Combination of Independent Component Analysis and Singular Value Decomposition for emotional EEG source localization

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Abstract

Focusing on improving the performance of EEG-based emotion recognition and exploring emotional scalp region, this paper presents a novel emotion-related independent components selection method based on Independent Component Analysis (ICA). Specifically, we first establish an optimal spatial-domain filter based on whole channel ICA to extract Independent Components (ICs). On this basis, the Emotion Related Independent Components (ERICs) are determined by evaluating the performance of these ICs through the "leave one IC out" method. Besides, the Singular Value Decomposition (SVD) is help to extract the spatial features. Average recognition accuracy using support vector machine as the classifier achieves 86.49%, which reveals the superiority of the proposed algorithm for emotion recognition.

Keywords: Independent Component Analysis, Singular Value Decomposition, emotional EEG source, emotion recognition

1. Introduction

Electroencephalogram (EEG) signal, generated from Autonomous Nervous System (ANS), can describe the relationship between psychological changes and emotions [1][2]. Recently, some remarkable EEG-based emotion recognition works have been carrying out explorations on the locations of emotion-related scalp region. Among them, Heller, W. found that alpha-power (8-12Hz) and gamma spectral (30-50Hz) changing at right parietal lobe are related to emotional responses [3][4]. Li, M et al. and Coan, J. A et al. investigated the relationship between the region of temporal/frontal lobe in gamma band and emotion tasks [5][6]. Whereas, emotion-related areas of the cerebral cortex are still uncertain so far, this would lead to a limitation on performance improvement in emotion recognition. Nowadays, researches are mainly concentrating on time/frequency characteristics to analyse the sources of emotion-related scalp region while the independence and spatial information of the source may be ignored. To explore the location of emotion-related sources and improve the recognition accuracy, we develop a novel selection method basing on the Independent Component Analysis (ICA) to obtain Emotion-Related Independent Components (ERICs).

2. Method

The fundamental flowchart of the proposed algorithm based on ICA and SVD is elaborated in Fig.1 and the key steps are as follows:

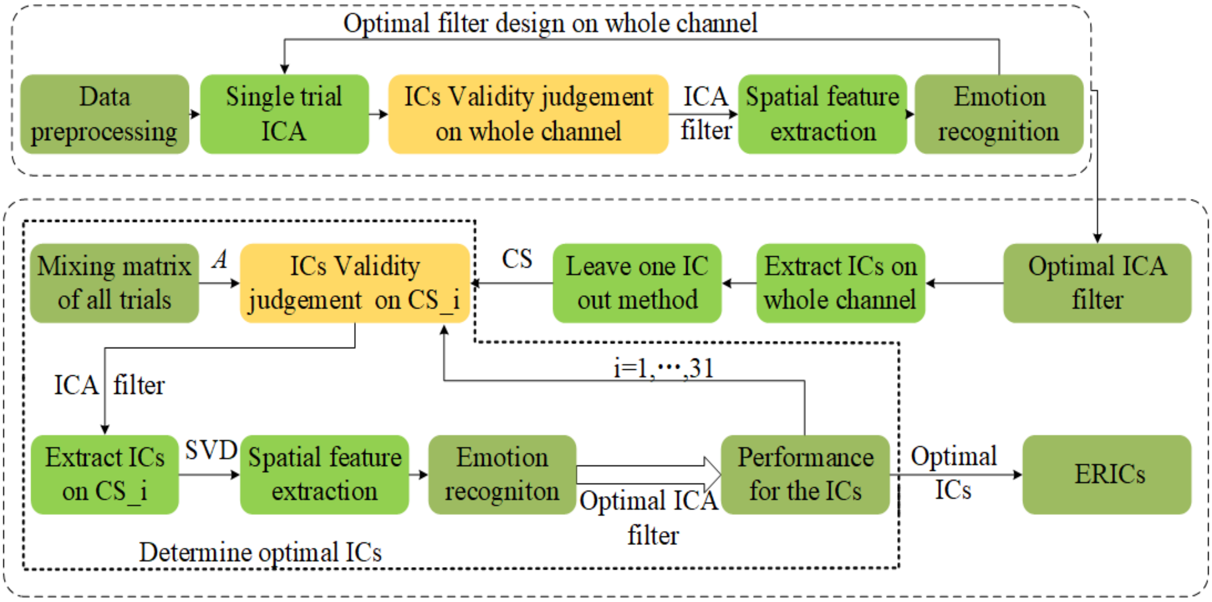


Figure 1. Extraction of ERICs for emotional EEG source localization.

