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Multi-Objective Optimisation for SSVEP Detection

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***Abstract*—Data-driven spatial filtering approaches have been widely used for steady-state visual evoked potentials (SSVEPs) detection toward the brain-computer interface (BCI). The existing methods tend to learn the spatial filter parameters for a certain stimulation frequency only using the training trials from the same stimulus, which may ignore the information from the other stimuli. In this paper, we propose a novel multi-objective optimisation-based spatial filtering method for enhancing SSVEP recognition. Spatial filters are defined via maximising the correlation among the training data from the same stimulus whilst minimising the correlation from different stimuli. We collected SSVEP signals using 16 electrodes from six healthy subjects at 4 different stimulation frequencies: 14Hz, 15Hz, 16Hz, and 17Hz. The experimental study was implemented, and our method can achieve an average recognition accuracy of 94.17%, which illustrates its effectiveness.**

***Index Terms*—Brain-computer interface (BCI), electroencephalography (EEG), steady-state visual evoked potential (SSVEP), multi-objective optimisation**

I. INTRODUCTION

Electroencephalographic (EEG)-based brain-computer interface (BCI) system has been widely explored in the past years due to its many advantages, such as portability, low cost and high temporal resolution [1]. Among various typical paradigms in the EEG, steady-state visual evoked potential (SSVEP) is the most employed one for analysing brain activities because it has a high signal-to-noise ratio (SNR) and fast communication rate [2]. Recent researches in many application scenarios such as character spelling and cleaning robot [3], [4] have also indicated the importance of SSVEP-based BCI technologies.

The main task of the SSVEP-based BCI system is to identify the target stimulus, so the subject can output various commands to control the external device by focusing on different visual stimulation. Thus far, many SSVEP recognition methods learned spatial filters to reduce artifacts and noises by extracting SSVEP features. Canonical correlation analysis (CCA) is one of the most popular multivariate statistical methods [5], which attempts to find a pair of weight vectors to maximize the correlation coefficient between multi-channel EEG signals and the reference signal. The sine and cosine waves are generally used to construct the reference signal at each stimulation frequency. The frequency corresponding to the maximum correlation coefficient is determined as the target stimulation. Considering the artificial reference signal lacks real EEG components, various SSVEP detection methods used individual calibration data to further optimise it. For instance, Zhang *et al.* [6] proposed an extension version of CCA (MwayCCA) which incorporates multi-dimension of EEG tensor to construct new reference templates. They further developed L1-regularization MwayCCA to improve MwayCCA by trial-way array optimization [7]. The multi-set CCA (MsetCCA) [8] extracts common features shared by multiple sets of real EEG signals which can provide better recognition performance compared to MwayCCA and L1-MwayCCA. As a more simple operation, Bin *et al.* [9] proposed individual template canonical correlation analysis (ITCCA) that turns to employ individual template signal acquired by averaging multiple training trials. However, in the aforementioned CCA-based target detection methods, the spatial filters were yielded between the single-trial testing data and the optimised template, which may also result in low recognition performance due to lack of spatial filter training. Therefore, the latest trend is to optimise the spatial filter based on individual templates in the training stage. For example, Wei *et al.* [10] introduced a training data-driven CCA to employ the continuous training data created by concatenating training trials, and continuous template signals as the two inputs of CCA, thus the model is more robust to noise. Whereas this model did not concern the relationship among trials from the same stimulus when training spatial filters. Nakanishi *et al.* [11] proposed task-related component analysis (TRCA) based on the idea that the source activity can be efficiently reproduced through a linear sum of observed multi-channel EEG signals, and finally solved by maximizing inter-trial covariance. However, they attempted to obtain the spatial filter of a specific target by the training data only from the same stimulus, and they ignored the information from the other stimuli, which could also be used to further improve the performance of the spatial filter.

In this study, we proposed a multi-objective optimisation-based spatial filtering model to enhance the performance for SSVEP detection. It trains the spatial filter for each stimulus efficiently by maximizing the correlation between the training signal and the individual template from the same target but minimising the correlation from the other targets. The performance was evaluated on a 16-channel SSVEP dataset including four frequencies recorded from six participants. The feasibility of the proposed method was verified with an average detection accuracy of 94.17%.

