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Spectrum-Enhanced TRCA (SE-TRCA): A novel approach for direction detection in SSVEP-based BCI

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ABSTRACT

The Steady State Visual Evoked Potential (SSVEP) is a widely used component in BCIs due to its high noise resistance and low equipment requirements. Recently, a novel SSVEP-based paradigm has been introduced for direction detection, in which, unlike the common SSVEP paradigms that use several frequency stimuli, only one flickering stimulus is used and it makes direction detection very challenging. So far, only the CCA method has been used for direction detection using SSVEP component analysis. Since Canonical Correlation Analysis (CCA) has some limitations, a Task-Related Component Analysis (TRCA) based method has been introduced for feature extraction to improve the direction detection performance.

Although these methods have been proven efficient, they do not utilize the latent frequency information in the EEG signal. Therefore, the performance of direction detection using SSVEP component analysis is still suboptimal. For further improvement, the TRCA-based algorithm is enhanced by incorporating frequency information and introducing Spectrum-Enhanced TRCA (SE-TRCA). SE-TRCA method can utilize frequency information in conjunction with spatial information by concatenating the EEG signal and its shifted version. Accordingly, the obtained spatio-spectral filters perform as a Finite Impulse Response (FIR) filter.

To evaluate the proposed SE-TRCA method, two different sorts of datasets (1) a hybrid BCI dataset (including SSVEP component for direction detection) and (2) a pure benchmark SSVEP dataset (including SSVEP component for frequency detection) have been used. Our experiments showed that the accuracy of direction detection using the proposed SE-TRCA and TRCA approaches compared to CCA-based approach have been increased by 23.35% and 28.24%, respectively. Furthermore, the accuracy of character recognition obtained from integrating P300 and SSVEP components in CCA, TRCA, and SETRCA approaches are 54.01%, 56.02%, and 58.56%, on the hybrid dataset, respectively. The evaluation of the SE-TRCA method on the benchmark SSVEP dataset demonstrates that the SE-TRCA method outperforms both CCA and TRCA, particularly regarding frequency detection accuracy. In this specific dataset, the SE-TRCA method achieved an impressive frequency detection accuracy of 98.19% for a 3-s signal, surpassing the accuracies of TRCA and CCA, which were 97.91% and 90.47%, respectively.

These results demonstrated that the TRCA-based approach is more efficient than the CCA approach to extracting spatial filters. Moreover, SE-TRCA, extracting both Spectral and spatial information from the EEG signal, can capture more discriminative features from the SSVEP component and increase the accuracy of classification. The results of this study emphasize the effectiveness of the proposed SE-TRCA approach across different SSVEP paradigms and tasks. These findings provide strong evidence for the method's ability to generalize well in SSVEP analysis.

1. Introduction

Brain-computer interface (BCI) is extensively used as an alternative communication channel to enable people with disabilities, especially those suffering from spinal cord injury, to communicate with other people and control external devices. Indeed, a BCI system identifies the user's intentions through the brain neurons' activity, then translates them into executable commands for a device. A BCI can be developed and implemented based on a variety of brain neuron activity measures, including electroencephalography (EEG),

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magnetoencephalography (MEG), electrocorticography (ECoG), Functional Near-Infrared Spectroscopy (fNIRS), functional magnetic resonance imaging (fMRI), and positron emission tomography (PET) [1–3]. Among these, EEG is one of the most popular modalities of sensing for BCI [4] due to its affordability, non-invasive nature, and suitability for portable applications. Furthermore, it provides a high level of temporal resolution [5,6]. EEG-based BCI systems are categorized according to the type of brain activities, including Event-related desynchronization (ERD), Event-related synchronization (ERS), Slow Cortical Potential (SCP), P300 Evoked Potential, and Steady State Visual Evoked Potential (SSVEP) [2,4,6–8]. Using computational algorithms and artificial intelligence techniques, a BCI system is expected to extract these components from an EEG signal and interpret them into applicable commands.

Among these EEG signal components, the P300 and SSVEP components have been widely adopted due to the high information transfer rate and minimal user training requirements [8–13]. P300 is the most prominent ERP component, which is identified by its amplitude and latency. P300 is a positive deflection in the user's EEG signal with a latency of about 300 ms from the onset of a target stimulus. This component is evoked in the oddball paradigm, in which a series of stimuli appear such that the probability of the target stimulus is much lower than other stimuli. In this case, when the target stimulus is illustrated, the P300 component is evoked [14–17]. A clear advantage in the P300 paradigm is that the number of commands or stimuli can be relatively large. For example, there are 36 stimuli in the matrix speller paradigm [18]. However, in P300-based BCI systems, the presentation of stimuli needs to be repeated several times to increase the accuracy (e.g., the intensification of stimuli in the matrix speller is repeated up to 15 times). Consequently, this increases the time duration of the experiment and reduces the information transfer rate (ITR) [19]. Another weakness of P300-based BCI systems is that this may not be applicable to every subject. For instance, people suffering from oculomotor control disease cannot use properly and comfortably the most common P300 paradigm, the matrix Speller [5]. In recent research [20], a limitation in the analysis of the P300 component has been identified. This limitation involves treating P300 detection as a binary problem, where all non-target trials are considered as a single group. In their study, they addressed this limitation by categorizing non-target trials into several groups based on predefined criteria. By employing a multiclass-based approach, they proposed an approach to resolve the P300 detection problem more effectively [20].

SSVEP is a periodic electrophysiological response of the brain to repetitive visual or auditory stimuli with a specific frequency. When the subject focuses on one of the stimulus frequencies, the SSVEP response is evoked in the subject's EEG signal. The SSVEP response appears in the same fundamental frequency as the stimulus and its harmonics [21]. A significant advantage of SSVEP-based BCI is that it either does not require any training data or requires a very small amount of training data (for calibration-based methods) [22–25]. It is very easy to perform the experiment for most subjects and there is no need to train the subject although it may cause seizure in some subjects [2]. In addition, in the SSVEP paradigm, unlike P300, the number of unique stimulus frequencies utilized as commands is limited, and not every frequency can be used. Therefore, techniques such as Phase coding [26,27] and Frequency Coding [28] have been proposed to compensate for this limitation.

Most of EEG-based BCI systems usually employ one paradigm, especially P300 or SSVEP. A traditional P300 paradigm has more target options; however, detecting the target takes a longer time, which increases experiment time duration and reduces ITR. Although SSVEP-based paradigm has fewer target options for the subject compared to P300-based paradigm, it takes less time to detect target stimulus frequency. ITR cannot be increased beyond a certain limit even using techniques such as phase coding and frequency coding [29]. In fact, in BCI systems, there is always a trade-off between the number of target options and ITR, such that, as the number of stimuli (target options) increases, the experiment time duration increases, and the ITR decreases, and vice versa.

According to the aforementioned limitations of P300-based and SSVEP-based BCI systems, a single BCI, which only uses one paradigm, limits its performance. Recent studies have introduced a hybrid BCI approach to improve system performance and increase ITR [2,4,6–8]. A hybrid BCI is obtained using two or more EEG components (such as SSVEP, P300, or Motor Imagery) or other physiological signals to extract more discriminative features from the user's EEG data. The main goals of developing a hybrid BCI system can be summarized as follow: (1) enhancing classification accuracy and improving system performance, (2) increasing the number of target options in a paradigm to increase the number of commands available to the user [8], (3) extracting discriminative and informative features by employing different components of EEG signals, and (4) reducing the time duration for displaying stimuli and detecting the user's target [30]. For the development of hybrid BCI systems, researchers have introduced a variety of combinations. Considering SSVEP-based systems have higher ITR and require less training time among all types of BCI systems [31], the SSVEP component is usually combined with either the P300 components [16,32–35] or MI [36–38]. The study [39] introduced the hybrid BCI concept of combining P300 and SSVEP for the first time. The combination of P300-SSVEP can be considered as one of the best hybrid BCI systems since the speed of stimuli presentations and consequently, ITR increase with SSVEP, and the number of target options can also be increased with P300 [8,40].

In the study [41], this concept was also attempted by presenting a hybrid BCI speller where two components of P300 and SSVEP were combined simultaneously. A significant increase in the accuracy, speed, and ITR of the system was observed with this hybrid BCI speller system. For the P300 section of the paradigm, a Triple Rapid Serial Visual Presentation (RSVP) paradigm was used, where three characters were simultaneously displayed as one stimulus. The SSVEP component was then employed to specifically identify the target character among the three characters. Indeed, target character recognition is a two-step process that relies on the correct detection of both the P300 and SSVEP components. The reported results indicate that the performance of the final accuracy is limited by SSVEP detection. Therefore, in the current study, our goal is to provide a sophisticated approach to improve the accuracy of SSVEP detection, which would subsequently improve the final accuracy as well.

Canonical Correlation Analysis (CCA) was first used to detect SSVEP frequency by Lin et al. [42]. In the common CCA approach, sine-cosine waves are used to construct the reference signal and then it is used to calculate the canonical correlation between the EEG signal and the reference signal [42]. The common CCA approach (also called standard CCA), despite its effectiveness, has a series of basic limitations. One of the standard CCA limitations is that it does not take full advantage of harmonic information in SSVEP frequency detection. To solve this problem, the Filter Bank CCA (FBCCA) algorithm was developed so that it could effectively use harmonic information in the construction of features [43]. The standard CCA also has the drawback that it only uses the maximum value of correlation coefficients as a classification feature, even though other correlation coefficients can provide useful information as well. The Fusing CCA algorithm overcomes this problem by combining the correlation coefficients in a nonlinear and very simple way and providing more discriminative classification features [44]. One of the main problems of the standard CCA is the use of pre-constructed sine-cosine reference signals. Several studies [22,23,26,45–49] have indicated that such signals may not be optimal because they do not possess the characteristics of a real EEG signal and they do not have inter-trial or inter-subject variability information [22]. Moreover, they do not consider phase information [46], and may even overfit CCA. And these issues may affect the performance of CCA in SSVEP frequency detection. Additionally, CCA-based approaches require the extraction of two distinct projection vectors for the EEG signal and the reference signal, which will double the computational cost and complexity as well as the number of free parameters.

To tackle those issues in CCA, alternative methods [24,25,50] have been presented in which only one projection vector is calculated, and the computational cost is reduced. However, in these methods, contrary to CCA, the constraint of orthogonality (the constraint of orthogonality ensures that the extracted components represent distinct and independent brain signals) has been removed in the projection vectors. One of these methods is Task-Related Component Analysis (TRCA), which was first introduced by Nakanishi [24] to detect SSVEP frequency and has significantly outperformed CCA. In this study, we proposed a TRCA-based feature extraction approach to extract discriminative features for direction detection using SSVEP component analysis. Multiple studies [51–56] have proven that including spectral information in the signal filtering process can significantly improve the algorithm's performance. Since CCA and TRCA methods do not utilize frequency information during feature extraction, to further improve SSVEP component analysis for direction detection, we propose incorporating frequency information into TRCA, thus referring to it as Spectrum-Enhanced TRCA (SE-TRCA). In SE-TRCA, in addition to spatial information, spectral information is also incorporated in the feature extraction. As a result, more discriminative features were extracted and can further improve the SSVEP detection performance.

The contributions of this study can be summarized as follows:

- We introduce the SE-TRCA method, a novel approach for extracting discriminative features by combining spatial and spectral information.
- The utilization of the SE-TRCA-based feature extraction framework in the direction detection procedure using SSVEP analysis offers a promising methodology for improving performance.
- The superior performance of the proposed SE-TRCA method, surpassing both CCA and TRCA, in terms of both direction detection and frequency detection using SSVEP analysis highlights its potential for advancing these areas of research.
- The superior performance of the proposed method on two different datasets with different paradigms and tasks proves the generalizability of SE-TRCA in SSVEP analysis.

