Cross Domain Correlation Maximization for Enhancing the Target Recognition of SSVEP-Based Brain–Computer Interfaces

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***Abstract*— The target recognition performance of steady-state visual evoked potential (SSVEP)-based brain-computer interfaces can be significantly improved with a training-based approach. However, the training procedure is time consuming and often causes fatigue. Consequently, the number of training data should be limited, which may reduce the classification performance. Thus, how to improve classification accuracy without increasing the training time is crucial to SSVEP-based BCI system. This study proposes a transfer-related component analysis (TransRCA) method for addressing the above issue. In this method, the SSVEP-related components are extracted from a small number of training data of the current individual and combined with those extracted from a large number of existing training data of other individuals. The TransRCA method maximizes not only the inter-trial covariances between the source and target subjects, but also the correlation between the reference signals and SSVEP signals from the source and target subjects. The proposed method was validated on the SSVEP public Benchmark and BETA datasets, and the classification accuracy and information transmission rate of the ensemble version of the proposed TransRCA method were compared with those of the state-of-the-art eCCA, eTRCA, ttCCA, LSTeTRCA, and eIISMC methods on both datasets. The comparison results indicate that the proposed method provides a superior performance compared with these state-of-the-art methods, and thus has high potential for the development of a SSVEP-based brain-computer interface system with high classification performance that only uses a small number of training data.**

***Index Terms*— Brain–computer interface, steady-state visual evoked potentials, transfer learning, spatial filter.**

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I. Introduction

A BRAIN-COMPUTER interface (BCI) is a communication channel that allows users to control external devices based on brain signals without using conventional peripheral nerve and muscle pathways [1]. BCIs are widely used to help individuals with disabilities convey their intentions to external devices in various applications, such as controlling a wheelchair, manipulating a robot arm, moving a mouse cursor, and typing characters with a speller [2]. Among them, spelling alphanumeric characters is the most convenient, direct, and informative way of communication for disabled people [3].

Most conventional non-invasive BCI spellers are based on electroencephalogram (EEG) signals such as motor imagery, the P300 component, and steady-state visual evoked potentials (SSVEPs) [3]. SSVEPs are both time- and phase-locked responses of the visual nervous system induced by visual stimulation with stationary periodic oscillations [4]. In SSVEP based spellers, each character flashes at a unique frequency (SSVEP stimulation). Thus, a fixation on each target character will induce a unique corresponding SSVEP. Through the identification of SSVEPs, the BCI system can recognize and output the target character at which the user is gazing. SSVEP-based BCIs have been attracting much attention because of their multi-command output, high classification accuracy, and high information transmission rate (ITR) [5].

The target recognition algorithm is the core technology in SSVEP-based BCIs. According to whether the training (calibration) data are available, these target recognition algorithms can be divided into two principal categories, i.e., training-free and training-based methods [6]. The training-free method

can realize plug-and-play operation without the need for training procedures in advance. In the training-free approach, spatial filtering methods such as minimum energy combination (MEC) [7], canonical correlation analysis (CCA) [8], and filter bank CCA (FBCCA) [9] are used to filter out the noisy signals to improve the signal-to-noise ratio of the SSVEPs. Basically, such training-free methods use an artificial SSVEP model composed of a series of sine and cosine signals to detect SSVEPs.

Recent studies have shown that, compared with artificial SSVEP models, an individualized SSVEP model obtained from a training procedure can better represent individual-specific SSVEPs and are more robust to noise or non-stationary signals, thereby significantly improving classification performance [10], [11]. Some of the latest training-based identification methods, such as extended CCA (eCCA) [12], task-related component analysis (TRCA) [13] and ensemble TRCA (eTRCA) [14], can achieve substantially higher recognition performance than training-free methods. By contrast, if the training data are insufficient, their performance will deteriorate significantly [14]. Thus, a training-based method needs a large number of training data obtained in advance. In addition, this training procedure is susceptible to changes in the environment and electrode placement, and the data must be re-collected before each use, which is time consuming and becomes an additional burden in practical use. Therefore, for a practical SSVEP-based BCI, a more efficient learning strategy based on a small number of training data would be desirable [1].

Transfer learning is a powerful machine learning technique used to reduce the time of repetition in the training procedure. It can transfer labeled data from distinct trials/subjects/tasks/devices, referred to as the source domains, to the current ones, referred to as the target domains [15]. According to the original definition of SSVEPs, the amplitude and phase of the oscillation components caused by visual stimulus remain unchanged over a long duration [16]. Although the SSVEPs of different subjects may differ, the spectral distribution characteristics of the discrete frequency components induced by the same SSVEP stimulus should be similar. If such general and essential characteristics of the SSVEPs of source subjects (a set of selected subjects whose data were used as training data, hereafter abbreviated as SS) can be fully learned and transferred to the target subject (the current subject whose data will be identified, hereafter abbreviated as TS), the detector can achieve high performance at a low training cost.

As a benchmark target recognition algorithm for SSVEPs, CCA is a multi-variable statistical method used to analyze the correlation relationship between two sets of variables. The basic principle of CCA used to detect SSVEPs is as follows: A pair of spatial filters are used to filter the multi-channel SSVEP signals and reference signals (a series of sine-cosine signals reflecting the fundamental and harmonic oscillation characteristics of the SSVEPs) separately to obtain a pair of linear combinations (canonical variables). The correlation between these two canonical variables indicates the overall relevance relationship between the original two sets of linear combinations, thus extracting the frequency components of the SSVEPs [17]. The CCA method optimizes the spatial filter by maximizing the correlation between the pair of canonical variables, i.e., the correlation between the SSVEP signals and reference signals [6]. Some extensions of the standard CCA have been proposed to improve performance, such as the L1-regularized multi-way CCA (L1-MCCA) [18], individual template-based CCA (IT-CCA) [19], multiset CCA (MsetCCA) [20], filter bank CCA (FBCCA) [9], and eCCA [12]. Although these extensions of the CCA method optimize the sine-cosine references or subject-specific references, the essence is still the optimization of the spatial filter by maximizing the correlation between the SSVEP signals and reference signals. However, in this optimization, only the average value of the sample not the entire sample distribution is considered.

Another benchmark target recognition algorithm for SSVEPs is the TRCA method, which learns the spatial filter that reduces the background EEG interference by maximizing the inter-trial covariance [13], [14]. In this approach, it is assumed that the neuroimaging data obtained during the execution of a task is composed of some specific task-related components (e.g., the hemodynamic responses of SSVEPs) and task-unrelated components (interference signals such as head motion artifacts) [21]. On the basis of this consideration, TRCA presumes that the signals that consistently and steadily appear in each task trial can be regarded as the components related to the task [13]. By maximizing the sum of the covariance between task trials, the consistent activities across trials can be enhanced and extracted as the task-related components [14]. Although some extensions of TRCA methods, such as ensemble TRCA (eTRCA) [14] and group TRCA (gTRCA) [22] have been proposed, the essence of maximizing the sum of the covariance between task trials remains unchanged, but the correlation between the SSVEP signals and the reference signals is not considered. Moreover, the optimization objective of TRCA is only allowed one spatial filter, which restricts its usability among different types of data.