The remaining paper is arranged as follows. The multi-

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objective optimisation-based target recognition methodology is described in Section II. The results are provided in Section III. Section IV and V present the discussion and conclusion.

II. Our Methods

A. EEG data collection

1) Subjects: This study collected SSVEP activities from six healthy subjects (three female and three male, mean age: twenty-six years) when they focused on four visual flickers modulated at different frequencies. All participants have normal or corrected to normal vision. Each subject has read and signed a participant consent form approved by the Research Ethics Committee of the University of Leeds.

2) Stimulus Design: The four stimulation LEDs were presented on a SSVEP box and flickered at different frequencies, 14Hz, 15Hz, 16Hz, and 17Hz, respectively. The experimental paradigm of each participant contains five blocks, and each block includes 4 trials corresponding to 4 visual stimulation. A green light is close to one of the stimuli, which indicates the target LED. In each trial, all stimuli began to flash at the same time and last for 5s in which the participant should focus on the target flicker and avoid eye movement. Following the flickering, all stimuli are blank for 5s for the subject to take a short rest to reduce visual fatigue. After four trials, there was a few seconds of a break before the next block starts.

3) EEG Recording: All experiment equipment is provided by the g.tec medical engineering GmbH. In this study, SSVEP signals were collected from 16 channels (P3, Pz, P4, P5, PO3, POz, PO4, P6, P7, PO7, O1, Oz, O2, PO8, P8, CZ), with a ground electrode over FPz and a reference electrode on the right earlobe. The g.USBamp amplifier was used to record EEG signals and sample data at 256Hz. The latency delay in the subject's visual system is taken into consideration, and the data epochs were collected in $[0.14s, (0.14+d)s]$ where d refers to the data length used for target identification. The Chebyshev Type I Infinite impulse response (IIR) filter was designed in this study to implement the band-pass filter, and the EEG signals were filtered with the band [13-40] Hz.

B. Data processing and target identification

In this study, we present a multi-objective optimisation-based model to detect the SSVEP response evoked by which visual stimulation. The single-trial individual calibration data is denoted by $\boldsymbol{\chi}_i^h \in \mathbb{R}^{N_c \times N_s}$. Hereinafter, i represents the stimulus index, h represents the index of training trials, N_c is the number of channels and N_s is the number of samples. The single-trial template signal obtained by averaging training trials is defined as $\overline{\boldsymbol{\chi}}_i = \frac{1}{N_t}\sum_{h=1}^{N_t} \boldsymbol{\chi}_i^h \in \mathbb{R}^{N_c \times N_s}$ where N_t is the number of training trials. Therefore, the continuous training signal and the continuous individual template are represented as $\boldsymbol{\chi}_i = [\boldsymbol{\chi}_i^1, \boldsymbol{\chi}_i^2, ..., \boldsymbol{\chi}_i^{N_t}] \in \mathbb{R}^{N_c \times (N_s \times N_t)}$ and $\overline{\boldsymbol{X}}_i = [\overline{\boldsymbol{\chi}}_i, \overline{\boldsymbol{\chi}}_i, ..., \overline{\boldsymbol{\chi}}_i] \in \mathbb{R}^{N_c \times (N_s \times N_t)}$, respectively. The averaged reference signal can efficiently improve the SNR of EEG signals which helps to train the spatial filter with better performance compared with the artificially constructed signal.

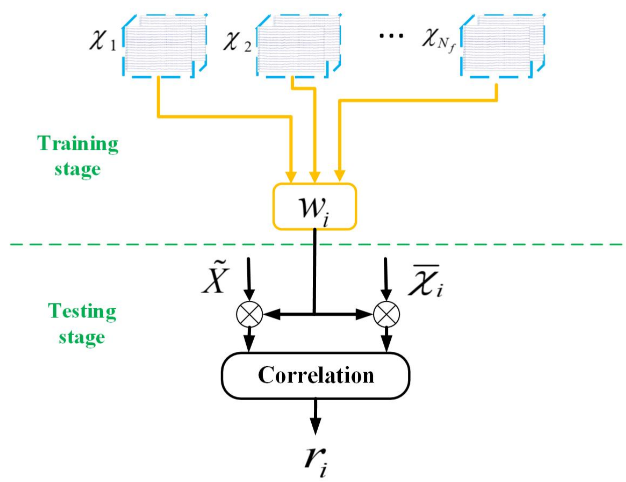

Fig. 1: Flowchart of the proposed multi-objective optimisation-based target identification method.