The paper is organized as follows. The introduction and literature review are presented in Section 1. Section 2 describes RSVP and SSVEP paradigms, datasets used for evaluation, CCA, and TRCA methods. Section 3 provides the feature extraction procedure of CCA, TRCA, and proposed SE-TRCA for direction detection using SSVEP component analysis on the mentioned datasets. The experimental results and discussion are presented in Section 4 and Section 5, respectively. Finally, we conclude the paper in Section 6.

2. Background

2.1. RSVP and SSVEP paradigms

RSVP, an innovative paradigm, has recently gained attention in the field of brain-computer interface (BCI) systems, particularly in the context of BCI spellers. The RSVP paradigm involves presenting distinct stimuli consecutively at the center of a screen [57]. In our previous study, we employed a standard triple RSVP paradigm, wherein 27 characters, comprising 26 English alphabets and the symbol ".", were organized into 9 groups. Each group consisted of 3 characters, with each character positioned in one of the three directions: left, right, or bottom. Table 1 provides all 9 stimuli used in the experiment.

Table 1
Arrangement of characters group in triple RSVP paradigm corresponding to 9 stimuli.

Stimulus number	1	2	3	4	5	6	7	8	9
Left direction	H	I	C	B	O	M	X	A	E
Right direction	R	F	N	Q	J	U	K	L	G
Bottom direction	T	S	.	V	Z	Y	P	W	D

As depicted in Fig. 1, a series of 9 stimuli are presented consecutively at the center of the screen. In RSVP paradigm, the presentation of stimuli is repeated multiple times to enhance recognition accuracy. Within this paradigm, the 9 stimuli are presented in a randomized order. During the experiment, participants were instructed to concentrate on the target character. When the target stimulus, comprising 3 characters, appeared, it elicited the P300 component in the subject's brain signal. Through analysis of the brain signal and detection of the P300 response, the target group can be identified. However, it is important to note that only the target stimulus containing 3 characters has been identified, not the specific target character itself. To ascertain the precise position of the target character, SSVEP paradigm has been incorporated into this paradigm for direction detection.

The SSVEP paradigm is a well-established and widely adopted technique in the BCI system. In this paradigm, participants are presented with visual flickering stimuli at specific frequencies. These stimuli elicit neurological responses at harmonic frequencies, resulting in distinguishable oscillatory activity in the visual cortex. By analyzing SSVEP component using EEG, researchers can infer participants' intentions or preferences, such as target selection or attentional focus. Traditionally, the typical SSVEP paradigm involves using multiple flickering stimuli, each with a distinct frequency, corresponding to different options. However, a recent advancement in the field introduced a novel SSVEP paradigm that utilizes a single flickering stimulus to detect several options. For instance, according to Fig. 2 a 15 Hz flickering stimulus is placed at the center of the screen, and participants are instructed to focus on one of three available directions: left, right, or bottom. By analyzing the SSVEP components, the target direction, corresponding to the participant's focus, can be identified. In fact, the novel SSVEP paradigm introduced within the studies [8], [36] significantly diverges from the frequency-based SSVEP BCIs discussed earlier. In contrast to detecting targets based on power spectra, the proposed SSVEP paradigm categorizes the spatial patterns of SSVEP power distribution across the scalp. As mentioned in the research [8] and [36] they have used this type of SSVEP paradigm to discriminate 4 and 9 different spatial positions, respectively. overall, the novel SSVEP paradigm is a sort of spatial-decoded SSVEP instead of a frequency-coded one (traditional SSVEP with several frequency stimuli).

2.2. Data description

To assess the effectiveness of the proposed methodology, two different types of SSVEP datasets: a hybrid BCI speller dataset and a benchmark pure SSVEP dataset [58] were used.

We utilized the dataset associated with a Hybrid BCI Speller from [41] to evaluate our proposed method. The data was derived by combining SSVEP and P300 components, where a Triple RSVP paradigm [59,60] was employed to evoke the P300 component, and a single flickering stimulus at a specific frequency was employed to derive the SSVEP component, simultaneously illustrated in Fig. 3. In the RSVP paradigm, a total of 27 characters including 26 English alphabet characters and a "." symbol were divided into 9 stimuli, where each stimulus consists of three characters. The three characters in each stimulus are placed in three different directions (i.e., left, right, and bottom) on the screen and these 9 stimuli of characters randomly appear one by one for 5 repetitions. The appearance of each stimulus sustains for 230 ms. Meanwhile, a square for SSVEP analysis is placed in the middle of the screen surrounded by the three characters, and flickers with a frequency of 15 Hz. In the RSVP paradigm, only the target stimulus with three characters can be detected, however, the exact target character in the stimulus cannot be detected. Previous studies [61,62] suggest the center stimulus can help detect the exact point of the test subject

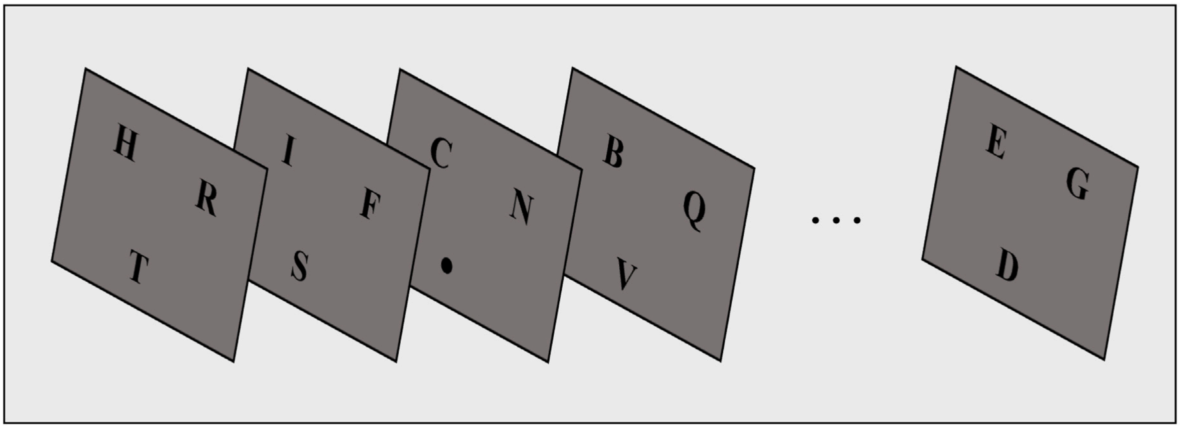

Fig. 1. Triple RSVP paradigm. Each stimulus including 3 characters is presented in the center of the screen.

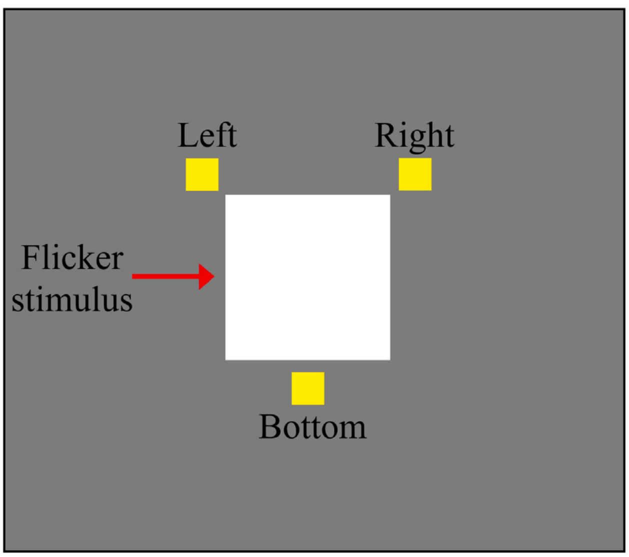

Fig. 2. The Novel SSVEP paradigm for direction detection.

using a flickering square with a certain frequency, thus the exact target character can be identified. The dataset was collected from six test subjects during one session using a 32-channel g.Hlamp (G.Tech Company) device including active electrodes in accordance with the standard 10–20 system. In this dataset, for analysis of P300 component analysis, it must be notated that each repetition consists of 9 stimuli, including three characters, which are randomly presented to the subject. One of these stimuli is the target (P300), while the remaining 8 are non-target (non-P300) stimuli. Simultaneously, a flickering stimulus is intensified with a frequency of 15 Hz. Nine EEG trials corresponding to the stimuli are separated in each repetition to identify the target group. Specifically, out of the 9 stimuli, one is the P300 and the remaining 8 are non-P300 stimuli. For the direction detection using SSVEP analysis, the EEG signal from the beginning to the end of each repetition is utilized to detect the direction. According to Fig. 4 It should be noted that if consecutive repetitions information is to be used for identifying the target character, in the P300 analysis section, the EEG trials of each repetition are examined individually. Finally, the target group is identified by voting across repetitions. However, for SSVEP analysis, the EEG signal from the start of the first repetition to the end of the considered repetition is concatenated to construct a continuous signal, which is then used for analysis. We remove the first repetition because of the noise and only utilize the remaining 4 repetitions for our experiments. The data preprocessing manners (e.g., signal filtering) are deployed by following [41].

For further evaluation, a pure SSVEP dataset has been utilized in this research comprising BCI Speller data with a total of 40 targets, as described by Wang et al. [58]. This dataset consists of 64-channel EEG recordings obtained from 35 healthy participants, including eight experienced individuals and 27 naive individuals. The visual stimuli were encoded using the Frequency and Phase Modulation method, with stimulus frequencies ranging from 8 Hz to 15.8 Hz in intervals of 0.2 Hz. The phase difference between neighboring frequencies was set at 0.5π. Each stimulus had a duration of 5 s, and the data were sampled at a frequency of 250 Hz. For each subject, the data is organized as a four-dimensional matrix with dimensions of [64, 1500, 40, 6]. These dimensions represent the number of electrodes, time points, targets, and blocks, respectively. Each subject's data matrix consists of 240 trials (40 targets x 6 blocks), with each trial containing 64 channels and 1500 time points. The overall duration of the data is 6 s, including 0.5 s before the start of the stimulus, 5 s during the stimulus, and 0.5 s after the stimulus.

2.3. CCA in SSVEP

The CCA is one of the most classic statistical methods which is used to compute the correlation between two multivariate data. It was first applied by [42] for SSVEP frequency detection. Let $X \in \mathcal{R}^{N_c \times N_s}$ be any EEG signal, where N_c, N_s denote EEG channel number and data length, respectively. Let $Y \in \mathcal{R}^{2N_h \times N_s}$ be constructed reference signal consisting of sine and cosine functions, where N_h denotes the number of harmonics. The reference signal (i.e., Y_k) for kth stimulus frequency can be constructed by:

$$Y_k = \begin{bmatrix} sin(2\pi f_k t) \\ cos(2\pi f_k t) \\ sin(2\pi N_h f_k t) \\ cos(2\pi N_h f_k t) \end{bmatrix}, \tag{1}$$

where $t = \left[\frac{1}{f_s}, \frac{2}{f_s}, \dots, \frac{N_s}{f_s}\right]$ and f_s is sampling rate of EEG signal. CCA method requires that X and Y have the same length. Then, CCA is utilized to compute the correlation coefficient vectors between the multi-channel EEG signal and each reference signal with different stimulus frequencies. For this purpose, the spatial filters $W \in \mathcal{R}^{N_c \times 1}$ and $V \in \mathcal{R}^{2N_h \times 1}$ are extracted by the CCA according to the equation 2 somehow linear combinations (canonical variables) $Z_x = W^T X$ and $Z_y = V^T Y$ have the highest canonical correlation. Thirdly, the maximum correlation coefficient in each coefficient vector is selected as a potential feature set for determining the SSVEP signal frequency. Finally, we select the frequency, which is corresponding to the optimal

