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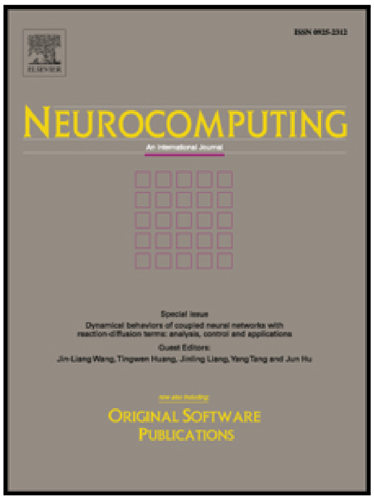

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Highlights

- DMCCA is innovatively implemented to maximize the correlation within the features of real EEG signals that are mapped by fully connected NNs and reference templates
- Complex relationship between EEG signals and reference templates are learned by DMCCA
- DMCCA has excellent performance on frequency recognition, especially within a short TW

Efficient representations of EEG signals for SSVEP frequency recognition based on deep multiset CCA

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Conflict of interest

The authors declared that they have no conflicts of interest to this work.

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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Abstract

Canonical correlation analysis (CCA) has been widely used for frequency recognition in steady-state visual evoked potential (SSVEP) based brain–computer interfaces (BCIs). However, linear CCA-based methods may be insufficient given the complexity of EEG signals. A nonlinear feature extraction method based on deep multiset CCA (DMCCA) is proposed for SSVEP recognition to fully utilize the real EEG and constructed sine–cosine signals. In DMCCA, neural networks are trained to learn the nonlinear representations of multiple sets of EEG signals at the same frequency by maximizing the overall correlation within the representations and reference signals. Therefore, reference signals are augmented with the extracted features for frequency recognition. Finally, the proposed method is evaluated using SSVEP signals collected from 10 subjects. DMCCA-based method outperforms others in terms of classification accuracy compared with CCA- and multiset CCA-based methods. The proposed DMCCA-based method has substantial potential for improving the recognition performance of SSVEP signals.

Keywords: Brain–computer interface; electroencephalogram; multiset canonical correlation analysis; steady-state visual evoked potential.

1. Introduction

Brain–computer interface (BCI), which aims to realize the connection between the brain and computer, does not require the use of peripheral muscle tissue to directly communicate with the real world [1–6]. The communication and environmental control capabilities can be rebuilt by the implementation of BCIs for severely disabled people without the need for muscle movement [7]. Recently, brain communication technology based on steady-state visual evoked potential (SSVEP) has been widely studied because it requires less training cost for higher accuracy and information transfer rate [8, 9].

Many research works have indicated that significant SSVEP signals can be detected in the occipital region of the cerebral cortex when subjects focus on a visual stimulus at a specific frequency and such signals are the same or have higher harmonic signals than that of stimulation frequency [10, 11]. Although EEG signals gradually stabilize with the increase in stimulation time, other brain activities and some background noises are unavoidable. The extraction of efficient features of EEG signals is the key to recognize the SSVEP frequency with high accuracy in a short time window (TW) and further develop high-performance SSVEP-based BCI applications.

Among the various detection approaches, canonical correlation analysis (CCA) is commonly used for frequency recognition [12, 13]. Lin et al. first applied CCA on multi-channel information of SSVEP signals, and the correlation between these signals and manually constructed templates was maximized [14]. Compared with the traditional power spectral density analysis, CCA-based methods can significantly improve the performance of frequency recognition. Except for the artificial reference templates, real EEG signals are also considered in numerous studies for improved recognition performance due to the interference from spontaneous EEG activities [15]. Zhang et al. proposed the multiway extension of CCA (MwayCCA), which combines multi-dimension signals to optimize the reference templates for SSVEP recognition [16]. In this way, L1-regularized MwayCCA-based method is further presented to obtain the optimal reference templates from multiple dimensions of EEG signals [17]. Pan et al. proposed phase constraint CCA for SSVEP frequency recognition by incorporating the phase information learned from training data to optimize reference signals [18]. Zhang et al. used multiset CCA (MsetCCA) to determine common features among multiple sets of EEG signals that can achieve better SSVEP recognition performance than that of artificial reference templates [19].

Incorporating specific information existing in real EEG signals of different subjects, the aforementioned studies reduce the effect of spontaneous EEG activities in SSVEP data and improve the SNR of SSVEP signals to a certain extent. These algorithms mainly consider a linear relationship; however, nonlinearities inevitably exist in the real signals, rendering the linear models insufficient [20]. In addition, the spectrum is related to the Fourier coefficient and changes when the fast Fourier transform is applied to successive segments of the EEG signals [21]. Therefore, nonlinear versions of CCA, such as kernel CCA (KCCA) and deep CCA (DCCA), have been studied [22, 23]. Given that kernel-based methods are limited for large-scale data due to the fixed kernel, DCCA that learns the nonlinear representations of variables by neural network (NN) is utilized for complex issues [23]. The information within the real signals must be extracted to achieve improved recognition performance because DCCA only considers the nonlinear correlation between EEG signals and reference templates.

In this study, deep multiset CCA (DMCCA)-based method is introduced for SSVEP frequency recognition. DMCCA can learn the nonlinear representations of multiple sets of signals through NN transformations. Based on the idea that the information in real EEG signals and reference templates contribute to the excellent recognition performance, DMCCA is innovatively implemented to maximize the correlation within the features of real EEG signals that are mapped by fully connected NNs and reference templates. Thus, the reference templates are augmented with the extracted features to recognize the frequency of signals. Using the data recorded from 10 subjects, the proposed method was evaluated, and excellent performance on frequency recognition, especially within a short TW, was obtained.

The rest of the paper is arranged as follows. Methods including CCA, MCCA and DMCCA are described in Section 2. The experiment is briefly introduced in Section 3. The results of the proposed method are provided in Section 4 and corresponding discussion are presented in Section 5. Finally, conclusion is given in Section 6.