2.1. Data preprocessing

The 32-channel EEG datasets used in our work are obtained from the MAHNOB-HCI-TAGGING DATABASE [7].The classification task is performed among three classes of emotion (pleasant, neutral valence and unpleasant) according to the valence dimension. Considering the fact that the gamma band plays a significant role than other band in emotion recognition [5][8], we first use a bandpass filter of 30-50Hz to extract gamma rhythm. To ensure the stability of emotion elicitation and avoid the multi-emotion in an observation period, we further split the pre-processed EEG signals into segments of 8s with 50% overlap using the rectangle window [9], and regard one data segment as a trial.

2.2. Single trial ICA analysis

We consider a single trial $\mathbf{x}=[x_1,\ldots x_n]^T$ mentioned above as instantaneous mixture, which can be separated by information maximization approach [11] combined with natural gradient [12]. Instantaneous mixture is the simplest form of ICA algorithm which can be modeled as $\mathbf{x}=\mathbf{As}$, where $\mathbf{A}$ represents mixing matrix and $\mathbf{s}=[s_1,\ldots,s_n]^T$ denotes the source signals. The goals of employing ICA algorithm are to learn the unmixing matrix $\mathbf{W}$ and obtain the estimate of source signals $\mathbf{y}=[y_1,\ldots,y_n]^T$, which means $\mathbf{W}=\mathbf{A}^{-1}$ and $\mathbf{y}=\hat{\mathbf{s}}=\mathbf{Wx}$, where $\hat{\bullet}$ denotes the estimate of $\bullet$.

Each row of $\mathbf{y}$ can be regarded as an Independent Component(IC), and a random column $a_i,(i=1,\ldots,n)$ in $\mathbf{A}$ includes projection coefficients from i^{th} IC to each electrodes. To acquire the maximum projected position of each IC, we calculate the maximum value of each column for $|\mathbf{A}|$, and then save the index of the maximum values into a matrix $\mathbf{D}_{1\times n}$, in which the elements of $\mathbf{D}_{1\times n}$ represent the indexes of EEG channels.

2.3. ICs validity judgement and spatial feature extraction

In order to obtain the ICs related to the specific scalp region at the same time, we continue to perform the validity judgement of selected ICs on a channel set. We give a k-channels set $\mathbf{CS}$ to explain the process, specifically, if the matrix $\mathbf{D}_{1\times n}$ includes $No.Chan_{CS_1},\ldots,No.Chan_{CS_i},\ldots,No.Chan_{CS_k}$ simultaneously (here, $No.Chan_{CS_i}$ is the index of EEG channel, and $Chan_{CS_i}$ is the electrode label of the i^{th} channel in CS), we infer that these ICs on the $\mathbf{CS}$ is valid.

For a random trial $\mathbf{x}$ that have conformed validity judgement of ICs, we choose the corresponding column vector to establish the ICA filter bank $\{\mathrm{w}_1,\ldots,\mathrm{w}_k\}$ and employ the filter bank to linearly project each trial to extract ICs ($u_1^n,\ldots,u_k^n$) for different emotional states. Let $\hat{\mathbf{S}}=\left[u_1^n,\ldots,u_k^n\right]^T$ and perform Singular Value Decomposition (SVD) on $\hat{\mathbf{S}}$:

$$\hat{\mathbf{S}}=\mathbf{U\Sigma V}^T \tag{1}$$

$\mathbf{U}$, $\mathbf{V}$ are orthogonal matrices, $\mathbf{\Sigma}$ is diagonal matrix. Finally the $\mathbf{SF}$ = [$\lambda_1 v_1,\ldots,\lambda_j v_j,\ldots,\lambda_{k-1}v_{k-1}$] is regarded as the feature. $\mathbf{SF}$ is the abbreviation of spatial feature. λ_j is the j^{th} non-zero element on the diagonal of $\mathbf{\Sigma}$, v_j is the j^{th} column element vector of $\mathbf{V}$.

