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DW-FBCSP: EEG emotion recognition algorithm based on scale distance weighted optimization *

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***Abstract*—Emotion calibration is measured by the valence and arousal scales and the ideal center is used to directly divide valence arousal into high scores and low scores. This division method has a big classification and labeling defect, and the influence of emotion stimulation material on the subjects cannot be accurately measured. To address this problem, this paper proposes an EEG emotion recognition algorithm (DW-FBCSP: Distance Weighted Filter Bank Common Spatial Pattern) based on scale distance weighted optimization to optimize the classification according to the distance of the scores from ideal center. This method is a natural extension of CSP that optimize the user's EEG signal projection matrix. Then, the LDA classifier is used to recognize emotions using the features set which fused the selected features and the features extracted by the projection matrix. The results show that the mean correct rate of the valence and arousal achieves 81.14% and 84.45% using the DEAP dataset. The results demonstrate that our proposed method outperforms better than some other results published in recent years.**

I. Introduction

Emotion feeling is a phase of neurobiological activity, the key component of emotions and emotion-cognition interactions[1]. It contains psychological and physical changes, which are closely related to our lives [2]. Emotion recognition refers to the recognition of people's emotional changes under external stimuli, and is widely used in mental state detection, personality prediction and other fields [3].

For emotion recognition, the traditional method is to extract features from peripheral physiological signals such as ECG, skin conductivity, respiration, and EMG [4]. In recent years, the use of EEG signals for emotion recognition has become more and more popular[5].Emotion stimulation materials usually come in the form of music videos, etc. After the test, the user was asked to fill in the valence-arousal rating scales to qualitatively measure the emotional inducing situation of the tester.

EEG is the electrical signal of the human brain epidermis. It is a non-stationary signal. Some studies have shown that different emotions have obvious changes in different spectral and spatial domains [6]. Based on the physiological characteristics of the spatial and frequency domain changes of EEG under different emotions, the emotion recognition of EEG can be realized through the spectral-spatial optimization algorithm. The CSP algorithm is a classic spatial optimization algorithm. The goal of Common Spatial Pattern (CSP) is to design spatial filters that lead to new time series whose variances are optimal for the discrimination of two classes of EEG[7]. Algorithms such as FBCSP, and SBCSP [8 9] combine spatial filters with frequency domain filtering to achieve simultaneous optimization of the spatial and frequency domains of EEG signals.

However, the traditional spectral-spatial optimization algorithm and neural network algorithm directly use the ideal center point of valence arousal as the basis for label classification ignoring the valence arousal score, that is, the cognitive difference of the subjects to the emotional stimulus. In this article, we propose an EEG emotion recognition algorithm based on scale distance weighted optimization. Taking the distance score of the scale into consideration, add the weighting coefficient of the scale score to the training set to generate an optimized projection matrix. The data set used in this article is the public EEG dataset DEAP [10].

The remainder of this paper is organized as follows.: Section 2 introduces the implementation steps of the EEG emotion recognition algorithm based on scale distance weighted optimization. Section 3 describes the related experimental results, and Section 4 and Section 5 analyze the experimental results and give conclusion. The results show that adding distance weighting to optimize the EEG signal projection matrix can improve the performance of emotion recognition based on the tester's quantitative perception.

II. Methodology

A. CSP

The EEG emotion signal can be divided into two emotion categories $\boldsymbol{E}_1$ and $\boldsymbol{E}_2$ according to the scores of valence or arousal. The normalized covariance matrix is shown as

$$c_i = \frac{\boldsymbol{E}_i \boldsymbol{E}_i^{\mathrm{T}}}{\operatorname{trace}\left(\boldsymbol{E}_i \boldsymbol{E}_i^{T}\right)} \tag{1}$$

The trace(E) represents the trace of matrix E and i=1,2 which 1 means high valence or arousal and 2 means low valence or arousal. The mean covariance matrix of each class, $\overline{\boldsymbol{C}_1}$ and $\overline{\boldsymbol{C}_2}$, can be computed by averaging over the trials.