2. Methods

2.1 CCA for SSVEP recognition

CCA can reflect the overall correlation between two sets of variables and is thus widely used for SSVEP frequency recognition [13, 24, 25]. Lin et al. first applied CCA for SSVEP frequency recognition due to the frequency characteristics of SSVEP signals [14]. Given two sets of variables, $\boldsymbol{X} \in \Re^{m\times k}$ and $\boldsymbol{Y} \in \Re^{n\times k}$, CCA aims to find a pair of weight vectors, $\boldsymbol{w}_x \in \Re^{m}$ and $\boldsymbol{w}_y \in \Re^{n}$, which will maximize the correlation between $\boldsymbol{x} = \boldsymbol{w}_x^T \boldsymbol{X}$ and $\boldsymbol{y} = \boldsymbol{w}_y^T \boldsymbol{Y}$ as follows:

$$\max_{\boldsymbol{w}_x, \boldsymbol{w}_y} \rho = \frac{E\left[\boldsymbol{x}\boldsymbol{y}^T\right]}{\sqrt{E\left[\boldsymbol{x}\boldsymbol{x}^T\right]E\left[\boldsymbol{y}\boldsymbol{y}^T\right]}} = \frac{\boldsymbol{w}_x^T \boldsymbol{X}\boldsymbol{Y}^T \boldsymbol{w}_y}{\sqrt{\boldsymbol{w}_x^T \boldsymbol{X}\boldsymbol{X}^T \boldsymbol{w}_X \boldsymbol{w}_y^T \boldsymbol{Y}\boldsymbol{Y}^T \boldsymbol{w}_y}}, \tag{1}$$

where *m*, *n* are the number of variables in $\boldsymbol{x}$ and $\boldsymbol{y}$, and *k* is the number of collected samples. ρ is the correlation coefficient between $\boldsymbol{x}$ and $\boldsymbol{y}$.

Therefore, CCA can be implemented to analyze the correlation between EEG signals and the constructed sine–cosine reference templates. Suppose EEG signals of *M* trials $\boldsymbol{X}_m \in \Re^{C \times T}, m = 1, 2, ..., M$ are sampled at the *m*th stimulus frequency f_m with *C* channels and *T* time points. Reference templates $\boldsymbol{Y}_m \in \Re^{2N_h \times T}$ are constructed as shown below to recognize the frequencies of such signals.

$$\boldsymbol{Y}_m = \begin{Bmatrix} \sin(2\pi f_m t) \\ \cos(2\pi f_m t) \\ \vdots \\ \sin(2\pi N_h f_m t) \\ \cos(2\pi N_h f_m t) \end{Bmatrix}, \quad t = [\frac{1}{f_s}, \frac{1}{f_s}, \cdots, \frac{T}{f_s}], \tag{2}$$

where N_h is the number of harmonics, and f_s refers to the sampling rate. The frequency f of the target signal can be calculated as follows:

$$f = \arg\max_m \rho_m, m = 1, 2, ..., M, \tag{3}$$

where ρ_m is calculated between the signals and *m*th reference template using Eq. (1).

2.2 MsetCCA for SSVEP recognition

Many studies have revealed the excellent performance of CCA-based recognition methods [26, 27]. However, these methods mainly focus on the correlation analysis between EEG signals and constructed reference templates and ignore the information in real EEG signals, which may degrade the recognition performance, especially in a short TW length. Therefore, Zhang et al. used the MsetCCA to extract potential common features of multiple training datasets at the same stimulus frequency [19]. The objective function, which maximizes the largest eigenvalue of the correlation matrix (MAXVAR), is described as follows to illustrate the mechanism of MsetCCA:

$$\begin{aligned} &\max_{\boldsymbol{v}_1,\ldots,\boldsymbol{v}_N} \rho = \sum_{i \neq j}^{N} \boldsymbol{v}_i^T \boldsymbol{X}_i \boldsymbol{X}_j^T \boldsymbol{v}_j \\ &s.\,t.\ \ \frac{1}{N} \sum_{i=1}^{N} \boldsymbol{v}_i^T \boldsymbol{X}_i \boldsymbol{X}_j^T \boldsymbol{v}_j = 1 \end{aligned}, \tag{4}$$

where the N sets of variables $\boldsymbol{X}_i \in \Re^{I_i \times J}$, $i = 1, 2, \ldots, N$ with I_i dimensions and J sample points have been normalized to zero mean and unit variance. Lagrange multipliers are introduced to solve the aforementioned function, and the MAXVAR can be achieved by the following eigenvalue problem.

$$\boldsymbol{A}\boldsymbol{v} = \lambda \boldsymbol{B}\boldsymbol{v}, \tag{5}$$

where $\boldsymbol{A} = \begin{bmatrix} \boldsymbol{0} & \cdots & \boldsymbol{X}_1 \boldsymbol{X}_N^T \\ \vdots & \ddots & \vdots \\ \boldsymbol{X}_N \boldsymbol{X}_1^T & \cdots & \boldsymbol{0} \end{bmatrix}$ and $\boldsymbol{B} = \begin{bmatrix} \boldsymbol{X}_1 \boldsymbol{X}_1^T & \cdots & \boldsymbol{0} \\ \vdots & \ddots & \vdots \\ \boldsymbol{0} & \cdots & \boldsymbol{X}_N \boldsymbol{X}_N^T \end{bmatrix}$. The solution of Eq. (4) is $\boldsymbol{v} = \left[\boldsymbol{v}_1^T, \boldsymbol{v}_2^T, \ldots, \boldsymbol{v}_N^T\right]$ with the largest eigenvalue obtained by Eq. (5).

After joint spatial filtering, the overall correlation between canonical variables from multiple sets of variables is maximized. The original signals at the mth frequency can be transformed into the optimized templates $\boldsymbol{Z}_m = \left[\boldsymbol{v}_1^T \boldsymbol{X}_1, \boldsymbol{v}_2^T \boldsymbol{X}_2, \ldots, \boldsymbol{v}_N^T \boldsymbol{X}_N\right]$. The recognition is then executed between the test signals $\hat{\boldsymbol{X}}$ and $\boldsymbol{Z}_m$ instead of the reference $\boldsymbol{Y}_m$ in Eq. (2).