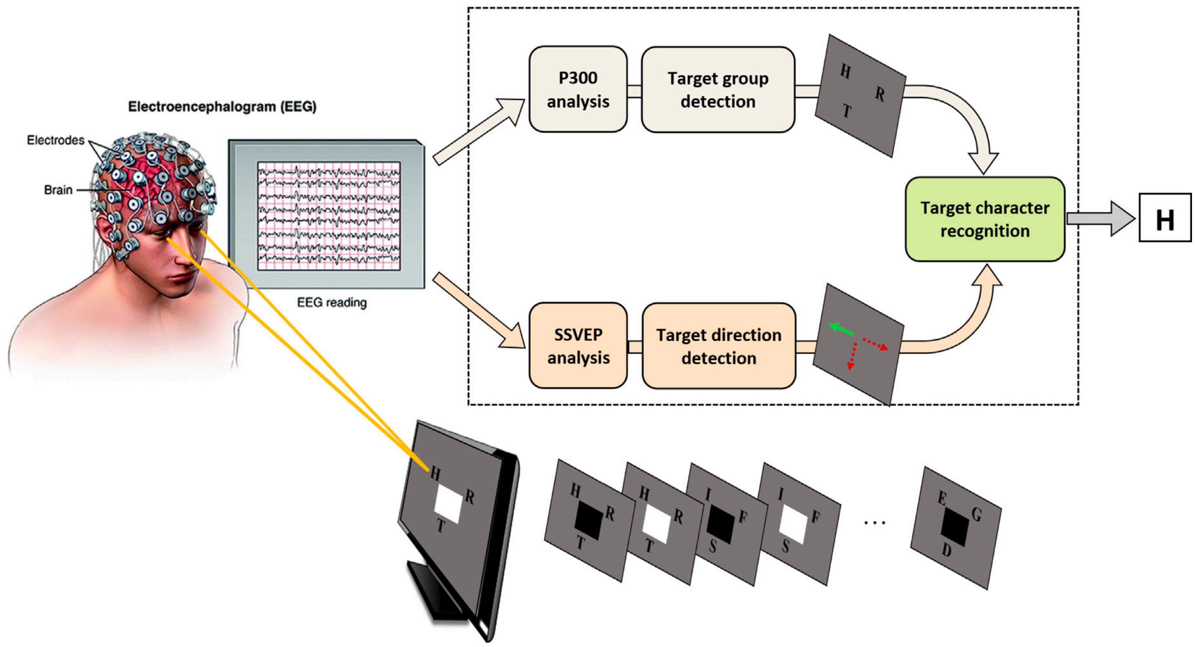

Fig. 3. Character detection procedure in hybrid BCI speller paradigm combining Triple RSVP and SSVEP paradigms.

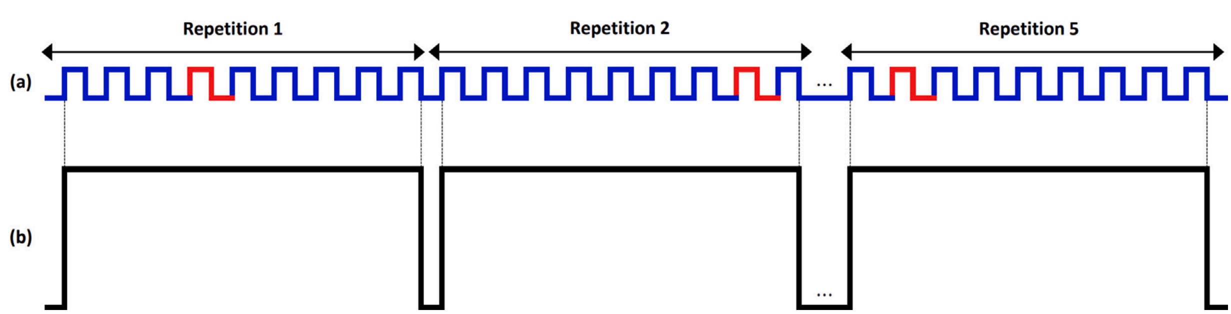

Fig. 4. Trigger time of stimuli presentation in the mentioned hybrid BCI paradigm. (a) RSVP paradigm stimuli and (b) flickering stimulus in SSVEP paradigm.

feature (i.e., the maximum one) in the feature set, from the stimulus frequencies as the SSVEP frequency.

$$\rho = \arg\max_{W,V} \frac{\mathrm{corr}(Z_x, Z_y)}{\sqrt{\mathrm{var}(Z_x)}\sqrt{\mathrm{var}(Z_y)}} = \arg\max_{W,V} \frac{W^T X Y^T V}{\sqrt{W^T X X^T W}\sqrt{V^T Y Y^T V}} \tag{2}$$

2.4. TRCA in SSVEP

The TRCA method is proposed to enhance the evoked potentials (i.e., SSVEP components in this work) which are not easy to detect in the EEG signals in that the EEG signals are always contaminated by noise and other brain activities. Previous studies [24,63] have shown that the TRCA method can substantially make evoked potentials more prominent compared to other brain activities and can suppress a lot of noise, which facilitates the detection of the SSVEP components. We use $\bar{X}_{k,i} \in \mathcal{R}^{N_c \times N_s}$ to denote the ith trial of EEG signal with length of N_s and channel number of N_c from kth class (trial group). Each channel of EEG signal should be normalized over the entire duration to be a fixed dynamic range by using the zero-mean and unit-variance method. Then the inter-trial cross-covariance is calculated according to the Equation 3.

$$S = \frac{1}{N_t(N_t-1)N_s} \sum_{i \neq j;(i,j)=1}^{N_t} \bar{X}_{k,i} \bar{X}_{k,j}^T, \in \mathcal{R}^{N_c \times N_c}. \tag{3}$$

Then, the EEG signal of all the training trials of each specific stimulus is concatenated and a two-dimensional continuous signal is constructed.

$$\ddot{X}_k = \left[\bar{X}_{k,1}, \bar{X}_{k,2}, \dots, \bar{X}_{k,N_t}\right], \in \mathcal{R}^{N_c \times (L)} \tag{4}$$

where $L = N_s \times N_t$ and N_t represents the number of trials. Then the covariance matrix of the continuous signal is calculated according to Eq. (5).

$$Q = \frac{1}{T} \ddot{X}_k \ddot{X}_k^T, \in \mathcal{R}^{N_c \times N_c}. \tag{5}$$

In practice, it is easier to calculate the S matrix as follows:

$$S = \frac{N_t}{(N_t-1)N_s}(UU^T - \frac{1}{N_t}V), \in \mathbf{R}^{N_c \times N_c} \tag{6}$$

where U and V matrices are defined as follows:

$$U = \frac{1}{N_t} \sum_{i=1}^{N_t} \bar{X}_{k,i}, \in \mathcal{R}^{N_c \times N_s}$$

$$V = \frac{1}{N_t} \sum_{i=1}^{N_t} \bar{X}_{k,i} \bar{X}_{k,i}^T \in \mathcal{R}^{N_c \times N_c}. \tag{7}$$

According to the Q and S matrices, the TRCA problem is defined as follows:

$$\max w^T S w \tag{8}$$

$$s.t. \quad w^T Q w = 1 \tag{9}$$

A constrained optimization problem is obtained which is solved according to the following equation. Using the Lagrange multiplier, the optimization problem is converted to the following equation.

$$\hat{w} = \operatorname{argmax} \frac{w^T S w}{w^T Q w} \tag{10}$$

Now, the optimization problem can be solved using generalized eigenvalue decomposition and the N_c eigenvectors and eigenvalues are obtained. The eigenvectors are sorted in descending order according to their eigenvalues, and the first eigenvectors are implemented as spatial filters to extract task-related information (SSVEP).

3. Methodology

It is important to acknowledge that the dataset utilized in this research embodies a Hybrid BCI speller paradigm, incorporating two distinctive components, P300 and SSVEP. This paradigm was originally introduced by S. Jalilpour et al. [41]. Within this framework, the identification of the target character involves a two-step process: firstly, recognizing the target group(using the P300 component) in which the target character is also located, and secondly, determining the correct direction (using the analysis of the SSVEP component) that the user is staring at. In fact, first, the group containing the target character is recognized and then the direction in which the target character is located is detected, and eventually, the combination of these two steps leads to the identification of the target character. If the target group is recognized accurately but its direction is misjudged, the target character cannot be correctly identified vice versa. The results reported in the study [41] based on this dataset revealed that the accuracy of the P300 component detection is higher than SSVEP component analysis, and SSVEP component poses certain limitations and adversely affects the final accuracy. Given that direction detection using the SSVEP component remains a challenge within this dataset, our objective is to propose an effective approach for extracting discriminative features from the SSVEP component, enabling the detection of the target direction and ultimately enhancing the overall accuracy of the system. As of now, CCA algorithm has been used to extract the feature in order to detect the direction from SSVEP component [41,61,62]. In this section, CCA algorithm is first described as a classic method for the analysis of SSVEP frequency detection. Several studies have proposed more efficient methods than CCA to analyze the SSVEP component, such as TRCA. we introduce an optimal approach based on TRCA that we can extract more discriminative features by SSVEP analysis and finally perform the process of direction detection accuracy with higher accuracy. Finally, for further improvement, we have improved the TRCA algorithm to perform better. Therefore, the SE-TRCA algorithm is presented to detect the direction from the SSVEP component with higher accuracy.

3.1. Direction detection using SSVEP analysis

As illustrated in Fig. 3, in this hybrid BCI, one of the steps in target character recognition is to correctly recognize the direction by analyzing the SSVEP components. In this section, the feature extraction procedures based on CCA, TRCA, and SE-TRCA methods are described. Then, the classification procedure using extracted features is explained.

3.1.1. CCA-based feature extraction

As aforementioned, the subject focuses in one of three directions: left, right, and bottom in the experiment for data collection. Suppose $\bar{X}_{k,1}, \bar{X}_{k,2}, \dots, \bar{X}_{k,N_t}, \in \mathcal{R}^{N_c \times N_s}$ are training trial of $k-th$ group and Y is a reference signal constructed according to Eq. (1). Since only a single frequency has been implemented in SSVEP paradigm, one reference signal is constructed for all groups with $f_k = 15$ Hz and $N_h = 2$. To calculate spatial filters using CCA, the training trials of each group are first concatenated to create a continuous signal as Eq. (4). Reference signals are duplicated N_t times to have the same data length as a continuous EEG signal.

$$\ddot{X}_k = \left[\bar{X}_{k,1}, \bar{X}_{k,2}, \dots, \bar{X}_{k,N_t}\right], \quad k = 1,2,3$$

$$\ddot{Y} = \left[Y, Y, \dots, Y\right] \tag{11}$$

Where $\ddot{X}_k \in \mathcal{R}^{N_c \times (L)}$ and $\ddot{Y} \in \mathcal{R}^{2N_h \times (L)}$ and $L = N_s \times N_t$ and N_t indicates the number of training trials of each group. It must be mentioned that $N_c = 9$ (i.e., including $[P_7, P_3, P_z, P_4, P_8, P_{o3}, P_{o4}, O_1, O_2]$) since usually only 9 channels placed in occipital region are used in SSVEPs analysis. The spatial filters W_k and V_k of each class can now be extracted by applying CCA on the continuous signals and the reference signal as Eq. (2). Since $N_c = 9$ and $2N_h = 4$, therefore 4 spacial filters are extracted for each class named $w_{k,M}$, where $k \in \{1,2,3\}$ and $M \in \{1,2,3,4\}$. These four filters of each class are indeed eigenvectors obtained from Eq. (2) and are sorted in descending order. In order to extract classification features, the spatial filters W_k and V_k are applied to the EEG test signal and reference signal, respectively. As a result, two linear transforms are obtained as $Z_1 = W_k^T \times X$ and $Z_2 = V_k^T \times Y$. Then, the ordinary correlation of two linear transforms Z_1 and Z_2 are calculated, denoted by F_k. As presented in Algorithm 1 this procedure is repeated for all groups and feature vectors F_1, F_2 and F_3 are obtained. These features are fused as $F = \begin{bmatrix} F_{1,1}, F_{1,2}, F_{1,3}, F_{1,4} \\ F_{2,1}, F_{2,2}, F_{2,3}, F_{2,4} \\ F_{3,1}, F_{3,2}, F_{3,3}, F_{3,4} \end{bmatrix}$, and classification features are obtained for EEG test signal, X. The details of CCA-based feature extraction approach are summarized in Algorithm 1.

