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Discriminative Feature Extraction via Multivariate Linear Regression for SSVEP-based BCI

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***Abstract*—Many of the most widely accepted methods for reliable detection of steady-state visual evoked potentials (SSVEPs) in the electroencephalogram (EEG) utilize canonical correlation analysis (CCA). CCA uses pure sine and cosine reference templates with frequencies corresponding to the visual stimulation frequencies. These generic reference templates may not optimally reflect the natural SSVEP features obscured by the background EEG. This paper introduces a new approach that utilizes spatio-temporal feature extraction with multivariate linear regression (MLR) to learn discriminative SSVEP features for improving the detection accuracy. MLR is implemented on dimensionality-reduced EEG training data and a constructed label matrix to find optimally discriminative subspaces. Experimental results show that the proposed MLR method significantly outperforms CCA as well as several other competing methods for SSVEP detection, especially for time windows shorter than 1 second. This demonstrates that the MLR method is a promising new approach for achieving improved real-time performance of SSVEP-BCIs.**

***Index Terms*—Brain-Computer Interface (BCI), Canonical Correlation Analysis (CCA), Electroencephalogram (EEG), Steady-State Visual Evoked Potential (SSVEP), Multivariate Linear Regression (MLR).**

I. Introduction

A Brain-computer interface (BCI) is a system that allows a direct connection between a human brain and a computer [1], [2], [3]. Many BCI systems are aimed to help individuals suffering from severe neuromuscular disorders, such as amyotrophic lateral sclerosis (ALS), to establish an augmentative communication channel between the brain and the outside world [4], [5]. In recent years, several different BCI modalities have been developed that utilize various brain responses including sensorimotor rhythms, event-related potentials, and visual-evoked potentials [6], [7], [8], [9], [10], [11]. Due to the comparatively favorable information transfer rates (ITR) and lower training requirements, SSVEP-based BCIs have attracted widespread attention [12], [13], [14], [15], [16].

An SSVEP is a periodic brain response evoked in the occipital and occipito-parietal areas of the brain by a visual stimulus flashing at a fixed frequency [17]. SSVEP responses normally include the fundamental frequency of the visual stimulus as well as its harmonics (see an example in Fig. 1). Accordingly, SSVEP-based BCIs convey the desired commands by using algorithms that detect different frequency components corresponding to the visual stimuli.

In the past decade, numerous methods have been proposed for EEG pattern recognition [18], [19], [20], [21], [22], [23], [24], [25]. A typical approach for SSVEP target detection is power spectral density analysis (PSDA) [26]. Through a fast Fourier transform (FFT), the frequency with the maximal PSD value is detected as the target frequency. However, PSDA approaches are highly sensitive to background noise when using a single channel, and require comparatively longer time windows to estimate the spectrum with sufficient frequency resolution [27], [28]. These drawbacks lead to relatively low SSVEP recognition accuracy for shorter time windows, which result in suboptimal information transfer rates (ITR) and limit the real-time performance of the BCI system.

To improve SSVEP recognition performance, Friman et al. [28] introduced a minimum energy combination (MEC) method while Lin et al. [27] proposed a canonical correlation analysis (CCA)-based method. Both methods used sine-cosine reference templates to achieve multi-channel optimization via spatial filters. This strategy has been shown to increase the signal-to-noise ratio of the extracted features resulting in improved SSVEP recognition performance. The CCA method has been demonstrated to give better performance in comparison with PSDA and MEC. However, sine-cosine reference templates are not able to fully reflect the discriminative information embedded within SSVEP brain responses, thus may result in suboptimal detection accuracies [29].

Several methods have been recently proposed based on the extension of CCA [30], [31], [32], [33], [34], [35], [36], [37]. Pan et al. proposed a phase-constrained CCA (PCCA) method by embedding the phase information estimated from training data into the reference signals [30]. Zhang et al. introduced a multiway extension of CCA (MCCA) to construct more effective reference signals by maximizing the correlation between the multiple dimensions of EEG tensor data and sine-

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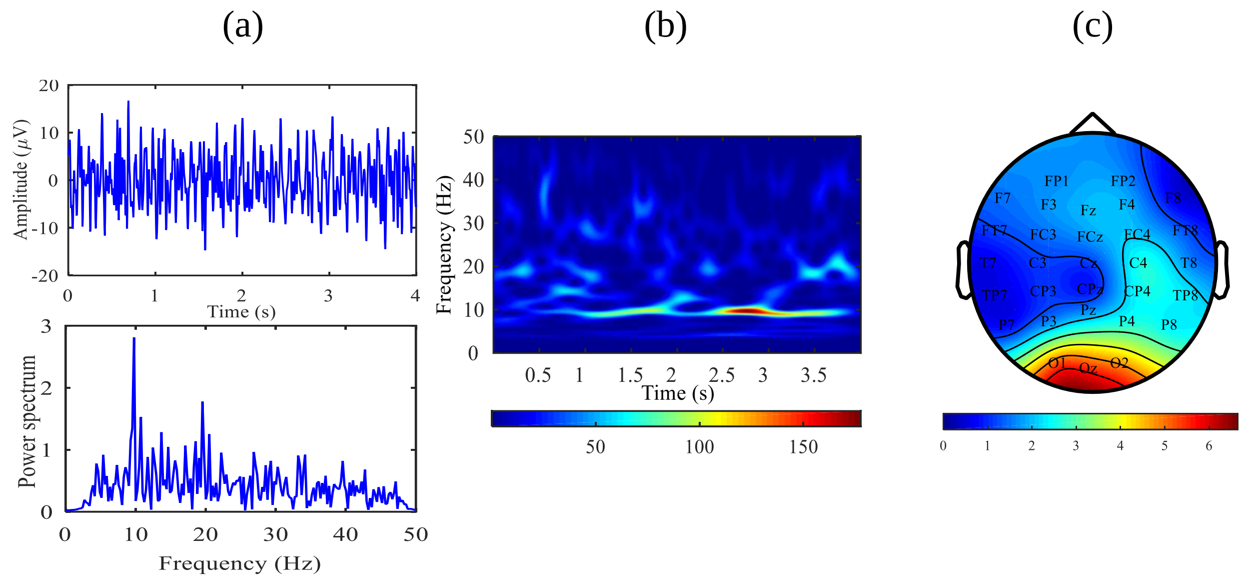

