Journal of Southeast University (English Edition) Vol. 31, No. 1, pp. 55 - 60 Mar. 2015 ISSN 1003—7985

Single-trial EEG-based emotion recognition using temporally regularized common spatial pattern

Cheng Minmin Lu Zuhong Wang Haixian

(Key Laboratory of Child Development and Learning Science of Ministry of Education, Southeast University, Nanjing 210096, China)
(Research Center for Learning Science, Southeast University, Nanjing 210096, China)

Abstract: This study addresses the problem of classifying emotional words based on recorded electroencephalogram (EEG) signals by the single-trial EEG classification technique. Emotional two-character Chinese words are used as experimental materials. Positive words versus neutral words and negative words versus neutral words are classified, respectively, using the induced EEG signals. The method of temporally regularized common spatial patterns (TRCSP) is chosen to extract features from the EEG trials, and then single-trial EEG classification is achieved by linear discriminant analysis. Classification accuracies are between 55% and 65%. The statistical significance of the classification accuracies is confirmed by permutation tests, which shows the successful identification of emotional words and neutral ones, and also the ability to identify emotional words. In addition, 10 out of 15 subjects obtain significant classification accuracy for negative words versus neutral words while only 4 are significant for positive words versus neutral words, which demonstrate that negative emotions are more easily identified.

Key words: emotion recognition; temporal regularization; common spatial patterns(CSP); two-character Chinese words; permutation test

doi: 10.3969/j.issn.1003-7985.2015.01.010

As a form of the objective world of human reflection, emotion is an important part of human psychology. We are, in fact, unconsciously observing and judging other people's emotions every moment, and making corresponding responses to them, while others are doing exactly the same. Thus, it can be said that emotion recognition is a basic ability in one's social life and plays an important role in identifying others' emotions, understanding their psychology, and then predicting their behavior, which are a great advantage in handling relationships with others better. Since Bruce and Young's research back in the 1980's, emotion recognition has become one of the focus issues in the field of cognitive science research.

Emotion recognition studies first began with recognition based on non-physiological signals, such as facial expression[1], voice tone, and sometimes eye movements[2]. In general, people in some emotional states produce certain facial muscle movements and expressive patterns. These corresponding relations are used to identify different emotions. The features used in the above methods for emotional classification are usually based on the behavioral data observed. However, behavioral data has the disadvantage of being unreliable and can even be disguised. Moreover, for disabled persons who have a special disease, the methods may be applied with difficulty.

Physiological signals, from the autonomic nervous system and central nervous system, are more direct avenues of emotion expression. Particularly, the signal from the central nervous system comes directly from the human brain. It is hard to fake. Compared with other physiological signals, it is more stable and is receiving increasing interest from researchers. Because of the high temporal resolution of the electroencephalogram (EEG), which can record the dynamic process of emotions, emotion recognition based on EEG signals is currently being carried out. Li et al. [3] used the gamma band (roughly 30-100 Hz) filtered from the recorded EEG signal to classify sadness and happiness. Classification accuracies around 93% are achieved on 10 subjects. Lee et al. [4] built an effective emotion recognition system to classify the proposed 3D fuzzy visual and EEG features using an adaptive neuro-fuzzy inference classifier.

As a main way to express oneself in daily life, language is closely related to human emotion. Compared with the EEG-based emotion recognition with the stimuli of emotional pictures, videos[4], and even music[5], language is barely used as an emotional stimulus because of the far lower emotional arousal. Furthermore, the commonly used feature for the problem of emotional word recognition is event-related potential (ERP), i.e., the average across several EEG trials[6]. In this study, we consider the challenging problem of classifying emotional words based on a single-trial EEG signal.

We address the emotional word classification using the algorithm developed by the brain-computer interface

Received 2014-11-15.

Biographies: Cheng Minmin (1984—), female, graduate; Wang Haixian (corresponding author), male, doctor, professor, hxwang@seu.edu.cn.

Foundation items: The National Natural Science Foundation of China (No. 61375118), the Program for New Century Excellent Talents in University of China (No. NCET-12-0115).