2.3 DMCCA for SSVEP recognition

CCA- and MsetCCA-based methods generally consider the linear relationship within EEG signals or between EEG and reference signals. However, given that nonlinearities inevitably exist in the real EEG signals, the traditional CCA has been extended to nonlinear versions, such as KCCA [22]. Kernel-based methods are limited to large-scale datasets due to the setting of fixed kernels. Alternatively, NN is a state-of-the-art option with excellent performance in representation learning [23]. Therefore, DMCCA, which is the nonlinear extension of MsetCCA, is introduced in this study. The DMCCA algorithm and the illustration of DMCCA-based method for SSVEP recognition are presented below.

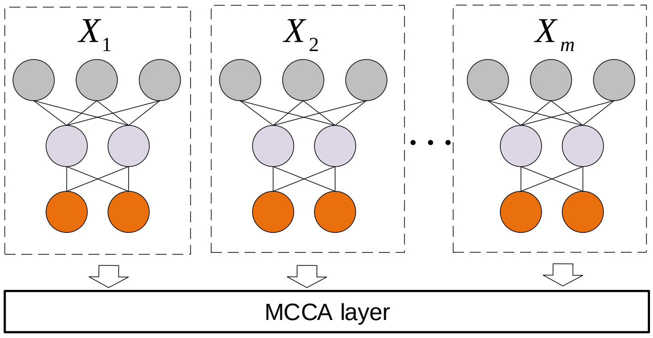


Fig. 1. Schematic of DMCCA. Multiple sets of variables $\boldsymbol{X}_i$ are transformed by a group of fully connected neural networks. These NNs are optimized by the MsetCCA object, which maximizes the correlation of the output of these neural networks.

The DMCCA comprises multiple NNs with an MsetCCA layer at the top, and the schematic of DMCCA is shown in Fig. 1. For N sets of variable $\boldsymbol{X}_i \in \Re^{I_i \times J}, i = 1, 2, ..., N$, each set is transformed into $f_i(\boldsymbol{X}_i) \in \Re^{O_i \times J}$ by a fully connected NN, where O_i is the number of neurons at the output layer of each NN. Notably, these NNs are not connected to each other. The output of the ith neuron in the jth layer can be calculated as follows:

$$h_i^j = \sigma\left(\boldsymbol{W}_i^j \boldsymbol{x}^{j-1} + b_i^j\right), \tag{6}$$

where $\boldsymbol{x}^{j-1}$ is the input of the neuron, and $\boldsymbol{W}_i^j, b_i^j$ are the parameters of NNs before the MsetCCA layer. $\sigma(\cdot)$ is the activation function, which can be sigmoid, tanh and so on.

After the feedforward calculation of the NNs, the output of the ith NN can be centered as

$$\boldsymbol{H}_i = f\left(\boldsymbol{X}_i\right) - \frac{1}{J} f\left(\boldsymbol{X}_i\right) \boldsymbol{1}_J \boldsymbol{1}_J^T, \tag{7}$$

where $\boldsymbol{1}_J$ is the J-dimensional column vector in which all components are equal to one. Therefore, DMCCA aims to maximize the correlation of all these output sets, which can be described as follows:

$$\begin{aligned} &\max_{\boldsymbol{w}_1, \dots, \boldsymbol{w}_N} \rho = \sum_{i \neq j}^{N} \boldsymbol{w}_i^T \boldsymbol{H}_i \boldsymbol{H}_j^T \boldsymbol{w}_j \\ &s.\,t.\ \ \frac{1}{N} \sum_{i=1}^{N} \boldsymbol{w}_i^T \boldsymbol{H}_i \boldsymbol{H}_i^T \boldsymbol{w}_i = 1 \end{aligned} . \tag{8}$$

Eq. (8) can be calculated by the following eigenvalue problem, which is adapted for the feedforward calculation in MsetCCA layer of DMCCA (Appendix A).

$$\boldsymbol{R}\boldsymbol{w} = \lambda \boldsymbol{S}\boldsymbol{w}, \tag{9}$$

where $\boldsymbol{R} = \begin{bmatrix} \boldsymbol{0} & \cdots & \boldsymbol{H}_1\boldsymbol{H}_N^T \\ \vdots & \ddots & \vdots \\ \boldsymbol{H}_N\boldsymbol{H}_1^T & \cdots & \boldsymbol{0} \end{bmatrix}$, $\boldsymbol{S} = \frac{1}{N}\begin{bmatrix} \boldsymbol{H}_1\boldsymbol{H}_1^T & \cdots & \boldsymbol{0} \\ \vdots & \ddots & \vdots \\ \boldsymbol{0} & \cdots & \boldsymbol{H}_N\boldsymbol{H}_N^T \end{bmatrix}$, and the scaling factor N is omitted. The solution $\boldsymbol{w} = \left[\boldsymbol{w}_1^T, \boldsymbol{w}_2^T, ..., \boldsymbol{w}_N^T\right]$ corresponds to the largest eigenvalue. Backpropagation algorithm with mini-batch samples is generally used for the training to search the optimal solution $\boldsymbol{w}^* = \left[\boldsymbol{w}_1^*, \boldsymbol{w}_2^*, ..., \boldsymbol{w}_N^*\right]$. The gradient of the object in Eq. (8) is derived from Eq. (10), and the detailed derivation is presented in Appendix B.

$$\frac{\partial \rho}{\partial \boldsymbol{H}_i} = \boldsymbol{w}^T\left(\frac{\partial R}{\partial \boldsymbol{H}_i} - \rho \frac{\partial S}{\partial \boldsymbol{H}_i}\right)\boldsymbol{w}. \tag{10}$$