Fig. 1. SSVEP characteristics under stimulus frequency of 10 Hz: (a) Waveform and power spectrum of EEG signal at channel Oz; (b) Time-frequency information derived by Morlet wavelet transform from channel Oz; (c) Scalp topography of power spectrum summed at 10 Hz and its second and third harmonics.

cosine signals [31]. MCCA and its L1-regularized extension (L1MCCA) [29] have been confirmed to provide improved SSVEP detection performance compared to CCA. A common and individual feature analysis (CIFA)-based method was proposed to learn the common SSVEP features, which also outperformed CCA, especially for shorter time windows [33].

One drawback of the CCA algorithm and its extensions is that they only consider a fixed set of ideal frequency templates. This potentially leads to the problem of only representing the within-class information while neglecting any between-class information. As a result, the optimal class discriminability may not be achieved. The present study proposes to exploit the within-class and between-class information via a multivariate linear regression (MLR)-based method to extract more discriminative features of SSVEP.

For the proposed approach, the training data are parsed by stimulus frequency and specifically labeled. The observations are concatenated by channel and principal component analysis (PCA) is used for dimensionality reduction. MLR is implemented on the reduced feature space and the corresponding label matrix to extract the discriminative features, which are classified using a k-nearest-neighbour (k-NN) classifier. Experimental results show superior performance of the proposed MLR-based method compared to several competing methods, including CCA, MCCA, and CIFA.

II. Methodology

A. SSVEP recognition based on CCA

Canonical correlation analysis (CCA) is a multivariable statistical method that aims to reveal the underlying correlation between two sets of data [38], [39], [40] and was first introduced to SSVEP recognition by Lin et al. (2007) [27]. Consider an EEG signal $\mathbf{X} \in \mathbb{R}^{C\times P}$ and a constructed reference signal $\mathbf{Y} \in \mathbb{R}^{2H\times P}$ comprised of sine-cosine waves at a certain stimulus frequency. C denotes the number of channels, P represents the number of temporal samples, and H is the number of included harmonics ($H = 2$ for this study). CCA seeks two vectors $\mathbf{w} \in \mathbb{R}^{C}$ and $\mathbf{v} \in \mathbb{R}^{2H}$ to maximize the linear correlation between the two projections $\mathbf{w}^T\mathbf{X}$ and $\mathbf{v}^T\mathbf{Y}$, through solving the following optimization problem:

$$\max \rho = \max_{\mathbf{w},\mathbf{v}} \frac{\mathbf{w}^T\mathbf{X}\mathbf{Y}^T\mathbf{v}}{\sqrt{\mathbf{w}^T\mathbf{X}\mathbf{X}^T\mathbf{w}\mathbf{v}^T\mathbf{Y}\mathbf{Y}^T\mathbf{v}}}. \quad (1)$$

The maximization of this objective function is solved using generalized eigenvalue decomposition [39]. Assuming there are M candidate stimulus frequencies, CCA computes the maximal correlation coefficients ρ_m between $\mathbf{X}$ and $\mathbf{Y}_m (m = 1, 2, ..., M)$. Subsequently, the SSVEP target frequency f_t is recognized as:

$$f_t = \max_{m} \rho_m,\ m = 1, 2, \ldots, M. \quad (2)$$

B. SSVEP recognition based on MCCA

The generic sine-cosine reference templates used in CCA may produce suboptimal performance as ideal sinusoid signals can fail to reflect the true nature of the SSVEP responses. Recently, multiway canonical correlation analysis (MCCA) [31] has been proposed to optimze the reference signals at each stimulus frequency by exploiting tensor analysis [41]. Through collaboratively maximizing correlation between the multiple dimensions of EEG tensor data and constructed sine-cosine templates, a new reference signal is achieved that contains sample features of the corresponding stimulus frequency.

Consider a three-way tensor $\mathcal{X} \in \mathbb{R}^{C\times P\times T}$ (channels $\times$ temporal points $\times$ trials) that contains multi-channel EEG signals from T training trials from a given stimulus frequency, and reference signal $\mathbf{Y} \in \mathbb{R}^{2H\times P}$ containing the original sine-cosine reference templates. MCCA aims to learn three projection vectors $\mathbf{w}_1 \in \mathbb{R}^{C}$,$\mathbf{w}_3 \in \mathbb{R}^{T}$ and $\mathbf{v}_1 \in \mathbb{R}^{2H}$ that maximize the correlation between $\tilde{\mathbf{x}} = \mathcal{X}\times_1\mathbf{w}_1^T\times_3\mathbf{w}_3^T$ and

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$\tilde{\mathbf{y}} = \mathbf{v}^T\mathbf{Y}$, where $\mathcal{X}\times_k \mathbf{w}^T$ is defined as the projection at k-th way of tensor data. The target function can be formalized as:

$$\max \rho = \max_{\mathbf{w}_1,\mathbf{w}_2,\mathbf{v}} \frac{E[\tilde{\mathbf{x}}\tilde{\mathbf{y}}^T]}{\sqrt{E[\tilde{\mathbf{x}}\tilde{\mathbf{x}}^T]E[\tilde{\mathbf{y}}\tilde{\mathbf{y}}^T]}}. \quad (3)$$

An alternating iteration algorithm based on CCA has been proposed to solve this optimization problem [31]. After the optimal projection vectors $\tilde{\mathbf{w}}_1, \tilde{\mathbf{w}}_3$ are solved, the learned reference signal is presented as: $\mathbf{z} = \mathcal{X}\times_1\tilde{\mathbf{w}}_1^T\times_3\tilde{\mathbf{w}}_3^T$. For each stimulus frequency $f_m(m = 1, 2, \ldots, M)$, the corresponding reference signal $\mathbf{z}_m$ is used for calculating the maximal correlation coefficients with test EEG data.