Citation: Cheng Minmin, Lu Zuhong, Wang Haixian. Single-trial EEG-based emotion recognition using temporally regularized common spatial pattern[J]. Journal of Southeast University (English Edition), 2015, 31 (1): 55 -60. [doi: 10.3969/j.issn.1003-7985.2015.01.010]

(BCI) community, which depends heavily on the accurate recognition of the EEG corresponding to different mental processes. In the BCI community, the technique of common spatial patterns (CSP)[7] is one of the most popular classification methods that learn spatial filters by maximizing the discriminability of two classes. Mathematically, CSP is formulated as the simultaneous diagonalization of two covariance matrices. Its efficiency has been demonstrated in EEG-based motor imagery recognition[8], abnormal components extraction in EEG, localization of sources, and so on. CSP, however, has an inherent drawback for the estimation of covariance matrices using the conventional strategy. Specifically, CSP does not take the temporal structure information of EEG time courses into account in the estimation of covariance matrices.

Accordingly, we proposed temporally regularized CSP (TRCSP) to integrate temporal information in the covariance matrices[9]. TRCSP has demonstrated potential for single-trial EEG classification.

In this study, we use TRCSP to classify different emotions induced by Chinese words. After describing the TRCSP algorithm, the details of our two-character Chinese words experiment are reported. Then, the process of data analysis is described, followed by the experimental results and discussion.

1 TRCSP Method

The aim of CSP is to learn the optimal spatial filters that maximize the variance of one class while minimizing the variance of the other class. Mathematically, the CSP function is given by

$$J(\boldsymbol{\omega}) = \frac{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{X}_1^{\mathrm{T}}\boldsymbol{X}_1\boldsymbol{\omega}}{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{X}_2^{\mathrm{T}}\boldsymbol{X}_2\boldsymbol{\omega}} = \frac{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{C}_1\boldsymbol{\omega}}{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{C}_2\boldsymbol{\omega}} \tag{1}$$

where $\boldsymbol{X}_i$ is the data matrix for class i; $\boldsymbol{C}_i$ is the spatial covariance matrix of the EEG signals from class i; $\boldsymbol{\omega}$ is the spatial filter. The spatial filter is solved by the generalized eigenvalue equation,

$$\boldsymbol{C}_1\boldsymbol{\omega} = \lambda \boldsymbol{C}_2\boldsymbol{\omega} \tag{2}$$

CSP is usually regularized so as to accommodate prior information. The regularized objective function becomes

$$J(\boldsymbol{\omega}) = \frac{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{C}_1\boldsymbol{\omega}}{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{C}_2\boldsymbol{\omega} + \alpha P(\boldsymbol{\omega})} \tag{3}$$

where $P(\boldsymbol{\omega})$ is a penalty function measuring how much the spatial filter satisfies the given prior information, and α is a user-defined positive constant. Specifically, the TRCSP adds the temporal structure information of the EEG signals into the classical CSP. TRCSP has been successfully used in the data sets from BCI competitions.

The temporal structure of EEG trials is captured using the technique of locally linear embedding (LLE)[10]. We utilize LLE to consider the temporally local relationship of EEG samples within the time course of EEG epochs. The relationship is expressed in terms of a locally linear representation. Mathematically, LLE models each sample as a linear combination of its k nearest neighbors, and tries to preserve this locally linear relationship in a transferred low-dimensional space. Different from conventional LLE, in which the k nearest neighbors are identified with respect to the Euclidean distance, we choose the k nearest neighbor EEG samples in terms of time points since we are interested in the temporal structure information of the EEG time course. LLE seeks a low-dimensional filtered space that preserves the temporal structure information of EEG trials as faithfully as possible. The cost function is thus written as

$$\Phi(\boldsymbol{\omega}) = \boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{X}\boldsymbol{L}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{\omega} \tag{4}$$

where the Laplacian matrix $\boldsymbol{L}$ reflects the temporal structure information.