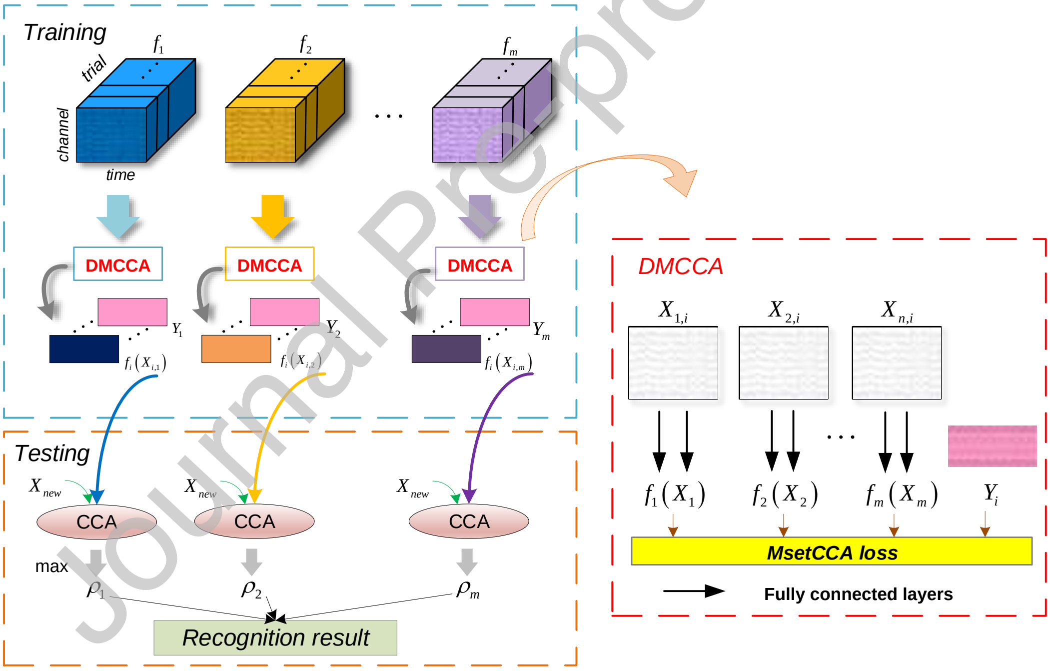


Fig. 2. Illustration of DMCCA-based method for SSVEP recognition. $\boldsymbol{X}_{i,j}$ is the EEG signals for the *i*th trial at the *j*th frequency, and $\boldsymbol{Y}_i$ is the reference signal at the *i*th stimulus frequency. $\boldsymbol{X}_{i,j}$ and $\boldsymbol{Y}_i$ are inserted into a DMCCA network to extract the most efficient features $f\left(\boldsymbol{X}_{i,j}\right)$. Recognition can be implemented among $\boldsymbol{X}_{new}$ and $f\left(\boldsymbol{X}_{i,j}\right)$, $\boldsymbol{Y}_i$ using the CCA-based method.

For every trial in SSVEP recognition, the common features behind the linear or nonlinear signals must be extracted. Fig. 2 shows that the DMCCA is used to extract the efficient features for the complex signals together with the reference templates at a fixed frequency. Assume that the EEG and reference signals are respectively collected as $\boldsymbol{X}_{1,m}, \boldsymbol{X}_{2,m}, ...\boldsymbol{X}_{N,m}, m = 1, 2, ..., M$ and $\boldsymbol{Y}_m$. Given that the reference signals are formed in a standard way, $\boldsymbol{Y}_m$ is not transformed by the NN and thus directly inputted into the MsetCCA layer. After training the DMCCA, augmented signals $\left[f_1\left(\boldsymbol{X}_{1,m}\right), f_2\left(\boldsymbol{X}_{2,m}\right), ..., f_N\left(\boldsymbol{X}_{N,m}\right), \boldsymbol{Y}_m \right]$ are treated as the reference templates. Therefore, recognition can be implemented between the new data $\boldsymbol{X}_{new}$ and these templates using Eq. (3). The recognition logic is the same as CCA- or MsetCCA-based methods.

3 Experimental evaluation

The SSVEP data used in this paper include 10 subjects $S_1, S_2, ..., S_{10}$ (with ages ranging from 21 to 27, all male). All subjects were in good health and had normal vision (or normalized after correction). In the experiment, the subjects sat in a comfortable chair 60 cm away from the target stimulus. The stimulator was a 17-inch CRT monitor with a screen refresh rate of 85 Hz and a resolution of 1024 × 768. Four red target stimuli are available, and the frequencies of the visual stimuli are 6, 8, 9, and 10 Hz.

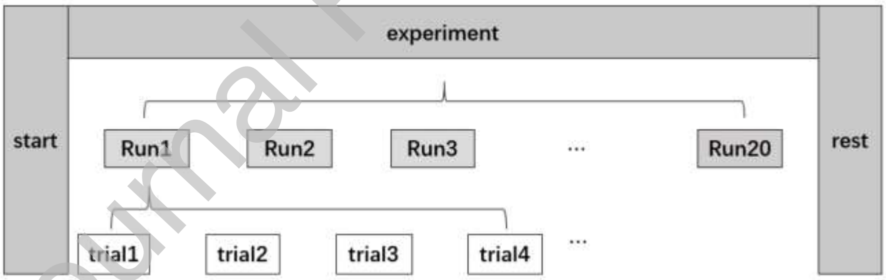


Fig. 3. Experimental procedure.

Each subject performed 20 runs at a specific target frequency, and four targets are involved. In the experiment, the subjects should concentrate on one of the flickered stimulations for 4 s, and each target was flashed 20 times. The EEG signals were collected at a sampling frequency of 250 Hz and recorded by the NuAmps amplifier with bandpass filters of 0.1–70 Hz. The electrodes are placed according to the international 10–20 system, and a strong SSVEP signal can usually be detected in the occipital region of the scalp. Therefore, eight channels, including O1, Oz, O2, P7, P3, Pz, P4, and P8, were selected to acquire the signals. Band-pass filtering between 4 and 45 Hz was implemented for further analysis, and a six-order Butterworth filter was performed on the EEG data. The proposed method in this paper was evaluated according to fivefold cross-validation and compared with CCA- and MsetCCA-based methods. In DMCCA, subnetworks are designed with 8-8-8-4 neurons. Rectified linear unit (relu) is the activation and the training optimizer is ‘Adam’ together with epoch=200.

4. Results

As shown in Fig. 4, the accuracies of the CCA, MsetCCA, and DMCCA for each of the 10 subjects are compared at different TWs (between 0.5 to 4.0 s with an increment of 0.5 s).

