Multimodal Emotion Classification Method and Analysis of Brain Functional Connectivity Networks

Xiaofang Sun, Xiangwei Zheng, Tiantian Li, Yalin Li, and Lizhen Cui, *Member, IEEE*

***Abstract*— Since multimodal emotion classification in different human states has rarely been studied, this paper explores the emotional mechanisms of the brain functional connectivity networks after emotional stimulation. We devise a multimodal emotion classification method fusing a brain functional connectivity network based on electroencephalography (EEG) and eye gaze (ECFCEG) to study emotional mechanisms. First, the nonlinear phase lag index (PLI) and phase-locked value (PLV) are calculated to construct the multiband brain functional connectivity networks, which are then converted into binary brain networks, and the seven features of the binary brain networks are extracted. At the same time, the features of the eye gaze signals are extracted. Then, a fusion algorithm called kernel canonical correlation analysis, based on feature level and randomization (FRKCCA), is executed for feature-level fusion (FLF) of brain functional connectivity networks and eye gaze. Finally, support vector machines (SVMs) are utilized to classify positive and negative emotions in multiple frequency bands with single modal features and multimodal features. The experimental results demonstrate that multimodal complementary representation properties can effectively improve the accuracy of emotion classification, achieving a classification accuracy of 91.32±1.81%. The classification accuracy of pupil diameter in the valence dimension is higher than that of additional features. In addition, the average emotion classification effect of the valence dimension is preferable to that of arousal. Our findings demonstrate that the brain functional connectivity networks of the right brain exhibit a deficiency. In particular, the information processing ability of the right temporal (RT) and right posterior (RP) regions is weak in the low frequency after emotional stimulation; Conversely, phase synchronization of the brain functional connectivity networks based on PLI is stronger than that of PLV.**

***Index Terms*— Eye gaze, brain functional connectivity network, multimodal feature fusion, emotion classification.**

Manuscript received 19 October 2021; revised 7 February 2022, 4 May 2022, and 17 June 2022; accepted 15 July 2022. Date of publication 20 July 2022; date of current version 25 July 2022. This work was supported in part by the Natural Science Foundation of Shandong Province under Grant ZR2020LZH008, Grant ZR2021MF118, and Grant ZR2019MF071; in part by the Shandong Provincial Key Research and Development Program (Major Scientific and Technological Innovation Project) under Grant 2021CXGC010506 and Grant 2021SFGC0104; and in part by the National Nature Science Foundation of China under Grant 91846205. *(Corresponding author: Xiangwei Zheng.)*

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Digital Object Identifier 10.1109/TNSRE.2022.3192533

I. Introduction

Affective computing is a multidisciplinary field involving computer science, psychology, and cognitive science, and its potential applications include disease diagnosis, human-computer interaction (HCI), entertainment, autonomous driving assistance, marketing, teaching, etc. [1] Emotion classification methods can be divided into two categories. One is to use human body signals, such as facial expressions, voices, gestures, body postures, etc., which has the advantage of it being simple to collect experimental data. However, humans can hide their true emotional states and change the reliability of these data. The other is the use of internal physiological signals, including EEG, eye gaze, temperature, electrocardiography, electromyography, respiration, etc. [2] These internal physiological signals are objective, dissimulated, and forged reliable physiological signal data for emotion classification research [3].

EEG signals after emotional stimulation in the brain are nonlinear and oscillating. The linear measurement of all the brain electrical information of the brain cannot be accurately and comprehensively conducted. Nonlinear measurement can effectively avoid the above problems and reveal the working state of and information feedback from the brain under emotional stimulation [4]. EEG is the product of the gaze of the brain neurons after the synapses are activated. Many studies have shown that EEG is an effective physiological signal suitable for physiological experiments and biological feature research [5]–[7].

From the perspective of affective computing, the brain functional connectivity network is one of the visual expressions of information interactions between discrete neural units in different brain regions. Functional connectivity is the dynamic coordination between different neural units in the brain functional connectivity network space and their interrelationships in time [8]. The methods of constructing the brain functional connectivity network include linear construction and nonlinear construction [9]; in particular, the linear construction methods include Pearson's correlation [10], partial coherence (time-domain) [11] and partial coherence (frequency domain) [12], while nonlinear methods mainly include synchronization likelihood [13], mutual information [14], PLI [15], PLV [16], etc.

Many researchers have made outstanding contributions to the development of emotion classification. However, there remain challenges to be overcome.