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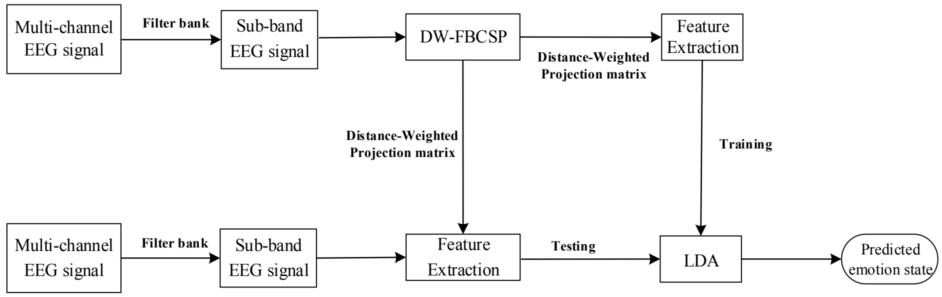

Fig.1 The flowchart of the emotion recognition algorithm

The composite covariance matrix and its eigenvalue decomposition is as follows

$$\boldsymbol{C}_c=\overline{\boldsymbol{C}_1}+\overline{\boldsymbol{C}_2}=\boldsymbol{U}_c\boldsymbol{\Lambda}_c\boldsymbol{U}_c^T \tag{2}$$

$\boldsymbol{U}_c$ is a matrix of normalized eigenvectors with corresponding matrix of eigenvalues, $\boldsymbol{\Lambda}_c$. The whitening transformation is given by

$$\boldsymbol{P}=\sqrt{\boldsymbol{\Lambda}_c^{-1}}\boldsymbol{U}_c \tag{3}$$

The CSP is extracted based on the simultaneous diagonalization of whitened covariance matrices

$$\boldsymbol{S}_1=\boldsymbol{P}\boldsymbol{C}_1\boldsymbol{P}^{\mathrm{T}} \quad \text{and} \quad \boldsymbol{S}_2=\boldsymbol{P}\boldsymbol{C}_2\boldsymbol{P}^{\mathrm{T}} \tag{4}$$

The sum of the eigenvalues of the two types of sample data is always 1, and the formula can be rewritten as

$$\boldsymbol{S}_1=\boldsymbol{B}\boldsymbol{\Lambda}_1\boldsymbol{B}^{\mathrm{T}} \quad \text{and} \quad \boldsymbol{S}_2=\boldsymbol{B}\boldsymbol{\Lambda}_2\boldsymbol{B}^{\mathrm{T}} \tag{5}$$

$$\boldsymbol{\Lambda}_1+\boldsymbol{\Lambda}_2=\boldsymbol{I} \tag{6}$$

In this way, the Spatial filter $\boldsymbol{M}$ is given by

$$\boldsymbol{M}=\boldsymbol{B}^{\mathrm{T}}\boldsymbol{P} \tag{7}$$

Then the reconstructed signal $\boldsymbol{Z}$ can be denoted as

$$\boldsymbol{Z}=\boldsymbol{M}^T\boldsymbol{E} \tag{8}$$

B. Distance Weighted - Filter Bank Common Spatial Pattern (DW-FBCSP)

The algorithm in this paper takes the distance to ideal center point into consideration, give every training set a weight according to the distance to ideal center point, generates an optimized projection matrix, and gives this spectral-spatial optimization. And the sum of the weights of all the samples within the class should be 1. The weighting coefficient is defined as:

$$\boldsymbol{W}_i=\frac{s_i^p}{\sum_{i=1}^{n}s_i^p} \tag{9}$$

Among them, $\boldsymbol{s}_i=|l_i-t|$ is the distance between the label of the first sample and the ideal center point, l_i is the score of one emotion test, t is the ideal center point, n is training set number and p is an adjustable parameter. When p=0, it is equivalent to doing average weighting. Then the formular (2) can be optimized as:

$$\boldsymbol{C}_c=\sum_{i=1}^{n}W_{1i}*c_{1i}+\sum_{i=1}^{j}W_{2i}*c_{2i}=\boldsymbol{U}_c\boldsymbol{\Lambda}_c\boldsymbol{U}_c^T \tag{10}$$