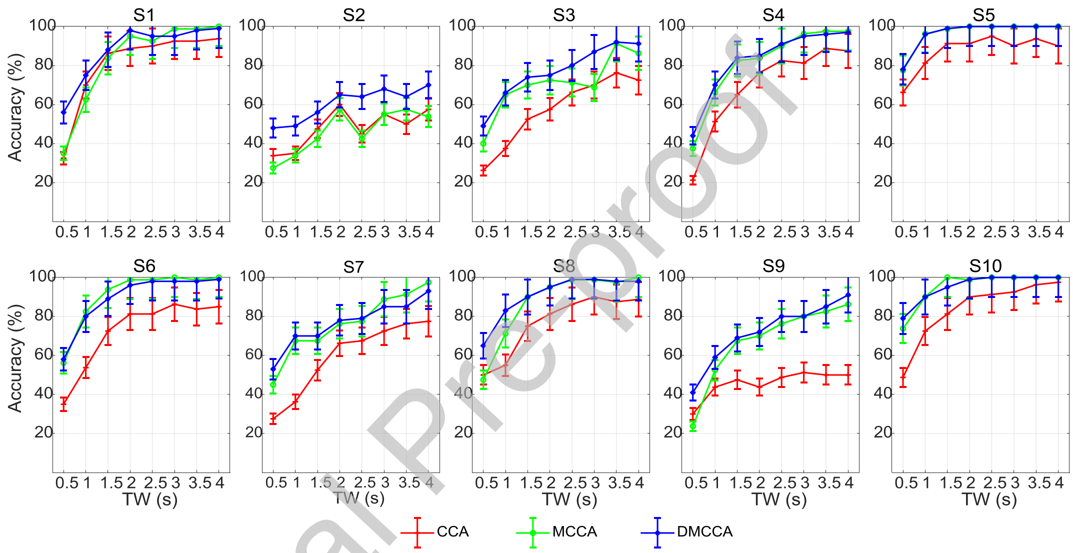


Fig. 4. Accuracies of frequency recognition of the 10 subjects derived by the CCA, MsetCCA, and DMCCA methods (C = 8).

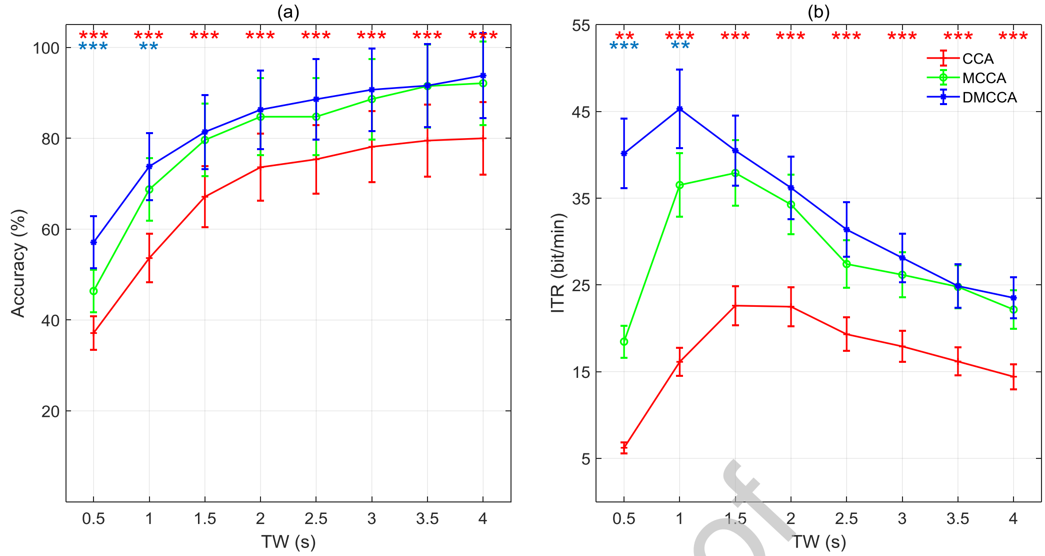


Fig. 5. Average accuracies of frequency recognition and information transfer rates (ITRs) of the 10 subjects derived by the CCA, MsetCCA, and DMCCA methods at various TWs (C = 8). The significant difference between CCA, MsetCCA, and DMCCA methods obtained by one-way repeated measure ANOVAs is denoted by '***' (CCA: $p < 0.001$), '**' (CCA: $p < 0.01$), '*' (CCA: $p < 0.05$), '***' (MsetCCA: $p < 0.001$), '**' (MsetCCA: $p < 0.01$), and '*' (MsetCCA: $p < 0.05$).

Fig. 5 depicts the average accuracy of various subjects at different TWs. The proposed DMCCA-based method consistently outperforms MsetCCA and CCA methods at most TWs (except for 3.5 s, where DMCCA = MsetCCA). The three methods achieved the highest ITR at different TWs (DMCCA = 46.09 at TW = 1 s, MsetCCA = 37.91 at TW = 1.5 s, and CCA = 22.61 at TW = 1.5 s), and DMCCA reached the peak faster than CCA and MsetCCA (Fig. 5). The considerable difference has been marked in Fig. 5. At TW of less than 1 s, the proposed method performed better than CCA and MsetCCA methods.

Fig. 6 depicts the averaged accuracies of these methods at various channels with TW less than 1 s. For C = 4, 6, and 8, DMCCA-based method exhibits better accuracies than those of CCA- and MsetCCA-based methods for each stimulus frequency, especially at short TWs and small channels.