1) Most emotion classification methods based on EEG signals only use single modal or multiple EEG channels, and they do not integrate different modes of the emotional neural mechanism [17]–[20].
2) Most extracted features from EEG are temporal and frequency dimensions, while few works have extracted and integrated spatial features by constructing brain functionality networks to study the emotional mechanism [21]–[23].
3) In the field of multimodal emotion classification, existing feature fusion methods do not comprehensively embody the deep relationship among different features, especially the feature relationship from different modalities [24]–[27].

In this paper, emotions are labelled from multiple dimensions, and they are classified into binary categories from the dimensions of valence and arousal. We investigated whether the brain functional connectivity network and eye gaze have complementary effects on emotion classification. After the analysis of brain functional connectivity networks, eye gaze features and multimodal fusion effects, we could study the neural mechanism of emotional stimulation and the complementarity between multimodal features. The main contributions of this paper are as follows.

- An emotion classification method based on the multimodal fusion of brain functional connectivity networks based on EEG and eye gaze (ECFCEG) is proposed to explore the left and right brain connections based on the brain functional connectivity networks of PLI and PLV.
- Five global features and two local features of the brain functional connectivity networks and five features of eye gaze signals from the perspective of affective computing are analysed to explore the influences of different features on emotional mechanisms from different angles.
- A multimodal feature fusion method called kernel canonical correlation analysis, based on the feature level and randomization (FRKCCA) algorithm, is designed to fuse the global and local features of the brain functional connectivity networks and eye gaze features, improving upon the feature fusion effect and enhancing the complementarity of physiological signals.
- Experiments indicate that the brain functional connectivity networks of the right brain are defective after emotional stimulation, and in the lower frequency bands, the information processing ability of the right brain RT and RP regions is weak.

The remainder of this paper is organized as follows. Section 2 introduces the related literature on brain functional connectivity networks, eye gaze signals, and multimodal emotion classification methods. Section 3 introduces relevant information about the dataset utilized in the paper and expresses the framework adopted in the research of the multimodal emotion classification method based on brain functional connectivity networks. Section 4 shows the specific steps, experimental results, and analysis of the experimental methods adopted. Section 5 discusses the brain functional connectivity network mechanism in different human states after emotional stimulation. Section 6 is a brief conclusion on the research work and future work.

II. Related Work

In this section, we review EEG-related emotion classification and some key techniques, including brain functional connectivity networks, eye gaze and different modal feature fusion methods.

A. EEG

In recent years, emotion classification based on EEG signals has been widely used in mental disease diagnoses, affective computing, HCI, and other related fields. Li *et al.* proposed a transferable attention neural network (TANN) for EEG signal emotion classification from the perspective of neuroscience, which adaptively learns emotional discrimination information through local and global attention mechanisms [17]. Zheng *et al.* proposed a novel consciousness emotion recognition method using event-related potential (ERP) components and modified multiscale sample entropy (MMSE) [18].

B. Brain Functional Connectivity Network

The evaluation of brain functional connectivity networks and graph theory have become powerful tools to help study emotion classification. Zhu *et al.* analysed recorded EEG and utilized the PLI to capture the emotional perception of phase synchronization and classified emotions based on a convolutional neural network (CNN) [19]. Wang *et al.* constructed PLV-based brain functional connectivity networks, extracted two features of functional integration and functional separation, and analysed the differences in brain connectivity of discrete emotions [28].

C. Eye Gaze

Studies have shown that eye gaze signals are related to emotions, and humans' gaze time, saccade, pupil diameter, gaze sequence, and gaze distance are affected by emotional stimulation. Tarnowski *et al.* used video stimulation to extract 18 features related to eye gaze signals (fixation, saccade and pupil diameter) and used an SVM classifier and the leave-one-out verification method for ternary emotion classification [29]. Peng et al discussed the changes in brain networks and EOG signals to study the changes in cognitive ability when using a brain computer interface (BCI) based on SSVEPs. EOG signals are characterized by the blink amplitude and the speed

