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Robust Spatial Filters on Three-Class Motor Imagery EEG Data Using Independent Component Analysis

Bangyan Zhou, Xiaopei Wu*, Lei Zhang, Zhao Lv, Xiaojing Guo

The Key Laboratory of Intelligent Computing & Signal Processing, Ministry of Education,
Anhui University, Hefei, China
Email: zby@ahu.edu.cn, *wxp2001@ahu.edu.cn

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Abstract

Independent Component Analysis (ICA) was often used to separate movement related independent components (MRICs) from Electroencephalogram (EEG) data. However, to obtain robust spatial filters, complex characteristic features, which were manually selected in most cases, have been commonly used. This study proposed a new simple algorithm to extract MRICs automatically, which just utilized the spatial distribution pattern of ICs. The main goal of this study was to show the relationship between spatial filters performance and designing samples. The EEG data which contain mixed brain states (preparing, motor imagery and rest) were used to design spatial filters. Meanwhile, the single class data was also used to calculate spatial filters to assess whether the MRICs extracted on different class motor imagery spatial filters are similar. Furthermore, the spatial filters constructed on one subject's EEG data were applied to extract the others' MRICs. Finally, the different spatial filters were then applied to single-trial EEG to extract MRICs, and Support Vector Machine (SVM) classifiers were used to discriminate left hand、right-hand and foot imagery movements of BCI Competition IV Dataset 2a, which recorded four motor imagery data of nine subjects. The results suggested that any segment of finite motor imagery EEG samples could be used to design ICA spatial filters, and the extracted MRICs are consistent if the position of electrodes are the same, which confirmed the robustness and practicality of ICA used in the motor imagery Brain Computer Interfaces (MI-BCI) systems.

Keywords

ICA; Spatial Filter; Motor Imagery; BCI; SVM

1. Introduction

Brain-Computer Interfaces (BCI) translate brain signals into control signals that allow the user to communicate with the outside world without using muscles or peripheral nerves [1]. In recent years, ICA has been successful-

*Corresponding author.

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ly used to identify brain related signals and artifacts from Electroencephalography (EEG) data in BCI system [2] [3]. In this paper, the chosen ICA algorithm was Infomax [4]. Here, a new algorithm was proposed to extract movement related independent components (MRICs) automatically, which were used to classify the different brain states corresponding to different motor imagery activities.

Meanwhile, we studied the influences of different design samples on ICA spatial filters performance. On one hand, lots of trials, including motor imagery state or rest state [5], were commonly used to optimize ICA spatial filters. In theory, more trials would provide more information that can help improve the classification accuracy. However, using more trials would increase the burdens of data acquisition and computation. In this study, different time segments of small number of trials, which contain all different brain states during the experiments, were used to design ICA spatial filters. On the other hand, ICA is an unsupervised algorithm [6], so there is no previous knowledge about the class labels of the motor imagery data. In this paper, the single class data was used to design spatial filters to assess whether the MRICs extracted by the ICA spatial filters constructed on different single class motor imagery data were similar. Furthermore, the state-to-state method [5] and the session-to-session method [7] have been proposed. In this study, a subject-to-subject method, which applied spatial filters constructed on one subject's motor imagery EEG data to extract the others' MRICs, was proposed. The method was investigated by cross validation among nine subjects. In addition, Support Vector Machine (SVM) [8] classifiers were used to discriminate left hand, right hand and foot imagery movements. The main goal of this study is to assess whether different EEG segments would influence the performance of ICA spatial filters, and confirm the practicality of ICA used in MI-BCI system for its robustness.

2. Experimental Paradigm and Dataset

The performances of the algorithms were evaluated on BCI Competition IV Dataset 2a. The datasets were recorded from nine healthy subjects. For each subject, two sessions on different days were recorded. During each session, the subjects were asked to perform 288 trials of four different motor imagery tasks, namely left hand, right hand, foot and tongue motor imagery (72 trials per class). Each trial began with an acoustic cue "beep" (at t = 0 s), and along with a fixation cross appeared on the black screen. After two seconds (at t = 2 s), an arrow cue, which pointed either to the left, right, down or up, appeared for 1.25 s on the screen. The subjects were then instructed to image the corresponding imaginary movement between 3 s and 6s. After 6 s (at t = 6 s), the screen was black again, allowing the subjects to relax. The timing scheme is shown in **Figure 1** right.