2.4. ERICs selection

First, the optimal ICA filter that designed on whole channels is applied to extract the corresponding ICs. Thus, 32 ICs for 32 observation channels, which according to the ICs-electrode mapping mode, can be acquired. In order to assess the relevance between emotion and ICs, we then apply the “leave one IC out” method for ERICs selection, that is one IC ($u_j, j=1,\ldots,32$) is taken out and the $\mathbf{SF}$ for emotion recognition is extracted on the rest of the ICs. In this way, we can acquire a recognition accuracy ac_j in the absence of u_j, and attain recognition accuracy vector $\mathbf{ChanAc}=\{ac_1,\ldots,ac_j,\ldots,ac_{32}\}$ through 32-rounds tests in same way. To select the ERICs by evaluating the decreased recognition accuracy that induced by the absence of special IC, we define $\mathbf{ACC}=\{da_1,\ldots,da_j,\ldots,da_{32}\}$ as follows:

$$da_j=\max(\mathbf{ChanAc})-ChanAc_j \tag{2}$$

where, $\max(\bullet)$ denotes the selection of the maximum value in observation vector. It is worthy to note that the greater the degradation of the performance, the higher emotion correlation this IC has, then we get 31 test channel sets in Fig.2 for selecting ICs. Finally, the step named “Determine optimal channel set” in Fig. 1 is performed repeatedly on the test channels sets, the ICs that on the optimal channel set are regarded as the ERICs.

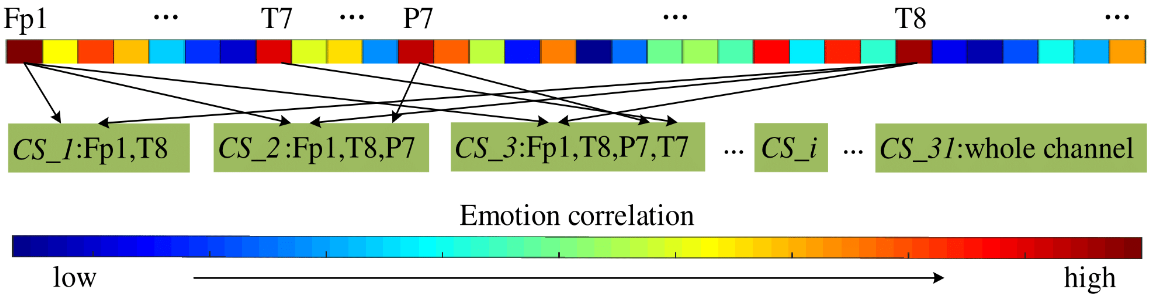


Figure 2. The generation process of 31 test channel sets for a subject. CS_i represents a test channel set for selecting ICs. The colored rectangular boxes show the emotional correlation of the channels, which obtained by ACC from a single subject.

3. Experiments and results

To validate the feasibility of the proposed method, ten subjects' data from the database mentioned above are involved in our experiment. We divide single subject's EEG data to average two parts, one part is to generate the channel sets CS and another part is used to select the optimal channel set. The recognition ratios based on these test channel sets are illustrated in Fig. 3. It shows that the recognition accuracy is rising steadily and stabilized at a high level. For each subject, we choose ICs on the channel set with the highest ratio (marked with a white triangle) as the ERICs.