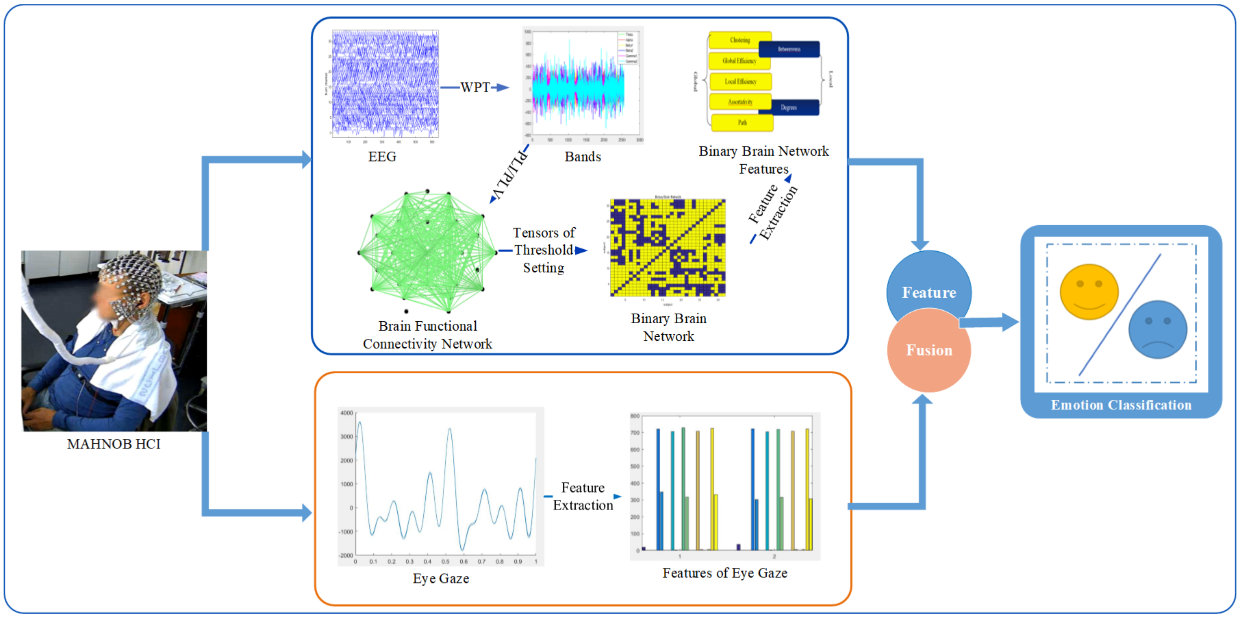


Fig. 1. The framework of our proposed ECFCEG method.

of saccades, and brain networks were synchronously estimated using the instantaneous phase of EEG signals [30].

D. Multimodal Methods

With the development of pervasive data collection devices for EEG and eye gaze, different modalities have been used for emotion classification to improve BCI performance. Wu and Zheng used the multimodal fusion method of deep canonical correlation analysis (DCCA) to fuse the features of brain functional connectivity networks with eye gaze features [31]. Zhang *et al.* used a hierarchical fusion convolutional neural network model to combine six channels (FP1, FP2, AF3, AF4, F3, and F4) and four PPS signals, including galvanic skin response (GSR), respiratory zone (RESP), skin temperature (TEMP) and chest instrument (PLET), to perform hierarchical network construction [24]. Siddharth *et al.* used a deep learning-based convolution-deconvolution network method to extract EEG features and facial expression features for multimodal fusion [25]. Shu and Wang used the restricted Boltzmann machine (RBM) to model the intrinsic dependencies among various physiological signals, extracted the features of EEG and surrounding physiological signals, and classified emotions using support vector machines (SVMs) [26]. Tan *et al.* proposed a short-term emotion classification framework based on spatiotemporal EEG patterns of peak neural network (SNN) models for the emotional classification of audiovisual stimuli [27].

III. Materials and Methods

Fig. 1 illustrates the proposed multimodal ECFCEG method. The process of the ECFCEG method is described as follows.

Step 1: Obtain the original EEG signals and eye gaze signals, and perform the preprocessing of data time normalization and interception of the number of trials.

Step 2: Apply wavelet packet transform (WPT) to preprocess the EEG signals of each experiment of each subject and divide them into Delta, theta, alpha, beta1, beta2, gamma1, and gamma2 frequency bands.

Step 3: Apply PLI and PLV to establish brain functional connectivity networks.

Step 4: Convert the brain functional connectivity networks based on PLI and PLV into binary brain networks using the threshold setting method of a tensor.