Algorithm 1: CCA-Based feature extraction approach

input : Training-trials: $\bar{X}_{k,1}, \bar{X}_{k,2}, \dots, \bar{X}_{k,N_t}$
New-Trial: X % multi-channel EEG signal
Reference signal: Y
% N_t : # of training trials
% k : index of groups (1: left, 2: right, 3: bottom).

output: $F = \begin{bmatrix} F_{1,1}, F_{1,2}, F_{1,3}, F_{1,4} \\ F_{2,1}, F_{2,2}, F_{2,3}, F_{2,4} \\ F_{3,1}, F_{3,2}, F_{3,3}, F_{3,4} \end{bmatrix}$, % New feature vector

Step 1: Concatenating

$$\ddot{X}_k = \left[\bar{X}_{k,1}, \bar{X}_{k,2}, \dots, \bar{X}_{k,N_t}\right], \quad k = 1,2,3$$
$$\ddot{Y} = \left[Y, Y, \dots, Y\right]$$

Step 2: Calculating spatial filters using CCA

$$W_k, V_k = CCA(\ddot{X}_k, \ddot{Y})$$

% $W_k = [w_{k1}|w_{k2}|, \dots, |w_{kM}]$
% $V_k = [v_{k1}|v_{k2}|, \dots, |v_{kM}]$
% $M \in \{1,2,3,4\}$: # of spatial filters

Step 3: Applying extracted filters

$$Z_{1,k} = W_k^T X$$
$$Z_{2,k} = V_k^T Y$$

Step 4: Calculating correlation

$$F_k = corr(Z_{1,k}, Z_{2,k})$$

3.1.2. Proposed TRCA-based feature extraction

A two-stage TRCA-based approach is applied to extract SSVEP-related features from EEG signals. In the first stage, spatial filters are calculated by TRCA from training trials. In the second stage, the feature is extracted using obtained spatial filters. Assume that $\bar{X}_{k,1}, \bar{X}_{k,2}, \dots, \bar{X}_{k,N_t}, \in \mathcal{R}^{N_c \times N_s}$ are the training trials of $k-th$ group, $k \in \{1,2,3\}$ and X is a EEG test trial. First, the average of each group's trials is calculated as $\widetilde{X}_k = \frac{1}{N_t}\sum_{i=1}^{N_t} \bar{X}_{k,i}$. Indeed, $\widetilde{X}_k$ is used as a reference signal instead of a constructed sin-cos signal in CCA. Since there are three groups in the dataset (left, right, and bottom), three TRCA algorithms are applied to calculate spatial filters. Six spatial filters are extracted based on training trials of each group named $w_{k,M}$, where $k \in \{1,2,3\}$ and $M \in \{1,2,\dots,6\}$. As a result, three sets of spatial filters W_1, W_2, W_3 are calculated for the left, right and bottom groups, respectively. Then spatial filters are utilized in the feature extraction stage. For this purpose, the extracted filters are applied on both EEG trials X and averaged training trial of each group $\tilde{X}_k$. Therefore, two filtered signals $Z_1 = W_k^T \times X$ and $Z_2 = W_k^T \times \tilde{X}$ are obtained for each group. Next, the ordinary correlation between Z_1 and Z_2 is calculated. This procedure is repeated for training and test trials. Eventually, the obtained values are fused as a corresponding feature vector of trial X. The optimal number of filters is obtained $m = 3$, so for each class 3 features are extracted, and by concatenating features a feature vector with size of 9×1 is constructed. More details are depicted in the Algorithm 2. Then, a classifier is trained using training data to classify a new trial. The extracted features of test trials are fed into the trained classifier, and its output (direction) is predicted using the trained classifier. The details of CCA-based feature extraction approach are summarized in Algorithm 2.

Algorithm 2: TRCA-Based feature extraction approach

input : Training-trials: $\bar{X}_{k,1}, \bar{X}_{k,2}, ..., \bar{X}_{k,N_t}$
New-Trial: X % multi-channel EEG signal
Reference signal: Y
% N_t : # of training trials
% k : index of groups (1: left, 2: right, 3: bottom).

output: $F = \begin{bmatrix} F_{1,1}, ..., F_{1,5}, F_{1,6} \\ F_{2,1}, ..., F_{2,5}, F_{2,6} \\ F_{3,1}, ..., F_{3,3}, F_{3,4} \end{bmatrix}$, % New feature vector

Step 1: Calculating individual templates

$\tilde{X} = mean(\bar{X}_{k,1}, \bar{X}_{k,2}, ..., \bar{X}_{k,N_t})$

Step 2: Calculating spatial filters using TRCA

$W_k = TRCA(\bar{X}_{k,1}, \bar{X}_{k,2}, ..., \bar{X}_{k,N_t})$

% $W_k = [w_{k1}|w_{k2}|, ..., |w_{kM}]$
% $M \in \{1, 2, 3, 4\}$: # of spatial filters

Step 3: Applying filters

$Z_{1,k} = W_k^T X$
$Z_{2,k} = W_k^T \tilde{X}_k$

Step 4: Calculating correlation

$F_k = corr(Z_{1,k}, Z_{2,k})$

3.1.3. Proposed SE-TRCA

This section describes our proposed feature extraction approach used for SSVEP component analysis. It must be noted that SSVEP component has been used to extract features for direction detection. Since Studies [24,63] have demonstrated that TRCA-based methods outperform CCA-based methods, a TRCA-based approach has been utilized for SSVEP component-related feature extraction. In addition, we have improved the TRCA approach for further improvement. Based on the studies [20,53], it has been presented that concatenating shifted signals with original signals can yield spectral filters as well as spatial filters in filter extraction. Therefore, discriminative features are derived that play an important role in target detection. Motivated by the current methods [20,53,64], we extend the TRCA method and propose a spectrum-enhanced TRCA method (named as Spectrum-Enhanced TRCA or SE-TRCA) by incorporating frequency information with the corresponding spatial information in EEG signals. Compared to the previous TRCA method, the proposed SE-TRCA method yields more discriminative features, which can further improve the classification performance. To capture the features containing both spatial and frequency information, we design a sort of spatial–spectral filter. In order to extract spatio-spectral filters by SE-TRCA, it is necessary to first apply a temporal shift to the EEG signal, as noted $\delta_\tau \bar{X}_{k,i}, \in \mathcal{R}^{N_c \times N_s}$ where τ is the amount of time delay. The temporal shift is performed through a linear shift. Then by channel-wised concatenating the shifted signal with the original signal a new signal is constructed as $\hat{X}_{k,i} = \begin{bmatrix} \bar{X}_{k,i} \\ \delta_\tau \bar{X}_{k,i} \end{bmatrix}$. Where i is the trial number and k is the trial group number.

A new signal $(\hat{X}_{k,i})$ is constructed for each training trial $(\bar{X}_{k,i})$, which contains the trial itself and its shifted. The generated signals are then fed into the TRCA algorithm. In the other words, $\hat{X}_{k,i}$ must be used into Eqs. (4):(8) instead of $\bar{X}_{k,i}$ and the TRCA algorithm generates the filter $\hat{w} = \begin{bmatrix} w_0 \\ w_\tau \end{bmatrix}$. Half of the obtained filter coefficients are related to the original signal, while the other half are related to the shifted signal.

In order to demonstrate how SE-TRCA method can analyze frequency information, suppose that $\bar{X}_{k,i} = \begin{bmatrix} x_1 \\ \vdots \\ x_{Nc} \end{bmatrix}$ and $\delta_\tau \bar{X}_{k,i} = \begin{bmatrix} \delta_\tau \bar{X}_1 \\ \vdots \\ \delta_\tau \bar{X}_{Nc} \end{bmatrix}$ denote EEG signal and its shifted version respectively. Then, they are concatenated and a new EEG signal is obtained as follows:

$$\hat{X}_{k,i} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{Nc} \\ \delta_\tau x_1 \\ \delta_\tau x_2 \\ \vdots \\ \delta_\tau x_{Nc} \end{bmatrix}.$$

SE-TRCA method is applied on $\hat{X}_{k,i}$ and filter coefficient $\hat{w} = \begin{bmatrix} w_0 \\ w_\tau \end{bmatrix}$ is obtained and the expanded form is as follows:

$$\hat{w}^T = [w_1^0, \quad w_2^0, \quad \cdots, \quad w_{Nc}^0, \quad w_1^\tau, \quad w_2^\tau, \quad \cdots, \quad w_{Nc}^\tau]$$

Eventually, this filter is applied on EEG trials in the feature extraction procedure as Eq. (12)

$$\hat{Z}_1 = \hat{w}^T \hat{X} --> \hat{Z}_1 = w_0^T \bar{X} + w_\tau^T(\delta_\tau \bar{X}) = w_0^T \bar{X}[n] + w_\tau^T(\delta_\tau \bar{X}[n-\tau]) \quad (12)$$

As can be seen, it performs as an FIR filter. Indeed, in addition to spatial filtering, spectral filtering is implemented simultaneously. Accordingly, in addition to spatial information, frequency information is also utilized in the construction of features.

3.1.4. Proposed SE-TRCA based feature extraction

As shown in Fig. 5, to extract features using SE-TRCA method, the first training trials $(\bar{X}_{k,i})$ must be shifted in the time domain as $\delta_\tau \bar{X}_{k,i}$. Then each trial and its shifted are concatenated to construct a new trial as $\hat{X}_{k,i} = \begin{bmatrix} \bar{X}_{k,i} \\ \delta_\tau \bar{X}_{k,i} \end{bmatrix}$. Now the training trials of each group are formed like $\hat{X}_{k,1}, \ldots \hat{X}_{k,N_t}$, $k \in \{1, 2, 3\}$. The average of each group's trials is calculated and used as a reference signal as follows: $\tilde{X}_k = \frac{1}{N_t} \sum_{i=1}^{N_t} \hat{X}_{k,i}$. Then, a new averaged reference signal is obtained as $\bar{\bar{X}}_{k,i} = \begin{bmatrix} \tilde{X}_{k,i} \\ \delta_\tau \tilde{X}_{k,i} \end{bmatrix}$. A procedure similar to TRCA is implemented to extract filters. Eventually, the filter $\hat{w}_{k,M} = \begin{bmatrix} w_0 \\ w_\tau \end{bmatrix}$ is obtained, where $k \in \{1, 2, 3\}$, $M \in \{1, 2, \ldots, 6\}$, $\tau \in \{1, 2, 3, 4\}$. Half of the obtained filter coefficients are related to the original signal, while the other half are related to the shifted signal. The signal filtering is performed by using the obtained filters as follows:

$$\hat{W}_k = [\hat{w}_{k1}|\hat{w}_{k2}|, \ldots, |\hat{w}_{kM}]$$
$$\hat{z}_1 = \hat{W}_k^T \hat{X}, \quad \hat{z}_1 = w_0^T X + w_\tau^T(\delta_\tau X)$$
$$\hat{z}_2 = \hat{W}_k^T \bar{\bar{X}}_k, \quad \hat{z}_2 = w_0^T \tilde{X}_k + w_\tau^T(\delta_\tau \tilde{X}_k)$$

3.1.5. Classification

After the features are extracted by one of the methods including CCA, TRCA, or SE-TRCA, they are applied to the classifier. Then, the classifier predicts the direction of the subject's attention (left, right, or bottom). It should be noted that the non-linear support vector