C. SSVEP recognition based on CIFA

Another alternative method for SSVEP feature mining is called common and individual feature analysis (CIFA) [42]. The CIFA method is based on the concept of multiset analysis [33] to extract the latent common components shared by multiple EEG segments at the same stimulus frequency. These hidden common components are considered to more accurately reflect the real SSVEP features. Contrary to the feature learning method performed by MCCA, CIFA extracts the SSVEP features completely from the training data without the need of sine-cosine references.

Consider a set of EEG data groups denoted as $\mathbf{X}_k \in \mathbb{R}^{D\times L_k}(k = 1, 2, ...K)$ where K is the number of groups recorded at the same stimulus frequency, L_k is the number of samples in the k-th group and D is the dimensionality of each sample. Assume $\mathbf{A}_k \in \mathbb{R}^{D\times L_k}$ contains $R_k(R_k < D)$ latent variables from $\mathbf{X}_k$ and $\mathbf{B}_k \in \mathbb{R}^{L_k\times R_k}$ denotes the corresponding coefficient matrix. $\mathbf{A}_k$, $\mathbf{B}_k$ can be decomposed into two submatrices: $\mathbf{A}_k = [\bar{\mathbf{A}}\ \tilde{\mathbf{A}}_k]$ and $\mathbf{B}_k = [\bar{\mathbf{B}}_k\ \tilde{\mathbf{B}}_k]$, respectively. Here $\bar{\mathbf{A}} \in \mathbb{R}^{D\times J}$ contains the J common features shared by the multiple groups of EEG segments and $\tilde{\mathbf{A}} \in \mathbb{R}^{D\times(R_k-J)}$ contains the $R_k - J$ individual features in $\mathbf{X}_k$. The matrices $\bar{\mathbf{B}}_k$ and $\tilde{\mathbf{B}}_k$ contain the coefficients corresponding to $\bar{\mathbf{A}}$ and $\tilde{\mathbf{A}}_k$, respectively. Hence, the CIFA method aims to solve the following matrix factorization problem:

$$\begin{aligned} \min_{\bar{A}} \ & \sum_{k=1}^{K} ||\mathbf{X}_k - \bar{\mathbf{A}}\bar{\mathbf{B}}_k^T - \tilde{\mathbf{A}}_k\tilde{\mathbf{B}}_k^T||_F^2 \\ s.t. \ & \bar{\mathbf{A}}^T\mathbf{A} = \mathbf{I}_J, \tilde{\mathbf{A}}_k^T\tilde{\mathbf{A}}_k = \mathbf{I}_{R_k-J}, \\ & \bar{\mathbf{A}}^T\tilde{\mathbf{A}}_k = 0, k = 1, 2, ..., K. \end{aligned} \quad (4)$$

Let the QR decomposition of $\mathbf{X}_k = \mathbf{Q}_k\mathbf{R}_k(k = 1, 2, ..., K)$, and define $\mathbf{Z}_k = \mathbf{R}_k\mathbf{B}_k^{\dagger}$. Then the optimization problem is transformed into:

$$\min_{\bar{\mathbf{A}}} \sum_{k=1}^{K} ||\mathbf{Q}_k\mathbf{Z}_k - \bar{\mathbf{A}}||_F^2 \quad s.t.\ \bar{\mathbf{A}}^T\bar{\mathbf{A}} = \mathbf{I}. \quad (5)$$

The solution of (5) is found by the algorithm called common orthogonal basis extraction [33]. $\bar{\mathbf{A}}$ denotes the extracted common SSVEP features of a particular stimulus. For M stimulus frequencies, the common features $\bar{\mathbf{A}}_m(m = 1, 2, ...M)$ at each frequency can be extracted. For a new test observation, $\hat{\mathbf{x}} \in \mathbb{R}^D$, the SSVEP frequency is recognized as:

$$f_t = \arg\max_{f_m} ||\hat{\mathbf{x}}^T\mathbf{A}_m||_2,\ (m= 1, 2, \ldots ,M). \quad (6)$$

In [42], each training sample is formed by the concatenation of temporal points from multiple channels. The training samples are then evenly divided into K groups preceded by implementing CIFA. Here CIFA is directly implemented on multiple multichannel EEG segments to extract the common features so that better recognition performance is achieved in comparison with the previous strategy.

D. SSVEP recognition based on MLR

MCCA and CIFA have been confirmed to achieve better SSVEP recognition accuracy than CCA. However, a potential problem is that both methods extract SSVEP features from each stimulus frequency individually. Although this allows them to effectively decrease the within-class dispersion, any between-class information is disregarded. As a result, the MCCA and CIFA methods may not be able to provide the optimal discriminant features for SSVEP recognition.

This study introduces a multivariate linear regression (MLR)-based strategy to extract more discriminative SSVEP features that further improve the recognition accuracy. A label matrix is constructed by specifically labeling the training data of each class using vectorized notation. After a dimensionality reduction step using PCA, MLR is implemented on the training data and the constructed label matrix to find the optimal discriminative subspace.

MLR is a well-studied technique for regression via minimizing the sum-of-squares cost function. It has recently been applied to estimate the time-frequency electrophysiological responses from single trial EEG [43]. MLR can also be used for classification by defining an appropriate class label matrix [44], [45], [46]. Consider EEG training data $\mathbf{X} = [\mathbf{x}_1, \ldots , \mathbf{x}_N] \in \mathbb{R}^{D\times N}$ where D denotes the feature dimensionality (D = C channels $\times$ P temporal points) and N is the number of training samples. The training samples are recorded at M distinct stimulus frequencies. It is worth noting that D is generally high compared to N in the context of BCI applications.