Step 5: Extract the five features (gaze, saccade, pupil diameter, gaze point sequence, and gaze distance) of eye gaze and extract the five global features of brain functional connectivity networks, including the clustering coefficient, average shortest path length, assortativity coefficients, global efficiency and local efficiency. The two local features of brain functional connectivity networks include betweenness centrality and node degree

Step 6: Devise the FRKCCA algorithm to fuse features of eye gaze signals and brain functional connectivity networks.

Step 7: Apply SVM to classify emotions with single modal features and fused multimodal features.

A. Materials

In this study, the MAHNOB-HCI EEG public dataset is used for single modal and multimodal emotion classification. Twenty-seven participants of different genders and different cultural backgrounds participated in the emotion classification experiments. They watched 20 emotional video stimuli and self-reported emotions that they felt according to arousal, valence, advantage, predictability, etc. The labels of this emotional experiment used valence and arousal to evaluate the degree of emotional stimulation. The physiological signals, including ECG, EEG (32 channels), respiratory amplitude, and skin temperature, were recorded at a sampling frequency of 256 Hz. The eye gaze sampling frequency was 60 Hz [32].

TABLE I
WAVELET COEFFICIENT INDEX AND FREQUENCY BANDS

Bands	Wavelet Coefficient	Frequency Range
Delta	W6.1 - W6.3	1Hz - 3Hz
Theta	W6.4 - W6.7	4Hz - 7Hz
Alpha	W6.8 - W6.12	8Hz - 12Hz
Beta1	W6.13 - W6.19	13Hz - 19Hz
Beta2	W6.20 - W6.30	20Hz - 30Hz
Gamma1	W6.31 - W6.45	31Hz - 45Hz
Gamma2	W6.46 - W6.60	46Hz - 60Hz

B. Preprocessing

In the preprocessing stage, the time of the original experimental signal was uniformly intercepted at 80 s, and the sampling frequency was 256 Hz, so the time sampling point was 80 * 256. The 80s included only one emotional stimulation video. At the same time, considering the stress and fatigue of the subjects, the experimental data of the middle 30 s, that is, the experimental data from 30 s to 60 s, were extracted from the experimental data of 80 s. A bandpass frequency filter from 4.0 to 45.0 Hz was applied first. Then, the data were averaged to the reference electrode standardization technique (REST). Independent component analysis (ICA) was used to remove EEG artifacts.

Wavelet transform (WT) is a nonstationary time scale analysis method suitable for EEG signal analysis [33]. Continuous wavelet transform (CWT) generates a highly redundant representation of EEG signals in the time scale domain [34], [35], and is computationally very time-consuming [36]. Discrete wavelet transform (DWT) is generally more computationally efficient than CWT [37], and it has excellent time and frequency resolution, which can adapt to the frequency content of the examination mode to achieve the best time-frequency resolution in all frequency ranges. Therefore, DWT was selected for frequency band division of EEG signals. Subsequently, db6 wavelet coefficients of the WPT were utilized to decompose the experimental data into seven frequency bands (Delta, Theta, Alpha, Beta1, Beta2, Gamma1, and Gamma2) [38]. The wavelet coefficient index and frequency bands are shown in Table I.

C. Construction of Brain Functional Connectivity Networks Based on PLI and PLV

The electrode of each EEG signal is regarded as a node in the graph of the brain functional connectivity networks, and at the same time, the PLI and the PLV are used to calculate the edges between the nodes in the brain functional connectivity networks. The PLI is a method to measure the asymmetry of the phase difference distribution between two signals, and it is more sensitive to the phase synchronization level [39]. The phase change of instant t is shown in formula (1):

$$\mathrm{PLI} = |< \mathrm{sign}\left[\Delta\varphi\ (\mathrm{t})\right] >| \tag{1}$$

The asymmetry index of the phase difference distribution can be obtained from the phase difference $\Delta(t)$ of the t time series.

At the same time, to calculate the phase changes of each electrode of the brain, the PLV is calculated to capture the nonlinear phase synchronization [40]. Assuming that the EEG signals of any two electrodes are $x(t)$ and $y(t)$, the phases of these two signals at instant t are respectively expressed as $\phi_x(t)$ and $\phi_y(t)$, respectively, and the phase change of the instant t is expressed by formula (2):

$$\Delta\varphi(\mathrm{t}) = \left|\varphi_{\mathrm{x}}(\mathrm{t}) - \varphi_{\mathrm{y}}(\mathrm{t})\right| \tag{2}$$

The PLV is calculated as the connection between any two electrodes in the time series t, which is the edge of the brain functional connectivity network as in formula (3):

$$\mathrm{PLV} = \left|\frac{1}{\mathrm{N}}\right| \sum_{\mathrm{j}=0}^{\mathrm{N}-1} \mathrm{e}^{\mathrm{i}\Delta\varphi(\mathrm{t})} \tag{3}$$

where N is the number of electrodes.