Twenty-two EEG electrodes (with left mastoid serving as reference and right mastoid as ground) were used to record cortical potential. The configuration of electrodes distribution is shown in **Figure 1** left. The data was sampled at 250 Hz and bandpass-filtered between 0.5 Hz and 100 Hz. An additional 50 Hz notch filter was enabled to suppress line noise.

In this paper, three of the four classes motor imagery data (left hand, right hand and foot) were selected to evaluate our algorithms. In order to assess the robustness to artifacts and outliers of ICA, no treatments (discarded or artifact correction) were performed. The raw EEG data was only bandpass-filtered between 8 Hz and 35 Hz, which covering mu and beta rhythms bands.

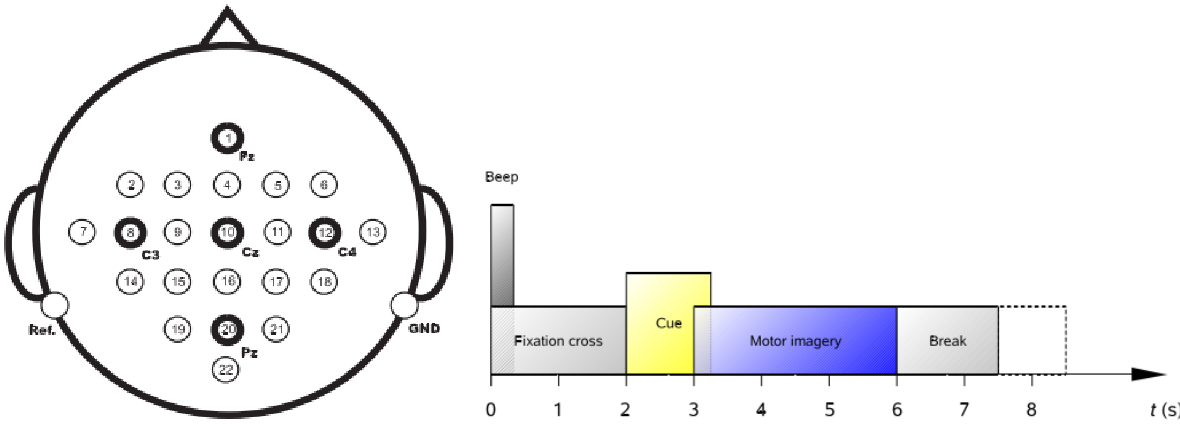

Figure 1. Layout of EEG electrodes (left) and Timing scheme of paradigm (right) for BCI Competition 2008 Datasets 2a.

3. Methods

3.1. ICA Algorithm

ICA is a Blind Source Separation (BSS) algorithm. Assume that there is an N-dimensional unknown vector of hidden independent sources $\mathbf{S}_N = [s_1,\ldots,s_N]^T$. The measured multi-channel EEG signals $\mathbf{X}_N = [x_1,\ldots,x_N]^T$ can be considered as the following liner mixture of sources.

$$\mathbf{X}_N = \mathbf{A}\mathbf{S}_N \tag{1}$$

where $\mathbf{A}$ is an unknown mixture matrix. The goal of ICA is to obtain hidden sources with the unmixing matrix $\mathbf{W}$ by following matrix transformation.

$$\mathbf{U}_N = \mathbf{W}\mathbf{X}_N \tag{2}$$

where unmixed signals $\mathbf{U}_N$ are the estimate of $\mathbf{S}_N$. Each row of $\mathbf{W}$ is a spatial filter for estimating ICs and each column of $\mathbf{A}$ (equals $\mathbf{W}^{-1}$) is a spatial pattern, which consists of electrode weights of ICs [5]. The same goal of different ICA algorithms is to make the estimated sources u_i ($I = 1,2,\ldots N$) statistically independent. In this paper, instead of using the standard Infomax code, the computer code of ICA algorithm was written in our own. The independence criterion of information maximization and natural gradient optimization algorithm were used. The final iterative optimization formula of matrix $\mathbf{W}$ is as follows.

$$\begin{gathered} \Delta\mathbf{W} \propto \left[\mathbf{I} - E\left[\mathbf{K}\cdot tanh(\mathbf{U})\mathbf{U}^T + \mathbf{U}\mathbf{U}^T\right]\right]\mathbf{W} \\ k_{ii} = 1(\text{super-Gaussian}); k_{ii} = -1(\text{sub-Gaussian}) \end{gathered} \tag{3}$$

where $E[\ ]$ is statistical average. $\mathbf{K}$ is the switch matrix corresponding to sources' different probabilistic models. Here, the ICA algorithm uses the diagonal elements k_{ii} to switch between super- and sub-Gaussian model [9].