To avoid possible over-fitting, PCA is first implemented on $\mathbf{X}$ for dimensionality reduction. For this analysis the principal components accounting for 99% of the total variance were included. Assume $\tilde{\mathbf{X}} = [\tilde{\mathbf{x}}_1, \ldots , \tilde{\mathbf{x}}_N] \in \mathbb{R}^{S\times N}$ denotes the EEG data with reduced feature dimensionality $S < \min(D, N)$, and $\mathbf{x}^{(i)} \in \mathbb{R}^S$ is the i-th sample. A label matrix is constructed corresponding to the training samples in $\tilde{\mathbf{X}}$. There exist many encoding schemes for construction of the label matrix [45], [47], [48], the most popular of which, known as the one-of-M class coding, is adopted for the present approach. For a training sample $\tilde{\mathbf{x}}^{(i)}$ belonging to class m, its label is specified as:

$$\mathbf{y}^{(i)} = [y_1, y_2, \ldots , y_M]^T,\ y_j = \begin{cases} 1 & if \quad j = m \\ 0 & if \quad j \neq m. \end{cases} \quad (7)$$

A label matrix is then constructed by $\mathbf{Y} = [\mathbf{y}^{(1)}, \ldots , \mathbf{y}^{(N)}] \in \mathbb{R}^{M\times N}$. MLR aims to find discriminative subspaces by minimizing the sum of squared residuals as follows:

$$\min_{\mathbf{W},\mathbf{b}} \frac{1}{2}\sum_{i=1}^{N} ||\mathbf{y}^{(i)} - (\mathbf{W}^T\tilde{\mathbf{x}}^{(i)} + \mathbf{b})||_2^2, \quad (8)$$

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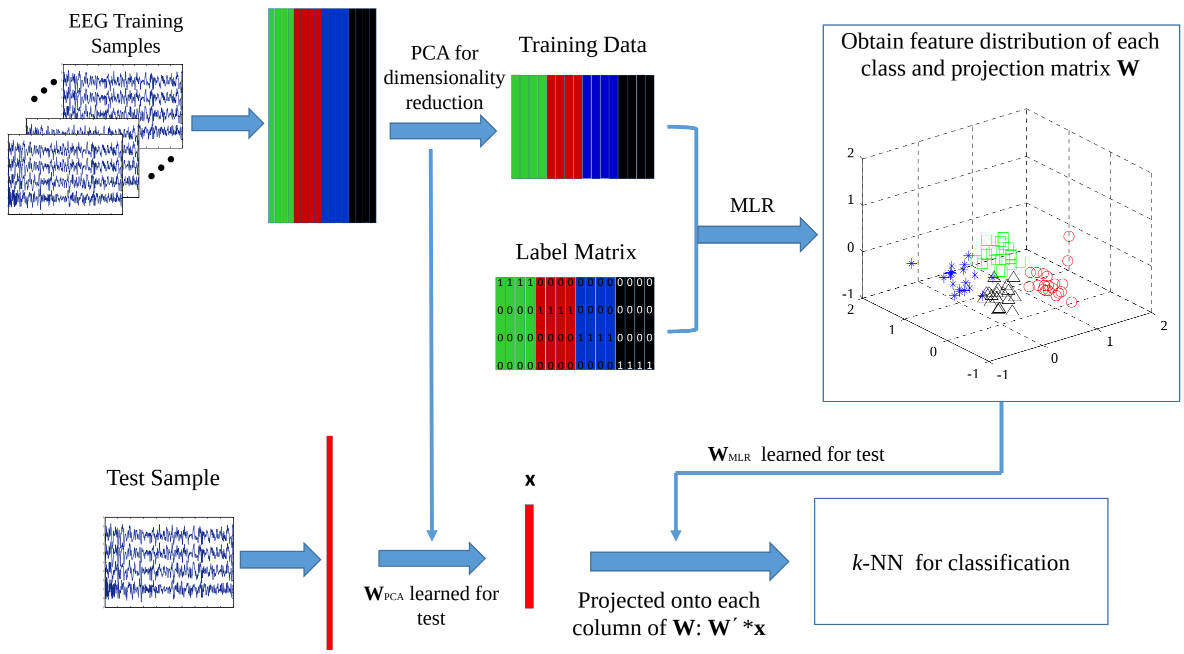

Fig. 2. Illustration of the MLR-based method for SSVEP recognition. Different colors in training data represent samples from different classes. For feature distribution visualization, three features were selected to represent a sample.

where $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_C] \in \mathbb{R}^{S \times C}$ denotes the projection matrix and $\mathbf{b}$ is the model intercept. Indeed, $\mathbf{b}$ can be deduced by computing the partial derivative of $\mathbf{b}$:

$$\mathbf{b} = \frac{1}{N} \sum_{i=1}^{N} (\mathbf{y}^{(i)} - \mathbf{W}^T \tilde{\mathbf{x}}^{(i)}). \quad (9)$$

For convenient computation, training data $\tilde{\mathbf{X}}$ and label matrix $\mathbf{Y}$ are centered so that $\mathbf{b}$ is equal to a zero vector. The MLR model is then simplified as:

$$\mathbf{W} = \arg\min_{\mathbf{W}} \frac{1}{2} \sum_{i=1}^{N} ||\mathbf{y}^{(i)} - \mathbf{W}^T \tilde{\mathbf{x}}^{(i)}||_2^2, \quad (10)$$

or in a more compact form:

$$\mathbf{W} = \arg\min_{\mathbf{W}} \frac{1}{2} ||\mathbf{Y} - \mathbf{W}^T \tilde{\mathbf{X}}||_F^2, \quad (11)$$

where $\|\cdot\|_F$ denotes the Frobenius norm. The optimal solution is then simply given by:

$$\mathbf{W} = (\tilde{\mathbf{X}} \tilde{\mathbf{X}}^T)^{\dagger} \tilde{\mathbf{X}} \mathbf{Y}^T, \quad (12)$$

where $(\cdot)^{\dagger}$ denotes the Moore-Penrose pseudo-inverse. After learning the projection matrix via MLR between training samples and multi-class label matrix, the training data are projected onto a lower-dimensional space expanded by columns of $\mathbf{W}$ which represent the features of training data. Hence, sample features $\mathbf{Z} \in \mathbb{R}^{M \times N}$ can be extracted as: $\mathbf{Z} = \mathbf{W}^T \tilde{\mathbf{X}}$, and $\mathbf{z}_i \in \mathbb{R}^M$ denotes features corresponding to EEG sample $\mathbf{x}_i$. For subsequent test data, the dimensionality is also first reduced by PCA, then projected to the space learned by MLR. As a final step, the k-nearest-neighbour (k-NN) algorithm is adopted to classify the sub-space features extracted by the MLR. Five nearest neighbors (k=5) was used for this analysis.

