCA), as a well-known multivariate statistical method, has been successfully applied to SSVEP recognition [19, 20]. The CCA method provides a multi-channel optimization for signal-to-noise ratio (SNR) improvement followed by the SSVEP recognition using the maximal correlation coefficient without need of spectrum estimation. Significantly higher recognition accuracy has been achieved by the CCA method over the PSDA method [19, 20]. Although the CCA method usually works well in SSVEP-based BCIs [20, 21] and other related BCIs [22, 23], it is likely to encounter overfitting within a short TW (e.g., < 1 s) since the adopted reference signals for correlation analysis are pre-constructed sine-cosine waves including no features from training data [24, 25]. More recently, a multiway extension of CCA, called MCCA [24], was introduced to SSVEP recognition with a sophisticated calibration for
reference signal refining. The MCCA method implemented collaborative correlation maximization between the multiple dimensions of EEG tensor data and the pre-constructed sine-cosine waves to learn more effective reference signals. With the optimized reference signals, the MCCA method has shown better performance for SSVEP recognition than that of the CCA method [24]. However, model parameters of the MCCA method for reference signal refining were learned by still resorting to the pre-constructed sine-cosine waves but not completely based on training data.

In this study, we consider that a group of EEG data trials recorded at a certain stimulus frequency on a same subject should be naturally linked and share some common features. Such common features hidden in the EEG data may bear the real SSVEP characteristics, which could therefore be more effective reference signals for SSVEP recognition in using correlation analysis. Presently, Zhou et al. [26] has suggested that common feature extraction helped significantly improve the classification performance of images through a processing of multi-block data. Inspired by this suggestion, we introduce a common feature analysis (CFA)-based method to exploit the latent common features shared by a group of EEG data trials as the refined reference signals for SSVEP recognition in BCI application. EEG data recorded from ten healthy subjects are used to validate effectiveness of the CFA method in comparison with the CCA and the MCCA methods. Experimental results demonstrate that the proposed CFA method yields higher SSVEP recognition accuracy than those of the CCA and the MCCA methods, especially when using a short TW.

2. Methodology

2.1. Canonical correlation analysis (CCA)

CCA is a multivariate statistical method, first introduced by Hotelling et al. [27] to reveal the underlying correlation between two sets of data. Given two sets of random variables $X \in \mathbb{R}^{I \times J}$ and $Y \in \mathbb{R}^{I' \times J}$, CCA tries to find a pair of linear transforms $w \in \mathbb{R}^{I}$ and $v \in \mathbb{R}^{I'}$ to maximize the correlation between linear combinations $\tilde{x} = w^T X$ and $\tilde{y} = v^T X$ through solving the
following optimization problem

$$\max_{\mathbf{w}, \mathbf{v}} \rho = \frac{E[\mathbf{x}^T\mathbf{y}]}{\sqrt{E[\mathbf{x}^T\mathbf{x}]E[\mathbf{y}^T\mathbf{y}]}}$$

\[= \frac{\mathbf{w}^T\mathbf{V}_{xy} \mathbf{v}}{\sqrt{\mathbf{w}^T \mathbf{V}_{xx} \mathbf{w} \mathbf{v}^T \mathbf{V}_{yy} \mathbf{v}}}, \tag{1}\]

where $\mathbf{V}_{xx} = \mathbf{X}^T \mathbf{X}$ and $\mathbf{V}_{yy} = \mathbf{Y}^T \mathbf{Y}$ are the within-set covariance matrices and $\mathbf{V}_{xy} = \mathbf{X}^T \mathbf{Y}$ is the between-set covariance matrix. The maximization in (1) can be achieved by solving a generalized eigenvalue problem [28].