3.2. Identifying Independent Components

Usually, complex characteristic features have been used to identify MRICs [10]. In this paper, just the spatial distribution information of sources was used to recognize the independent components. From the spatial pattern, we can conclude that the distribution of sources should be consistent with the position of electrodes, which means that the source s_i should have the highest influence on the nearest measured electrode signal x_i. So we search the maximum values of every column of absolute value matrix ($|\mathbf{A}|$). If the row number of the maximum value was consistent with the row number of the measured electrode signal x_i, then the corresponding column number j of the maximum value was recorded, and the spatial filter for extracting sources s_i was w_j.

In this paper, ten MRICs (IC3, IC5, IC8, IC9, IC10, IC11, IC12, IC15, IC16, IC17), which have biggest weights on the nearest measured electrode signal x_3, x_5, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{15}, x_{16}, x_{17} respectively, were extracted from twenty-two channel EEG signals, because they represent brain activities from sensorimotor cortex areas. If the ten sources do not exist simultaneously with our method, it means the filter design fails. **Figure 2** shows spatial projections of selected ten motor ICs for one subject S3.

3.3. Feature Selection and Classification

For one single trial data x_i, the selected ten spatial filters w_j($j = 1,2,\ldots,10$) were used to extract MRICs by equation (4).

$$s_i = w_j x_i \tag{4}$$

The normalized variance f_i of each source was used as features of classifier.

$$f_i = var(s_i) / \sum_{i=1}^{10} var(s_i)\,. \tag{5}$$

Support Vector Machine (SVM) classifier with a Gaussian kernel was used to estimate the classification accuracy for each trial, and a 5-fold cross-validation was performed to avoid overfitting. Within each trial, the same time segment (3.5 - 5.5 s), which was the motor imagery periods, was used to train and test the classifier.

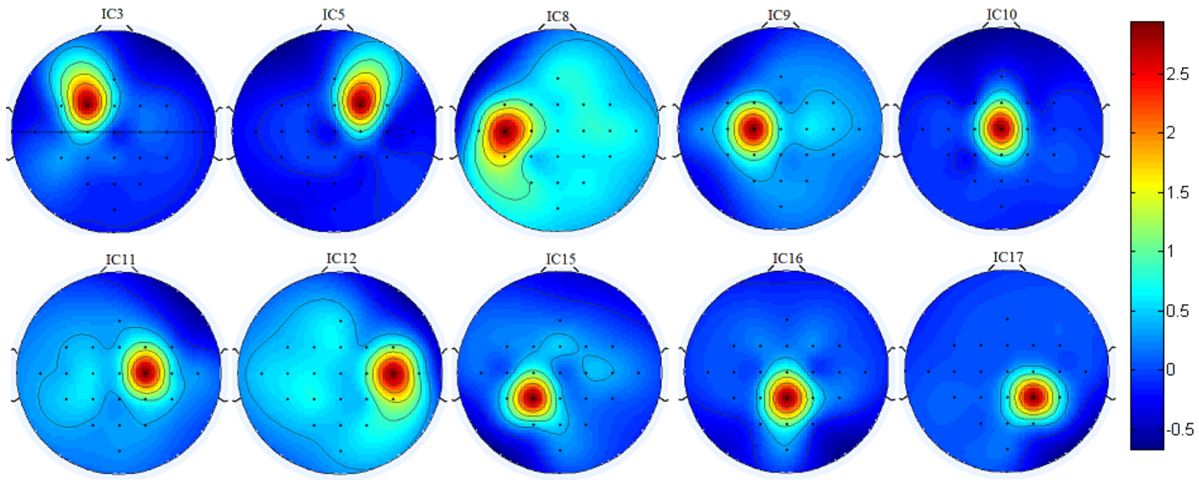

Figure 2. Topographic maps of subject S3 (BCI Competition IV Dataset 2a). The selected ten comonents (from left to right) are: IC3, IC5, IC8, IC9, IC10, IC11, IC12, IC15, IC16, IC17.