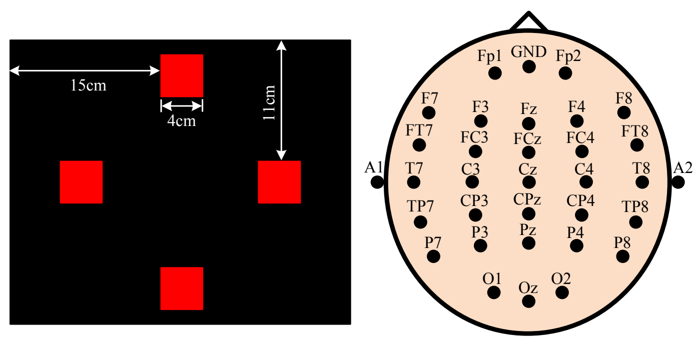

Fig. 3. Experimental layout and channel configuration for EEG recordings.

E. Data Collection

EEG data were acquired from ten healthy subjects (S1-S10, aged from 21 to 27 years all males). All subjects had normal or corrected-to-normal vision. During the experiment, 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. EEG data were recorded from 30 channels placed on the standard positions according to the 10-20 international system using a Nuamps amplifier (NuAmp, Neuroscan, Inc) with a 250 Hz sampling rate and high-pass and low-pass filters of 0.1 and 70 Hz, respectively. All channels were referenced to the average of two electrodes (A1, A2) and the ground electrode (GND) was placed on the forehead. Fig. 3 depicts the experimental stimulus layout and channel configuration for EEG recordings.

The SSVEP stimuli were composed of four red squares that simultaneously flickered at frequencies 6 Hz, 8 Hz, 9 Hz and 10 Hz, respectively. For each run, subjects were asked to focus

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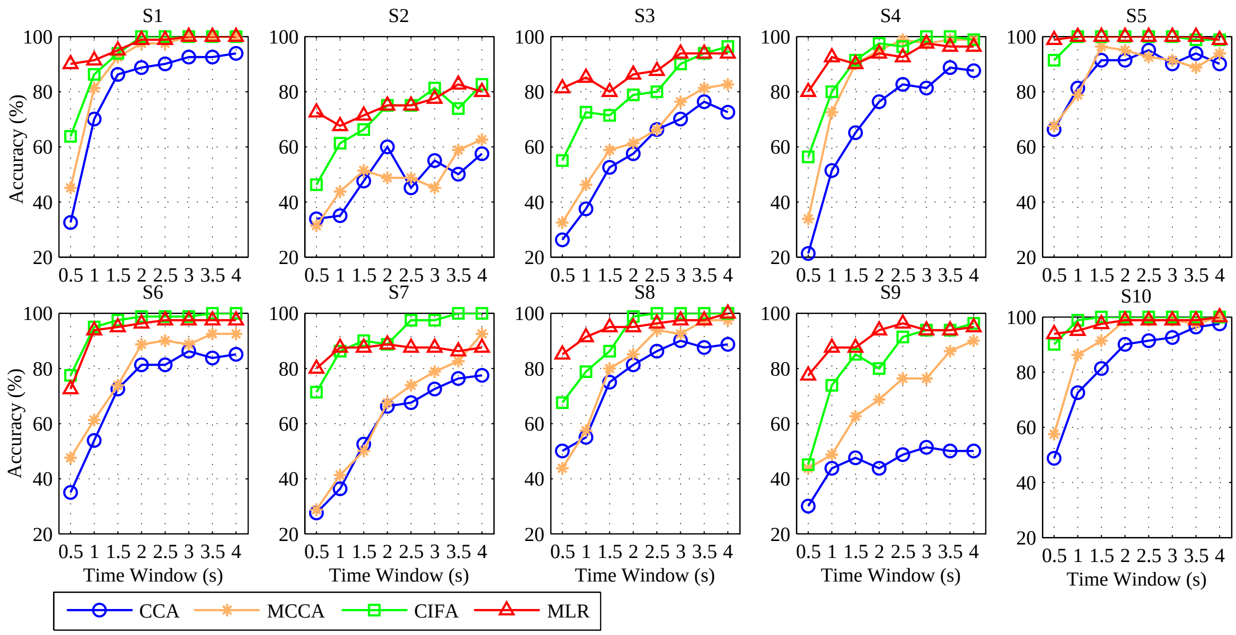

Fig. 4. SSVEP recognition accuracy of the ten subjects achieved by the CCA, MCCA, CIFA and MLR-based methods, with time window from 0.5 s to 4 s (0.5 s interval).