A CCA-based method was first applied to the SSVEP recognition for BCI application by Lin et al. [19]. Assume our task is to recognize the SSVEP from $M$ candidate stimulus frequencies. Consider a EEG data matrix $\mathbf{X} \in \mathbb{R}^{S \times P}$ ($S$ channels $\times$ $P$ points) and a pre-constructed reference signal set $\mathbf{Y}_m \in \mathbb{R}^{2H \times P}$ at the $m$-th stimulus frequency $f_m$ ($m = 1, 2, \ldots, M$) with sine-cosine waves, where $H$ denotes the number of harmonics. The maximal correlation coefficients $\rho_m$ are solved by CCAs between $\mathbf{X}$ and $\mathbf{Y}_m$ ($m = 1, 2, \ldots, M$), and are used as the classification scores for SSVEP recognition. The SSVEP frequency is then recognized as

$$f_t = \max_{f_m} f_m, \quad m = 1, 2, \ldots, M. \tag{2}$$

The CCA method has shown better SSVEP recognition performance than that of the PSDA method since it effectively enhanced the SNR through a multi-channel optimization [19, 20].

2.2. Multiway CCA

Despite efficiency of the CCA method, a potential problem is that the direct use of pre-constructed sine-cosine waves as the reference signals for SSVEP recognition may not result in the optimal accuracy, due to their lack of features from training data. Recently, Zhang et al. [24] proposed one method of multiway canonical correlation analysis (MCCA) to optimize the reference signals for SSVEP recognition. The MCCA method implements the reference signal optimization through collaboratively maximizing correlation between the multiple dimensions of a EEG tensor data and the pre-constructed sine-cosine waves. Consider a three-way tensor $\mathcal{X} = (\mathcal{X})_{i_1, i_2, i_3} \in \mathbb{R}^{S \times P \times N}$ ($S$ channels $\times$ $P$ points $\times$ $N$ trials) constructed by the multi-channel EEG signals from $N$ experimental training trials at a
certain stimulus frequency, and an original reference signals $\mathbf{Y} \in \mathbb{R}^{2H \times P}$ constructed by the sine-cosine waves. We then denote $\mathcal{X} \times_k \mathbf{w}^T$ by the $k$-th way projection of the tensor with a vector and define the following formulation

$$
\begin{align*}
(\mathcal{X} \times_1 \mathbf{w}^T)_{i_2,i_3} &= \sum_{i_1=1}^S x_{i_1,i_2,i_3} w_{i_1} \quad \text{for } k = 1, \\
(\mathcal{X} \times_3 \mathbf{w}^T)_{i_1,i_2} &= \sum_{i_3=1}^N x_{i_1,i_2,i_3} w_{i_3} \quad \text{for } k = 3.
\end{align*}
$$

The MCCA method aims to find three linear transforms $\mathbf{w}_1 \in \mathbb{R}^S$, $\mathbf{w}_3 \in \mathbb{R}^N$ and $\mathbf{v} \in \mathbb{R}^{2H}$ to maximize the correlation between linear combinations $\tilde{x} = \mathcal{X} \times_1 \mathbf{w}_1^T \times_3 \mathbf{w}_3^T$ and $\tilde{y} = \mathbf{v}^T \mathbf{Y}$ as

$$
\max_{\mathbf{w}_1, \mathbf{w}_3, \mathbf{v}} \frac{E[\tilde{x} \tilde{y}^T]}{\sqrt{E[\tilde{x} \tilde{x}^T] E[\tilde{y} \tilde{y}^T]}}.
$$

This maximization problem can be solved by an alternating iteration algorithm based on the ordinary CCA [24]. After deriving the optimal linear transforms $\tilde{\mathbf{w}}_1$ and $\tilde{\mathbf{w}}_3$, we estimate the optimized reference signal as $\mathbf{z} = \mathcal{X} \times_1 \tilde{\mathbf{w}}_1^T \times_3 \tilde{\mathbf{w}}_3^T$.

Instead of pre-constructed sine-cosine waves, the optimized reference signals $\mathbf{z}_m$ at the stimulus frequencies $f_m$ ($m = 1, 2, \ldots, M$) are used to compute the maximal correlation coefficients $\rho_m$ corresponding to a new test trial through (1). These maximal correlation coefficients are used as the classification scores for SSVEP recognition and the SSVEP frequency is then recognized according to (2). The MCCA method has been suggested to outperform the CCA method for SSVEP recognition [24].