Recently, some cross-subject methods have been proposed to use the knowledge from other subjects. Considering that the SSVEP features of different subjects are similar, Yuan et al. proposed the transfer template-based CCA (ttCCA) method [23], in which the source templates are obtained by averaging multiple trials from the existing SS and then using CCA to calculate the correlation coefficient with the test data of the current TS. Chiang et al. proposed the LST-TRCA method, which uses least-squares transformation (LST)-based transfer learning to transform the trials of the SS so that they are more similar to those of the TS, and combines them into a training set for TRCA training [24]. Wang et al. proposed the inter- and intra-subject correlation (IISMC) method [25], in which the subject-specific information and SSVEP task-related information are simultaneously obtained by maximizing the intra- and inter-subject correlations. Although these methods transfer cross-subject knowledge to improve the classification performance, they are still based on CCA and TRCA, the transfer ability of these methods is restricted by the limitations of the CCA and TRCA methods.

In response to the small number of training data available in practical BCI applications, this study aimed to enhance the detection of SSVEPs by combining the subject-specific SSVEP characteristics and SSVEP characteristics transferred from other subjects. Inspired by the CCA and TRCA methods, the transfer-related component analysis (TransRCA) method is proposed in this study, which maximizes the inter-trial covariances between the SS and TS. TransRCA also maximizes the correlation between the reference signals and SSVEP signals from both the SS and TS. Based on this strategy, the TransRCA method combines the advantages of both CCA and TRCA, in which both the frequency components and the task-related components can be extracted; thus, although it only relies on a small number of training data, it can still obtain fair recognition performance for BCI applications.

II. Methods and Materials

This study was carried out in accordance with the Declaration of Helsinki and approved by the ethics committee of the Affiliated Zhongda Hospital of Southeast University (No. 2016ZDSYLL002-Y01).

A. SSVEP Dataset

To evaluate the TransRCA method, the classification performance was tested on the SSVEP Benchmark datasets [26], [27]. The details of these two datasets are described as follows:

1) Benchmark Dataset: Wang et al. [26] published the Benchmark dataset in 2017. This dataset was recorded from 35 healthy subjects (17 female and 18 male subjects with an average age of 22 years) with normal or corrected-to-normal vision. The SSVEP data were recorded based on a 40-target BCI speller (consisting of five rows and eight columns of characters, including 26 English letters, ten digits, and four symbols). The 40 characters were coded using a joint frequency and phase modulation method [28], where the frequency ranges from 8 to 15.8 Hz in interval of 0.2 Hz, and the phase ranges from 0 to 1.5π in intervals of 0.5π. For each subject, the experiment consisted of six blocks, and each block contained 40 trials corresponding to all 40 characters displayed once in random order. Therefore, each character had six trials (we define the number of trials for each target as N_t, where $N_t = 6$) and thus 240 trials of data were recorded for each subject's data set. Each trial started with a 0.5-s visual cue, prompting the users to shift their eyes to the target character (i.e., the SSVEP target) as soon as possible. After the cue, all SSVEP stimuli flicker simultaneously for a 5-s duration. Then, the screen was blank for 0.5 s to enable the subject to rest before the next trial.

The whole-head EEG data were recorded using a Synamps2 EEG system (Neuroscan, Inc.) at a sampling rate of 1000 Hz with the bandwidth range of 0.15–200 Hz according to the international extended 10-20 system, and the reference electrode was placed at Cz. Electrode impedances were kept below 10 KΩ during recording. A notch filter of 50 Hz was applied to remove the power-line noise during recording and all data were downsampled to 250 Hz. In this study, nine-channel EEG data over the occipital region (Pz, PO5, PO3, POz, PO4, PO6, O1, Oz, and O2) and the data during [0.14 s, 0.14+d s] were selected as the SSVEP signals, where d is the data length used in the analysis. Adding a latency of 0.14 s in the SSVEP data analysis was recommended by the dataset creators [26].

2) BETA Dataset: Liu et al. [27] published the BETA dataset in 2020. This dataset was recorded from 70 healthy subjects (28 female and 42 male subjects with an average age of 25.14 years). Like the Benchmark dataset, the BETA dataset was also based on a 40-target BCI speller and was coded using a joint frequency and phase modulation method as described in the above Benchmark dataset. For each subject, the experiment consisted of four blocks, and each block contained 40 trials corresponding to all 40 characters displayed once in random order. Therefore, each character had four trials ($N_t = 4$) and thus 160 trials of data were recorded for each subject's data set. As for the Benchmark dataset, each trial started with a 0.5-s visual cue. After the cue, all SSVEP stimuli flickered simultaneously for a 2-s duration for the first 15 subjects and a 5-s duration for the remaining 55 subjects. After the flicking duration, there was a 0.5 s duration so that the subject could rest.

The EEG data acquisition for BETA dataset was exactly the same as the Benchmark dataset that is described above. In this study, the preprocessing used for the Benchmark dataset was also used for the BETA dataset. A notch filter of 50 Hz was applied to remove the power-line noise during recording and all data were downsampled to 250 Hz. The same nine-channel EEG data over the occipital region (Pz, PO5, PO3, POz, PO4, PO6, O1, Oz, and O2) and the data of [0.13 s, 0.13+d s] as for the above Benchmark dataset were selected as the SSVEP signals. Adding a latency of 0.13 s in SSVEP data analysis was recommended by the dataset creator [27].

B. CCA and eCCA

Standard CCA is a multi-variable statistical method that can maximize the correlation between two sets of data. Recently, it has been used as a benchmark training-free recognition algorithm for SSVEP-based BCIs [6]. By finding a pair of spatial filters w_X and w_{Y_n}, CCA can maximize the correlation between $x = X^T w_X$ and $y_n = Y_n^T w_{Y_n}$ using the following formula:

$$\begin{aligned}\max_{w_X, w_{Y_n}} \rho_n(x, y_n) &= \frac{E\left[x^T y_n\right]}{\sqrt{E\left[x^T x\right] E\left[y_n^T y_n\right]}} \\ &= \frac{E\left[w_X^T X Y_n^T w_{Y_n}\right]}{\sqrt{E\left[w_X^T X X^T w_X\right] E\left[w_{Y_n}^T Y_n Y_n^T w_{Y_n}\right]}}\end{aligned} \tag{1}$$

where X denotes the single trial multi-channel SSVEP signals and Y_n denotes the reference signals corresponding to the n-th SSVEP stimulus, which is constructed of a series of sine and cosine signals. The SSVEP target can be obtained by selecting the maximal correlation coefficients as follows:

$$f_t = \max_n \rho_n, \quad n = 1, 2, \ldots, N_f \tag{2}$$

where N_f denotes the number of SSVEP targets.