Filter Bank Common Spatial Pattern (FBCSP) is an algorithm improved by CSP and can divide the EEG signal into sub-bands. $\boldsymbol{E}_k$ represents the signal of the k-th sub-band extracted by the filter bank, and the reconstructed signal expressed by the distance weighted is as follows:

$$\boldsymbol{Z}_k=\boldsymbol{M}_k^T\boldsymbol{E}_k \tag{11}$$

These projections $\boldsymbol{Z}_k$ that maximizes the difference between two classes of variances corresponds to the maximum eigenvalue of the simultaneous diagonalization result. Finally, features of a trial given by FBCSP are defined as:

$$f_k=\log\left(\frac{\mathrm{var}(\boldsymbol{Z}_k)}{sum(\mathrm{var}(\boldsymbol{Z}_k))}\right) \tag{12}$$

C. Feature Extraction and Classification

After the DW-FBCSP algorithm optimizing projection matrix, the differences in the spatial distribution between different emotion data is increased. In order to improve the accuracy of the model, we extract more statistical features which can make full use of the emotional information carried by the signal. The statistical features are listed in Table1. After extracting statistical features and spatial projection features, we use the LDA classifier for classification. The dimensions of statistical features (energy, mean value, standard deviation, first-order difference and second-order difference) are 160(32 electrodes *5 features) and the dimensions of DW-FBCSP features are 32. The process of total algorithm is shown in Figure 1.

TABLE I. STATISTICAL FEATURES

Name	Description
Energy	$\boldsymbol{P}_x=\frac{1}{T}\sum_{-\infty}^{+\infty}\lvert x(t)\rvert^2$
Mean Value	$\mu_x=\frac{1}{T}\sum_{t=1}^{T}x(t)^2$
Standard Deviation	$\sigma_x=\sqrt{\frac{1}{T}\sum_{t=1}^{T}[x(t)-\mu_x]^2}$
First-order difference	$\delta_x=\frac{1}{T-1}\sum_{t=1}^{T-1}\lvert x(t+1)-x(t)\rvert$
First-order difference of second lag	$\gamma_x=\frac{1}{T-2}\sum_{t=1}^{T-2}\lvert x(t+2)-x(t)\rvert$