2.3. Common Feature Analysis (CFA)

It is worth noting that the model parameters of the MCCA method for reference signal refining are learned by still resorting to the pre-constructed sine-cosine waves but not completely based on training data. We expect that the SSVEP recognition accuracy could be further improved through a more sophisticated algorithm that learns the optimal reference signals for SSVEP recognition without need of any artificial template signal. This study considers that a group of EEG data trials recorded at a certain stimulus frequency $f_m$ on a same subject should be naturally linked and share some common features. These common features hidden in the EEG data may reflect more
accurately the real SSVEP characteristics at stimulus frequency $f_m$, and hence could be more effective reference signals for SSVEP recognition in using correlation analysis. Recently, a concept of common feature extraction has been suggested by Zhou et al. [26] to help enhance image classification performance. Inspired by this concept, we propose a common feature analysis (CFA)-based method to exploit the latent common features from a group of EEG data trials as natural reference signals for SSVEP recognition, and hence to improve the BCI performance.

Given multiple groups of EEG data matrices $X_k \in \mathbb{R}^{D \times L_k}$ ($k = 1, 2, \ldots, K$) recorded at the same stimulus frequency, where $L_k$ is the number of trials (samples) in $k$-th group, $D$ is the dimensionality of each trial ($D = S$ channels $\times P$ points), and $K$ is the number of groups, consider the matrix factorization problem of each group

$$
\min_{A_k, B_k} \|X_k - A_k B_k^T\|_F^2, \quad k = 1, 2, \ldots, K,
$$

where the columns of $A_k \in \mathbb{R}^{D \times R_k}$ consists of $R_k$ ($R_k < D$) latent variables (i.e., sources) from $X_k$, $B_k \in \mathbb{R}^{L_k \times R_k}$ denotes the corresponding coefficient matrix (i.e., loading). The CFA method assumes that multi-group data $X_k$ ($k = 1, 2, \ldots, K$) are naturally linked to each other and share some common sources (i.e., common features) such that

$$
A_k = [\tilde{A} \quad \tilde{A}_k], \quad k = 1, 2, \ldots, K,
$$

where $\tilde{A} \in \mathbb{R}^{I \times C}$ consists of $C$ shared common features, $\tilde{A}_k \in \mathbb{R}^{I \times (R_k - C)}$ contains the individual information in $X_k$, and $C \leq \min(R_1, R_2, \ldots, R_K)$. Based on this assumption, instead of individual factorization formulated in (5), the data matrices $X_k$ ($k = 1, 2, \ldots, K$) are re-factorized in a linked way

$$
X_k \approx A_k B_k^T = [\tilde{A} \quad \tilde{A}_k] \begin{bmatrix}
\tilde{B}_k^T \\
\tilde{B}_k^T
\end{bmatrix} = \tilde{A} \tilde{B}_k^T + \tilde{A}_k \tilde{B}_k^T, \quad k = 1, 2, \ldots, K,
$$

where $\tilde{B}_k$ and $\tilde{B}_k$ consist of the coefficients corresponding to $\tilde{A}$ and $\tilde{A}_k$, respectively. Hence, the common features $\tilde{A}$ can be extracted by implementing
simultaneous matrix factorization of all the data matrices as

$$\min_{\mathbf{A}} \sum_{k=1}^{K} \| \mathbf{X}_k - \mathbf{A}\mathbf{B}_k^T - \mathbf{A}_k\mathbf{B}_k^T \|_F^2$$

s.t. \( \mathbf{A}^T\mathbf{A} = \mathbf{I}_C \), \( \mathbf{A}_k^T\mathbf{A}_k = \mathbf{I}_{R_k-C} \),

\( \mathbf{A}^T\mathbf{A}_k = 0 \), \( k = 1, 2, \ldots, K \). \hspace{1cm} (8)

The optimal solution of (8) satisfies that

$$\mathbf{A}_k = \mathbf{X}_k\mathbf{B}_k^\dagger$$

where \( \mathbf{A}_k = [\mathbf{A} \hspace{0.5cm} \mathbf{A}_k] \), \( \mathbf{B}_k = [\mathbf{B}_k \hspace{0.5cm} \mathbf{B}_k] \), and \( \dagger \) denotes the Moore-Penrose pseudo inverse. We decompose each \( \mathbf{X}_k \) by QR decomposition as \( \mathbf{X}_k = \mathbf{Q}_k\mathbf{R}_k \), where \( \mathbf{Q}_k^T\mathbf{Q}_k = \mathbf{I} \), and define \( \mathbf{Z}_k = \mathbf{Q}_k\mathbf{R}_k \), \( (k = 1, 2, \ldots, K) \). Thus, for any \( k_1, k_2 \in \{1, 2, \ldots, K\} \), \( k_1 \neq k_2 \), we have