D. Binary Brain Networks and Their Features

In machine learning, redundant features are widely introduced and lead to performance decreases in recognition algorithms, such as overfitting and substantial time consumption [41]. There are a large number of weak connections and pseudo-connections in brain functional connectivity networks, which often blur the topology of core connections [42]. Therefore, we chose a reasonable connection selection strategy to reduce the connections of the unknown brain functional connectivity network caused by noise or emotional stimulation and decrease the connection network density of the brain functional connectivity network.The binarization process and feature extraction stage of the brain functional connectivity network are not carried out for cross-subject processing.

Considering that two construction methods are employed to construct brain functional connectivity network respectively, there is phase synchronization difference after phase capture, and the range of brain functional connection values is different, so the optimal threshold is not selected, so as to prevent the comparison difference between the two construction methods due to different optimal thresholds. Binary brain networks are constructed as follows.

Step 1: Set the initialization threshold T to 0.01 and the renewal coefficient t to 0.003.

Step 2: Perform matrix binarization based on the PLI or PLV brain functional connectivity network of seven frequency bands of each subject to convert it into a binary brain network.

Step 3: Set the number of loops K of each brain functional connectivity network to 10. A new threshold is generated by loops, and then a sub binary brain network is generated. Experiments show that K is the maximum number of loops, and if K is larger, a zero value network will appear.

Step 4: Judge whether the weights of the connection edges in the brain functional connectivity networks are greater than or equal to the threshold. If they are greater than or equal to the threshold, set the weights of the connection between the two nodes as 1; that is, there is a connection between the two nodes. Otherwise, set it to 0; that is, there is no connection between the two nodes, and a subbinary brain network is obtained.

Step 5: Repeat Step 4 to obtain all subbinary brain networks under a threshold based on the PLI and PLV.

TABLE II
THE FEATURES OF EYE GAZE

Eye Gaze Attributes	Features
Gaze	Time maximum, Time average, Variance, Skewness, Kurtosis,Gaze frequency, Frequency
Glance	Maximum, Average, Variance, Skewness, Kurtosis, Number of sweeps, Frequency, Total velocity
Pupil diameter (Left and right eyes alone)	Maximum, Average, Variance,Skewness, Kurtosis
Gaze sequence (Left and right eyes alone)	Maximum, Average, Variance,Skewness, Kurtosis
Gaze distance	Maximum, Average, Variance, Skewness, Kurtosis, Approach time ratio, Away time ratio, Average approach time, Average away time, Approach rate, Away rate

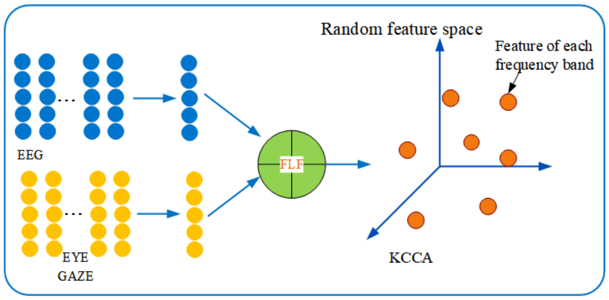


Fig. 2. Schematic diagram of FRKCCA model.

Step 6: Reset the threshold $T = T + t$ and increase to generate a new threshold; repeat Step 2 to Step 5, and continue to loop until all of the subbinary brain networks are generated.

To explore the mechanism of the brain functional connectivity network after emotional stimulation, from the global and local perspectives of the brain networks, five global features (i.e., clustering coefficient, average shortest path length, the assortivity coefficient, global efficiency and local efficiency) and two local features (betweenness centrality and node degree) are adopted from different perspectives of the spatial dimension [43].

E. Feature Extraction of the Eye Gaze

The five features of gaze, saccade, pupil diameter, gaze sequence, and gaze distance are related to emotional stimuli and are extracted from the eye-gaze signals. Detailed features are shown in Table II. To more comprehensively embody the influence of emotional stimuli on eye-gaze signals, we use a large number of frequency-domain statistical features to extract eye gaze features. For example, the five features, including gaze, saccade, pupil diameter, gaze point sequence, and gaze distance, are all used to calculate the maximum value, mean value, variance, skewness, kurtosis and so on. Then, the five features of all subjects are input into the SVM for emotion classification.