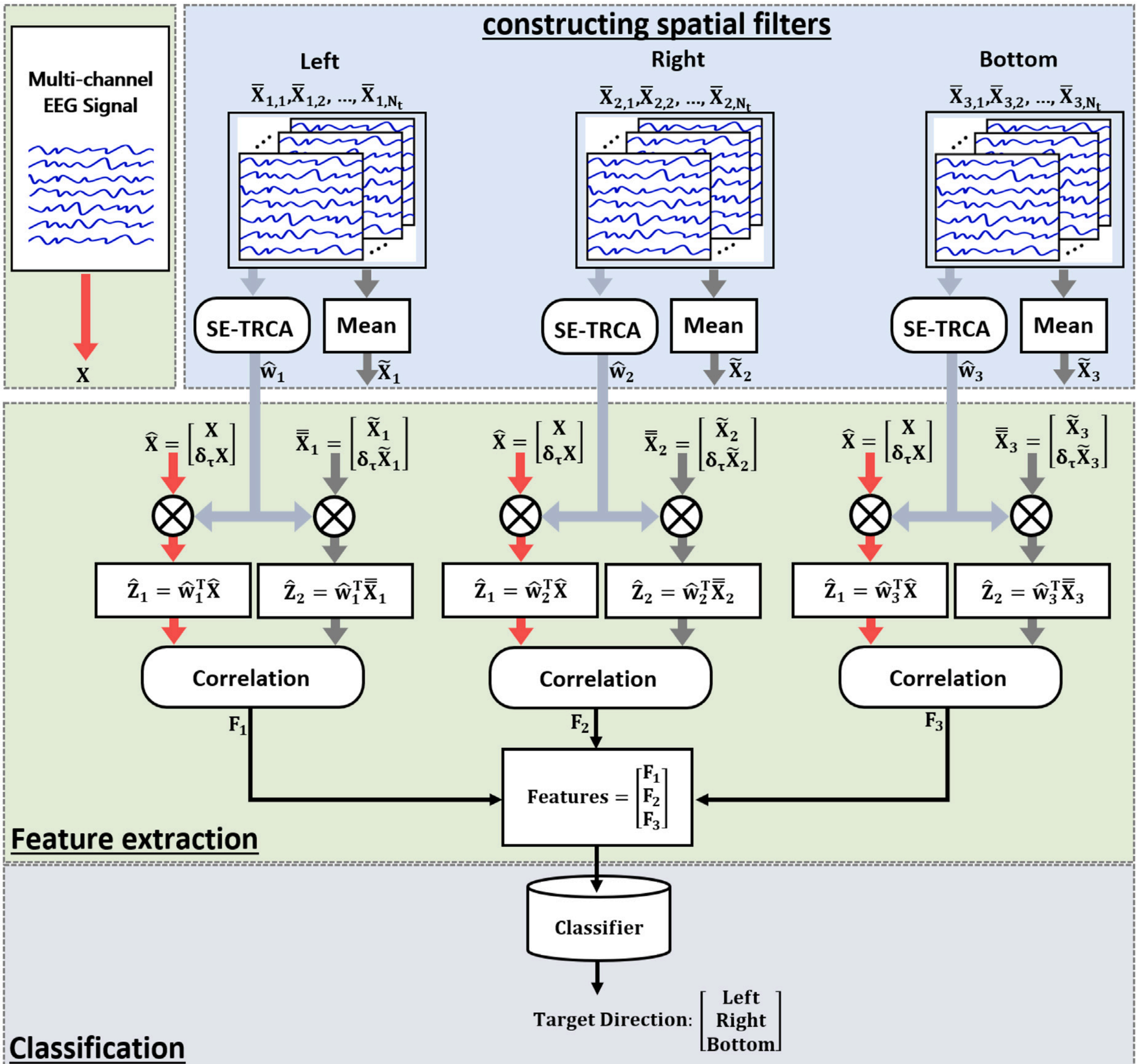

Fig. 5. Direction detection using SE-TRCA based feature extraction approach.

machine (SVM) with radial basis function (RBF) kernel was employed as a classifier. The Libsvm toolbox was utilized for implementing this classification approach [65].

3.2. Group detection using p300 analysis

In P300 analysis, the target group is detected through a binary classification problem including P300/Non-P300 detection. In each repetition, 9 stimuli (each stimulus includes 3 English alphabets) are presented for subjects, and one out of 9 stimuli is the target (P300) and the remaining 8 stimuli are non-target (non-P300). Although the main focus of this study was the development of a novel approach for direction detection using SSVEP analysis, we include P300 analysis because the final accuracy should be reported by combining the SSVEP and P300 accuracy. We followed our previous approach for P300 detection [41]. An FIR bandpass filter is used to filter the EEG signal of all channels in the frequency range $[0.5 - 25]$ Hz as the first step in pre-processing. Then, for epoching, the EEG signal from the stimulus onset to one second afterward is considered as a trial corresponding to the same stimulus (according to the 512 Hz sampling rate, each epoch includes 512 temporal samples). Using the Nyquist theorem, each trial is downsampled to 50 Hz (51 temporal samples). Since temporal samples are used as features, preprocessed signals of all channels are concatenated to construct a feature vector for each trial. Each trial must be vectorized to feed it as input to a classifier. Since the trial size becomes very large after vectorizing, Lasso method is employed to reduce its dimension to prevent overfitting while maintaining the necessary information of trials. For P300 detection, the regularized linear discriminant analysis (RLDA) was chosen as one of the most effective classifiers. RLDA is a variant of Fisher linear discriminant analysis (FLDA) that addresses the issue of overfitting by applying regularization techniques to the features [57,66]. Thus, RLDA was utilized for performing the classification in the P300 analysis. It should be noted that the k-fold cross-validation method with $K = 4$ was used to evaluate the model.

3.3. Evaluation metrics

In order to assess the efficacy of the proposed approach on the hybrid BCI dataset, Its performance along with TRCA and CCA are evaluated using the k-fold cross-validation technique with $k = 4$. During each iteration of the cross-validation, one subset was used for validation, while the remaining three subsets were utilized as training data. The accuracy was calculated by averaging the accuracies obtained from the four subsets. Each subset consisted of 24 characters and was specifically reserved for validation purposes. In the pure SSVEP dataset,

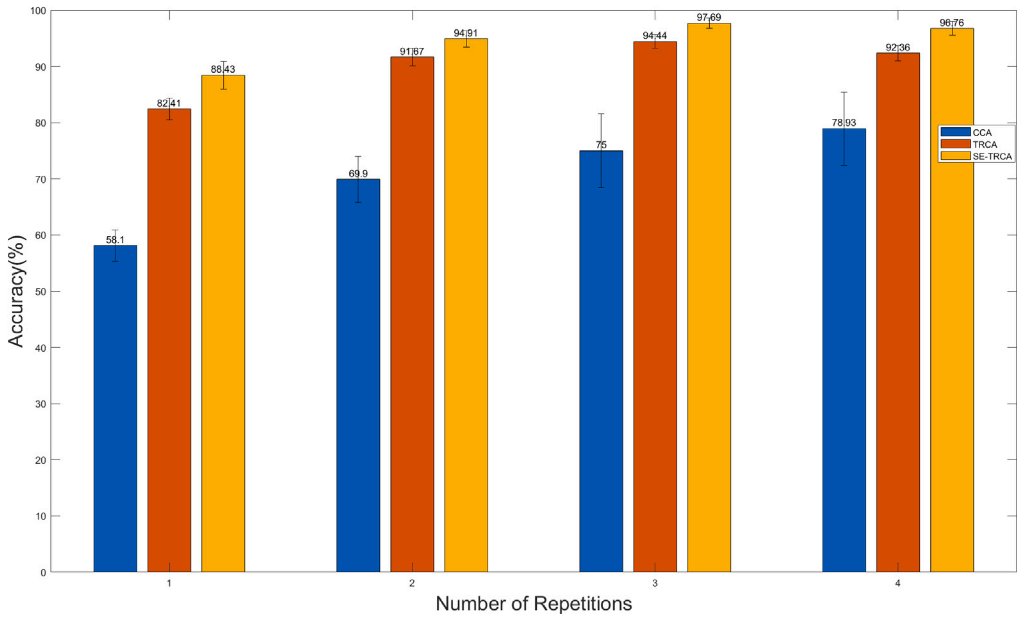

Fig. 6. Direction detection performance of the proposed SE-TRCA, as well as two baseline methods (i.e., CCA and TRCA) on SSVEP analysis of hybrid BCI dataset.

three frequency detection methods including CCA, TRCA, and the proposed SE-TRCA were employed and evaluated using the leave-one-out technique. In addition to the conventional criterion of classification accuracy, the performance of the proposed system was evaluated using the information transfer rate (ITR). ITR is a measure for assessing the performance of BCI systems, as it quantifies the amount of information that can be transmitted in one minute [46]. It is defined as follows:

$$ITR = (\log_2 N + P.\log_2 P + (1-P).\log_2[\frac{1-P}{N-1}])(\frac{60}{T}) \quad (13)$$

Where N, P, and T denote the number of classes, the accuracy of classification, and the duration (in seconds) needed for the completion of the spelling procedure, respectively [67].

4. Results

4.1. Comparative experiments

The direction detection accuracy of proposed SE-TRCA, as well as two baseline methods including TRCA and CCA, onhybrid BCI dataset, are presented in Fig. 6. All methods were compared with fine-tuned parameters, therefore the number of EEG channels, the temporal shift (i.e., τ), and the number of spatial filters (i.e., M) were set to 9, 3, and 4, respectively for our SE-TRCA. The parameter M is set to 3 for TRCA baseline method. it should be noted that The parameters were chosen by the grid search. As shown in Fig. 6, our proposed SE-TRCA method outperforms the TRCA and CCA baselines across all repetitions, where the classification accuracy (direction detection) increases by at least 7.3%, 3.6%, 3.4%, and 4.8% for each repetition, respectively.

Following [41], we also combined the P300 analysis with SSVEP analysis together to detect the target character. In this dataset, P300 detection is a 9−class classification task to detect the target group and SSVEP is a 3−class classification task to detect the target direction. We integrated the classification results of these two analyses such that The target character is correctly identified if both components P300 (target group) and SSVEP (target direction) are correctly detected. The target character is missed if either component is misclassified. It must mention that implemented P300 analysis method is the same, but SSVEP analysis is performed by the proposed SE-TRCA, TRCA, and CCA. The results are obtained over 6 subjects and presented the overall accuracy (%) and ITR (bit/min) in Table 2. It shows that the overall classification results are improved results from a more precise SSVEP analysis yielded by our proposed SE-TRCA method.

To conduct a more comprehensive comparison, the performance of the proposed model was also assessed alongside CCA and TRCA on the benchmark SSVEP dataset [58]. The aim on this database is to identify the frequency of a stimulus based on EEG signals. It is important to note that all three methods utilized the average EEG signal from the training trials as a reference signal. The leave-one-out approach was employed to evaluate the model, with five trials allocated for training and one trial for testing in each repetition. Tables 3 and 4 present the average accuracy and ITR achieved by each model across all subjects, respectively.

4.2. Parameter analysis

We first analyzed the impact of the number of EEG channels for different models on SSVEP analysis. Fig. 7 presents the classification accuracy under two modes of EEG channels (i.e., using 9 channels for the occipital regions and utilizing all 32 channels). It indicates that the setting of 9 EEG channels is better than the setting of 32 EEG channels for all approaches in each repetition.

