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Comparative Study of Algorithms based on Steady-state Visual Evoked Potential Detection

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Abstract

This study compares the performance of various aspects of the recently proposed algorithm for the detection of steady-state visual evoked potentials (SSVEPs): TRCA and SSCOR, with the addition of filter banks, and further develops an integration method to integrate filters corresponding to multiple stimulus frequencies. In this study, SSCOR detection algorithm is compared with TRCA detection algorithm using Benchmark dataset. The performance was evaluated in terms of classification accuracy and information transfer rate (ITR). The results show that the overall performance metrics of the SSCOR algorithm are better than those of the TRCA method.

Keywords

Brain-computer Interface(BCI); Electroen-cephalography (EEG) Steady-state Visual Evokedpotentials(SSVEP); Filter Bank.

1. Introduction

Brain-computer interface (BCI) provides a new communication channel between the brain and external devices and has received increasing attention in recent years. However, the low signal-to-noise ratio (SNR) of scalp-recorded EEG signals limits the information transmission rate of BCIs. In recent years, steady-state visual evoked potentials (SSVEPS)-based BCIs have received increasing attention because of their advantages of high information transmission rate and less user training. In SSVEP-based BCI, the user gazes at multiple visual flicker blocks labeled by frequency or phase, and the resulting SSVEP exhibits the same stimulus properties as the target. Therefore, SSVEPs can be analyzed by target recognition algorithms to identify target stimuli.

Target recognition algorithms are very important aspects of brain-computer interface systems and were first used for target detection by power spectral density analysis(PSDA) [1]. With the development of EEG signal processing techniques, spatial filtering techniques to improve the signal-to-noise ratio(SNR) of SSVEP by removing the background EEG signal have been applied to more efficient target identification methods. Widely used spatial filtering methods in SSVEP-based BCI include typical correlation analysis (CCA) [2], minimum energy combination (MEC) [3], and so on. These methods have been shown to be more effective than the PSDA-based methods. In recent years, many more advanced target detection algorithms have been proposed, and the best results are obtained by the TRCA [4] and SSCOR [5] algorithms, where the former improves the signal-to-noise ratio and suppresses background EEG interference by learning a spatial filter that improves the signal-to-noise ratio by maximizing the recurrence among multiple trials, and the latter similarly designs a spatial filter with a set of training data segments to learn a common SSVEP response space to extract relevant components.

The purpose of this study is to quantitatively compare the TRCA-based and SSCOR detection methods, while adding filter banks and integrated filter methods to further improve the algorithm identification performance based on these two algorithms. In evaluating the effectiveness and feasibility of these two methods for real BCI, the detection accuracy of the two methods is estimated separately from the simulated ITR.

2. Methodology

2.1. Data Source

Benchmark data from the brain-computer interface research group at Tsinghua University were used in this paper. EEG data were acquired using the Synamps2 EEG system with a sampling rate of 1000 Hz. data were acquired using a 64-electrode device based on the International Extended 10-20 system. data were collected from 35 subjects, with each subject acquiring 40 experiments, for a total of 6 sets. The duration of each experiment was 6 seconds. Specific information can be found in [6]. The data for each subject is a 4-dimensional matrix expressed as $X_{(cpfd)} \in R^{N_c \times N_p \times N_f \times N_d}$, Nc denotes the number of channels, Np denotes the number of sampling points, Nf denotes the number of targets, and Nd denotes the number of experimental blocks. EEG data from the nine electrode channels (Oz, O1, O2, Pz, POz, PO3, PO4, PO5, and PO6) most affected by SSVEP were used for analysis and evaluation in this study.

2.2. Target Recognition Algorithm

2.2.1. Task-Related Component Analysis(TRCA)

Task-related component analysis is able to extract task-related components by maximizing the reproducibility of EEG data in each task. Assuming two source signals: task-related component $s(t)$ and task-irrelevant component $n(t)$, the linear model of the acquired multichannel EEG signal is assumed to be:

$$x_j(t) = a_{1,j}s(t) + a_{2,j}n(t), \quad j = 1, 2, ..., N_c \tag{1}$$

where j is the channel index $a_{1,j}$ and $a_{2,j}$ is the mixing factor that projects the source signal to the EEG signal.The following equation is obtained by multiplying the multichannel EEG signal with the filter w :

$$y(t) = \sum_{j=1}^{N_c} w_j x_j(t) = \sum_{j=1}^{N_c} (w_j a_{1,j} s(t) + w_j a_2 n(t)) \tag{2}$$

when $\sum_{j=1}^{N_c} w_j a_{1,j} = 1$ and $\sum_{j=1}^{N_c} w_j a_{2,j} = 0$, get the final solution: $y(t) = s(t)$.