4. Results

4.1. ICA Filter Design Based on Different Time Segment Data

This section shows the relationship between ICA filter performance and training samples. The 0 - T_w time segment of one trial was selected, and ICA spatial filters were optimized on a $5T_w$ ($5 \times T_w$ seconds) time segment. The value of T_w was 1 s, 2 s, 3 s, 4 s, 5 s, 6 s, 7 s respectively, which gradually contains all brain states throughout the experiment (preparing state, motor imagery state and rest state). For each subject, the five trials were selected randomly, and a 10 × 22 spatial filter was designed to extract MRICs. Finally, the normalized variances of ten MRICs were used as features of SVM classifier for 5-fold cross-validation. The procedure was repeated 30 times, the mean classification accuracies were calculated for each subject (see **Table 1**), p.s., the trials of filter design failure were not included in.

As shown, the average accuracies of nine subjects obtained on different time segments were very similar. The maximum is 66.33% in 0 - 5 s, and the minimum is 65.11% in 0 - 1 s. Meanwhile, with the length of time segment increased, the average classification accuracy increased slightly in the front of 5 s. It may be because that data of longer duration provides more information to optimize ICA spatial filters. From all the seven different time segments results, we can conclude that any time segment EEG data can be used to design ICA spatial filters, even the non-motor-imagery data (0 - 1 s and 0 - 2 s) or mixed-state data(0 - 7 s), which demonstrated that the performance of ICA algorithm is not related closely to the train samples.

4.2. ICA Filter Design Based on Different Single Class Data

Usually the mixed class data was used to calculate ICA spatial filters. However in the Section 4.1, we have proved that even the non-labeled data (preparing state and rest state) can be used to design ICA spatial filters. In this section, this view was further proved by comparing the effect of different single class data on the performances of ICA spatial filters. For each subject, ICA spatial filters were designed only on single class EEG data, *i.e.*, used left hand motor imagery data (5 trials selected randomly from 72 trials of left hand motor imagery data) to design spatial filters, then the filters were used to extract MRICs from all the 216 trials (72 trials × 3 class), etc. Without loss of generality, 0 - 7 s continuous time segment was used to design ICA spatial filters, then a 5-fold cross-validation was performed by SVM classifier. The above procedure was repeated 30 times, and the average accuracies of all nine subjects were shown in **Figure 3**. As shown, for each subject, the average classification accuracies under the four cases were similar. For the same subject, the biggest difference of classification accuracies under four conditions was less than 4.5%. And under the same single class condition, the biggest difference of average classification accuracies of all nine subjects was only less than 1%. We thus can conclude that the performance of ICA spatial filters is not related closely to the class labels of train samples, and any class of motor imagery data could be used to design ICA spatial filters.

Table 1. Mean classification accuracies of 9 subjects in 0 - T_w segments.

Time	Subject										
	S1	S2	S3	S4	S5	S6	S7	S8	S9	Mean	Std
0 - 1 s	80.21	71.88	85.53	54.36	54.40	48.70	76.78	61.81	52.33	65.11	13.70
0 - 2 s	81.71	71.97	86.35	54.06	53.18	47.58	78.99	59.92	53.35	65.23	14.59
0 - 3 s	79.26	71.59	86.26	52.75	54.48	50.18	81.46	61.22	51.39	65.40	14.35
0 - 4 s	81.03	71.94	88.28	53.11	51.22	50.72	80.01	62.11	55.14	65.95	14.60
0 - 5 s	80.82	71.26	86.17	54.09	52.27	51.30	83.66	63.12	54.32	66.33	14.39
0 - 6 s	80.08	72.26	86.56	55.98	53.43	49.56	80.65	62.24	54.63	66.15	13.90
0 - 7 s	81.40	72.17	88.70	56.64	52.18	50.30	80.49	61.09	53.47	66.27	14.60