To determine the optimal number of spatial filters (i.e., M) and the optimal temporal shift (i.e., τ) for our SE-TRCA model, we grid search M and τ within $\{1,2,3,4,5,6\}$ and $\{1,2,3,4\}$, respectively in Fig. 8. It shows that the proposed SE-TRCA model is consistent under different values of parameters M and τ. The optimal number of spatial filters is $M = 4$, and the optimal value of temporal shift is $\tau = 3$. We also conducted an experiment to search for the best parameter M for the TRCA baseline method. As shown in Fig. 9, the optimal M for TRCA baseline is $M = 3$.

4.3. Visualization of SSVEP components

Compared to other regions, EEG electrodes in the occipital region are expected to record more active signals since this region is active during the SSVEP analysis. Fig. 10 visualizes the topography of spatial filter coefficients yielded by CCA, TRCA, and our proposed SE-TRCA approaches. In general, TRCA-based methods are superior to the CCA ones in occipital region detection. It is obvious that our proposed SE-TRCA performs better than CCA and TRCA baselines, where the activate occipital regions (see red circles in Fig. 10) can be better detected via

Table 2
Character recognition performance obtained by combining P300 detection and SSVEP component analysis (direction detection) using proposed SE-TRCA, as well as two baseline methods including CCA and TRCA (in hybrid BCI dataset).

Method	P300 + SSVEP (CCA)		P300 + SSVEP (TRCA)		P300 + SSVEP(SE-TRCA)	
Number of repetitions	Accuracy (%)	ITR (bit/min)	Accuracy (%)	ITR (bit/min)	Accuracy (%)	ITR (bit/min)
1	53.01 ± 3.48	44.99 ± 5.26	56.02 ± 3.69	49.43 ± 5.37	58.56 ± 3.52	53.06 ± 5.58
2	59.49 ± 3.76	27.27 ± 2.75	73.38 ± 3.01	38.49 ± 2.66	72.22 ± 3.10	37.43 ± 2.73
3	67.13 ± 3.24	22.19 ± 1.76	80.79 ± 2.52	30.50 ± 1.75	82.41 ± 2.00	31.37 ± 1.46
4	72.69 ± 2.67	18.89 ± 1.17	83.33 ± 2.25	24.02 ± 1.21	84.03 ± 2.31	24.32 ± 1.23

Table 3
Averaged Frequency detection accuracy ± Standard Error of methods using different data lengths (from 0.5 s to 3 s with a step size of 0.5 s) in pure SSVEP dataset.

Method	Time window					
	0.5 s	1 s	1.5 s	2 s	2.5 s	3 s
CCA	23.92 ± 3.26	60.83 ± 4.34	75 ± 3.78	82.86 ± 3.26	87.27 ± 2.72	90.47 ± 2.11
TRCA	46.20 ± 3.85	82.01 ± 3.19	91.32 ± 2.17	94.63 ± 1.44	96.73 ± 0.81	97.91 ± 0.50
SE-TRCA	**46.71 ± 3.64**	**83.64 ± 3.04**	**91.61 ± 2.28**	**95.23 ± 1.38**	**97.17 ± 0.73**	**98.19 ± 0.44**

Table 4
Averaged ITR ± Standard Error of methods using different data lengths (from 0.5 s to 3 s with a step size of 0.5 s) in pure SSVEP dataset.

Method	Time window					
	0.5 s	1 s	1.5 s	2 s	2.5 s	3 s
CCA	77.34 ± 17.62	150.16 ± 15.04	135.33 ± 9.63	117.74 ± 6.54	101.70 ± 4.58	89.35 ± 3.16
TRCA	177.90 ± 24.60	221.47 ± 11.97	177.49 ± 6.12	142.08 ± 3.26	118.59 ± 1.74	101.29 ± 0.97
SE-TRCA	181.01 ± 26.98	228.86 ± 12.39	178.50 ± 6.56	143.79 ± 3.68	119.67 ± 1.82	101.91 ± 0.99

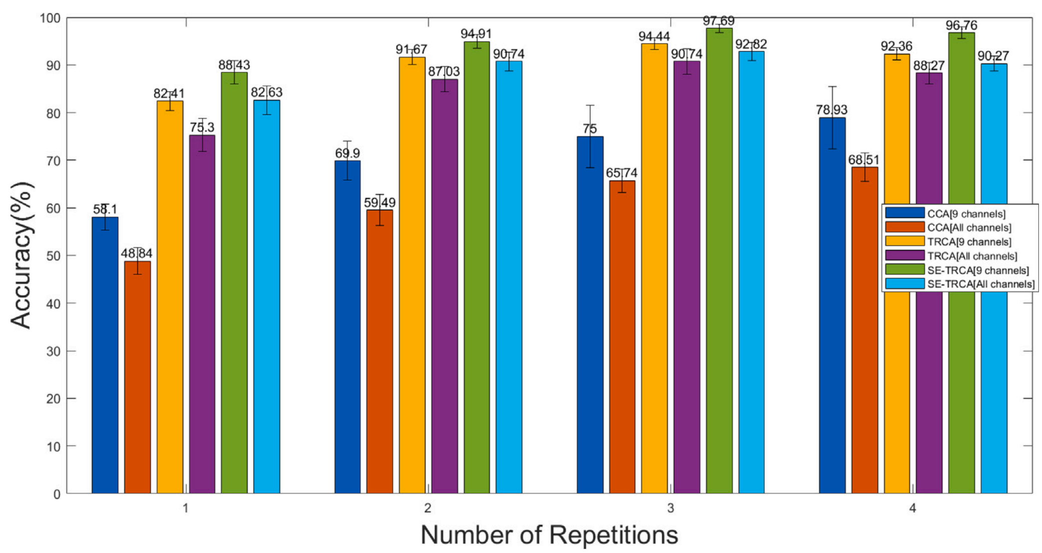

Fig. 7. The impact of the number of EEG channels in SSVEP component analysis on CCA, TRCA, and SE-TRCA approaches (for direction detection in hybrid BCI dataset).

our method compared to the traditional TRCA and CCA methods. The color scheme used in the topography figure represents activity levels, where "−1" or blue color indicates the lowest activity, and "+1" or red color indicates the highest activity.

5. Discussion

The proposed SE-TRCA approach in this paper demonstrates several advantages over the baseline methods, CCA, and state-of-the-art TRCA, in terms of accuracy, spatial filters, and frequency content. In the rapidly advancing field of BCIs, achieving high accuracy in classifying brain signals is of paramount importance. Our SE-TRCA method excels in this regard, as evidenced by the results presented in Tables 2, 3, and 4. The method consistently outperforms both TRCA and CCA baselines across all repetitions in the SSVEP component analysis task, showcasing its robustness and generalizability.

5.1. Accuracy

The results presented in Fig. 2 indicate that the SE-TRCA method outperforms both the TRCA and CCA baseline across all repetitions in the SSVEP classification task. The classification accuracy consistently increases by at least 7.3%, 3.6%, 3.4%, and 4.8% for each repetition, respectively, compared to the baselines. This improvement in accuracy demonstrates the effectiveness of the proposed SE-TRCA approach in capturing more discriminative features from the SSVEP component, resulting in enhanced classification performance. Furthermore, a statistical comparison was performed among the methods. According to Table 5, the paired t-test analysis between the methods (SE-TRCA vs. TRCA, SE-TRCA vs. CCA, and TRCA vs. CCA) reveals a significant enhancement in the direction detection accuracy of our proposed method compared to both CCA and TRCA methods ($\rho < 0.05$).

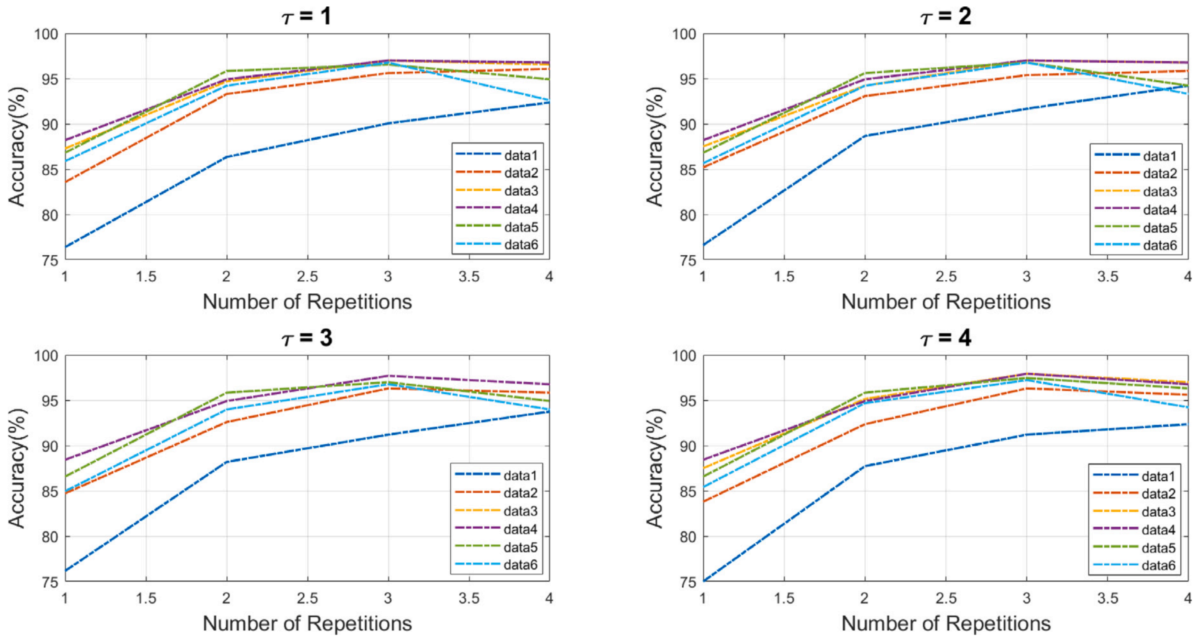

Fig. 8. Effects of temporal shift(τ) and number of spatial filters (M) in SE-TRCA method for direction detection in hybrid BCI dataset.

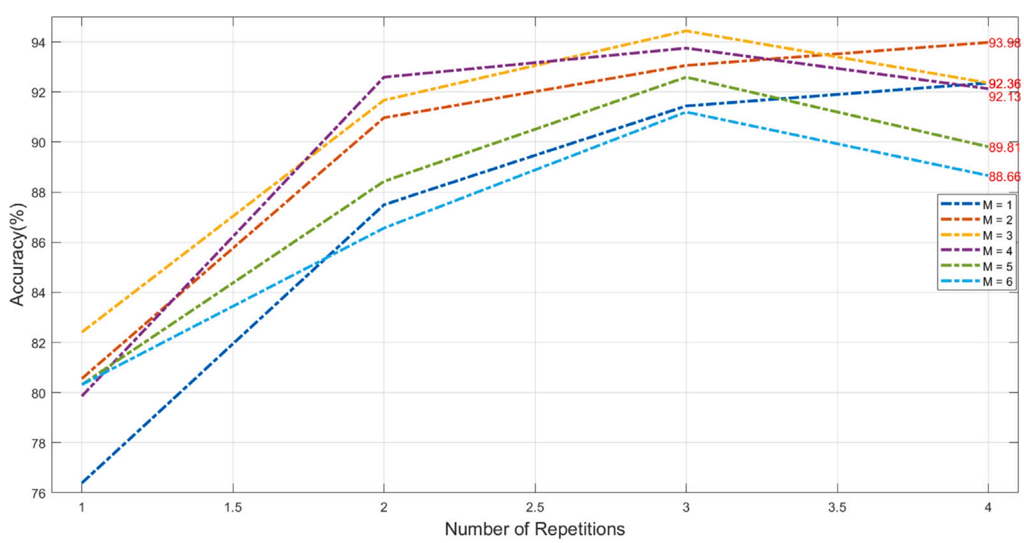

Fig. 9. Effects of number of spatial filters (M) in TRCA method for direction detection (Hybrid dataset).