Chen et al. proposed the eCCA method [12], in which, in addition to the canonical correlation between the test data and the sine-cosine reference signals, the canonical correlation between the test data and the individual training data were also calculated. Thus, essentially, eCCA is a training-based method developed from the training-free standard CCA method. The eCCA method is considered to have a classification performance that is superior to that of the standard CCA and the other extensions of standard CCA methods [10].

C. TRCA

As a benchmark training-based method, TRCA was introduced by Tanaka et al. to extract the task-related components by maximizing the reproducibility of the data over task trials [13]. The objective for the task-related component extraction can be achieved by maximizing the inter-trial covariance, while the maximization of the sum of the covariance can be simplified as the following Rayleigh–Ritz eigenvalue problem:

$$\widehat{w} = \underset{w}{\operatorname{argmax}} \frac{w^T S w}{w^T Q w} \tag{3}$$

where $\widehat{w}$ is the desired spatial filter for maximizing the reproducibility of the SSVEP features. The symmetric matrix S can be obtained as the sum of the covariance of all possible combinations of different task trials. Moreover, the symmetric matrix Q indicates the sum of the variances of each task trial. According to the Rayleigh–Ritz theorem, $\widehat{w}$ can be obtained as the eigenvectors of the matrix $Q^{-1}S$. The eigenvalues λ of $Q^{-1}S$, when arranged in a descending order, indicate the task consistency among task trials. If the signals contain no task-related components but only random variation, then the corresponding eigenvalues will be limited to small values [13].

In the application of SSVEP-based BCIs, TRCA is usually used as a spatial filter to eliminate the background activity embedded in the EEG data. Using the individual training data X_n of the n-th SSVEP stimulus, the corresponding spatial filter w_n can be obtained through TRCA. Once the spatial filter w_n is obtained, both the single trial test data X and the averaged training data for the n-th SSVEP stimulus $\overline{X}_n$ are filtered with w_n. Then, the target detection score can be calculated using Pearson's correlation coefficients as

$$r_n = \rho\left(X^T w_n,\ \overline{X}_n{}^T w_n\right) \tag{4}$$

where $\rho()$ is the Pearson's correlation calculation of two signals. Based on the detection scores corresponding to all SSVEP stimulus frequencies, the SSVEP target can be obtained as

$$f_t = \max_n r_n, \quad n = 1, 2, \ldots, N_f \tag{5}$$

D. TransRCA

In this study, we propose the TransRCA method, which combines the advantages of TRCA and CCA and maximizes the mean of the covariance between the trials from the SS and TS, as well as maximizing the mean of the covariance between the reference signals and training data from the SS trials and TS trials separately. Let the h-th trial of the SSVEP data of the SS and TS be described as $X_{SS,h}$, $h = 1, 2, \ldots, N_s$ and $X_{TS,h}$, $h = 1, 2, \ldots, N_t$. We define $C_{hs,ht}$ as the covariance between the hs-th trial of the SS and the ht-th trial of the TS. Then, $C_{hs,hs}$ and $C_{ht,ht}$ are the variances of each single trial of the SS and TS, respectively, expressed as

$$C_{hs,ht} = \mathrm{COV}\left(X_{SS,hs},\ X_{TS,ht}\right) \tag{6}$$

$$C_{hs,hs} = \mathrm{COV}\left(X_{SS,hs},\ X_{SS,hs}\right) \tag{7}$$

$$C_{ht,ht} = \mathrm{COV}\left(X_{TS,ht},\ X_{TS,ht}\right) \tag{8}$$

The mean of $C_{hs,ht}$, $C_{hs,hs}$, and $C_{ht,ht}$ under all possible combinations of trials is obtained as follows:

$$\begin{aligned} S_{SS,TS} = S_{TS,SS} &= \frac{1}{N_s N_t} \sum_{hs=1}^{N_s} \sum_{ht=1}^{N_t} C_{hs,ht} \\ &= \frac{1}{N_s N_t} \sum_{hs=1}^{N_s} \sum_{ht=1}^{N_t} \mathrm{COV}\left(X_{SS,hs},\ X_{TS,ht}\right) \end{aligned} \tag{9}$$

$$\begin{aligned} S_{SS} &= \frac{1}{N_s} \sum_{hs1,hs2=1}^{N_s} C_{hs1,hs2} \\ &= \frac{1}{N_s} \sum_{hs1,hs2=1}^{N_s} \mathrm{COV}\left(X_{SS,hs1},\ X_{SS,hs2}\right) \end{aligned} \tag{10}$$

$$\begin{aligned} S_{TS} &= \frac{1}{N_t} \sum_{ht1,ht2=1}^{N_t} C_{ht1,ht2} \\ &= \frac{1}{N_t} \sum_{ht1,ht2=1}^{N_t} \mathrm{COV}\left(X_{TS,ht1},\ X_{TS,ht2}\right) \end{aligned} \tag{11}$$

The desired pair of spatial filters $\widehat{w_{tar}}$ and $\widehat{w_{src}}$ of TransRCA can be constrained by solving the optimization problem as follows:

$$\left(\widehat{w_{tar}},\ \widehat{w_{src}}\right) = \underset{w_{tar}, w_{src}}{\operatorname{argmax}} \frac{w_{tar}^T S_{TS,SS} w_{src}}{\sqrt{w_{tar}^T S_{TS} w_{tar}} \sqrt{w_{src}^T S_{SS} w_{src}}} \tag{12}$$

The above equation can be treated as a generalized eigendecomposition problem. Hence, w_{tar} and w_{src} can be obtained as the eigenvalues corresponding to the eigenvectors of the matrices $S_{TS}^{-1} S_{TS,SS} S_{SS}^{-1} S_{SS,TS}$ and $S_{SS}^{-1} S_{SS,TS} S_{TS}^{-1} S_{TS,SS}$, respectively.