The multiple objectives optimisation-based spatial filtering model uses the training trials from all targets to learn each spatial filter via exploring various correlations among visual stimulation. To be specific, when the model trains the spatial filter $\hat{\boldsymbol{w}}_i$, i-th stimulus is defined as the "aim", and j-th stimulus ($j = 1, 2, .., N_f, j \neq i$) refers to the "non-aim". Here, N_f is the number of stimuli. This model provides the spatial filter $\hat{\boldsymbol{w}}_i$ by maximizing the correlation coefficient between continuous training signal $\boldsymbol{\chi}_i$ from "aim" and its continuous individual template $\overline{\boldsymbol{X}}_i$, whilst minimising the correlation between continuous training data from "non-aim" $\boldsymbol{\chi}_j$ and $\overline{\boldsymbol{X}}_i$. Therefore, N_f objective functions can be represented as:

$$
\begin{aligned}
&f_i(\boldsymbol{w}_i) = \rho(\boldsymbol{\chi}_i^{\mathsf{T}} \boldsymbol{w}_i, \overline{\boldsymbol{X}}_i^{\mathsf{T}} \boldsymbol{w}_i) \\
&f_j(\boldsymbol{w}_i) = \rho(\boldsymbol{\chi}_j^{\mathsf{T}} \boldsymbol{w}_i, \overline{\boldsymbol{X}}_i^{\mathsf{T}} \boldsymbol{w}_i),\ j = 1, 2, ..., N_f, j \neq i
\end{aligned}
\tag{1}
$$

where $\rho(\boldsymbol{a}, \boldsymbol{b})$ refers the Pearson correlation coefficient between vector $\boldsymbol{a}$ and vector $\boldsymbol{b}$. A multi-objective optimisation problem is given by the following statement:

$$
\begin{aligned}
&\underset{\boldsymbol{w}_i}{\text{minimize}}\ F(\boldsymbol{w}_i) = [-f_i(\boldsymbol{w}_i), f_j(\boldsymbol{w}_i)], \\
&\qquad\qquad j = 1, 2, ..., N_f, j \neq i \\
&\text{subject to } \boldsymbol{w}_i \in \boldsymbol{W}
\end{aligned}
\tag{2}
$$

The $\boldsymbol{W} \subseteq \mathbb{R}^{N_c}$ is the feasible set of solution vectors. The spatial filter $\hat{\boldsymbol{w}}_i$ can be solved as follow:

$$
\hat{\boldsymbol{w}}_i = \arg\min_{\boldsymbol{w}_i} F(\boldsymbol{w}_i) \tag{3}
$$

The solution $\hat{\boldsymbol{w}}_i$ need to satisfy all objective functions. The multi-objective optimisation problem is solved by the fgoalattain function in the Matlab. In the test process, for a single-trial testing EEG signal $\widetilde{\boldsymbol{X}} \in \mathbb{R}^{N_c \times N_s}$, it is spatially filtered with optimal weight vector $\hat{\boldsymbol{w}}_i$. Meanwhile, the single-trial template signal $\overline{\boldsymbol{\chi}}_i$ is also spatially filtered with $\hat{\boldsymbol{w}}_i$. The

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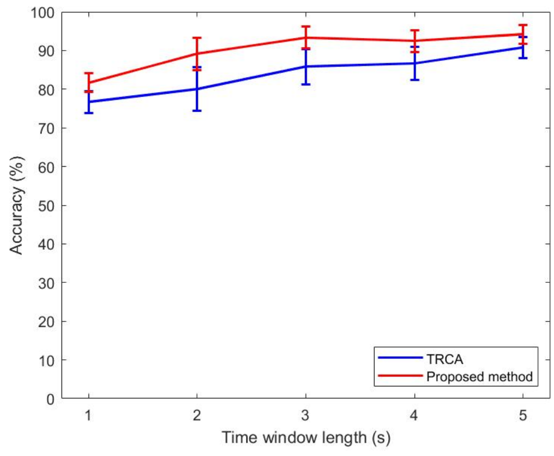