F. Feature Fusion Method (FRKCCA)

For basic tasks, such as regression or classification, random features exhibit little or no loss in performance while achieving drastic savings in computational requirements and reducing computational complexity [44]. In the study of multimodal feature fusion, the correlation analysis between ordinary features cannot meet expectations. To further explore the relationship between the two modalities, we use the mapping of features to a high-dimensional random space to study the special features. The fusion of multimodal features and randomizing the space from the point of view of the algorithm increase complementary representation properties and reduce the consumption.

The algorithm of FRKCCA is described as follows. First, the eye gaze features and the brain functional connectivity network features are fused by FLF at the feature level in the two dimensions of the seven frequency bands. We perform randomized nonlinear feature mapping on the experimental data, project the features to the high-dimensional randomized feature space, input the features into the KCCA model for feature fusion, and finally input the new fused features into the SVM model to research emotion classification.

The weight attenuation of randomization theory is consistent with a certain distribution speed; then, F_p is defined as formula (4):

$$F_p = \left\{ f(\mu) = \int R_d \alpha(w) \varphi \left(\mu^T w\right) d_w \right\} |\alpha(w) \leq C p(w)| \tag{4}$$

α is the weight of the R to R^d mapping, and φ represents the nonlinear mapping that satisfies $|\varphi(Z)| \leq 1$ by R to R^d. μ and w are vectors in the mapping space, $p(w)$ is the probability density value of the mapping vector w, and C is a regularization constant. The mapping function can be defined as formula (5):

$$f_m(\mu) = \sum_{i=1}^{m} \alpha_i \varphi \left(w_i^T \mu\right) \tag{5}$$

Assume that the features nonlinear mapping R to R^d of the dataset $D = \left\{\left(x_i, y_i\right)\right\}$ is a finite sample of input and output pairs extracted from a distribution Q (X, Y).

The mapping function f is searched by the method of minimizing risk, which is defined as formula (6):

$$R_{emp}(f) = \frac{1}{m} \sum_{i=1}^{m} c\left(f_m\left(x_i\right), y_i\right) \tag{6}$$

The loss function is defined as formula (7):

$$c(\hat{y}, y) = (\hat{y} - y)^2 \tag{7}$$

We use random sampling parameters $w_i \in R^d$ to optimize the above parameters and formulas (5) and (6), and we construct a multidimensional random feature space $z(X)$ for the input data $X \in R^{n\times d}$ [45], and its structure is defined as formula (8):

$$\begin{aligned} &w_1,\ldots,w_m \sim p(w)\\ &z_i = \left[\cos\left(w_i^T x_1 + b_i\right),\ldots,\cos\left(w_i^T x_n + b_i\right)\right] \in R^n\\ &z(X) = [z_1 \ldots z_m] \in R^{n\times m} \end{aligned} \tag{8}$$

The nonconvex optimization of formula (6) is transformed into a least-squares problem using the nonlinear random feature $z(X)$. The least-squares solution of nonconvex optimization is formula (9):

$$\min_{\alpha\in R^d} \|y - z(X)\alpha\|_2^2 \text{ s.t. } \|\alpha\|_\infty \le C \tag{9}$$

In the randomized feature space, we use KCCA to fuse the two types of features, and the kernel function adopts the Gaussian radial basis kernel function [46]. The KCCA is defined as formula (10):

$$\begin{aligned} &\sum 11\ ij = K\left(x_{1i}, x_{1j}\right) = e^{-\|x_{1i}-x_{1j}\|}/_{\sigma^2}\\ &\sum 22\ ij = K\left(x_{2i}, x_{2j}\right) = e^{-\|x_{2i}-x_{2j}\|}/\sigma_{\sigma^2}\\ &\sum 12\ ij = K\left(x_{1i}, x_{2j}\right) = e^{-\|x_{1i}-x_{2j}\|}\ |\ /_{\sigma^2} \end{aligned} \tag{10}$$

where σ is the width of a kernel. $K(x_1, x_2) = \varphi(x_1)\varphi(x_2)$ represents a nonlinear mapping of two features in a random feature space.