Fig. 1 and Supplementary Fig. 1 presents the flowchart of SSVEP target identification using the proposed TransRCA method. For the n-th SSVEP stimulus, X denotes the test data of single trial of TS; $\overline{X}_{tar,n}$ denotes the target templates, which can be obtained by averaging the training set $X_{tar,n}$ from the TS; $X_{src,j,n}$ denotes all the trials of the j-th subject in the source domain; $X_{src,n}$ is formed by concatenating all the $X_{src,j,n}$ of all subjects together in the trial dimension; $\overline{X}_{src,n}$ denotes the average template formed by averaging all the $X_{src,n}$ in the trial dimension; Y_n denotes the sine-cosine reference signals. We define w_X and w_Y as the CCA-based spatial filters obtained from X and Y_n; $w_{tar\_ref,n}$ and $w_{ref\_tar,n}$ are the TransRCA-based spatial filters obtained from $X_{tar,n}$ and Y_n; $w_{src\_ref,n}$ and $w_{ref\_src,n}$ are the TransRCA-based spatial filters obtained from $X_{src,n}$ and Y_n; and $w_{tar\_src,n}$ and

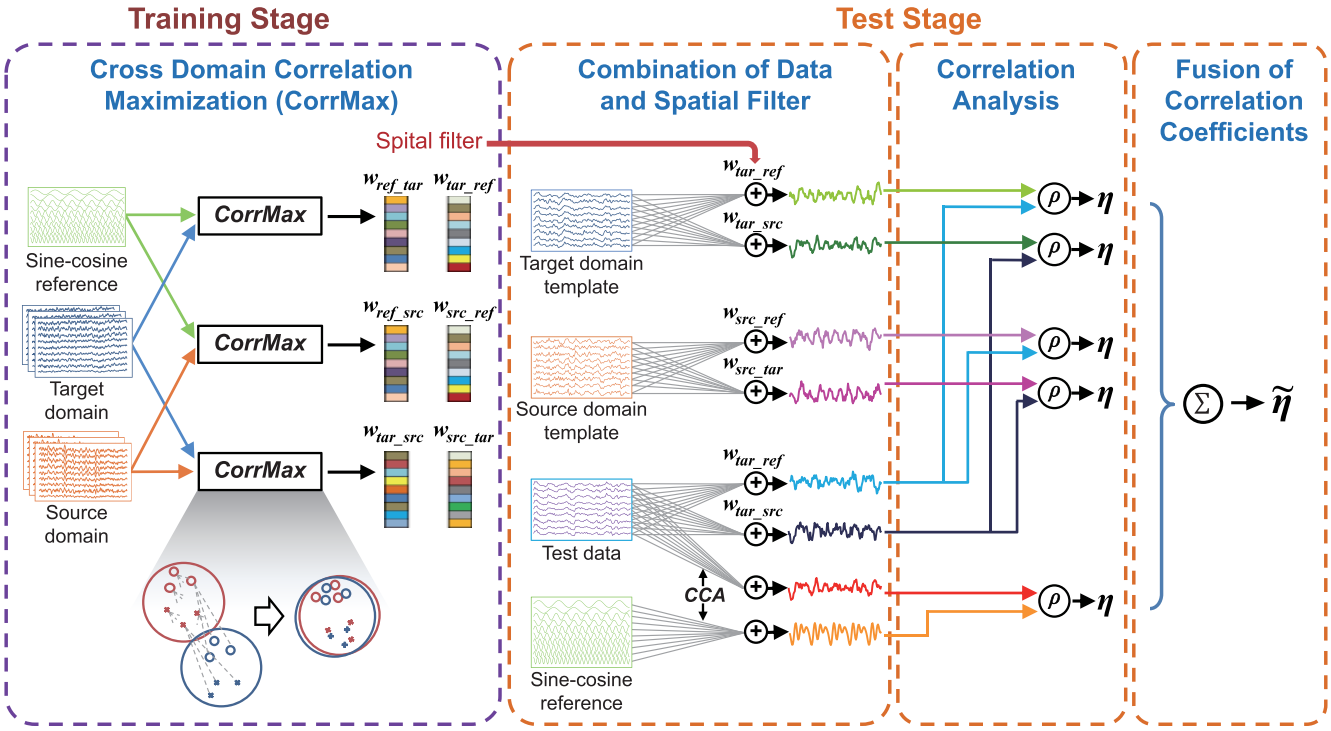

Fig. 1. Diagram of the proposed TransRCA method. w_{tar_ref} and w_{ref_tar} are the TransRCA-based spatial filters obtained from target domain and sine-cosine reference; w_{src_ref} and w_{ref_src} are the TransRCA-based spatial filters obtained from source domain and sine-cosine reference; w_{tar_src} and w_{src_tar} are the TransRCA-based spatial filters obtained from target domain and source domain; ρ and η represent Pearson's correlation calculation and correlation coefficient, respectively.

$w_{src\_tar,n}$ are the TransRCA-based spatial filters obtained from $X_{tar,n}$ and $X_{src,n}$. The whole procedure consists of training and test stages: in the training stage, the TransRCA-based spatial filters from i) $X_{src,n}$ and Y_n, ii) $X_{tar,n}$ and Y_n, and iii) $X_{src,n}$ and $X_{tar,n}$, are each calculated. In the test stage, five correlation coefficients, i.e., i) the canonical correlation of X and Y_n, and four different types of Pearson's correlation coefficients between the projected signals of ii) $X^T w_{tar\_ref,n}$ and $\overline{X}^T_{tar,n} w_{tar\_ref,n}$, iii) $X^T w_{tar\_ref,n}$ and $\overline{X}^T_{src,n} w_{src\_ref,n}$, iv) $X^T w_{tar\_src,n}$ and $\overline{X}^T_{tar,n} w_{tar\_src,n}$, and v) $X^T w_{tar\_src,n}$ and $\overline{X}^T_{src,n} w_{src\_tar,n}$ are each calculated as η_n. According to previous studies, the classification features based on an ensemble of multiple correlation coefficients perform better than those based on a single correlation coefficient [25], [29], [30]. Thus, for the n-th SSVEP stimulus, the following ensemble correlation vector η_n, which combines the five correlation coefficients η_n obtained in the test stage, is used in this study:

$$\begin{aligned}\eta_n &= [\eta_n(1), \eta_n(2), \eta_n(3), \eta_n(4), \eta_n(5)]^T \\ &= \begin{bmatrix} \rho\left(X^T w_X(X, Y_n), Y_n w_Y(X, Y_n)\right) \\ \rho\left(X^T w_{tar\_ref,n}, \overline{X}^T_{tar,n} w_{tar\_ref,n}\right) \\ \rho\left(X^T w_{tar\_ref,n}, \overline{X}^T_{src,n} w_{src\_ref,n}\right) \\ \rho\left(X^T w_{tar\_src,n}, \overline{X}^T_{tar,n} w_{tar\_src,n}\right) \\ \rho\left(X^T w_{tar\_src,n}, \overline{X}^T_{src,n} w_{src\_tar,n}\right) \end{bmatrix} \end{aligned} \tag{13}$$

The correlation coefficients are fused to form the detection scores corresponding to all SSVEP stimuli as follows:

$$\widetilde{\eta}_n = \sum_{i=1}^{5} \eta_n(i) \tag{14}$$

Finally, the SSVEP target can be identified using

$$f_t = \max_n \widetilde{\eta}_n, \quad n = 1, 2, \ldots, N_f \tag{15}$$

Because our proposed TransRCA method contains the essence of both CCA and TRCA methods and has certain similarities with the IISMC method, these three methods were used as the control methods to evaluate the SSVEP decoding performance using our proposed TransRCA method. In addition, ttCCA and LST-eTRCA were used as control methods because they are advanced cross-subject transfer learning methods. Moreover, because an ensemble method yields better performance, ensemble versions of the above-mentioned methods (if they exist) were used in this study. Thus, five control methods, i.e., the eCCA, eTRCA, ttCCA, LST-eTRCA, and eIISMC methods, were compared with the proposed eTransRCA method.