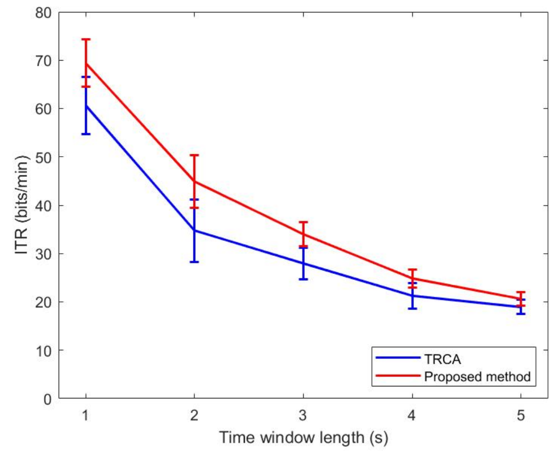

Fig. 2: Performance comparison between the proposed method and TRCA with various data lengths. (a) Average recognition accuracy, (b) ITRs across six subjects. The error bars represent standard errors.

correlation coefficient is calculated between these two vectors, and N_f coefficients can be computed in the same way as:

$$r_i = \rho(\widetilde{\boldsymbol{X}}^{\mathsf{T}}\hat{\boldsymbol{w}}_i, \overline{\boldsymbol{\chi}}_i^{\mathsf{T}}\hat{\boldsymbol{w}}_i),\ i = 1, 2, ..., N_f \tag{4}$$

The frequency of test SSVEP signal f is identified as the frequency of the template signal with the maximal correlation coefficient value:

$$f = \arg\max_{f_i} r_i, i = 1, 2, ..., N_f \tag{5}$$

The multi-objective optimisation-based model can design the spatial filter for each target which extracts more features of the same stimulus and reduce those of the other stimuli. The diagram of the proposed method is shown in Fig. 1. It is divided into two parts, namely the training stage and the testing stage. The training process aims to train the spatial filter and obtain the individual template signal for each target, and then the test process detects the current test trial belonging to which stimulus based on products of the training stage.

III. Results

To verify the effectiveness of the proposed multiple objectives optimization-based target identification method for the SSVEP-based BCI system, we compared its performance with TRCA. The TRCA extracts task-related components through maximizing the reproducibility to learn an efficient spatial filter in the training process [11]. Its test process is the same as that of the proposed algorithm. The feature extraction and target detection can use (4) and (5).

The classification accuracy and information transfer rates (ITRs) based on the same SSVEP dataset were regarded as indicators to assess their performance. The leave-one-out cross-validation was applied to compute the accuracy in which four blocks were employed as training data and one block was used as test data. Fig. 2 illustrates the averaged classification accuracy and ITRs across all subjects provided by the proposed method and the TRCA algorithm at various TWs, which range from 1s to 5s. As shown in Fig. 2, the multiple objectives optimisation-based method achieved higher accuracy and ITRs with different data lengths. Especially when the $TW = 2s$, the advantage of the proposed method is more obvious. Fig. 3 depicts the recognition accuracy for each subject with these two target recognition methods. For most subjects, the presented algorithm provided higher accuracy. In particular, Subject 4 and Subject 6 achieved 100% recognition

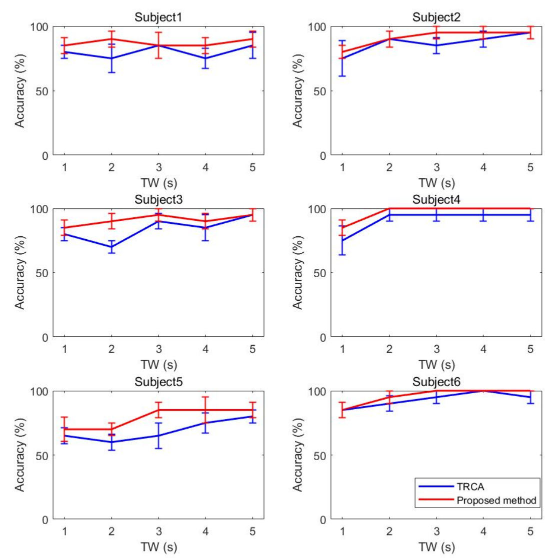

Fig. 3: SSVEP recognition accuracy derived by the TRCA and multi-objective optimisation-based target identification method for each subjects. The error bars indicate standard errors.