$$\begin{cases} \mathbf{Q}_{k_1}\mathbf{z}_{k_1,r} = \mathbf{Q}_{k_2}\mathbf{z}_{k_2,r} = \mathbf{a}_r \quad \text{if} \quad r \leq C, \\ \mathbf{Q}_{k_1}\mathbf{z}_{k_1,r} \neq \mathbf{Q}_{k_2}\mathbf{z}_{k_2,r} \quad \text{if} \quad r > C, \end{cases} \hspace{1cm} (10)$$

where \( \mathbf{z}_{k,r} \) and \( \mathbf{a}_r \) denote the \( r \)-th column of \( \mathbf{Z}_k \) and \( \mathbf{A} \), respectively. According to (10), the optimization problem formulated in (8) can be transformed into

$$\min_{\mathbf{A}} \sum_{k=1}^{K} \| \mathbf{Q}_k\mathbf{Z}_k - \mathbf{A}\|_F^2 \quad \text{s.t.} \quad \mathbf{A}^T\mathbf{A} = \mathbf{I}.$$ \hspace{1cm} (11)

An alternating least-square (ALS) iteration can be used to solve (11). First, fix \( \mathbf{Z}_k \) \( (k = 1, 2, \ldots, K) \) and transform (11) into the following formulation

$$\max_{\mathbf{A}} \text{tr}(\mathbf{P}^T\mathbf{A}) \quad \text{s.t.} \quad \mathbf{A}^T\mathbf{A} = \mathbf{I},$$ \hspace{1cm} (12)

where \( \text{tr}(\cdot) \) denotes the trace of matrix and \( \mathbf{P} = \sum_{k=1}^{K} \mathbf{Q}_k\mathbf{Z}_k \). Through the truncated singular value decomposition (SVD) on \( \mathbf{P} \): \( \mathbf{P} = \mathbf{E}\mathbf{A}\mathbf{V}^T \), where \( \mathbf{A} \in \mathbb{R}^{C \times C} \) is a diagonal matrix consisting of the largest \( c \) singular values, \( \mathbf{A} \) is then solved by

$$\mathbf{A} = \mathbf{E}\mathbf{V}^T.$$ \hspace{1cm} (13)

Then, fix \( \mathbf{A} \) and compute \( \mathbf{Z}_k \) by

$$\mathbf{Z}_k = \mathbf{Q}_k^T\mathbf{A}, \quad k = 1, 2, \ldots, K.$$ \hspace{1cm} (14)
Figure 1: Illustration of the CFA-based SSVEP recognition model. Assume $X_1, X_2, \ldots, X_M$ denote the EEG data trials recorded at the $M$ stimulus frequencies, respectively. Each of them is first split into $K$ groups of EEG data matrices $X_{1,m}, X_{2,m}, \ldots, X_{K,m}$ ($m = 1, 2, \ldots, M$). The CFA method is then implemented on the each $K$ groups of EEG data matrices to extract the common features $A_m$ ($m = 1, 2, \ldots, M$). The correlation between a new test trial $\hat{x}$ and each of the common features is computed by $\rho_m = \|\hat{x}^T A_m\|_2$. The SSVEP frequency is then recognized according to the maximal correlation.

The common features $\bar{A}$ shared by $X_k$ ($k = 1, 2, \ldots, K$) can be extracted through repeating the aforementioned alternating procedure.