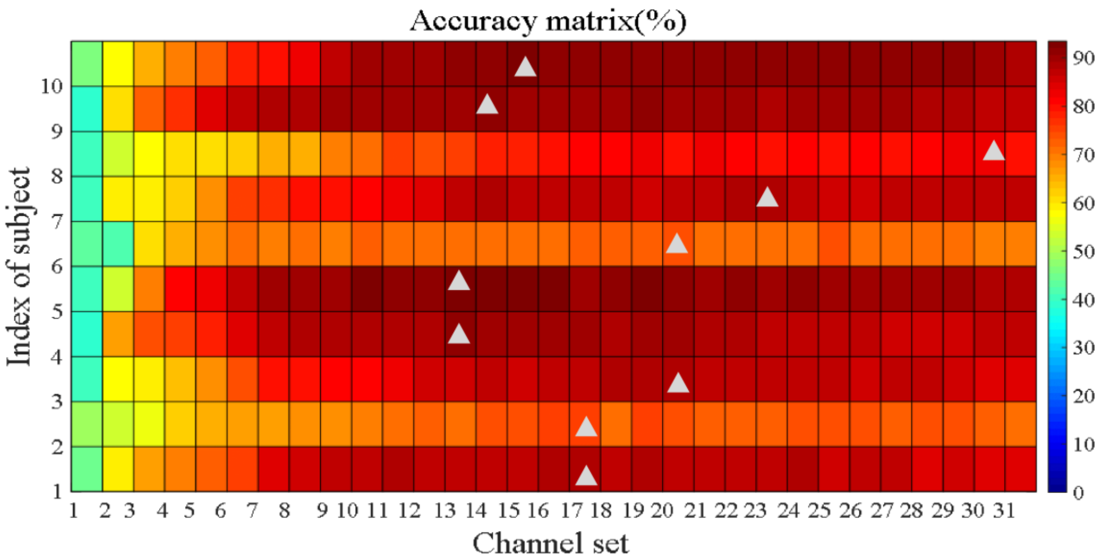
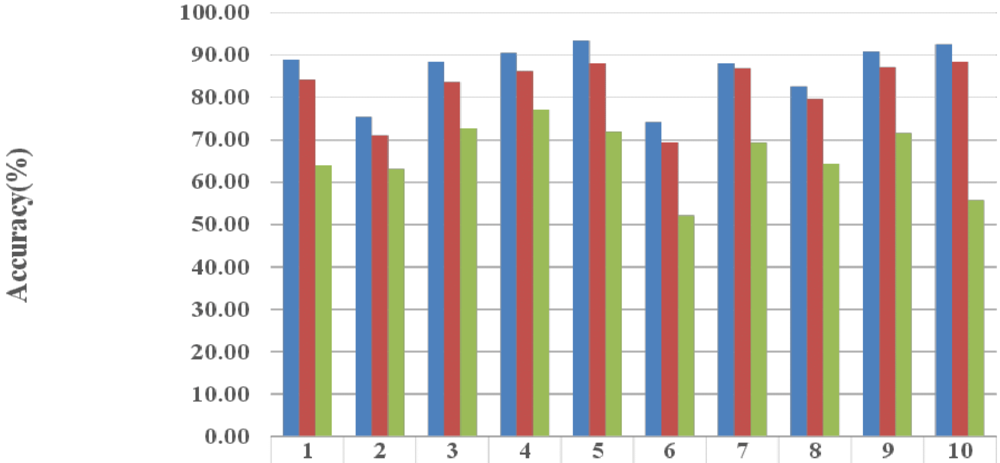


Figure 3. Recognition accuracy based on test channel sets for each subject. The box with a white triangle indicates the best recognition performance among 31 channel sets.

Furthermore, the comparison experiment results can be seen from Fig.4, which correspond to whole ICs, ERICs and traditional method based on power spectral density and asymmetry features [7], respectively. It is obviously that methods based on ICA algorithm achieve better performance than traditional time/frequency domain method, and the experiment results can also prove that spatial-domain feature provides richer distinguishable information to accurately identify different emotional states. Compared with result obtained by using whole

ICs, result of only using ERICs reaches higher accuracy since it removes irrelevant ICs which may have influence on the performance of emotion recognition. In a word, the experiment validates the feasibility of the proposed ERICs selection strategy as well as the ability of improving the recognition performance.



	1	2	3	4	5	6	7	8	9	10
ICA-based ERICs	88.87	75.41	88.37	90.53	93.44	74.12	88.12	82.57	90.89	92.55
ICA-based whole ICs	84.18	71.00	83.61	86.16	88.15	69.40	86.88	79.57	87.14	88.40
PSD+AMY	64.08	63.14	72.74	77.07	71.89	52.14	69.34	64.30	71.59	55.72

Figure 4. Recognition accuracy for different methods.

To evaluate the performance of the ERICs, the F1 scores and recognition rates for the classification in different modalities are given in the Table 1. Among three classes of emotion recognition, the "Pleasant" state achieves the highest accuracy ratio (88.23%), while the "Neutral-valence" state shows the lowest one (81.5%). It indicates that the emotion independent component in the "pleasant" state is more effective than that in the "unpleasant" and "Neutral-valence" states.

Table 1. The recognition accuracy and F1 score under three emotion tasks in case of the "ERICs".