The quantity $\Phi(\boldsymbol{\omega})$ is incorporated into the objective function of the classical CSP in order to penalize filters such that the temporal structure information is preserved. Formally, the objective function of TRCSP is given by

$$J(\boldsymbol{\omega}) = \frac{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{C}_1\boldsymbol{\omega}}{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{C}_2\boldsymbol{\omega} + \alpha(\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{X}\boldsymbol{L}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{\omega})} = \frac{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{C}_1\boldsymbol{\omega}}{\boldsymbol{\omega}^{\mathrm{T}}(\boldsymbol{C}_2 + \alpha\boldsymbol{X}\boldsymbol{L}\boldsymbol{X}^{\mathrm{T}})\boldsymbol{\omega}} \tag{5}$$

Maximizing $J(\boldsymbol{\omega})$ will lead to the minimization of $\Phi(\boldsymbol{\omega})$, thus modifying spatial filters so as to satisfy the prior information. The corresponding eigenvalue equation of Eq. (5) boils down to

$$\boldsymbol{C}_1\boldsymbol{\omega} = \lambda(\boldsymbol{C}_2 + \alpha\boldsymbol{X}\boldsymbol{L}\boldsymbol{X}^{\mathrm{T}})\boldsymbol{\omega} \tag{6}$$

Consequently, the filters $\boldsymbol{\omega}$ maximizing $J(\boldsymbol{\omega})$ are the leading eigenvectors corresponding to the largest eigenvalues. Conversely, we need to accordingly maximize the dual objective function,

$$J(\boldsymbol{\omega}) = \frac{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{C}_2\boldsymbol{\omega}}{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{C}_1\boldsymbol{\omega} + \alpha(\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{X}\boldsymbol{L}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{\omega})} = \frac{\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{C}_2\boldsymbol{\omega}}{\boldsymbol{\omega}^{\mathrm{T}}(\boldsymbol{C}_1 + \alpha\boldsymbol{X}\boldsymbol{L}\boldsymbol{X}^{\mathrm{T}})\boldsymbol{\omega}} \tag{7}$$

Eventually, the spatial filters used are the leading eigenvectors corresponding to the eigenvalue problems of Eqs. (5) and (7).

2 Experiment

2.1 Subjects

EEG signals were recorded from 16 healthy paid volunteers (8 males, aged between 19 and 25 years), who were all undergraduate students from various departments of Southeast University. All participants were native Chinese speakers, right-handed, and had normal or corrected-to normal vision. They reported no speech or hearing problems, and no history of neurological disorders. The study protocol conformed to the local ethics guidelines.

2.2 Stimuli and procedure

In the experiment, 480 two-character Chinese words (emotionally positive, negative, and neutral, each 160) were selected from the Modern Chinese Frequency Dictionary. The word frequency is in the range of 15 to 21 per million and the stroke is between 11 and 25. Meanwhile, 25 other undergraduate students also from Southeast University who were of the same age as the 16 subjects were chosen to evaluate the materials. The evaluation was made on a 9-point scale from two dimensions: emotional valence (positive on one side and negative on the other side) and arousal (from calm to excited). Based on the rating, 80 words with the matched scores for each emotional class were chosen as the experimental stimuli. Then the experimenter created 60 unreal two-character words with no realistic meaning as experimental target materials.

These 300 total words (emotionally positive, negative, neutral, and unreal words) were presented in random order using the software Stim2. At the beginning of each trial, a fixation cross ("+") appeared in the middle of the screen for 500 ms, followed by a blank screen for 500 ms. Then, a two-character Chinese word was presented for 500 ms, and a 1 500 ms interval with a blank screen was shown again. A new trial started after this long interval. The procedure is illustrated in Fig. 1. In order to make sure that the participants concentrated on the experiment, a button needed to be pressed when they saw an unreal word. If a subject failed to recognize the unreal word frequently, i. e., the button was wrongly pressed too many times, this data would be eliminated.

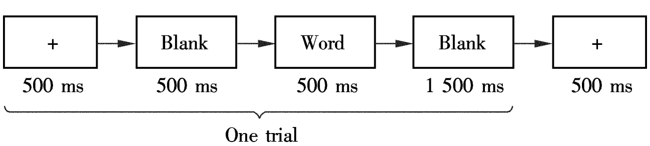

Fig. 1 Procedure for one trial in the study

2.3 Data acquisition

Continuous EEG was recorded using a 64-channel Quick Cap (Neuroscan Inc., El Paso, Texas, USA) with tin electrodes, referenced to the link of the left and right mastoids during online recording. Electrode impedances were maintained below 5 kΩ. A band pass of 0.05-100 Hz was used to continuously filter the recorded signals at a sampling rate of 1 000 Hz.