E. Data Splitting and Filtering Schemes

The data splitting schemes used for the proposed TransRCA method and the other cross-subject control methods (i.e., ttCCA, LST-eTRCA, and eIISMC) are the same, i.e., both datasets were subdivided into TS and SS groups, where, for

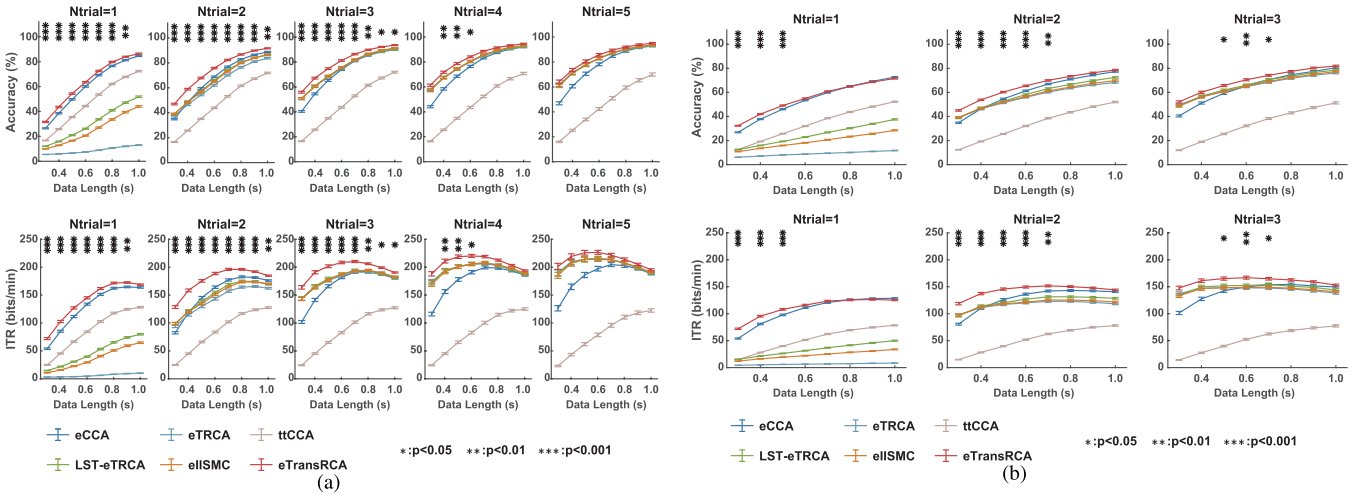

Fig. 2. Comparison of the classification accuracy and ITR results under different numbers of training data in the target domain and data lengths for the (a) Benchmark dataset and (b) BETA dataset. N_{trial} denotes the number of training trials in the target domain, the asterisk indicates that the accuracy of the TransRCA method is significantly better than that of the control methods (one-way analysis of variance and Bonferroni multiple comparisons test, where *, **, and *** indicate statistical significance at $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively), and the error bar represents the standard error.

the Benchmark dataset, one subject is the TS and 34 subjects are the SS, and for the BETA dataset, one subject is the TS and 69 subjects are the SS. The data were divided into training and test sets using a leave-p-out (LPO) cross validation method [31]. In this LPO method, the training set consists of two parts: i) the training set of TS, which is from the $N_{train} = 1, 2, \ldots, N_t - 1$ randomly selected trials of the TS ($N_t = 6$ for the Benchmark dataset and $N_t = 4$ for the BETA dataset); ii) the training set of the SS, which is composed of N_{ss} subjects randomly selected from the SS group. The training and test time required for different N_{ss} were investigated (see Supplementary Fig. 2) and it was found that the training and test time increase sharply after $N_{ss} = 10$ for both datasets. Because a practical model should find a good tradeoff between computational cost and efficiency [25], [32], N_{ss} was set to 10 in this study. By contrast, the test set consists of the $N_{test} = N_t - N_{train}$ trials of the TS. This process was repeated 10 times and the averaged classification results of these 10 times were calculated as the result for one TS.

In this study, to extract the independent frequency information embedded in the harmonic components, a five sub-band filter bank [9] (i.e., 8*n—90 Hz, $n \in [1, 5]$, type I Chebyshev IIR digital filter with high pass on the passband/stopband = [6/4, 14/10, 22/16, 30/24, 38/32 Hz], low pass on the passband/stopband = [90/100 Hz], passband ripple = 1 dB, stopband attenuation=20 dB, and peak-to-peak passband ripple = 0.5 dB) was performed for all the target recognition methods as data preprocessing.

F. ITR

The ITR is an important index for evaluating target recognition methods [33]. The ITRs under different numbers of training trials in the target domain corresponding to different target recognition methods were calculated using the following formula, proposed in [34] and [35]:

$$ITR = \frac{\log_2 C + P\log_2 P + (1-P)\log_2(\frac{1-P}{C-1})}{T/60} \quad (16)$$

where C is the number of targets for selection, P is the classification accuracy, and T is the time required to output a target selection in each trial. The calculation times of the SSVEP target recognition methods used in this study are all very short (<50 ms, calculated by a 3.5 GHz 8 core/16 threads, i9 11900k CPU with 64 GB RAM and MATLAB 2021a); hence, T can be approximated as the sum of the visual cue period (including the gaze shifting time) and the SSVEP observation duration.