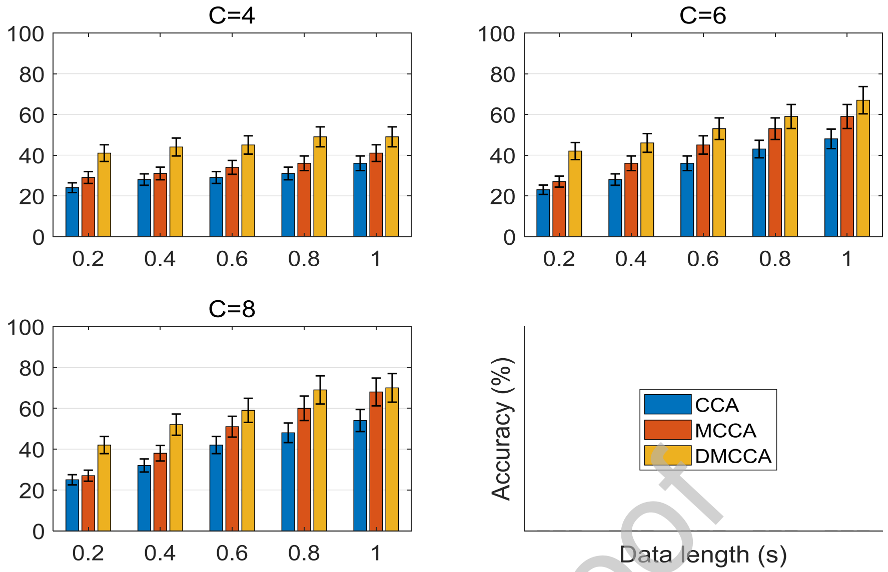


Fig. 6. Average SSVEP accuracies of the frequency recognition derived by the CCA, MsetCCA, and DMCCA methods under different channels (C = 4, 6, 8) at TWs from 0.2 s to 1 s (C = 4: O1, O2, P3, and P4; C = 6: O1, O2, P3, P4, P7, and P8; C = 8: O1, Oz, O2 P3, P4, Pz, P7, and P8).

Statistical method of one-way repeated measure ANOVAs is also implemented to reveal the remarkable differences in the results. For the average performance, DMCCA yielded better accuracy than CCA- and MsetCCA-based methods (DMCCA > CCA, $p < 0.001$; DMCCA > MsetCCA, $p < 0.05$). When the TW was less than 1 s, DMCCA obtained significantly higher accuracy than that of MsetCCA for all TWs. Table 1 shows that the significant accuracies of DMCCA are different from those of CCA and MsetCCA at nearly all data lengths when TW is less than 1 s. In addition, the differences in accuracies between DMCCA and MsetCCA were insignificant at TW = 0.6–1.0 s (C = 8, $p < 0.05$) and significant at TW = 0.2 s and TW = 0.4 s (C = 8, $p < 0.001$).

Table 1. Statistical analysis results of the accuracy difference between DMCCA and each of CCA and MsetCCA with different C at various TWs.

Method comparison	TW				
	0.2s	0.4s	0.6s	0.8s	1.0s
C = 4					
DMCCA versus CCA	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
DMCCA versus MsetCCA	$p < 0.005$	$p < 0.005$	$p < 0.005$	$p < 0.001$	$p < 0.05$

$C = 6$					
DMCCA versus CCA	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.005$	$p < 0.001$
DMCCA versus MsetCCA	$p < 0.001$	$p < 0.005$	$p < 0.005$	$p < 0.05$	p=0.05
$C = 8$					
DMCCA versus CCA	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
DMCCA versus MsetCCA	$p < 0.001$	$p < 0.001$	$p < 0.01$	$p < 0.05$	$p < 0.05$

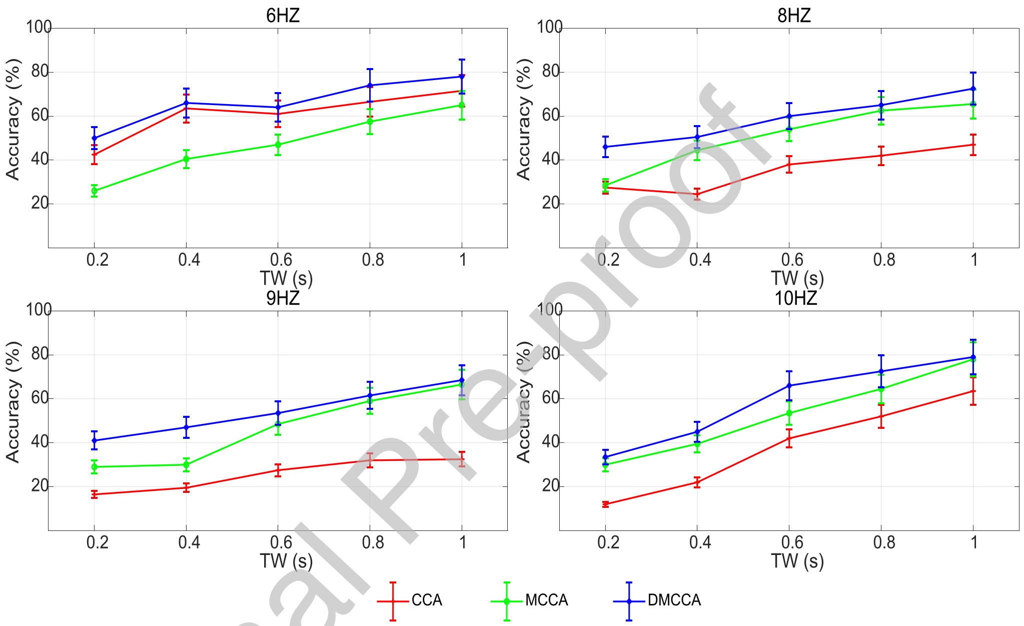


Fig. 7. Average SSVEP accuracies of the four stimulus frequency recognition derived by the CCA, MsetCCA, and DMCCA methods under different TWs from 0.2 s to 1 s ($C = 8$).

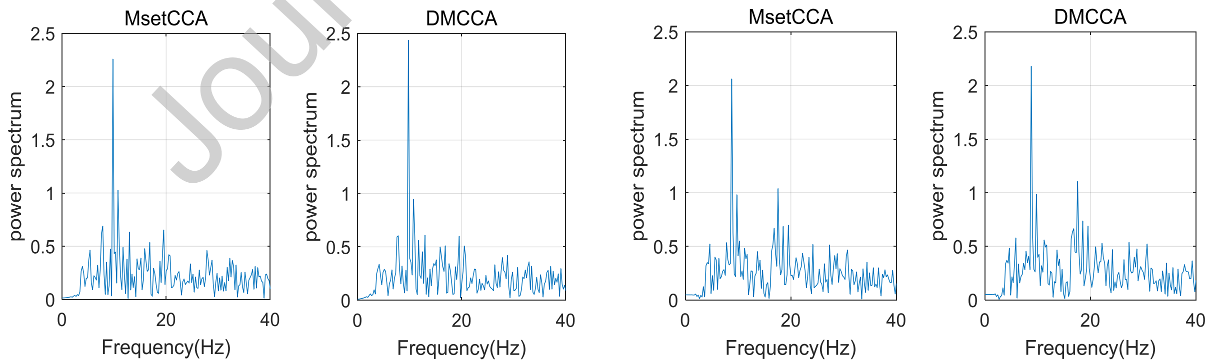
Fig. 7 depicts the averaged accuracy of frequency recognition for 10 subjects at four various frequencies when TW is less than 1 s. For the four frequencies, the DMCCA-based method consistently outperformed the two other methods.