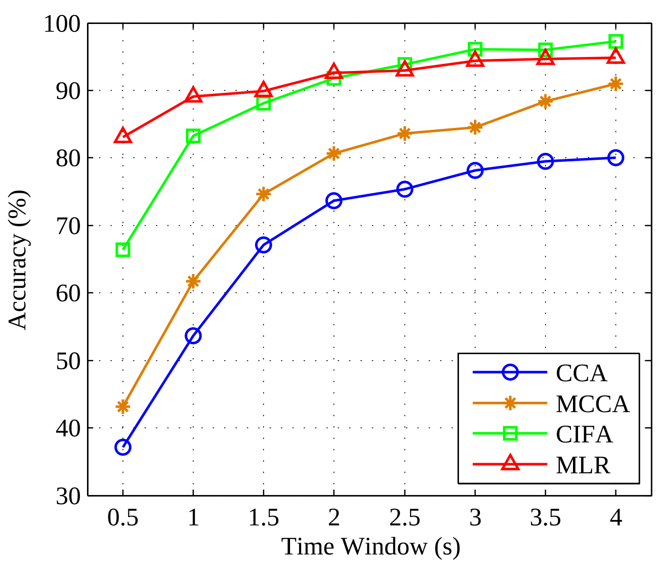

Fig. 5. Average recognition classification based on MLR-based method and other compared methods, with different time windows from 0.5 s to 4 s.

on each of the four red squares once for 4 s after each cue. The sequence of the target squares was randomized for each run. Each subject performed 20 experimental runs, which resulted in 80 total trials (4 trials per run, 20 trials for each frequency). Each respective stimulus was presented using the same initial phase for each trial and the resulting EEG observations were time-aligned for the data analysis.

F. Data Analysis

Since the occipital and parietal scalp areas have been demonstrated to contribute the most to SSVEP recognition [27], [49], the following eight channels were used for this anlysis: P7, P3, Pz, P4, P8, O1, Oz and O2. The EEG data were band-pass filtered from 4 Hz to 45 Hz using a zero-phase sixth-order Butterworth band-pass filter.

To validate effectiveness of the proposed MLR-based method on discriminative feature extraction of SSVEP, it was compared to CCA, MCCA, and CIFA for SSVEP detection. For each method, the average accuracy was evaluated using a leave-one-out cross-validation scheme. That is, the data from 19 runs were used as training data for feature extraction while the left-out run was used as test data. This procedure was repeated 20 times, once with each run serving as test data. The matlab code of the MLR method for SSVEP recognition is available [1].

III. Results

Fig. 4 depicts the SSVEP recognition accuracy for each of the ten subjects at various time windows from 0.5 s to 4 s with an interval of 0.5 s. Fig. 5 shows the average accuracy across all subjects in each time window. Overall, the MLR method yielded higher average accuracy in comparison with CCA and MCCA at all time windows. The accuracy improvement of the MLR method becomes even more pronounced for decreasing time window lengths. Higher accuracy was achieved by the MLR method than CIFA for time windows shorter than 1 s. Fig. 6 compares the SSVEP recognition accuracy averaged on subjects among the four methods at each of the stimulus frequencies. MLR consistently outperformed CCA and MCCA for all of the four stimulus frequencies. Also, MLR yielded higher accuracy for each stimulus frequency than CIFA for time windows shorter than 1 s.

Paired t-tests were implemented to determine significant differences between MLR and each of the other methods tested

[1]http://www.mathworks.com/matlabcentral/fileexchange/50876-mlrforssvepbci-demo

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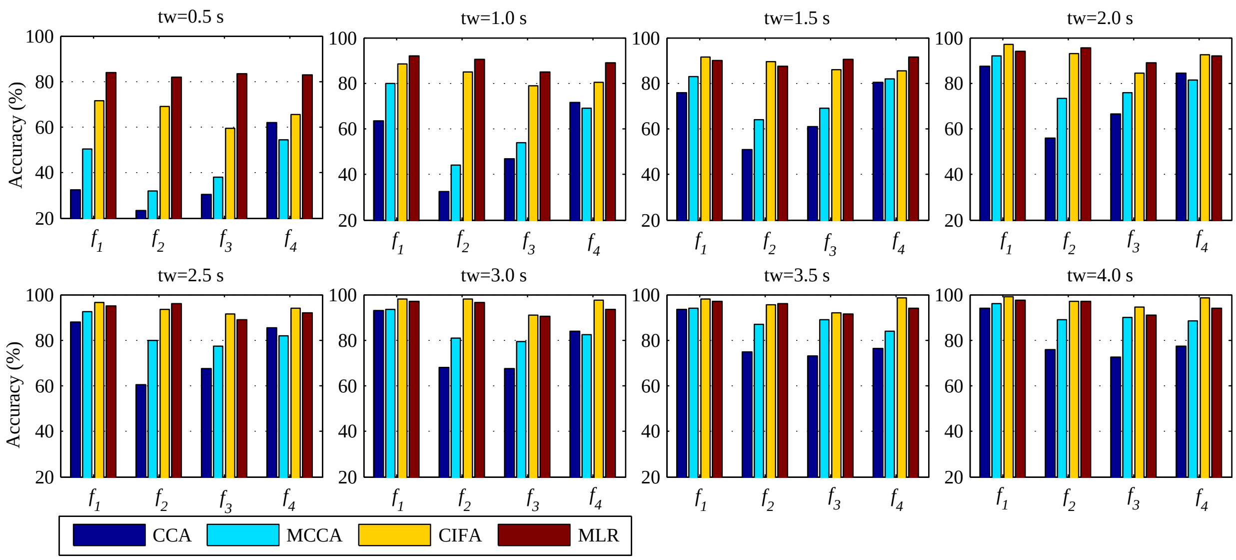

Fig. 6. Average recognition accuracy for each of the stimulus frequencies (f_1=10 Hz, f_2=9 Hz, f_3=8 Hz, f_4=6 Hz), with different time windows (tw).

TABLE I

STATISTICAL ANALYSIS OF THE ACCURACY DIFFERENCE BETWEEN THE MLR METHOD AND EACH OF THE CCA, MCCA, AND CIFA METHODS BY USING THE PAIRED T-TEST.