3 Data Analysis

3.1 Data preprocessing

Very few trials with false judgment of words or nonwords were rejected from two subjects at the very beginning, although we learned from communication with the two participants later that these errors were caused completely by accidental key pressing. Besides, data from one male subject was eliminated since there was a strong interference in his EEG signals because of his frequent involuntary body movements. EEG waves ranged from −200 to 1 000 ms after the onset of two-character words, with the 200 ms previous onset as the baseline. A blink-correction algorithm (spatial SVD) was applied offline. After the baseline correction, trials with amplitudes larger than 70 μV were rejected. These operations were performed using the Software Stim2. Then, the data format was converted by EEGLAB, an interactive Matlab toolbox for processing continuous and event-related EEG and other electrophysiological data, for later analysis. The EEG signals were further filtered in Matlab using a 8-30 Hz band-pass filter using a Butterworth filter with order 4. This frequency band includes alpha and beta rhythms[11].

3.2 Feature extraction and classification

We used TRCSP to perform the feature extraction. TRCSP has two parameters that need to be configured, i. e., k and α. The parameters were selected using the ten-fold cross validation method on the training sets. The first and last three spatial filters for feature extraction were calculated in TRCSP on the training sets. The EEG signals were filtered using the three pairs of spatial filters to extract features. Then, the features were placed into the linear discriminant analysis (LDA) classification.

4 Results and Discussion

4.1 Permutation test

A permutation test is usually used to assess the statistical significance of the performance of the classifier[12]. As a test based on computer simulation, permutation is especially suitable for small sample data sets. We use the permutation test in our work to assess the significance of the observed classification accuracy before we conclude that the results obtained in the cross-validation procedure are effective. Otherwise, we may decide that more data is needed before we can trust the detected pattern or trend in the EEG data. In other words, we investigated whether the classification accuracy was higher than chance. If so, we thus made sure that a successful classification was reached. Specifically, there was a label within each trial to identify its true emotional attribute, for example, "1" for emotional positive and "2" for emotional negative. Then, the label sequence for each subject's data was completely disrupted to make sure all the trials and the marks were completely randomly matched. Tab. 1 shows an example of label permutation.

Tab. 1 Demonstration of label order before and after they were disorganized in the permutation test

Emotion type	p	ne	n	n	p	n	ne	p
Real data set	1	3	2	2	1	2	3	1
Random data set	2	2	1	3	2	1	1	3

Note: p, ne, and n denote positive, neutral, and negative, respectively.

For the permutated data, the exact same data processing and classification were used. We repeated this whole process 100 times, resulting in 100 classification accuracies on the data with label replacement. For a significance level of 0.05, we declared that the emotional words could be identified if the classification accuracy on the original data set was ranked top five among the accuracies on the 100 permutated data sets, i. e., emotion recognition was successful. The test results are displayed in Tab. 2, in which only the top five numbers needed to make the judgment are presented.

Tab. 2 Results of the permutation test for some subjects and the top five classification accuracies on permutated data sets %

Emotion type	Parameters	S3	S4	S7	S10	S12	S15
Positive vs. neutral	The top five classification accuracy	55.10	55.41	56.64	54.36	57.86	56.49
		55.78	55.41	57.34	55.70	57.86	57.14
		55.78	57.43	57.34	57.05	58.57	57.14
		56.46	58.78	58.74	57.72	58.57	58.44
		58.50	59.46	59.44	58.39	60.00	60.39
	Real classification accuracy	**55.80**	52.03	46.15	52.35	**65.00**	48.70
Negative vs. Neutral	The top five classification accuracy	56.25	58.55	55.17	55.48	57.04	56.13
		56.94	58.55	56.55	56.16	57.04	56.13
		57.64	58.55	57.24	56.16	57.04	56.77
		57.64	59.21	59.31	58.22	59.15	60.65
		59.03	65.13	60.00	59.59	62.68	61.29
	Real classification accuracy	**56.94**	53.95	**61.40**	**57.60**	51.41	**56.13**

4.2 Results of emotion recognition

The results of the hypothesis tests showed that negative words were effectively identified from neutral ones in ten subjects, while positive words were successfully recognized in four subjects. Both of the two cases were prominent in Subject 3.

4.3 Classification performance

The data of the 15 subjects were used to perform emotion classification. We used two-class recognition to separately classify positive words versus neutral words, and negative words versus neutral words. The performance of classification, as well as mean accuracies and the corresponding standard deviations are reported in Tab. 3. The data that was verified as successful emotion recognition is marked in bold.