Overall, the result indicates that DMCCA-based methods outperform CCA- and MsetCCA- based methods in terms of the accuracy in SSVEP frequency recognition, especially at small TWs.

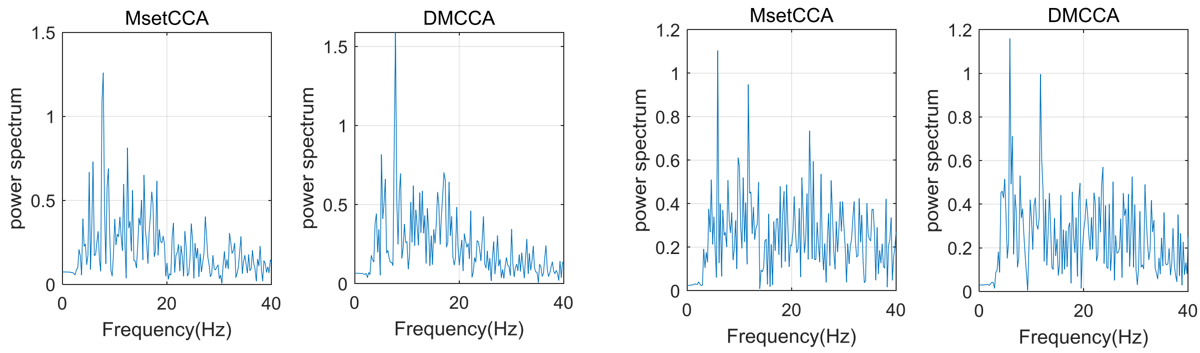
5. Discussion

Exploring and designing high-efficiency algorithms to recognize EEG signals in BCI systems remain a challenge. Many studies have been proposed to improve the performance of SSVEP-based BCI [28]. CCA and many extended algorithms have been developed to achieve improved performance of SSVEP frequency recognition [29, 30]. DMCCA is adopted to improve the recognition performance in this study to deal with the nonlinear characteristics in the EEG signals. From the comparison of the results, the DMCCA-based method exhibits advantages in short TWs and small number of channels. The improvement in recognition performance can be attributed to the nonlinear representations of EEG signals. In the field of pattern recognition, many studies have shown that well-designed algorithms are useful in learning the efficient features of classification models. Given that deep NNs have considerable potential in representation learning, the DMCCA-based method proposed in this paper can improve the performance of SSVEP frequency recognition based on the nonlinear representations learned by NNs.

Specifically, DMCCA extracts the common features of signals related to the stimulation frequency. Collecting effective training data during the training phase is cumbersome and time consuming to a certain extent, and the visual fatigue of the subject due to flickering stimuli during the experiment reduces the performance of the BCI. Therefore, reducing training time is crucial for SSVEP-based BCI. Compared with CCA- and MsetCCA-based methods, DMCCA can achieve high accuracy at short data lengths, which is a key characteristic of an efficient detection algorithm. Based on the results in Fig. 4, the DMCCA-based method has advantages in accuracies for different subjects compared with those of CCA and MsetCCA at short TWs. This characteristic of DMCCA is also noted in the number of electrodes required to achieve improved performance. To illustrate the advantage of the features extracted by DMCCA, Fig. 8 presents the power spectrum of the test signals.



(a) (b)



(c) (d)

Fig. 8. Power spectrums of test signals transformed by the reference templates extracted by DMCCA. The target frequencies are (a) 9.75, (b) 8.75, (c) 7.75 and (d) 5.75.

Compared with the traditional CCA-based method, the proposed DMCCA-based scheme can substantially improve the accuracies of SSVEP frequency recognition through a sophisticated calibration of reference signals from training data. Although DMCCA shows remarkable strength on improving the recognition performance, this method does not always prevail over other popular methods. The main limitations lie in the time-consuming training phase and artificial definition of hyper-parameters of the neural networks. Thus, the DMCCA-based method is preferred when the improvement of the performance of SSVEP-based BCI is needed. For the zero-trained SSVEP-based BCI, traditional methods can be considered in trade-off. Further works can focus on two aspects. Firstly, designing the structures of networks to search the optimal combination of the EEG signals among different trials. Secondly, classification methods can be improved since CCA cannot extract the discriminative features among different frequencies.

6. Conclusion

This study introduced a novel DMCCA model to improve the performance of SSVEP frequency recognition. The proposed method utilized NNs to learn the nonlinear representations of multiple sets of EEG signals at the same frequency by maximizing the overall correlation within the representation and constructed reference templates. In this way, these templates are augmented with such representations for frequency recognition. Results for the SSVEP signals collected from 10 subjects indicate that the DMCCA-based method effectively improves the accuracies at short TWs and is thereby regarded as a promising technique for efficient SSVEP frequency recognition.

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Appendix A: Solution of DMCCA

Let $\boldsymbol{R}=\begin{bmatrix} \boldsymbol{0} & \cdots & \boldsymbol{H}_1\boldsymbol{H}_N^T \\ \vdots & \ddots & \vdots \\ \boldsymbol{H}_N\boldsymbol{H}_1^T & \cdots & \boldsymbol{0} \end{bmatrix}$, $\boldsymbol{S}=\frac{1}{N}\begin{bmatrix} \boldsymbol{H}_1\boldsymbol{H}_1^T & \cdots & \boldsymbol{0} \\ \vdots & \ddots & \vdots \\ \boldsymbol{0} & \cdots & \boldsymbol{H}_N\boldsymbol{H}_N^T \end{bmatrix}$. The objective function in Eq. (8) is equal to Eq. (11), that is

$$\begin{aligned} &\max_{\boldsymbol{w}_1,\ldots,\boldsymbol{w}_N} \rho=\boldsymbol{w}^T\boldsymbol{R}\boldsymbol{w} \\ &s.\,t.\ \ \boldsymbol{w}^T\boldsymbol{S}\boldsymbol{w}=1 \end{aligned}, \tag{11}$$

where $\boldsymbol{w}=\left[\boldsymbol{w}_1^T,\boldsymbol{w}_2^T,\ldots,\boldsymbol{w}_N^T\right]$. By introducing the Lagrange multiplier λ, Eq. (11) can be transformed into

$$\max_{\boldsymbol{w}_1,\ldots,\boldsymbol{w}_N} \rho=\boldsymbol{w}^T\boldsymbol{R}\boldsymbol{w}-\frac{\lambda}{2}\left(\boldsymbol{w}^T\boldsymbol{S}\boldsymbol{w}-1\right). \tag{12}$$