Assume $M$ EEG data matrices $X_1, X_2, \ldots, X_M \in \mathbb{R}^{D \times N}$ are recorded from $N$ trials at the $M$ stimulus frequencies, respectively. We first split the data matrix $X_m$ into $K$ groups of matrices $X_{1,m}, X_{2,m}, \ldots, X_{K,m} \in \mathbb{R}^{D \times L_k}$ and extract $C$ common features $A_m \in \mathbb{R}^{D \times C}$ at the $m$-th stimulus frequency $f_m$ by the CFA method for $m = 1, 2, \ldots, M$. The correlation between a new test trial $\hat{x} \in \mathbb{R}^D$ and each of the common features is computed by $\rho_m = \|\hat{x}^T A_m\|_2$ ($m = 1, 2, \ldots, M$) and used as the classification score for SSVEP recognition. The SSVEP frequency is then recognized by using (2) again. Fig. 1 illustrates the CFA-based SSVEP recognition model.
3. Experimental Study

3.1. EEG Recordings

Ten healthy subjects (S1-S10, aged from 21 to 27 years, all males) were recruited for our experiment. All subjects had normal or corrected-to-normal vision. In the experiment, the subjects were seated in a comfortable chair 60 cm from a standard 17 inch CRT monitor (85 Hz refresh rate, 1024 × 768 screen resolution) in a shielded room. Four red squares were presented on the screen as stimuli (see Fig. 2 (a)). Each subject completed 20 runs with 5 to 10 min break after the first 10 runs. In each run, each stimulus was cued as the target followed by flickering of the four stimuli at different four frequencies: 6 Hz, 8 Hz, 9 Hz and 10 Hz, respectively. Subjects were asked to focus attention on the target for 4 s after each cue. A total of 80 trials data (4 trials in each run corresponding to the four stimulus frequencies, respectively) were recorded from each subject.

EEG signals were recorded by using the Nuamps amplifier (NuAmp, Neuroscan, Inc.) at 250 Hz sampling rate with high-pass and low-pass filters of 0.1 and 70 Hz, from 30 channels placed on the standard positions according to the 10-20 international system (see Fig. 2 (b)). All channels were referenced to the average of two mastoid electrodes (A1 and A2) and grounded to the electrode GND placed on the forehead. The EEG signals were band-pass filtered from 4 Hz to 45 Hz before further analysis by using a sixth-order forward-backward Butterworth bandpass filter.
Figure 3: Variation of SSVEP recognition accuracy for different pairs of integer parameters \( K \) and \( C \) \((C \leq 19/K)\) with time window lengths (TWs) from 1 s to 4 s, respectively. The pair giving the highest accuracy is marked by a white pentagram.

3.2. Experimental Evaluation

To validate effectiveness of the proposed CFA-based method for SSVEP recognition, it is compared to the CCA method [19] and the MCCA method [24]. In this study, only eight channels P7, P3, Pz, P4, P8, O1, Oz and O2 are used for analysis. The number of harmonics \( H \) is set to 2, which is required for the pre-construction of sine-cosine waves in the CCA and the MCCA methods. For both the CFA and the MCCA methods, the average recognition accuracy is evaluated by leave-one-out cross-validation. More specifically, we use the data from 19 runs to refine the reference signals while the data from the left-out run for validation, and repeat this procedure for 20 times such that each run serves once for validation. Average recognition accuracy of the CCA method is evaluated on the direct validation of 20 runs since it does not require training data for reference signal refining.

4. Results

Two integer parameters, i.e., the number of groups \( K \) splitted on the training data and the number of extracted common features \( C \), need to be pre-specified for the CFA method. Hence, we first investigate how effects of varying \( K \) and \( C \) on the SSVEP recognition accuracy. Fig. 3 presents the SSVEP recognition accuracies derived by using different pairs of \( K \) and \( C \) with TWs from 1 s to 4 s, respectively. For the different four TWs, the overall trend is that recognition accuracy increased with the increasing of \( K \).
Figure 4: SSVEP recognition accuracies of the ten subjects obtained by the CCA, the MCCA and the CFA methods, respectively, with time window lengths (TWs) from 0.5 s to 4 s (0.5 s interval). Parameter setting: $H = 2$ for the CCA and the MCCA methods; $K = 19$ and $C = 1$ for the CFA method.

and decreasing of $C$. The setting $K = 19$ and $C = 1$ resulted in the highest recognition accuracy for all of the four TWs, which was therefore adopted for further analysis of the CFA method.