The relationship K between the two features is calculated as formula (11):

$$K = \sum 11^{-\frac{1}{2}} \sum 12 \sum 22^{-\frac{1}{2}} \tag{11}$$

The singular value decomposition of formula (11) is shown in formula (12):

$$K = (\alpha_1, \alpha_2, \ldots, \alpha_K)\, D\, (\beta_1, \beta_2, \ldots, \beta_k)^T \tag{12}$$

G. Emotion Classification With SVM

In the field of emotion classification, SVM can use the kernel function to map to high-dimensional space and use the kernel function to solve nonlinear classification. The classification idea is simple and efficient, maximizing the interval between the sample and the decision surface, showing good prediction and working well for classification [47]. In this paper, the SVM is used as the classification model of single modal features and multimodal features. The SVM uses a discriminant function for model training, and the discriminant function is shown in formula (13):

$$g(x) = W^T x + b \tag{13}$$

SVM maps the classification features to another dimension space and performs feature classification by finding the largest hyperplane. The hyperplane is defined as formula (14):

$$W^T x + b = 0 \tag{14}$$

where W^T is a multidimensional vector, and b is a scalar. The maximum boundary and minimum error are calculated using formula (15):

$$\begin{aligned} &\min \varphi(\omega) = \frac{1}{2}\|\omega\|^2 + C\left(\sum_{i=1}^{n} \xi_i\right)\\ &\text{s.t. } y_i\left[\left(\omega^T x_i + b\right)\right] - 1 + \xi_i, \xi_i > 0,\ i = 1, 2, \ldots, n \end{aligned} \tag{15}$$

where C is the weight between the maximum boundary and the minimized error.

The kernel function of SVM adopts the radial basis kernel function (RBF) [48], and the learning method adopts the sequential minimum optimization (SMO) method. RBF is calculated as formula (16):

$$\mathrm{K}(\mathrm{x_i} \cdot \mathrm{x}) = \exp\left(-\mathrm{g}\,\|\mathrm{x} - \mathrm{x_i}\|^2\right) \tag{16}$$

The SVM classification function is calculated as formula (17):

$$\mathrm{f}(\mathrm{x}) = \mathrm{sgn} \sum_{i=1}^{\mathrm{n}} \mathrm{a_i y_i K}(\mathrm{x_i} \cdot \mathrm{x}) + \mathrm{b} \tag{17}$$

IV. Experiments and Analysis

A. Evaluation Metrics

In the following experiments, we adopt accuracy to evaluate the classification performance. Accuracy is the ratio of the number of samples accurately classified to the total number of samples.

$$\text{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \tag{18}$$

For the comparison between our proposed fusion method FRKCCA and single modal and other multimodal fusion methods, we use the mean to compare the accuracy and adopt the standard deviation to compare the model classification stability.

B. Experiments and Analysis of Brain Functional Connectivity Networks

The experimental data are divided into 80% and 20% as the training data and test data, respectively. Emotion classification adopts the method of tenfold cross-validation, and SVM parameters are selected in the training set. The grid search algorithm is utilized to find the best c and g in the range of [−10:10]. As shown in Fig. 3, the highest classification accuracy of the average feature of the brain functional connectivity networks constructed based on PLI was 76.82%. As we can see in Fig. 4, the highest classification accuracy of the average features of the brain functional connectivity networks constructed based on PLV is 70.49%. It can be concluded that the brain functional connectivity networks constructed by PLI show a strong ability to transmit information after being stimulated by emotions. As shown in Fig. 5, considering as an example the feature assortativity coefficient of brain functional connectivity networks based on PLI and PLV, the average emotion classification effect of the valence dimension is better than that of the arousal dimension.

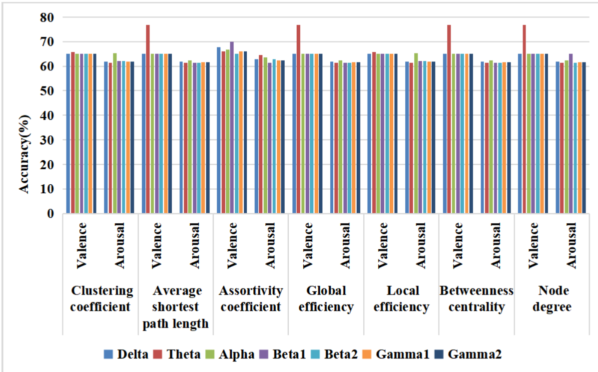


Fig. 3. Classification accuracy of brain functional connectivity networks based on PLI.