The performance of the SE-TRCA method was assessed using a pure SSVEP dataset. The results illustrate that the SE-TRCA method surpasses both CCA and TRCA, even regarding frequency detection accuracy. In the mentioned dataset, the SE-TRCA method achieved a frequency detection accuracy of 98.19% for a 3-second signal, while TRCA and CCA attained accuracies of 97.91% and 90.47%, respectively. Through the evaluation of the SE-TRCA method on two different datasets, it has been demonstrated that the proposed approach exhibits strong performance in both direction detection and frequency detection when applied to SSVEP analysis. This finding highlights the effectiveness of the SE-TRCA method in accurately detecting both the intended direction and frequency detection with SSVEP components.

Table 5
The paired t-test between methods based on the results of Figure for direction detection (SSVEP component analysis).

Methods	SE-TRCA vs. TRCA	SE-TRCA vs. CCA	TRCA vs. CCA
P-value	6.2e−3	3.1948e−12	1.2205e−05

5.2. Spatial filters

The SE-TRCA approach incorporates spatial information in the analysis of the SSVEP component. By utilizing spatial filters, the method can capture and integrate the spatial characteristics of the EEG signals recorded from the occipital region. As shown in Fig. 6, the topography of spatial filter coefficients obtained by SE-TRCA reveals its ability to better detect the active occipital regions compared to the traditional CCA method and even TRCA. This suggests that the SE-TRCA approach can effectively focus on the relevant brain regions involved in SSVEP generation, leading to improved feature extraction and subsequent classification accuracy.

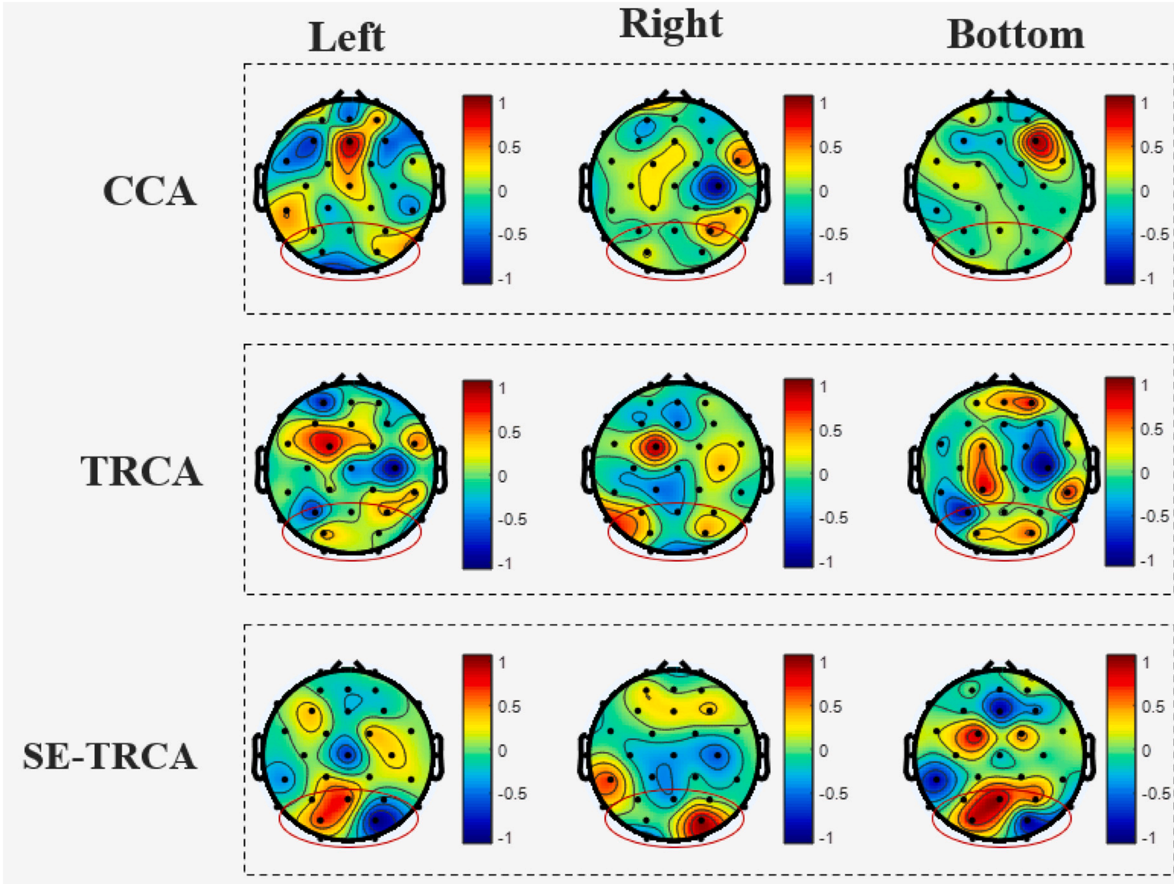

Fig. 10. Topography of spatial filter coefficients obtained using CCA, TRCA, and SE-TRCA approaches in direction detection analysis (Hybrid dataset). "+1" or red color indicates the highest activity, while "−1" or blue color indicates the lowest activity.

5.3. Frequency content

In addition to spatial information, the SE-TRCA approach also leverages spectral (frequency) information. By considering both spatial and spectral aspects, SE-TRCA can extract more discriminative features from the SSVEP component. This is particularly important in SSVEP-based tasks where the frequency content of the EEG signals carries valuable information about the attended visual stimulus. By combining the strengths of both spatial and spectral analyses, SE-TRCA enhances the extraction of relevant frequency components associated with SSVEP, leading to improved classification performance. Nevertheless, a constraint exists in the implementation of SE-TRCA, where the constructed FIR filter is limited to only two terms. Specifically, during the optimization process of SE-TRCA, certain coefficients of the FIR filter are determined while other coefficients are assigned zero values, suggesting that the filter has not undergone full optimization.

6. Conclusion

In this study, we proposed a novel approach, named SE-TRCA, for feature extractions in the concept of direction detection and frequency detection by SSVEP component analysis. The task of direction detection in novel SSVEP paradigms poses significant challenges, and to our best knowledge, only CCA has been utilized in this area thus far. However, due to certain limitations associated with CCA, we introduced a novel framework based on TRCA for feature extraction in direction detection. The TRCA-based feature extraction method has significantly outperformed CCA. Since, both CCA and TRCA solely extract spatial information, frequency information is ignored. Therefore we extended TRCA method and proposed SE-TRCA method in which the original EEG signals are concatenated with its shifted version to extract frequency information. The proposed SE-TRCA can capture and integrate both spectral (frequency) information and spatial information, from which more discriminative features can be extracted for classification tasks (e.g., direction detections in SSVEP paradigm). We evaluate our proposed approach on a hybrid BCI dataset and a benchmark pure SSVEP dataset. The experimental results manifest the superiority of our method compared with CCA and TRCA baselines. CCA, TRCA, and SE-TRCA methods were evaluated on a hybrid BCI dataset to determine their direction detection accuracy. The results showed that the SE-TRCA method achieved the highest accuracy of 96.76% for four repetitions, followed by TRCA with an accuracy of 92.36%, and CCA with an accuracy of 78.93%. Additionally, when applied to a pure SSVEP dataset, the frequency detection accuracy of the three methods was assessed. The SE-TRCA method demonstrated the highest accuracy of 98.19%, while TRCA achieved an accuracy of 97.91%, and CCA attained an accuracy of 90.47%. These findings highlight the superior performance of the proposed SE-TRCA method in various paradigms and tasks, supporting its wider applicability and generalizability in SSVEP analysis.

Implementation of the proposed method on MEG dataset can be investigated in further studies. Subsequent studies can prioritize the enhancement of the FIR filter design in the SE-TRCA method, as the current implementation is constrained to only two terms. Specifically, future research can focus on refining and optimizing the FIR filter by expanding its number of terms and allowing for non-zero coefficients to be obtained through the training process.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] H.-J. Hwang, S. Kim, S. Choi, C.-H. Im, EEG-based brain-computer interfaces: A thorough literature survey, Int. J. Hum.-Comput. Interact. 29 (12) (2013) 814–826.

[2] A. Katyal, R. Singla, A novel hybrid paradigm based on steady state visually evoked potential & P300 to enhance information transfer rate, Biomed. Signal Process. Control 59 (2020) 101884.

[3] S. Mouli, R. Palaniappan, DIY hybrid SSVEP-P300 LED stimuli for BCI platform using EMOTIV EEG headset, HardwareX 8 (2020) e00113.

[4] E. Yin, T. Zeyl, R. Saab, T. Chau, D. Hu, Z. Zhou, A hybrid brain–computer interface based on the fusion of P300 and SSVEP scores, IEEE Trans. Neural Syst. Rehabil. Eng. 23 (4) (2015) 693–701.

[5] A.M. Mijani, M.B. Shamsollahi, M.S. Hassani, A novel dual and triple shifted RSVP paradigm for P300 speller, J. Neurosci. Methods 328 (2019) 108420.

[6] M. Xu, H. Qi, B. Wan, T. Yin, Z. Liu, D. Ming, A hybrid BCI speller paradigm combining P300 potential and the SSVEP blocking feature, J. Neural Eng. 10 (2) (2013) 026001.

[7] Y. Li, J. Pan, F. Wang, Z. Yu, A hybrid BCI system combining P300 and SSVEP and its application to wheelchair control, IEEE Trans. Biomed. Eng. 60 (11) (2013) 3156–3166.

[8] B. Allison, J. Faller, C. Neuper, 14| BCIS that use steady-state visual evoked potentials or slow cortical potentials, Brain-Comput. Interfaces: Princ. Pract. (2012) 241.

[9] G. Bin, X. Gao, Z. Yan, B. Hong, S. Gao, An online multi-channel SSVEP-based brain–computer interface using a canonical correlation analysis method, J. Neural Eng. 6 (4) (2009) 046002.

[10] G. Townsend, B.K. LaPallo, C.B. Boulay, D.J. Krusienski, G. Frye, C. Hauser, N.E. Schwartz, T.M. Vaughan, J.R. Wolpaw, E.W. Sellers, A novel P300-based brain–computer interface stimulus presentation paradigm: Moving beyond rows and columns, Clin. Neurophysiol. 121 (7) (2010) 1109–1120.

[11] J. Jin, B.Z. Allison, E.W. Sellers, C. Brunner, P. Horki, X. Wang, C. Neuper, Optimized stimulus presentation patterns for an event-related potential EEG-based brain–computer interface, Med. Biol. Eng. Comput. 49 (2) (2011) 181–191.

[12] G.R. Müller-Putz, D.S. Klobassa, C. Pokorny, G. Pichler, H. Erlbeck, R.G. Real, A. Kübler, M. Risetti, D. Mattia, The auditory p300-based SSBCI: A door to minimally conscious patients? in: 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, 2012, pp. 4672–4675.

[13] S. Gao, Y. Wang, X. Gao, B. Hong, Visual and auditory brain–computer interfaces, IEEE Trans. Biomed. Eng. 61 (5) (2014) 1436–1447.

[14] E. Donchin, M.G. Coles, Is the P300 component a manifestation of context updating? Behav. Brain Sci. 11 (3) (1988) 357–374.

[15] T.W. Picton, The P300 wave of the human event-related potential, J. Clin. Neurophysiol. 9 (4) (1992) 456–479.

[16] C.J. Gonsalvez, J. Polich, P300 amplitude is determined by target-to-target interval, Psychophysiology 39 (3) (2002) 388–396.

[17] R. Fazel-Rezai, B.Z. Allison, C. Guger, E.W. Sellers, S.C. Kleih, A. Kübler, P300 brain computer interface: Current challenges and emerging trends, Front. Neuroeng. (2012) 14.

[18] L.A. Farwell, E. Donchin, Talking off the top of your head: Toward a mental prosthesis utilizing event-related brain potentials, Electroencephalogr. Clin. Neurophysiol. 70 (6) (1988) 510–523.