III. Results

During transfer learning, the number of training trials in the target domain will affect the classification performance of the target recognition method. In addition, the time required for target identification will also affect the classification performance. Thus, a comparison of the classification accuracy and ITR under different numbers of training trials in the target domain and different data length corresponding to different target recognition methods for the Benchmark dataset and BETA dataset are shown in Fig. 2, where the upper row represents classification accuracy, and the lower row represents ITR results. In addition, the asterisks in the figure indicate that the classification accuracy and ITR of the TransRCA method are significantly better than that of the control methods (one-way analysis of variance and Bonferroni multiple comparisons test, where *, **, and *** indicate statistical significance at $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively). According to Fig. 2, the classification accuracy increases with increases in data length. The proposed TransRCA method obtained a significantly higher accuracy than the other methods under most conditions. In addition, the highest ITRs for most

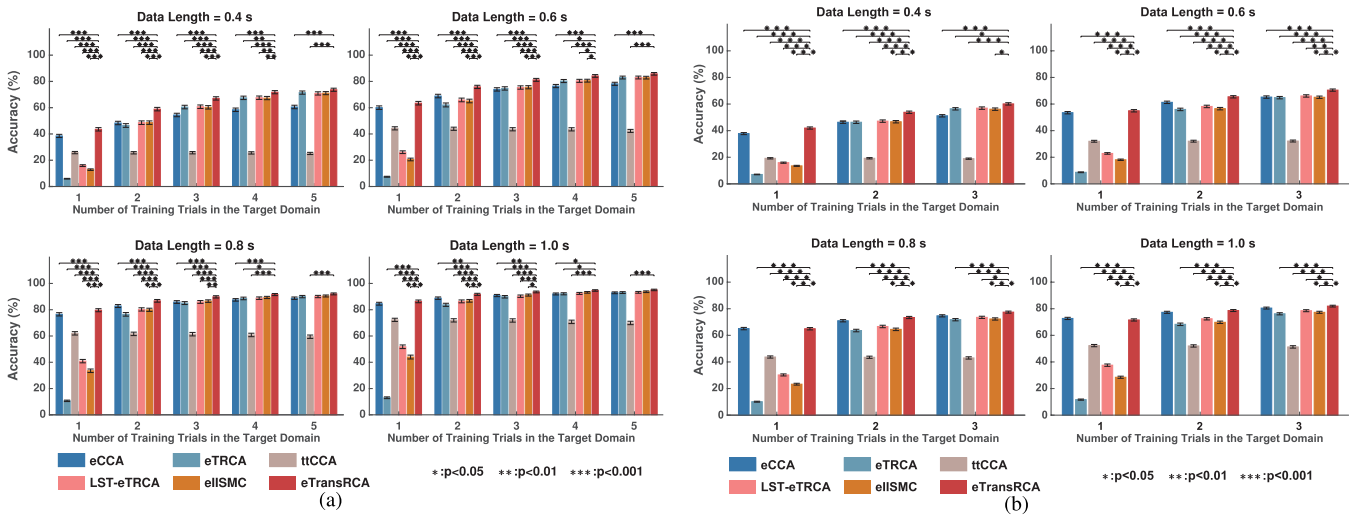

Fig. 3. Comparison of the classification accuracy results under different numbers of training trials in the target domain and data lengths for the (a) Benchmark dataset and (b) BETA dataset. The asterisk indicates that the accuracy of the TransRCA method is significantly better than that of the control methods (one-way analysis of variance and Bonferroni multiple comparisons test, where *, **, and *** indicate statistical significance at $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively), and the error bar represents the standard error.

cases were obtained with medium data lengths. As it did for accuracy, the proposed TransRCA method obtained ITRs that were significantly higher than the other methods under most conditions. In general, a data length of 0.6 s consistently obtains the best or second best ITR values for the top three training trial conditions (three, four, and five trials), outranking the results of other methods when the aggregated ranks of all three conditions are considered.

According to Fig. 2.a, it is obvious that the classification accuracy increases as the number of training trials in the target domain increases. However, under all five training trial conditions and for all six target recognition methods, the classification accuracy increases with increases in data length. In addition, the accuracies of proposed TransRCA method significantly outperformed the five other control methods under most conditions for the Benchmark dataset. Similar trends have also been found for the BETA database (Fig. 2.b), and it was also found that the proposed TransRCA method obtained the highest accuracy under most conditions.

Further statistical analysis was performed on the averaged classification accuracy for different target recognition methods under different numbers of training trials in the target domain for the Benchmark and BETA datasets at different data length. The results are shown in Fig. 3. The asterisk indicates that the accuracy of the TransRCA method is significantly better than that of control methods (one-way analysis of variance and Bonferroni multiple comparisons test, where *, **, and *** indicate statistical significance at $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively). It was found that, in general, the classification accuracy tends to decrease in the order of eTransRCA>LST-eTRCA>eIISMC>eTRCA>eCCA>ttCCA for all data length conditions. Our proposed eTransRCA has an averaged classification accuracy that is higher than those of all other methods. To compare the classification accuracy of various methods in more detail, the classification accuracies under different numbers of training trials when the data length is 0.6 s for both the Benchmark and BETA datasets are shown in Tables I and II, respectively.

TABLE I
CLASSIFICATION ACCURACY UNDER DIFFERENT NUMBERS OF TRAINING TRIALS WHEN THE DATA LENGTH IS 0.6 FOR THE BENCHMARK DATASET

N_{train}	eCCA	eTRCA	ttCCA	LST-eTRCA	eIISMC	eTransRCA
1	60.02	7.43	44.29	26.12	20.58	63.42
2	68.87	62.10	43.96	65.90	65.11	75.83
3	73.93	74.66	43.58	75.36	75.57	81.19
4	76.48	80.30	43.53	80.44	80.57	84.17
5	78.17	82.96	42.32	82.98	82.88	85.78

N_{train}: numbers of training trials in the target domain.

TABLE II
CLASSIFICATION ACCURACY UNDER DIFFERENT NUMBERS OF TRAINING TRIALS WHEN THE DATA LENGTH IS 0.6 FOR THE BETA DATASET

N_{train}	eCCA	eTRCA	ttCCA	LST-eTRCA	eIISMC	eTransRCA
1	53.50	8.70	32.02	22.88	18.11	54.95
2	61.30	55.97	32.09	58.20	56.53	65.45
3	65.25	64.81	32.20	66.09	65.12	70.49

N_{train}: numbers of training trials in the target domain.

Considering the limitation of the small number of training data in BCI applications, the evaluation of the classification performance given a small number of training data is more important than when given an adequate number of data. According to Figs. 2, and 3, the proposed eTransRCA clearly has a better classification performance than the other methods, especially when the number of training data is small (one or two trials). It should be noted that, as the strongest competitor of our method, eIISMC yields significantly poor performance when given a small number of training data. It was also found