Methods Comparison	Time Window							
	0.5 s	1 s	1.5 s	2 s	2.5 s	3 s	3.5 s	4 s
MLR vs. CCA	$p<0.0001$	$p<0.0001$	$p<0.0001$	$p<0.001$	$p<0.005$	$p<0.005$	$p<0.01$	$p<0.005$
MLR vs. MCCA	$p<0.0001$	$p<0.0001$	$p<0.005$	$p<0.01$	$p<0.05$	$p<0.05$	$p<0.05$	$p=0.096$
MLR vs. CIFA	$p<0.005$	$p<0.05$	$p=0.24$	$p=0.63$	$p=0.58$	$p=0.15$	$p=0.45$	$p=0.08$

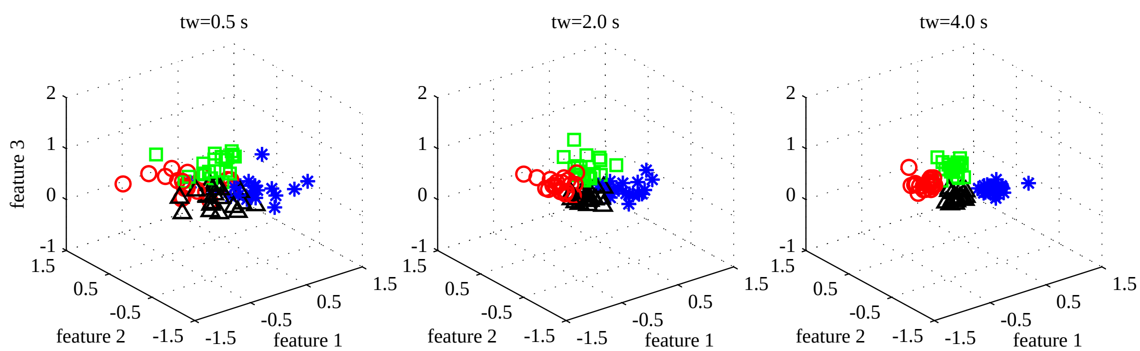

Fig. 7. Feature distributions of test samples at different time windows (tw), extracted by MLR with leave-one-out cross-validation from subject S1. Three features were selected from fours for each sample for visualization.

(see Table I). MLR achieved significantly higher accuracies over CCA for all time windows and significantly higher accuracies over MCCA for time windows 0.5-3.5 s. Compared to CIFA, MLR provided significant higher accuracies for time windows shorter than 1 s while no significant accuracy difference was observed between the two methods for time windows longer than 1 s.

In order to visualize the feature distributions, three features were selected from the four total features of the MLR-projected subspace to represent each test sample. Fig. 7 shows the feature distributions of subject S1 extracted from the MLR method at 0.5 s, 2 s and 4 s time windows, respectively. The MLR method yielded discriminable feature distributions even at very short time windows, i.e., 0.5 s. Feature discriminibility continued to increase as the length of the time window increased.

To more comprehensively validate the effectiveness of MLR, the recognition accuracy was evaluated using different numbers of training runs (see Fig. 8). For CIFA and MLR, the recognition accuracy showed steady increases with increasing amounts of training data. MCCA yielded higher accuracy than MLR when using five training runs at time windows longer

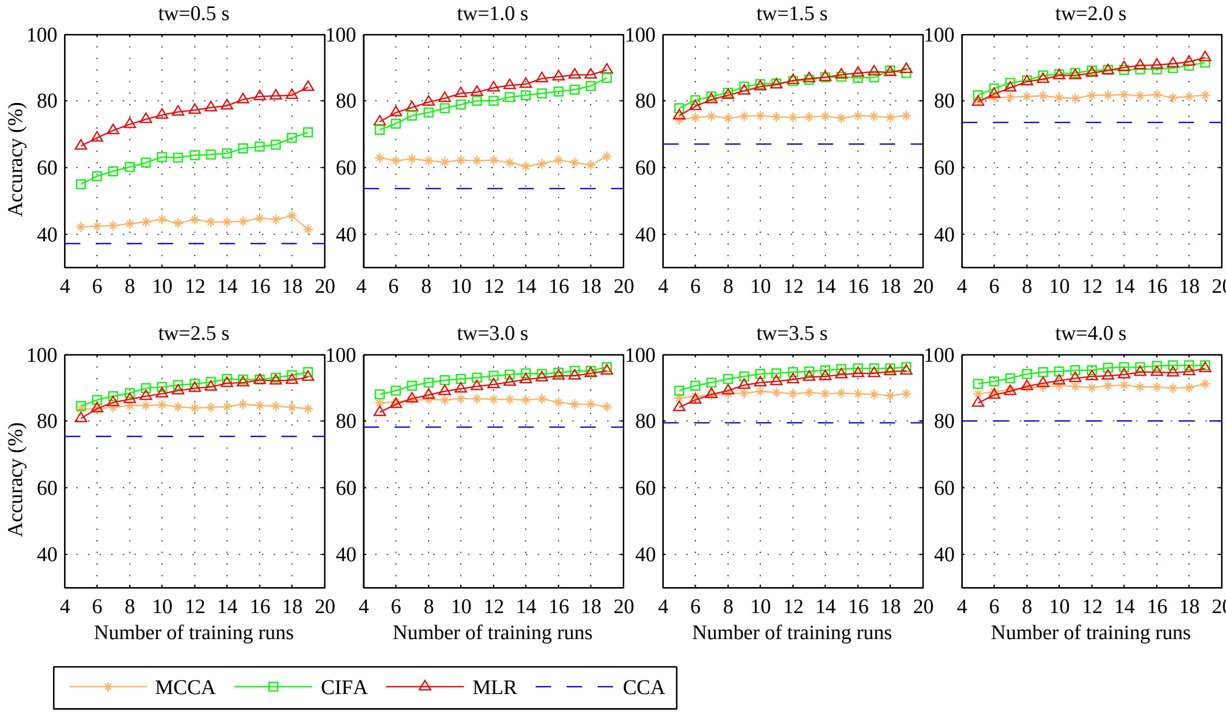

Fig. 8. Average accuracy for SSVEP recognition obtained by using different numbers of training runs at different time windows (tw), respectively. Each training run contained four samples corresponding to the four stimulus frequencies, respectively. For comparison, the accuracy of CCA is shown by a flat dashed line since no training data is required.

than 2 s. CIFA performed better than MLR when using a small number of training runs at time windows longer than 2 s. However, most importantly, MLR consistently outperformed MCCA and CIFA for all numbers of training runs at time windows shorter than 1 s. The aforementioned results indicate that the MLR method is promising to improve the real-time performance of SSVEP-based BCI.