Fig. 4 and Fig. 5 show the SSVEP recognition accuracy of each subject and the averaged accuracy of ten subjects derived by the CCA, MCCA and CFA methods, respectively, with TWs from 0.5 s to 4 s (0.5 s interval). For most subjects (except for S9), the CFA method outperformed the CCA and MCCA methods when the TW was less than 1 s. The CFA achieved higher average accuracy than those of the CCA and the MCCA methods at most TWs. Superiority of the CFA method was gradually enhanced with the reduction of TW. Statistical analysis was also implemented for the accuracy difference between each two of the CCA, MCCA and CFA methods by using the paired-sample t-test (see Table 1). The statistical analysis results show that the proposed CFA method performed significantly better than the CCA method over 0.5 s to 4 s TWs, and achieved significantly higher accuracy than that of the MCCA method when the TW was less than 1 s.
Figure 5: Averaged SSVEP recognition accuracy on the results of ten subjects shown in Fig. 4.

Table 1: Statistical analysis of accuracy difference between each two of the CCA, MCCA and CFA methods by using the paired-sample t-test.

<table>
<thead>
<tr>
<th>Method Comparison</th>
<th>Time window length (TW)</th>
<th>0.5 s</th>
<th>1 s</th>
<th>1.5 s</th>
<th>2 s</th>
<th>2.5 s</th>
<th>3 s</th>
<th>3.5 s</th>
<th>4 s</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCCA vs. CCA</td>
<td>p&lt;0.05</td>
<td>p&lt;0.005</td>
<td>p&lt;0.05</td>
<td>p=0.051</td>
<td>p&lt;0.01</td>
<td>p=0.066</td>
<td>p&lt;0.05</td>
<td>p&lt;0.05</td>
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</tr>
<tr>
<td>CFA vs. CCA</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.001</td>
<td>p&lt;0.0005</td>
<td>p&lt;0.0005</td>
<td>p&lt;0.005</td>
<td>p&lt;0.01</td>
<td>p&lt;0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CFA vs. MCCA</td>
<td>p&lt;0.0005</td>
<td>p&lt;0.05</td>
<td>p=0.10</td>
<td>p=0.38</td>
<td>p=0.70</td>
<td>p=0.93</td>
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</table>

5. Discussion and Conclusions

The CCA method [19] implemented SSVEP recognition by directly using the pre-constructed sine-cosine waves as reference signals without any information from training data. The MCCA method [24] was to refine the reference signals for SSVEP recognition by still resorting to the pre-constructed sine-cosine waves but not completely based on training data. This study introduced a common feature analysis (CFA)-based method to learn the natural reference signals for SSVEP recognition by exploiting the latent common features from a group of EEG data trials without resorting to the pre-constructed sine-cosine waves. The refined reference signals resulted in more discriminative information on the test data, especially within a short TW. Fig. 6 presents the classification scores corresponding to different reference
signal frequencies (6, 8, 9 and 10 Hz) derived from the leave-one-out cross-validation of S1 and S10 with time window length of 1 s by the CCA, the MCCA and the CFA method, respectively, when each of the four frequencies was used as the target frequency $f_t$.

Computational time of the CFA method for reference signal refining was also compared to that of the MCCA method to validate its computational efficiency (see Fig. 7). The computation environment was under Matlab R2009a on a laptop with 1.20 GHz CPU (3 GB RAM). With a TW of 0.5 s, the CFA method achieved higher computational efficiency than the MCCA method. Slower convergence of the MCCA method might be caused by the insufficient data length. With a TW of 1 s, the CFA method achieved a comparable computational efficiency with the MCCA method. The computational efficiency of CFA method gradually decreased with the increasing of TW. However, the computational time of both the CFA and the MCCA
methods was very short compared to the time spent on the training data recording, and hence could be ignored.

In addition to the CCA method, a multivariate synchronization index (MSI) method [29] and a minimum energy combination (MEC) method [30] have recently been introduced to SSVEP recognition also through resorting to the pre-constructed sine-cosine waves. Hence, the reference signals refined by the CFA method could also be used instead of sine-cosine waves in the MSI and the MEC methods to improve their performance, which is worthy of further study.

In summary, experimental results based on the EEG data from ten healthy subjects demonstrated that the proposed CFA method significantly improved the SSVEP recognition accuracy within a short TW (i.e., less than 1 s) in comparison with the CCA and the MCCA methods. Such superiority suggests that the CFA method is promising for development of a high-speed SSVEP-based BCI.

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