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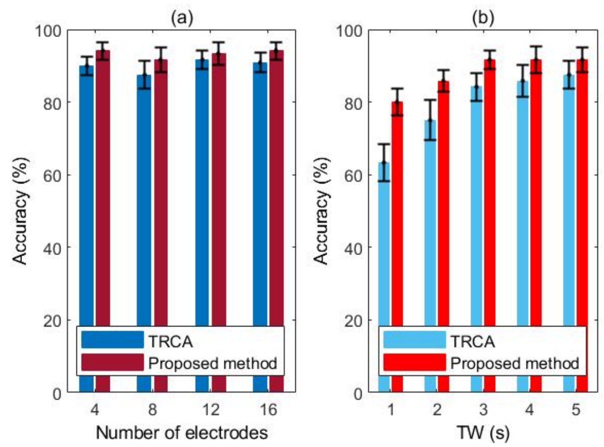

Fig. 4: Averaged detection accuracy with (a) different numbers of electrodes with 5s TW. (b) 8 channels with 1s-5s data lengths across subjects. The error bars indicate standard errors.

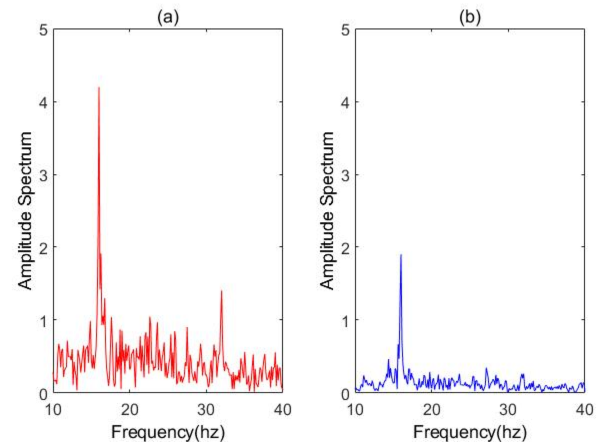

Fig. 5: Single-sided amplitude spectrum of the test signal transformed by spatial filters trained by (a) the proposed model and (b) TRCA. The target frequency is 16Hz.

accuracy with some TWs.

IV. Discussion

A. Parameter optimisation

Fig. 4 (a) shows the classification accuracy across subjects with different number of channels using 5s data length (C=4, 8, 12 and 16). Although some confidence intervals appear to overlap, the proposed method still shows comparable accuracy with regard to the TRCA at each number of channels, which demonstrates that spatial filters yielded by training signals from entire stimuli have potential in target identification. Fig. 4 (b) depicts the averaged accuracy of these methods with 8 electrodes with 1s-5s data lengths. The presented spatial filtering method achieved higher accuracy regardless of TWs, which further confirms that its effectiveness does not depend on the number of electrodes.

B. Spectral analysis

In our study, the multi-objective optimisation-based model focuses on training the spatial filter to extract distinct features of the SSVEP signal. As an example, Fig. 5 (a) and (b) illustrate the amplitude spectrum of the filtered SSVEP signals provided by the presented method and TRCA in response to 16Hz. Fig. 5 (a) shows the superiority of the spatial filter learned from the proposed model which provides a higher amplitude of target frequency. Besides, it captured more harmonic features from filtered test data compared with Fig. 5 (b). The extracted characteristic contributes to identifying the target more effectively.

V. Conclusion

A novel multiple objectives optimisation-based spatial filtering method was proposed to improve the recognition performance for the SSVEP-based BCI system. The presented algorithm used the training data from all visual stimulation to learn the spatial filter for each target by setting multiple objectives functions. Experimental results on four frequencies' SSVEP dataset collected from six healthy participants verified its effectiveness with various data lengths. This work provides a potential and practical direction for the implementation of SSVEP-based BCIs. Future work will apply relatively large dataset and explore more forms of the multi-objective optimisation model in the SSVEP field.

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