[19] J. Jin, S. Li, I. Daly, Y. Miao, C. Liu, X. Wang, A. Cichocki, The study of generic model set for reducing calibration time in P300-based brain–computer interface, IEEE Trans. Neural Syst. Rehabil. Eng. 28 (1) (2019) 3–12.

[20] M.N. Cherloo, H.K. Amiri, M.R. Daliri, Ensemble regularized common spatio-spectral pattern (ensemble RCSSP) model for motor imagery-based EEG signal classification, Comput. Biol. Med. 135 (2021) 104546.

[21] F.-B. Vialatte, M. Maurice, J. Dauwels, A. Cichocki, Steady-state visually evoked potentials: Focus on essential paradigms and future perspectives, Progr. Neurobiol. 90 (4) (2010) 418–438.

[22] Y. Zhang, G. Zhou, Q. Zhao, A. Onishi, J. Jin, X. Wang, A. Cichocki, Multiway canonical correlation analysis for frequency components recognition in SSVEP-based BCIs, in: International Conference on Neural Information Processing, Springer, 2011, pp. 287–295.

[23] Y. Zhang, G. Zhou, J. Jin, M. Wang, X. Wang, A. Cichocki, L1-regularized multiway canonical correlation analysis for SSVEP-based BCI, IEEE Trans. Neural Syst. Rehabil. Eng. 21 (6) (2013) 887–896.

[24] M. Nakanishi, Y. Wang, X. Chen, Y.-T. Wang, X. Gao, T.-P. Jung, Enhancing detection of SSVEPs for a high-speed brain speller using task-related component analysis, IEEE Trans. Biomed. Eng. 65 (1) (2017) 104–112.

[25] Y. Zhang, E. Yin, F. Li, Y. Zhang, T. Tanaka, Q. Zhao, Y. Cui, P. Xu, D. Yao, D. Guo, Two-stage frequency recognition method based on correlated component analysis for SSVEP-based BCI, IEEE Trans. Neural Syst. Rehabil. Eng. 26 (7) (2018) 1314–1323.

[26] J. Pan, X. Gao, F. Duan, Z. Yan, S. Gao, Enhancing the classification accuracy of steady-state visual evoked potential-based brain–computer interfaces using phase constrained canonical correlation analysis, J. Neural Eng. 8 (3) (2011) 036027.

[27] Z. Zhang, C. Wang, K.K. Ang, A.A.P. Wai, C.G. Nanyang, Spectrum and phase adaptive CCA for SSVEP-based brain computer interface, in: 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, IEEE, 2018, pp. 311–314.

[28] Y. Zhang, P. Xu, T. Liu, J. Hu, R. Zhang, D. Yao, Multiple frequencies sequential coding for SSVEP-based brain-computer interface, PLoS One 7 (3) (2012) e29519.

[29] J. Tong, D. Zhu, Multi-phase cycle coding for SSVEP based brain-computer interfaces, Biomed. Eng. Online 14 (1) (2015) 1–13.

[30] K.-S. Hong, M.J. Khan, Hybrid brain–computer interface techniques for improved classification accuracy and increased number of commands: A review, Front. Neurorobot. (2017) 35.

[31] R. Fazel-Rezai, S. Amiri, A. Rabbi, L. Azinfar, A review of P300, SSVEP, and hybrid P300/SSVEP brain-computer interface systems, 2013.

[32] M. Wang, I. Daly, B.Z. Allison, J. Jin, Y. Zhang, L. Chen, X. Wang, A new hybrid BCI paradigm based on P300 and SSVEP, J. Neurosci. Methods 244 (2015) 16–25.

[33] M.H. Chang, J.S. Lee, J. Heo, K.S. Park, Eliciting dual-frequency SSVEP using a hybrid SSVEP-P300 BCI, J. Neurosci. Methods 258 (2016) 104–113.

[34] N. Rathi, R. Singla, S. Tiwari, Towards a role-based authentication system based on SSVEP-P300 hybrid brain–computer interfacing, Behav. Inform. Technol. (2021) 1–17.

[35] J. Han, C. Liu, J. Chu, X. Xiao, L. Chen, M. Xu, D. Ming, Effects of inter-stimulus intervals on concurrent P300 and SSVEP features for hybrid brain-computer interfaces, J. Neurosci. Methods 372 (2022) 109535.

[36] L.-W. Ko, S. Ranga, O. Komarov, C.-C. Chen, Development of single-channel hybrid BCI system using motor imagery and SSVEP, J. Healthcare Eng. 2017 (2017).

[37] Z. Wang, Y. Yu, M. Xu, Y. Liu, E. Yin, Z. Zhou, Towards a hybrid BCI gaming paradigm based on motor imagery and SSVEP, Int. J. Hum.–Comput. Interact. 35 (3) (2019) 197–205.

[38] X. Chi, C. Wan, C. Wang, Y. Zhang, X. Chen, H. Cui, A novel hybrid brain-computer interface combining motor imagery and intermodulation steady-state visual evoked potential, IEEE Trans. Neural Syst. Rehabil. Eng. (2022).

[39] B.Z. Allison, Toward ubiquitous bcis, in: Brain-Computer Interfaces, Springer, 2009, pp. 357–387.

[40] E. Yin, Z. Zhou, J. Jiang, F. Chen, Y. Liu, D. Hu, A novel hybrid BCI speller based on the incorporation of SSVEP into the P300 paradigm, J. Neural Eng. 10 (2) (2013) 026012.

[41] S. Jalilpour, S.H. Sardouie, A. Mijani, A novel hybrid BCI speller based on RSVP and SSVEP paradigm, Comput. Methods Programs Biomed. 187 (2020) 105326.

[42] Z. Lin, C. Zhang, W. Wu, X. Gao, Frequency recognition based on canonical correlation analysis for SSVEP-based BCIs, IEEE Trans. Biomed. Eng. 53 (12) (2006) 2610–2614.

[43] X. Chen, Y. Wang, S. Gao, T.-P. Jung, X. Gao, Filter bank canonical correlation analysis for implementing a high-speed SSVEP-based brain–computer interface, J. Neural Eng. 12 (4) (2015) 046008.

[44] T. Liu, Y. Zhang, L. Wang, J. Li, P. Xu, D. Yao, Fusing canonical coefficients for frequency recognition in SSVEP-based BCI, IEEE Access 7 (2019) 52467–52472.

[45] G. Bin, X. Gao, Y. Wang, Y. Li, B. Hong, S. Gao, A high-speed BCI based on code modulation VEP, J. Neural Eng. 8 (2) (2011) 025015.

[46] Y. Wang, M. Nakanishi, Y.-T. Wang, T.-P. Jung, Enhancing detection of steady-state visual evoked potentials using individual training data, in: 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Ieee, 2014, pp. 3037–3040.

[47] Y. Zhang, G. Zhou, J. Jin, X. Wang, A. Cichocki, Frequency recognition in SSVEP-based BCI using multiset canonical correlation analysis, Int. J. Neural Syst. 24 (04) (2014) 1450013.

[48] Y. Jiao, Y. Zhang, Y. Wang, B. Wang, J. Jin, X. Wang, A novel multilayer correlation maximization model for improving CCA-based frequency recognition in SSVEP brain–computer interface, Int. J. Neural Syst. 28 (04) (2018) 1750039.

[49] Q. Wei, S. Zhu, Y. Wang, X. Gao, H. Guo, X. Wu, A training data-driven canonical correlation analysis algorithm for designing spatial filters to enhance performance of SSVEP-based BCIs, Int. J. Neural Syst. 30 (05) (2020) 2050020.

[50] S. Mahmood, J. Shin, I. Farhana, M.R. Islam, M.K.I. Molla, Frequency recognition of short-time SSVEP signal using CORRCA-based spatio-spectral feature fusion framework, IEEE Access 9 (2021) 167744–167755.

[51] S. Lemm, B. Blankertz, G. Curio, K.-R. Muller, Spatio-spectral filters for improving the classification of single trial EEG, IEEE Trans. Biomed. Eng. 52 (9) (2005) 1541–1548.

[52] G. Dornhege, B. Blankertz, M. Krauledat, F. Losch, G. Curio, K.-R. Muller, Combined optimization of spatial and temporal filters for improving brain-computer interfacing, IEEE Trans. Biomed. Eng. 53 (11) (2006) 2274–2281.

[53] M.N. Cherloo, H.K. Amiri, M.R. Daliri, Spatio-spectral CCA (SS-CCA): A novel approach for frequency recognition in SSVEP-based BCI, J. Neurosci. Methods 371 (2022) 109499.

[54] C.M. Wong, B. Wang, Z. Wang, K.F. Lao, A. Rosa, F. Wan, Spatial filtering in SSVEP-based BCIs: Unified framework and new improvements, IEEE Trans. Biomed. Eng. 67 (11) (2020) 3057–3072.

[55] V.P. Oikonomou, An adaptive task-related component analysis method for SSVEP recognition, Sensors 22 (20) (2022) 7715.

[56] Y. Zhang, D. Guo, F. Li, E. Yin, Y. Zhang, P. Li, Q. Zhao, T. Tanaka, D. Yao, P. Xu, Correlated component analysis for enhancing the performance of SSVEP-based brain-computer interface, IEEE Trans. Neural Syst. Rehabil. Eng. 26 (5) (2018) 948–956.

[57] L. Acqualagna, B. Blankertz, Gaze-independent BCI-spelling using rapid serial visual presentation (RSVP), Clin. Neurophysiol. 124 (5) (2013) 901–908.

[58] Y. Wang, X. Chen, X. Gao, S. Gao, A benchmark dataset for SSVEP-based brain–computer interfaces, IEEE Trans. Neural Syst. Rehabil. Eng. 25 (10) (2016) 1746–1752.

[59] Z. Lin, C. Zhang, Y. Zeng, L. Tong, B. Yan, A novel P300 BCI speller based on the triple RSVP paradigm, Sci. Rep. 8 (1) (2018) 1–9.

[60] A.M. Mijani, M.B. Shamsollahi, M.S. Hassani, S. Jalilpour, Comparison between single, dual and triple rapid serial visual presentation paradigms for P300 speller, in: 2018 IEEE International Conference on Bioinformatics and Biomedicine, BIBM, IEEE, 2018, pp. 2635–2638.

[61] J. Chen, D. Zhang, A.K. Engel, Q. Gong, A. Maye, Application of a single-flicker online SSVEP BCI for spatial navigation, PLoS One 12 (5) (2017) e0178385.

[62] A. Maye, D. Zhang, A.K. Engel, Utilizing retinotopic mapping for a multi-target SSVEP BCI with a single flicker frequency, IEEE Trans. Neural Syst. Rehabil. Eng. 25 (7) (2017) 1026–1036.

[63] H. Tanaka, Group task-related component analysis (gTRCA): A multivariate method for inter-trial reproducibility and inter-subject similarity maximization for EEG data analysis, Sci. Rep. 10 (1) (2020) 1–17.

[64] Y. Zhang, D. Guo, D. Yao, P. Xu, The extension of multivariate synchronization index method for SSVEP-based BCI, Neurocomputing 269 (2017) 226–231.

[65] C.-C. Chang, C.-J. Lin, LIBSVM: A library for support vector machines, ACM Trans. Intell. Syst. Technol. (TIST) 2 (3) (2011) 1–27.

[66] J. Höhne, M. Schreuder, B. Blankertz, M. Tangermann, A novel 9-class auditory ERP paradigm driving a predictive text entry system, Front. Neurosci. 5 (2011) 99.

[67] V.P. Oikonomou, S. Nikolopoulos, I. Kompatsiaris, A bayesian multiple kernel learning algorithm for ssvep bci detection, IEEE J. Biomed. Health Inform. 23 (5) (2018) 1990–2001.