Emotion	Modality	ERICs
Pleasant	Accuracy	88.23%
	F1-score	0.8697
Neutral-valence	Accuracy	81.50%
	F1-score	0.8319
Unpleasant	Accuracy	82.92%
	F1-score	0.8431

Moreover, we draw the topography map to analyse the emotion-related scalp region according to the mean of **ACC***s* over all subjects. From Fig. 5, we can observe that the ICs located on the lateral temporal, prefrontal and occipital scalp regions are crucial for emotion recognition. This result is consistent with the reports of literature [5] and [10].

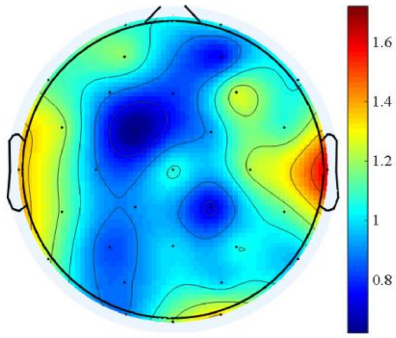


Figure 5. The topography map based on the mean of ACCs over all subjects.

4. Conclusion

In this work, we present an EEG-based emotion recognition method using ICA to improve the performance of emotion recognition. The main properties of this method are: (i) the spatial features obtained by ICA and SVD are first applied to EEG for emotion recognition, (ii) the independence of the emotion related sources is first considered, (iii) the emotion-related independent components can describe the emotion-related scalp region and (iv) experiment results confirm both the validity of ERICs in the cerebral cortex and the ability to recognize three-class emotion tasks with a high accuracy (86.49%).

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References

[1] Wioleta S. Using physiological signals for emotion recognition[C]//2013 6th International Conference on Human System Interactions (HSI). IEEE, 2013: 556-561, doi:10.1109/HSI.2013.6577880

[2] Ghare P S, Paithane A N. Human emotion recognition using non linear and non stationary EEG signal[C]//2016 International Conference on Automatic Control and Dynamic Optimization Techniques (ICACDOT). IEEE, 2016: 1013-1016, doi: 10.1109/ICACDOT.2016.7877739

[3] Heller W. Neuropsychological mechanisms of individual differences in emotion, personality, and arousal[J]. Neuropsychology, 1993, 7(4): 476, doi:10.1037/0894-4105.7.4.476

[4] Sarlo, M., Buodo, G., Poli, S., & Palomba, D.:'Changes in EEG alpha power to different disgust elicitors: the specificity of mutilations', Neuroscience letters, 2005, 382, (3), pp. 291-296, doi:10.1016/j.neulet.2005.03.037

[5] Li, M., & Lu, B. L.: 'Emotion classification based on gamma-band EEG', Annual International Conference of the IEEE, Medicine and Biology Society, September, 2009, pp. 1223-1226, doi:10.1109/IEMBS.2009.5334139

[6] Coan, J. A., & Allen, J. J.: 'Frontal EEG asymmetry as a moderator and mediator of emotion', Biological psychology, 2004, 67, (1-2), pp. 7-50, doi:10.1016/j.biopsycho.2004.03.002

[7] Soleymani, M., & Pantic, M.: 'Multimedia implicit tagging using EEG signals', IEEE International Conference, Multimedia and Expo, July 2013, pp. 1-6,doi:10.1109/ICME.2013.6607623

[8] Candra H, Yuwono M, Chai R, et al. Investigation of window size in classification of EEG-emotion signal with wavelet entropy and support vector machine[C]//2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2015: 7250-7253.

[9] Wang, X. W., Nie, D., & Lu, B. L.: 'Emotional state classification from EEG data using machine learning approach', Neurocomputing, 2014, pp. 94-106, doi:10.1016/j.neucom.2013.06.046

[10] Nie, D., Wang, X. W., Shi, L. C., & Lu, B. L.: 'EEG-based emotion recognition during watching movies', International IEEE/EMBS Conference, Neural Engineering, April 2011, pp. 667-670, doi:10.1109/NER.2011.5910636
[11] Bell A J, Sejnowski T J. An information-maximization approach to blind separation and blind deconvolution[J]. Neural computation, 1995, 7(6): 1129-1159.
[12] Amari S I. Natural gradient works efficiently in learning[J]. Neural computation, 1998, 10(2): 251-276.