Tab. 3 Classification accuracies of TRCSP %

Subject	Classification accuracies	
	Positive vs. neutral	Negative vs. neutral
S1	50.34	**58.40**
S2	51.11	**59.10**
S3	**55.80**	**56.94**
S4	52.03	53.95
S5	**55.10**	44.14
S6	45.71	54.05
S7	46.15	**61.40**
S8	**57.24**	48.98
S9	46.58	**56.85**
S10	52.35	**57.60**
S11	48.30	**60.40**
S12	**65.00**	51.41
S13	48.92	**56.64**
S14	53.47	**58.22**
S15	48.70	**56.13**
Mean	51.79	55.61
Std	4.92	4.40

4.4 Discussion

ERP analysis was also performed on this experimental data. The result showed that emotional words could induce larger brain wave amplitudes than emotionally neutral words in some primary ERP components.

In the experiments of emotional word recognition, researchers have considered whether the amplitude of P2 increase was related to the subject's lexical semantic processing depth. That occurred only when the participants in the experiment really understood the emotional words and had actually processed the emotional information, then the changes in P2 amplitude could be seen[13]. Compared to neutral stimuli, emotional stimuli usually induced larger P2 amplitudes[14]. In the ERP analysis of our research, larger P2 waves were observed after the onset of emotional words (positive words and negative words) than neutral ones, which confirmed this widely accepted research result. Conversely, the presence of the P2 wave itself had confirmed that the stimuli in our experiment were fully processed, i. e., our experiment was effective. The P2 waveforms are shown in Fig. 2.

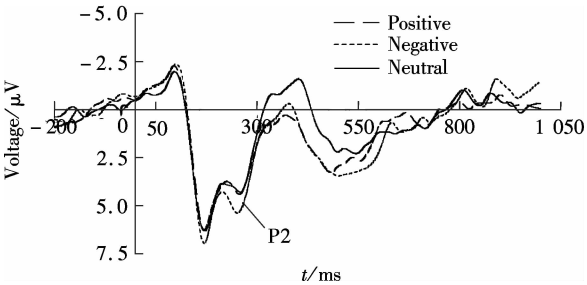

Fig. 2 P2 waveforms for positive, negative and neutral words on electrode CZ

However, the statistical analysis showed that there was no significant difference between the P2 waves induced by positive words and neutral words, while the amplitude's increase induced by negative words had a statistical significance. This kind of ERP wave performance completely matched our classification result, i. e., the recognition performance of negative words was better than that of positive words. This is probably because negative emotion was more intense for people even if the positive materials had the same level of arousal as the negative ones. Yuan et al. [15] found that there were no significant differences among the ERP amplitudes induced by picture stimuli with three different emotional valences (extremely positive, moderately positive, and neutral) in an implicit emotional task while an opposite result was obtained for negative stimuli. When participants were in the execution of an explicit emotional classification task, the increase of the happiness intensity could not lead to ERP amplitude changes[16]. These studies reached a conclusion that the processing of positive emotional stimuli in the human brain was not as sensitive as that of negative stimuli. So, negative emotional words may be more easily recognized.

Individual differences in the test results are clearly observed, which is in conformity with the general conclusion that emotions are known to be very subjective and dependent on previous experience. It is the subjectivity of emotion in different people that causes the diversity in the classification results.

In our classification experiment, like the method of some recognition research on motor imagery (MI), all electrodes throughout the whole brain were used instead of the 21 chosen electrodes used in the ERP analysis. Selecting more emotion-related electrodes according to the particular emotion will be investigated in our next study[17].

5 Conclusion

In this study, we performed research on recognizing emotional information in two-character Chinese words. The TRCSP approach was used to classify the two-class materials. TRCSP was shown to be effective in the complex cognitive process of emotional processing. Importantly, this study verified the ability to identify emotion in Chinese words, and showed the possibility of language emotion recognition research, which is crucial for BCI research nowadays.

References

[1] Anderson K, McOwan P W. A real-time automated system for the recognition of human facial expressions [J]. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 2006, **36**(1): 96 – 105.

[2] Alghowinem S, Goecke R, Wagner M, et al. Eye movement analysis for depression detection [C]//*IEEE International Conference on Image Processing*. Melbourne, Australia, 2013: 4220 – 4224.