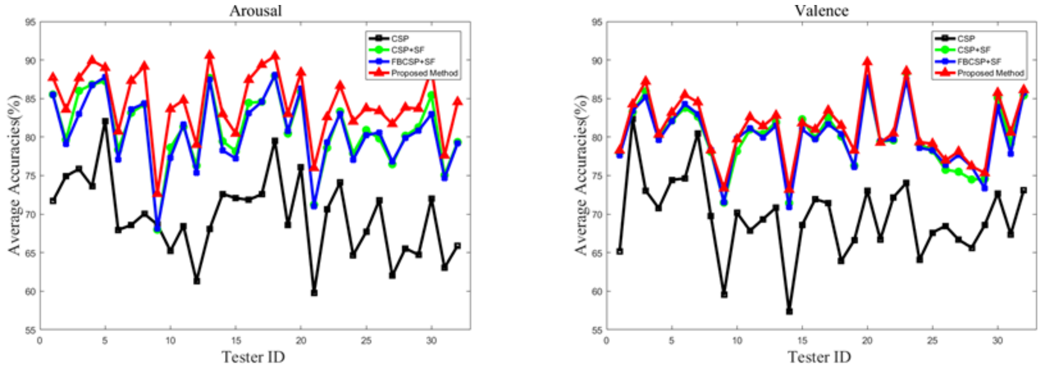

Fig.2 Arousal and Valence classification results of 32 testers

III. Result

In this section, to validate the efficiency of the DW-FBCSP algorithms, the DEAP data set is used to verify the classification effect. The DEAP database selected a total of 32 participants for the experiment, including 16 men and 16 women, ranging in age from 19 to 37 years old each of them watched 40 excerpts of one-minute duration music videos. The sample rate of DEAP dataset is 128hz. Since each subject has only 40 samples, it is far from enough to train the model. Therefore, this article divides each signal into 12 segments. Each 5 s signal is regarded as a new trial data. The scores of the valence and arousal are distributed between 1-9 points. The threshold is set to 5 points. Those with a score greater than 5 are regarded as high valence or arousal while those with less than 5 are regarded as low valence or arousal. A 5-fold cross-validation was used, and each object was repeated 10 times.

This paper compares four methods, CSP, CSP and statistical features(SF), FBCSP and statistical features(SF), and the Proposed method. The results of the 32 testers are shown in Figure 2. The average classification correct rate of the proposed methods can reach 81.14% in valence, and 84.45% in arousal .The valence classification results increased 1.1% and 3.41%, and the arousal classification results increased 1.15% and 3.80% compared with the CSP+SF and FBCSP+SF. The comparisons with other literature are shown in Table2.

In Figure 3, we choose the top three pairs of testerID with the largest and smallest classification accuracy improvement as 10 and 1 (the biggest lift and the smallest lift); 24 and 5 (the second biggest lift and the second smallest lift); 8, 20 (the third biggest lift and the third smallest lift).

Figure 4 shows the EEG topographic map of tester 1 in the DEAP data set. The four columns on the left correspond to tester1 experiment1 (Valence: 7.71, Arousal: 7.60), and the four columns on the right correspond to tester 1 experiment 35 (Valence: 2.06, Arousal: 8.15). The test time of each group is 63s, among which, 0.5-2.5s, 10.5-12.5s, 20.5-22.5s, 30.5-32.5, 40.5-42.5, 50.5-52.5, 60.5-62.5 are selected for a total of 7 trail of EEG signals and every row represents a trail. The trail of 0.5 -2.5s listed in the first row shows the tester in a calm state.

TABLE II. Results Compare With Other Ariticals

Methods	Valence	Arousal
Proposed Method	81.14	84.45
CSP	69.65	69.75
CSP+SF	80.04	81.04
FBCSP+SF	79.99	80.66
Sander Koelstra (2012)[10]	57.6	62.0
Zhang(2016)[11]	81.21	81.76
Mert(2018)[12]	72.87	75.00