This problem can be solved by maximizing the inter-trial covariance with the following equation:

$$\omega = \arg\max \frac{w^{\mathrm{T}} S w}{w^{\mathrm{T}} Q w} \tag{3}$$

The matrix S represents the sum of all possible combinations of trials with different frequencies:

$$S = \sum_{\substack{i,j=1 \\ i \neq j}}^{N_d} \mathrm{Cov}(X_i, X_j) \tag{4}$$

The matrix Q denotes the sum of autocovariances for each frequency correspon- ding to trial:

$$Q=\sum_{i,j=1}^{N_d} \mathrm{Cov}\left(X_i, X_j\right) \tag{5}$$

The solution of the optimal weight vector w_{trca} of Equation (3) is calculated from the eigenvectors of the matrix $Q^{-1}S$.

2.2.2. Sum of Squared Correlations (SSCOR)

Sum of Squared Correlations maps a given EEG data to a common SSVEP space by constructing mappings w_{sscor} . The equation of the sum of squares correlations is as follows.

$$\max \sum_{i<j}^{N_d} \rho\left(w_i^T X_i, w_j^T X_j\right)^2 \tag{6}$$

Constraining the above objective function according to the SSVEP requirements:

$$\begin{gathered} \max \sum_{i=2}^{N}\left(w_1^T C_{(1,i)} w_i\right)^2 \\ \text{subject to } w_i^T C_{i,i} w_i = 1, \ \forall i \end{gathered} \tag{7}$$

$\mathrm{C}_{1,i}$ denotes the cross-covariance matrix between the template signal and the SSVEP data segment, and $\mathrm{C}_{i,i}$ denotes the auto-covariance matrix. The constraints in (7) can be decomposed $\mathrm{C}_{i,i}=K_i^T K_i$. by defing $G_i = K_1^{-1} C_{(1,i)} K_i^{-1}$ and $v_i = K_i w_i$ .Solve the above optimization problem using the Lagrangian method and find the eigenvector corresponding to the largest eigenvalue. The final representation of the spatial filter is as follows:

$$w_{sscor}=K_i^{-1} v_i \tag{8}$$

Finally, the test data are projected into the optimized SSVEP space by w_{sscor} .

2.2.3. Filter-bank Analysis

In this study, the filter bank analysis method [9] was used to mine the useful information in the harmonic components. The EEG data were divided into Nb subbands, and then the target detection method was applied to each subband separately, and the spatial filters were learned for each subband component to obtain the target detection scores of each subband corresponding to the target frequency, and then the correlation coefficients of the subband components were combined by weighted sum of squares to obtain the final detection scores as follows:

$$\tilde{\rho} = \sum_{n=1}^{N_b} w(n) \bullet \left(\rho_k^n\right)^2 \tag{9}$$

where $w(n) = n^{-1.25} + 0.25 \ \ and \ \ n \in \left[1 \ \ N_b\right]$ is used to compensate for the decrease in SNR of SSVEP with increasing frequency.

2.2.4. The Ensemble Approach

This study uses an ensemble approach to optimize the spatial filter and improve the SNR by extracting the common information of SSVEP [8]. An integrated spatial filter is finally created by concatenating all weighting vectors Nf. The SSVEP ensemble spatial filter $W \in R^{N_c \times N_f}$ is designed as follows:

$$W = [w_1, w_2, ..., w_{N_f}] \tag{10}$$

2.3. Performance Evaluation

In this study, detection accuracy and ITR are used as the main performance metrics for evaluating target detection methods.. Using the funnel-one cross-validation method, the data were divided into five training groups and one test group, and the spatial filters were derived from the training data, and SSVEP templates were constructed for each target frequency. the ITR (bits/minute) used in this study is defined as follows:

$$ITR = \frac{60}{T}\left\{\log_2 N + P\log_2 \frac{(1-P)}{(N-1)}\right\} \tag{11}$$

where P is the accuracy rate, T is the average time for target selection, and N is the number of targets.

3. Result

The average detection accuracy and simulated ITR of the basic SSCOR and TRCA methods are shown in Figure.1. The comparison between SSCOR and TRCA shows that the accuracy and ITR of SSCOR are higher than those of TRCA after a time window length of 0.5 s. However, all data of SSCOR before 0.5 s are inferior to those of TRCA, and the SSCOR method does not perform as well as In addition, the maximum value of ITR (239.57 bit/min) is present in the SSCOR method.

The average detection accuracy of SSCOR and TRCA integrated methods and simulated ITR are shown in Figure 2. With the addition of the integrated method, the accuracy and ITR of both SSCOR and TRCA improved to some extent compared to their previous performance. In the long time window (after 0.5s), the overall accuracy of TRCA is slightly higher than that of SSCOR, but in the case of the ITR score, SSCOR reaches its highest score of 289.01 bits/min at around 0.4s, while TRCA reaches its maximum value of 262.63 bits/min at around 0.5s.