[3] Li M, Lu B L. Emotion classification based on gamma-band EEG [C]//2009 *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Minneapolis, MN, USA, 2009: 1223 – 1226.

[4] Lee G, Kwon M, Sri S K, et al. Emotion recognition based on 3D fuzzy visual and EEG features in movie clips [J]. *Neurocomputing*, 2014, **144**: 560 – 568.

[5] Daimi S N, Saha G. Classification of emotions induced by music videos and correlation with participants' rating [J]. *Expert Systems with Applications*, 2014, **41**(13): 6057 – 6065.

[6] Hinojosa J A, Méndez-Bértolo C, Pozo M A. Looking at emotional words is not the same as reading emotional words: behavioral and neural correlates [J]. *Psychophysiology*, 2010, **47**(4): 748 – 757.

[7] Blankertz B, Tomioka R, Lemm S, et al. Optimizing spatial filters for robust EEG single-trial analysis [J]. *IEEE Signal Processing Magazine*, 2008, **25**(1): 41 – 56.

[8] Guger C, Ramoser H, Pfurtscheller G. Real-time EEG analysis with subject-specific spatial patterns for a brain-computer interface (BCI) [J]. *IEEE Transactions on Rehabilitation Engineering*, 2000, **8**(4): 447 – 456.

[9] Cheng M M, Wang H X, Lu Z H, et al. Temporally regularized filters for common spatial patterns by preserving locally linear structure of EEG trials [C]//*The 21st International Conference on Neural Information Processing*. Kuching, Malaysia, 2014: 167 – 174

[10] Roweis S T, Saul L K. Nonlinear dimensionality reduction by locally linear embedding [J]. *Science*, 2000, **290**(5500): 2323 – 2326.

[11] Bos D O. EEG-based emotion recognition [EB/OL]. [2014-12-20]. http://hmi.ewi.utwente.nl/verslagen/capita-selecta/CS-Oude_Bos-Danny.pdf.

[12] Ojala M, Garriga G. Permutation tests for studying classifier performance [J]. *Journal of Machine Learning Research*, 2010, **11**: 1833 – 1863.

[13] Kanske P, Kotz S A. Concreteness in emotional words: ERP evidence from a hemifield study [J]. *Brain Research*, 2007, **1148**: 138 – 148.

[14] Bernat E, Bunce S, Shevrin H. Event-related brain potentials differentiate positive and negative mood adjectives during both supraliminal and subliminal visual processing [J]. *International Journal of Psychophysiology*, 2001, **42**(1): 11 – 34.

[15] Yuan J J, Zhang Q L, Chen A T, et al. Are we sensitive to valence differences in emotionally negative stimuli?

Electrophysiological evidence from an ERP study [J]. *Neuropsychologia,* 2007, **45**(12): 2764 - 2771.
[16] Leppänen J M, Kauppinen P, Peltola M J, et al. Differential electrocortical responses to increasing intensities of fearful and happy emotional expressions [J]. *Brain Research*, 2007, **1166**: 103 - 109.
[17] Lotte F, Guan C T. Regularizing common spatial patterns to improve BCI designs: unified theory and new algorithms [J]. *IEEE Transactions on Biomedical Engineering*, 2011, **58**(2): 355 - 362.

基于时域正则化共空间模式的单次脑电情绪识别

成敏敏　陆祖宏　王海贤

(东南大学儿童发展与学习科学教育部重点实验室,南京 210096)
(东南大学学习科学研究中心,南京 210096)

摘要:通过使用单次提取脑电信号的分类技术进行情绪词的脑电(EEG)识别研究. 以中文情绪双字词为实验材料,通过其诱发的 EEG 信号,对正性词与中性词、负性词与中性词分别进行分类. 使用时域正则化的共空间模式对单次提取脑电信号进行特征提取,并利用线性判别分析方法进行特征分类,分类准确率集中于 55%~65%. 置换检验验证了实验分类准确率的统计学显著性,表明了情绪词和中性词的成功识别,也有效地证实了基于脑电信号的语言情绪信息的可识别性. 此外,在 15 名被试中,10 名被试的负性词与中性词识别率显著,而仅有 4 名被试的正性词与中性词识别率显著,说明负性情绪更易被识别.

关键词:情绪识别;时域正则化;共空间模式;中文双字词;置换检验
中图分类号:TP391