The maximum of the object can be calculated as

$$\frac{\partial\rho}{\partial\boldsymbol{w}}=\boldsymbol{R}\boldsymbol{w}-\lambda\boldsymbol{S}\boldsymbol{w}=0. \tag{13}$$

Therefore, the following eigenvalue problem can be introduced.

$$\boldsymbol{R}\boldsymbol{w}=\lambda\boldsymbol{S}\boldsymbol{w} \tag{14}$$

Appendix B: Derivation of MCNN Gradient

The gradient of the MsetCCA layer must be calculated to train DMCCA using the backpropagation algorithm. The feedforward calculation in the MsetCCA layer is described in Eq. (8), and mini-batch is used for training. For any parameter θ in the NNs of DMCCA, $\frac{\partial\rho}{\partial\theta}$ must be calculated. First, the derivation of Eq. (11) can be computed as

$$\frac{\partial\boldsymbol{R}}{\partial\theta}\boldsymbol{w}+\boldsymbol{R}\frac{\partial\boldsymbol{w}}{\partial\theta}=\rho\boldsymbol{S}\frac{\partial\boldsymbol{w}}{\partial\theta}+\rho\frac{\partial\boldsymbol{S}}{\partial\theta}\boldsymbol{w}+\frac{\partial\rho}{\partial\theta}\boldsymbol{S}\boldsymbol{w}. \tag{15}$$

Then, collecting the terms yields

$$\left(\boldsymbol{R}-\rho\boldsymbol{S}\right)\frac{\partial\boldsymbol{w}}{\partial\theta}=-\left(\frac{\partial\boldsymbol{R}}{\partial\theta}-\rho\frac{\partial\boldsymbol{S}}{\partial\theta}\right)\boldsymbol{w}+\frac{\partial\rho}{\partial\theta}\boldsymbol{S}\boldsymbol{w}. \tag{16}$$

Multiplying $\boldsymbol{w}^T$ in both sides of Eq. (16):

$$\boldsymbol{w}^T\left(\boldsymbol{R}-\rho\boldsymbol{S}\right)\frac{\partial\boldsymbol{w}}{\partial\theta}=-\boldsymbol{w}^T\left(\frac{\partial\boldsymbol{R}}{\partial\theta}-\rho\frac{\partial\boldsymbol{S}}{\partial\theta}\right)\boldsymbol{w}+\frac{\partial\rho}{\partial\theta}\boldsymbol{w}^T\boldsymbol{S}\boldsymbol{w}. \tag{17}$$

Given the symmetry of $\boldsymbol{R}$ and $\boldsymbol{S}$,

$$\frac{\partial\rho}{\partial\theta}=\frac{1}{N}\boldsymbol{w}^T\left(\frac{\partial\boldsymbol{R}}{\partial\theta}-\rho\frac{\partial\boldsymbol{S}}{\partial\theta}\right)\boldsymbol{w}. \tag{18}$$

For any parameter $\boldsymbol{\theta}_i$ in the ith NN, $\frac{\partial\boldsymbol{R}}{\partial\boldsymbol{\theta}_i}=\frac{\partial\boldsymbol{R}}{\partial\left[\boldsymbol{H}_i\right]_{jk}}\frac{\partial\left[\boldsymbol{H}_i\right]_{jk}}{\partial\boldsymbol{\theta}_i}$ and $\frac{\partial\boldsymbol{S}}{\partial\boldsymbol{\theta}}=\frac{\partial\boldsymbol{S}}{\partial\left[\boldsymbol{H}_i\right]_{jk}}\frac{\partial\left[\boldsymbol{H}_i\right]_{jk}}{\partial\boldsymbol{\theta}_i}$ can be obtained based on the chain rule. Suppose $\boldsymbol{R}_{ab}$ indicates $\boldsymbol{H}_a\boldsymbol{H}_b^T$ in $\boldsymbol{R}$, $a\neq b$ and $\boldsymbol{S}_i$ indicates $\boldsymbol{H}_i\boldsymbol{H}_i^T$. $\frac{\partial\boldsymbol{R}}{\partial\left[\boldsymbol{H}_i\right]_{jk}}$ and $\frac{\partial\boldsymbol{S}}{\partial\left[\boldsymbol{H}_i\right]_{jk}}$ can then be calculated as follows:

$$\frac{\partial\left[\boldsymbol{R}_{ab}\right]_{mn}}{\partial\left[\boldsymbol{H}_i\right]_{jk}}=\begin{cases}\left[\boldsymbol{H}_b^T\right]_{kn}, & if\ \ m=j,a=i,b\neq i\\ \left[\boldsymbol{H}_a\right]_{mk}, & if\ \ n=j,a\neq i,b=i\\ 0, & else\end{cases} \tag{19}$$

$$\frac{\partial\left[\boldsymbol{S}_i\right]_{mn}}{\partial\left[\boldsymbol{H}_i\right]_{jk}}=\begin{cases}2\left[\boldsymbol{H}_i\right]_{jk}, & if\ \ m=j,n=j\\ \left[\boldsymbol{H}_i\right]_{nk}, & if\ \ m=j,n\neq j\\ 0, & if\ \ m\neq j\end{cases}. \tag{20}$$

The training of DMCCA can be realized because $\frac{\partial\left[\boldsymbol{H}_i\right]_{jk}}{\partial\boldsymbol{\theta}_i}$ can be computed in the traditional way.

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