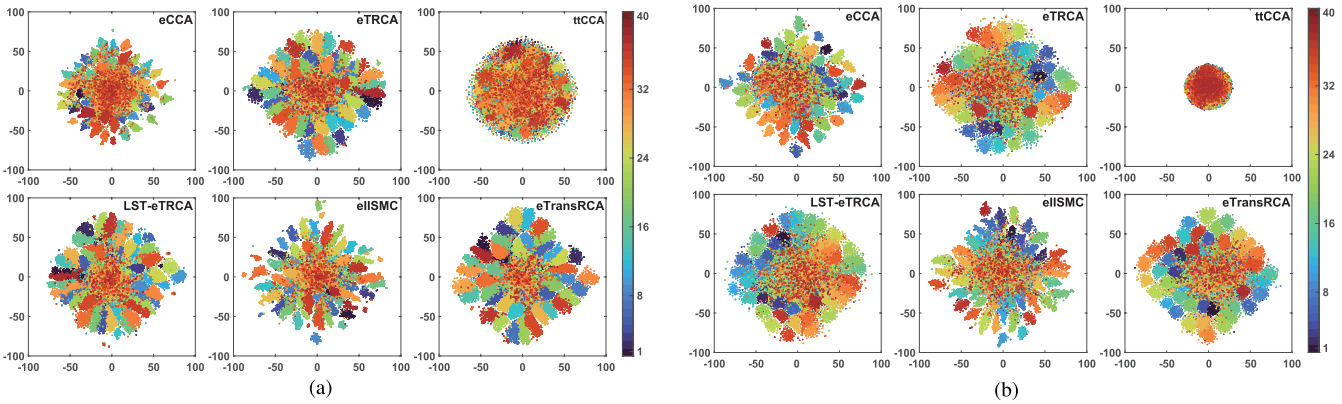

Fig. 4. Comparison of the 2D t-SNE visualization of the 40-dimensional features obtained by different methods using a 0.6-s data length when three target domain training trials were used for (a) all the subjects of the Benchmark dataset, where each point represents the data of one trial out of a total of 40 targets $\times$ 3 test trials $\times$ 10 repetitions $\times$ 35 subjects $=$ 42,000 trials, and each color corresponds to one of the 40 targets, and (b) all the subjects of the BETA dataset, where each point represents the data of one trial out of a total of 40 targets $\times$ 1 test trials $\times$ 10 repetitions $\times$ 70 subjects $=$ 28,000 trials, and each color corresponds to one of the 40 targets.

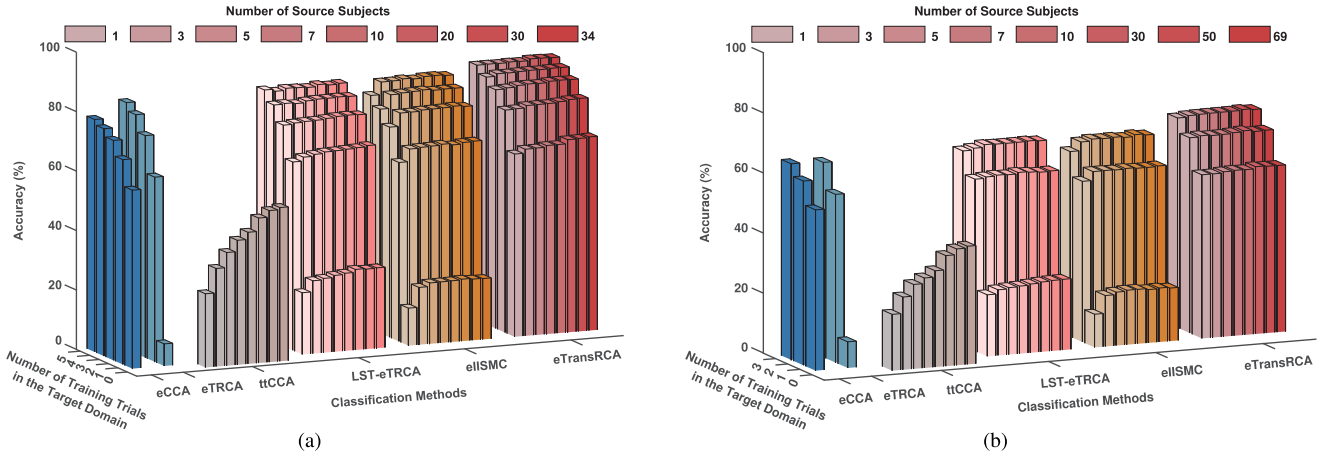

Fig. 5. Comparison of the classification accuracy results under different numbers of source subjects and numbers of training trials in the target domain for the (a) Benchmark dataset and (b) BETA dataset.

that eCCA performs significantly better than TRCA-based methods under the single training trial condition. However, it is still worse than eTransRCA, which combines the advantages of CCA and TRCA. In general, our proposed eTransRCA method has acceptable and stable performance, even when the number of training data is small or the length of the data is short.

Fig. 4 presents the t-distributed stochastic neighbor embedding (t-SNE) [36] projections of the feature vectors from the eCCA, eTRCA, ttCCA, LST-eTRCA, eIISMC, and eTransRCA methods using a 0.6-s data length when three target domain training trials were used for all subjects in both the Benchmark dataset and BETA dataset. It is clear that the t-SNE (Chebyshev distance) points obtained by the eTransRCA form uniformly dispersed clusters and have minimal overlaps among them. In this study, four commonly used internal measures for the evaluation of clustering validity, i.e., the Calinski-Harabasz index (CHI), silhouette coefficient (SC), Davies-Bouldin index (DBI) [37], and separation (SP) [38] were calculated for each of the six different target recognition methods (see Tables III and IV). The results in Tables III and IV reveal that the proposed eTransRCA method has a better clustering capability than the other five control methods (for CHI, SC, and SP, where higher values indicate better performance, whereas for DBI, smaller values indicate better performance) for both the Benchmark dataset and BETA dataset.

Fig. 5 shows a further comparison of the classification accuracy under different numbers of source subjects and numbers of training trials in the target domain for the Benchmark dataset and BETA dataset. When the training trials are small, the classification accuracy will increase rapidly as the size of these training trials is increased, but these increases gradually slow as the training trials become much larger, which is in line with the learning curve theory [39] (ttCCA does not use training trials in the target domain). Moreover, it is obvious that the classification accuracy is substantially reduced when the number of training trials is small for eTRCA, LST-eTRCA, and eIISMC, while such a trend is not obvious in our proposed TransRCA method. By contrast, it is clear that the classification accuracy increases with increases in the number of source subjects (eCCA and eTRCA do not use training trials in the source domain). This trend is particularly obvious when the number of source subjects is small, but with the further

TABLE III
COMPARISON OF INTERNAL MEASURES BASED ON THE T-SNE 2D REPRESENTATIONS FOR THE BENCHMARK DATASET

Methods	Indexes			
	CHI	SC	DBI	SP
eCCA	1419.07	-0.23	8.08	41.18
eTRCA	2349.56	-0.19	7.19	53.12
ttCCA	447.87	-0.33	16.00	26.74
LST-eTRCA	2394.36	-0.19	7.61	53.22
eIISMC	2531.48	-0.18	7.22	53.66
eTransRCA	3385.00	-0.12	4.50	58.52

CHI: Calinski-Harabasz index, SC: silhouette coefficient, DBI: Davies-Bouldin index, SP: separation.