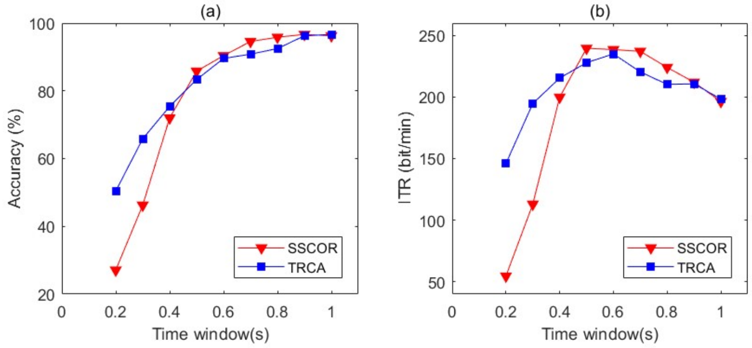

Figure 1. Performance Comparison of SSCOR and TRCA Base Algorithms. (a): denotes the average detection accuracy, (b): denotes the average analog information transmission number rate ITR

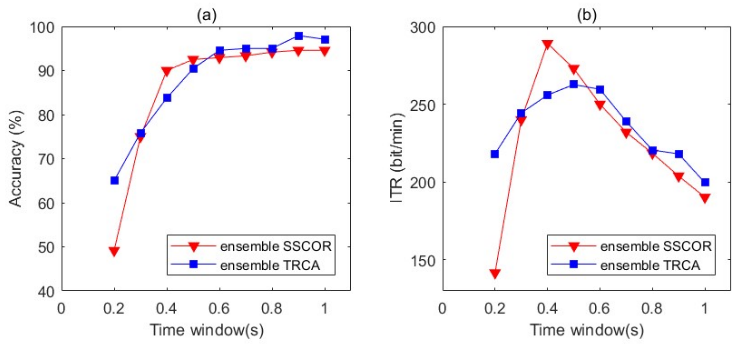

Figure 2. Performance comparison of SSCOR and TRCA with ensemble approach. (a): denotes the average detection accuracy, (b): denotes the average analog information transfer number rate ITR

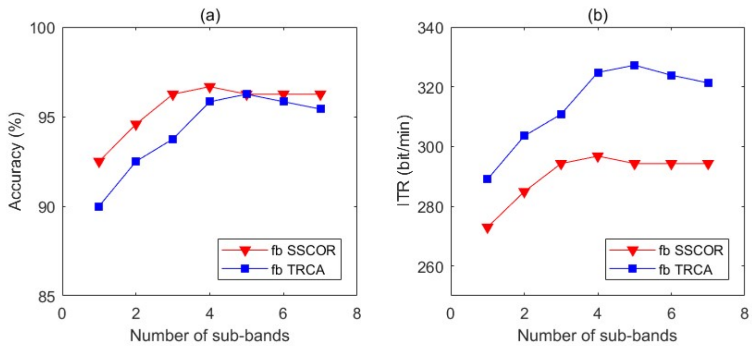

Figure 3. Performance comparison of SSCOR and TRCA with filter bank preprocessing. (a): denotes the average detection accuracy and (b): denotes the average analog information transmission number rate ITR

Filter banks were added to continue the comparison between these two methods. It has been shown in previous analyses that adding the integrated method can significantly improve performance, and both methods achieve good performance at a time length of 0.4 s. Therefore, 0.4 s was chosen as the condition for the subsequent analysis. the average detection accuracy and simulated ITR for SSCOR and TRCA with the addition of the filter bank are shown in Figure 3. It is clear from the figure that the SSCOR method always scores a little higher compared to the TRCA method and reaches a maximum value of 327.20 bits/min at a subband number of 5. From the simulated ITR performance above, it can be seen that the SSCOR method always has a higher performance compared to the TRCA method, thus proving its clear superiority.

4. Conclusion

In this study, a quantitative comparison of two target recognition methods based on SSCOR and TRCA in SSVEP-based BCI was conducted. The two methods were applied to a Benchmark dataset of 40 classes of targets, respectively, and the data were trained using the leave-one-out cross-validation method, which was evaluated in terms of detection accuracy and simulated ITR. In addition, based on the original method, an integration method is applied to find the common space filter as well as to further optimize the original base algorithm using the harmonic components of the filter bank, and the two algorithms are compared quantitatively. In summary, both methods show good performance, with SSCOR showing more outstanding performance for specific data lengths, and both methods perform better than TRCA in terms of accuracy as well as ITR after the integration process and the addition of filter banks. since the purpose of this study is to provide a comprehensive compa- rison of the existing methods, it is possible to further improve the performance of BCIs performance combinations will be investigated in future work.

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