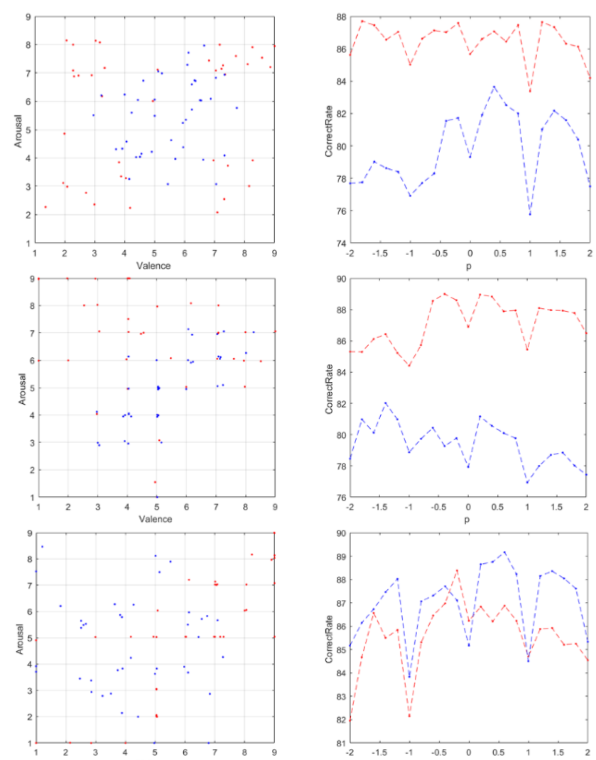

Fig.3 Recognition rate with the corresponding score distribution

IV. Discussion

This section discusses the resolution between different p-value and the classification results which can show the relationship between distance and weight. This section also analyzes the changes in brain activity at different frequencies shown in the EEG topographic map. The results show that the closer the scale scores, the greater the classification correct rate improved after distance weighting. It can give the influence of the optimization. If the original distance is larger, the influence of the distance weighting does not change too much.

The four columns represent theta, alpha, beta, and gamma rhythms. The red part represents the area with higher energy of brain electrical activity, and the blue part represents the area with lower energy activity. The left part of Figure 4 shows that positive emotion has a temporal lobe energy activity increasement in alpha rhythm. The frontal lobe and occipital lobe fluctuate in the gamma rhythm, and the energy in the temporal lobe also changes significantly.

The four columns on the right half are the changes in brain activity in the negative emotion of the same tester. The energy of temporal lobe has a decrease in negative emotion, and the parietal lobe activity increases in beta rhythm. In the future work, we will analyze more EEG topographic maps of the testers.

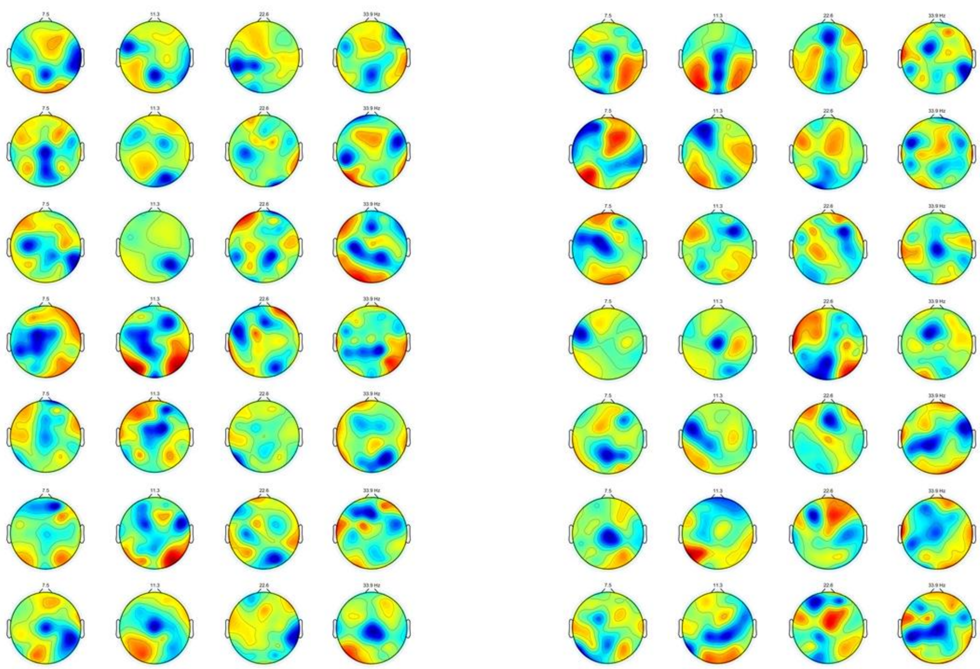

Fig.4 EEG topographic maps of different emotions with high valence on the left and low valence on the right

V. CONCLUSION

This paper proposes an emotion recognition algorithm based on weighted distance optimization. Compared with the traditional CSP algorithm, scale distance weighted optimization is added to generate a more optimized projection matrix which maximizes the difference between the two types of EEG signals. The results show that the closer the scale scores, the greater the classification correct rate improved after distance weighting The EEG topographic maps also visually display the changes in EEG activity induced by emotional materials.

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