TABLE IV
COMPARISON OF INTERNAL MEASURES BASED ON THE T-SNE 2D REPRESENTATIONS FOR THE BETA DATASET

Methods	Indexes			
	CHI	SC	DBI	SP
eCCA	635.43	-0.29	14.63	44.59
eTRCA	842.13	-0.26	10.33	49.91
ttCCA	114.65	-0.31	59.72	7.76
LST-eTRCA	982.50	-0.26	7.69	50.65
eIISMC	819.11	-0.25	8.80	50.11
eTransRCA	1071.43	-0.24	8.04	51.20

CHI: Calinski-Harabasz index, SC: silhouette coefficient, DBI: Davies-Bouldin index, SP: separation.

increase of the number of source subjects, the improvement in the accuracy is not significant. A more detailed diagram of the classification accuracy of the proposed eTransRCA method under different numbers of SS and numbers of training trials in the target domain is presented in Supplementary Fig. 3. According to this figure, the classification accuracy increases with increases in the number of SS. This increase is more pronounced when the number of SS is small, but as the number of SS increases, this increase tends to flatten out. In addition, the accuracy when the number of SS is larger is significantly higher than when this number is small, which shows that the SSVEP characteristics transferred from other subjects contribute to the classification. It is noteworthy that our proposed TransRCA method has relatively high and stable classification performance under almost all conditions with respect to the number of source subjects and number of training trials in the target domain, which shows that our method has excellent applicability and robustness.

IV. DISCUSSION

The number of trials required for the training procedure increases with the number of SSVEP targets. For a practical SSVEP-based BCI system, more than 40 SSVEP targets are generally required. In addition, studies have shown that if the training data are insufficient, the classification performance will be significantly reduced [14], [40]. Therefore, a large number of training trials during the training procedure is inevitable, which is time consuming and places an additional burden on the BCI user. How to expand the sample size from the existing data of trials/subjects/devices to reduce the training procedure has become a research trend and challenge in SSVEP research [11]. Transfer learning has been proven to be effective in solving the problem of insufficient sample size in SSVEP identification [15].

Recently, several methods based on the cross-subject transfer learning approach have been proposed. Among them, ttCCA uses a CCA-based spatial filter to form the group's mean source template and reference signals, and then uses them for the current TS [23]. However, the difference between source template and the current TS may be large, and thus the performance will deteriorate. The TransRCA proposed in this paper maximizes the covariance between all trial combinations of the source and target domains, it can bring the overall distribution of the target and source domains in the feature space closer together, and thus it can achieve better transfer performance.

The LST-TRCA method [24] uses a least-squares transformation to transform the data in the SS so that it is more similar to the template of the TS. It then trains a TRCA model with a combination of the transformed source domain data and target domain training data. When the source domain data quality is poor or the data contain high levels of noise, these interference components will be directly introduced into the training data of the TS. In contrast to the sample-based transfer of the LST-TRCA method, the proposed TransRCA method is based on feature-based transfer and projects the target domain and source domain into a subspace with high correlation, which enables the model to learn more common features and thus leads to better transfer performance.

The IISMC method combines both the intra- and inter-subject covariance maximization, which can exploit both the individual features of subjects in the target domain and features in common with subjects in the source domain [25]. However, because of the lack of sine-cosine references, IISMC cannot achieve the accuracy of the eCCA and ttCCA methods if there are only few training trials. Moreover, the inter-subject correlation maximization used in IISMC can only obtain one common spatial filter between the source and target subject, whereas the proposed TransRCA method can obtain pairs of spatial filters between the target domains and source domains, or between the target /source domains and the sine-cosine reference signals, which will lead to higher performance regardless of the number of training trials.

The TransRCA method proposed in this study synthetically considers four different sources of feature information. First, it considers transfer learning from SS; the TransRCA-based spatial filters can be learned from the TS and SS by maximizing the mean of the covariance between each single trial of the TS and SS. Second, the TransRCA-based spatial filter of the target domain can be learned by maximizing the mean of the covariance between each trial of TS and the reference signals. Third, the TransRCA-based spatial filter of the source domain can be learned by maximizing the mean of the covariance between each trial of the SS and reference signals. Last, the canonical correlation coefficient between the test data and reference signals is calculated. As mentioned in the Introduction, CCA and TRCA are the two benchmark methods of training-free and training-based recognition algorithms for

SSVEP identification, and they use different approaches to recognize SSVEPs. CCA mainly examines the fundamental and harmonic oscillation characteristics of SSVEPs, in which the correlation between the EEG data and reference signals are calculated. By contrast, TRCA emphasizes the reproducibility of the task-related components across trials, in which the sum of the covariance between trials is maximized. Both the oscillation characteristics of the SSVEPs and task-related components have been shown to be important features of SSVEP classification [6], [17]. In this study, we believe that the core concepts and advantages of the proposed TransRCA method are as follows: i) the use of multiple filters to filter the SSVEP signals, source and target templates, and reference signals to extract potential task-related components and frequency components as SSVEP features; ii) the use of paired spatial filters for the projections of the source and target domains, which has stronger transfer capability and better universality for different source data. In addition, it is a suitable approach for data with different dimensions, thus making transfer across devices and data types possible; iii) the construction of a strong classifier by combining correlation coefficients to synthesize the above features, which provides robust and accurate classification.

Recently, cross-stimulus transfer learning methods, e.g., multi-stimulus CCA (msCCA) [41] and subject transfer based CCA (stCCA) [32], has been proposed for SSVEP target recognition. In this approach, the SSVEP feature is learned not only from the target stimulus frequency but also from other stimulus frequencies. This cross-stimulus method has the advantage of needing fewer training data. However, if the training data of the TS are poor of quality, cross-stimulus training may not be satisfactory; in this situation, the cross-subject transfer learning method can provide a reliable template data and classifier that has good robustness. In this study, our proposed method only focused on transfer learning across subjects, and the accuracy obtained is slightly lower than that of the cross-stimulus method. However, our proposed method is not limited to cross-subject training, but can also be applied to cross-stimulus training. An extended version of TransRCA that combines cross-subject and cross-stimulus training is the next task in future work and is expected to achieve higher SSVEP recognition accuracy with fewer training data.

V. Conclusion

This study proposed the novel transfer-related component analysis (TransRCA) method to transfer the SSVEP features from other subjects, thus reducing the burden of the training procedure of SSVEP-based BCIs. The ensemble version of TransRCA obtained significant superior classification accuracy and ITR than the eCCA, eTRCA, ttCCA, LST-eTRCA, and eIISMC methods on both the Benchmark and BETA datasets. This indicates that the proposed TransRCA method can substantially reduce the training effort while maintaining high classification performance, which has high potential in BCI applications.

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