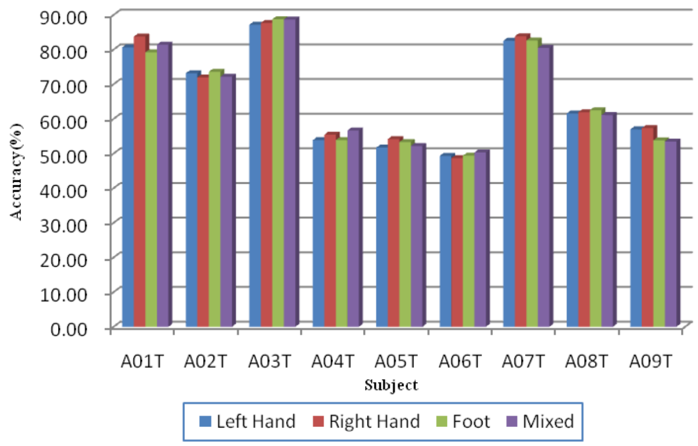

Figure 3. Average classification accuracies of nine subjects. The data for designing ICA spatial filters was left-hand, right-hand, foot and mixed-class motor imagery data respectively.

4.3. Subject to Subject Transfer

In this section, the subject-to-subject transfer was implemented on nine subjects. *i.e.*, the ICA spatial filters, which were calculated on one subject's 35-second (5 trials × 7 seconds) motor imagery EEG data, were used to extract the MRICs of all nine subjects. After that, the normalized variance features of the ten MRICs were applied to SVM classifier for training and testing. The procedure was also repeated 30 times. The average cross validation classification accuracies between subjects were compared in **Table 2**.

One obvious conclusion that can be seen in **Table 2** is that the highest accuracy is S3 (86.96%) while the lowest accuracy is S5 (46.96%). However, even when using the subject S5's data to design ICA spatial filters, the average accuracy was still the highest (67.64%). While the overall performance of ICA spatial filters designed on subjects S6 and S9 were slightly inferior, the average accuracies were just 62.23% and 61.15% respectively. All the results suggested that the ICA spatial filters constructed on one subject's motor imagery data also can be used to extract correct MRICs for other subjects, which reflected the similarity of brain structures.

5. Discussion and Conclusion

This study proposed a new simple algorithm to extract MRICs automatically, which just used the spatial pattern of ICs. The homemade ICA code based on Infomax theory was used to optimize spatial filters, and the performance of filters, constructed on different training data, was compared. The experiment results showed that any time segment and any class of EEG data can be used to design ICA spatial filters. This phenomenon suggested that the performance of ICA spatial filters have not much relationship with the brain state, which is convenient for practical application of ICA-BCI system. In addition, we fully believe that ICA algorithm has a strong ability to acquire similarity information of brain structures. Thus, if the positions of EEG electrodes are the same, ICA

Table 2. Average classification accuracies of subject-to-subject transfer between nine subjects.

Test	Subject for ICA filers design									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	Mean
S1	81.40	82.39	81.96	80.95	83.05	77.02	80.58	81.21	71.01	79.95
S2	72.48	72.17	68.08	67.47	72.18	66.68	66.04	71.98	66.11	69.24
S3	86.91	87.59	88.70	88.52	92.10	85.47	86.45	86.24	80.66	86.96
S4	55.46	52.65	55.95	56.64	53.80	50.31	53.38	55.67	50.11	53.77
S5	49.87	49.84	46.08	47.71	52.18	44.41	45.63	44.94	41.99	46.96
S6	50.26	49.57	48.38	49.43	54.24	50.30	54.87	47.33	51.50	50.65
S7	82.25	83.28	81.60	79.68	81.52	70.18	80.49	79.91	73.68	79.03
S8	63.73	62.98	70.82	67.64	62.73	61.80	61.61	61.09	61.82	63.80
S9	54.70	54.86	52.12	58.31	56.98	53.92	54.59	53.92	53.47	54.76
Mean	66.34	66.15	65.63	66.26	67.64	62.23	64.85	64.70	61.15	64.99
Std	14.71	15.47	15.89	14.48	14.99	13.75	14.48	15.51	12.75	2.08

spatial filters constructed on the different individual data sets should be consistent to some extent, which can be seen from the results of the subject-to-subject transfer. In summary, this study fully proved the robustness and practicality of ICA used in the MI-BCI systems.

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