The computational time was also compared among MCCA, CIFA and MLR using 19 runs of training data for feature extraction. The computation environment consisted of Matlab 2012a on a laptop with a 2.8 GHz CPU (4 GB RAM). The results of the computational time analysis are shown in Fig. 9. Both MCCA and CIFA involve iteration procedures during the optimization process, whereas MLR computes the optimal solution simply with a one-step matrix operation preceded by PCA. In general, computational time of the methods increases with increasing data window lengths since more mathematical operations are required. However, MCCA utilizes an iterative algorithm that can suffer from slower convergence speed when low correlations are encountered, such as when shorter windows are implemented. Thus, the computational time of the MCCA does not necessarily increase with increasing window lengths. Although all of the three methods can be efficiently implemented, MLR further decreases the computational time in comparison with MCCA and CIFA.

IV. Discussion and Conclusions

CCA has been widely adopted for SSVEP recognition since it provides an effective multichannel optimization for enhancing the SNR of SSVEP signals. However, the ideal sine-cosine references utilized by the CCA method fail to represent the full nature of the SSVEP signal thus resulting in sub-optimal detection accuracies. This is especially apparent for shorter time windows. Although the MCCA and CIFA methods have been proposed to overcome the shortcomings of the CCA method by using the SSVEP data to optimize the reference signals, they exploit only within-class information and disregard any between-class information. As a result, the optimal discriminative features may not be derived to give the best SSVEP recognition accuracy.

In this study, the proposed MLR method aims at finding the most discriminative SSVEP features through a simple but effective approach. From the experimental results, the MLR method performed well for most subjects especially when using relatively short time windows. It is worth noting that robust real-time performance is essential for practical BCI systems. These systems can potentially benefit from the discriminative SSVEP features extracted by the MLR method leading to quicker and more accurate target detections. As shown in Fig. 5, the MLR method yielded discriminable feature distributions even at a very short time window, i.e., 0.5 s. Higher feature discriminability was enhanced with the increasing of time window length. Fig. 6 additionally illustrates that the MLR method also achieves less class imbalance across time windows compared to the other approaches.

In the experimental study, the recognition accuracy was evaluated using leave-one-out cross-validation. That is, 19 runs of training data were used for feature extraction. The results in Fig. 8 show the MLR method achieves higher accuracies as the number of training runs is varied, for time windows

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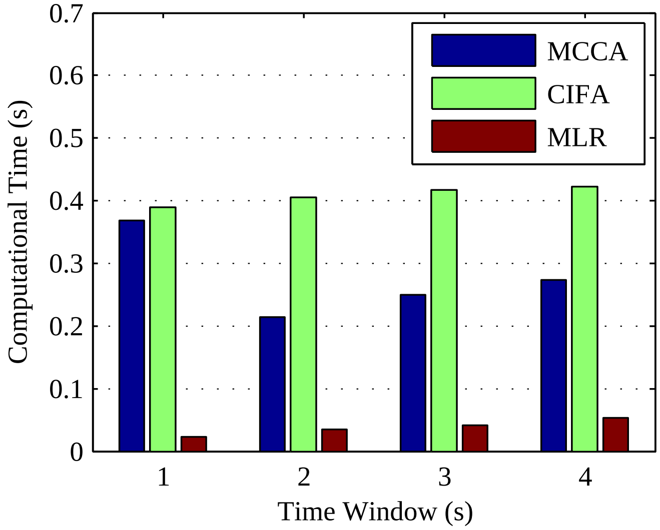

Fig. 9. Average computational time of the MCCA, CIFA and MLR methods for feature extraction at time window from 1 s to 4 s, respectively.

shorter than 1 s, compared to the other approaches. It should be noted that CCA does not require training, which is an important consideration for applications where training time is prohibitive. However, by comparing the relative accuracies in Fig. 6 and Fig. 8, MLR can outperform CCA with relatively few training runs, particularly for short time windows. Furthermore, the computational time results in Fig. 9 show that the MLR method can be implemented efficiently within 0.1 s. These results indicate that the MLR method is promising to improve not only the real-time performance but also practicability of SSVEP-based BCI. However, effectiveness of the MLR method is demonstrated on only four stimulus frequencies, which is sufficient for a reliable hierarchical menu system or for 2-dimensional directional control. A future study will investigate the performance of MLR for larger numbers of simultaneous target frequencies and compare the results to other demonstrated approaches for large numbers of targets [27]. Relatedly, the future study will also evaluate and compare the relative performance of MLR when an idle state is incorporated [50].

In the context of BCIs, the feature dimensionality is generally high compared to the number of available training samples. In this study, an unsupervised PCA was implemented for dimensionality reduction prior to MLR. It is reasonable to consider that the recognition performance can be further improved through designing a supervised method for dimensionality reduction [51], [52], [53], [54], [55], [56], [57], [58]. Additionally, this study also adopted a simple k-NN classifier for target recognition. Although the k-NN achieves favorable results, utilization of a more sophisticated classifier could further improve the SSVEP detection accuracy of the MLR-projected features. These two issues, as well as online validation of the results, will be investigated in future studies.

In summary, this study proposes a multivariate linear regression (MLR)-based method to improve performance of the SSVEP-based BCI. MLR is implemented on the dimensionality-reduced training data and the label matrix to extract the discriminative SSVEP features. The experimental results based on EEG data from ten subjects showed that the MLR-based method significantly outperformed several other competing methods in terms of classification accuracy, required training data, and computational time, for a short time window (i.e., shorter than 1 s). This superiority indicates that the proposed MLR method is promising to improve the real-time performance of SSVEP-based BCI.

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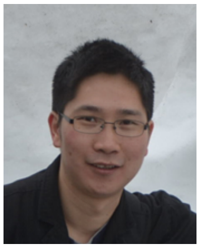

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