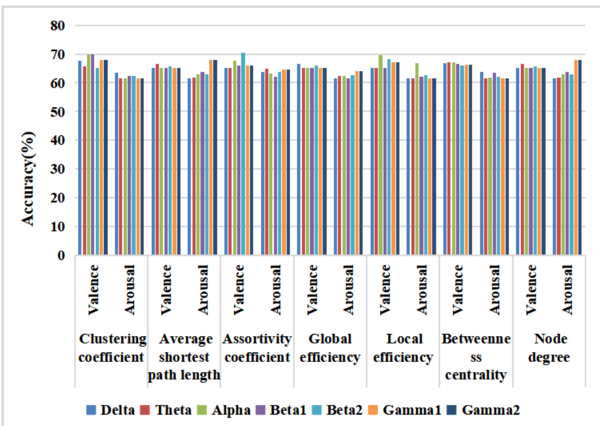


Fig. 4. Classification accuracy of brain functional connectivity networks based on PLV.

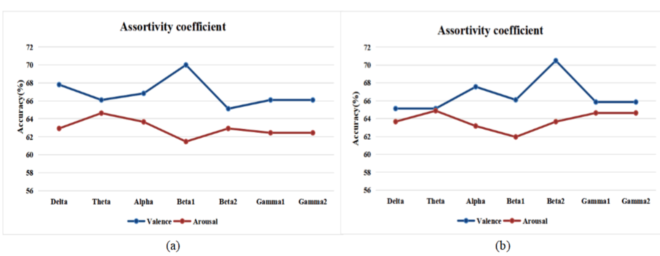


Fig. 5. Dimensional analysis of features based on PLI and PLV. (a) is the classification accuracy of the assortativity coefficient of brain functional connectivity networks based on PLI and (b) the classification accuracy of the assortativity coefficient of brain functional connectivity networks based on PLV.

C. Experiments and Analysis on Eye Gaze

We input the five features of gaze, glance, pupil diameter, gaze sequence, and gaze distance extracted from the eye gaze signals and all of the eye gaze features into the SVM model for emotion classification. The comparison of average classification accuracy is shown in Fig. 6. The analysis demonstrates that the classification effect of FLF is better than the classification accuracy of single-attribute features. Regarding the classification accuracy of single-attribute features, the classification accuracy of pupil diameter in the valence dimension is higher than that of other attribute features. At the same time, regardless of the single modal or FLF, the classification accuracy of the valence dimension is better than that of the arousal dimension.

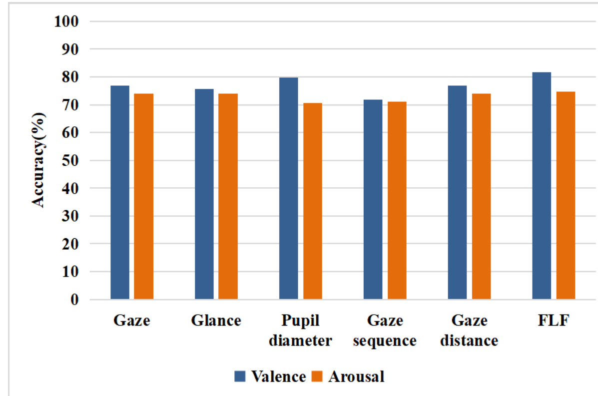


Fig. 6. Comparison of experimental results of eye gaze features emotion classification.

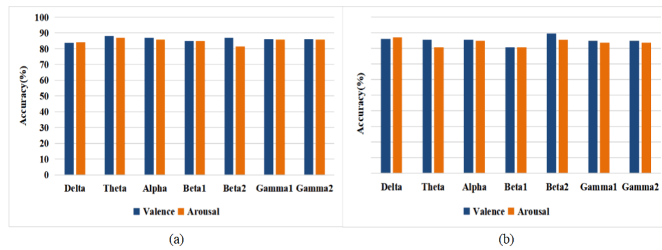


Fig. 7. Dimensional analysis of classification results of FLF features fusion based on PLI and PLV. (a)is the comparison of the valence and arousal dimension of the classification results of the FLF features fusion based on PLI, (b) is the comparison of the valence and the arousal dimension of the classification results of the FLF features fusion based on PLV.

D. Comparative Analysis of Single Modal Features and Multimodal Features

As shown in Fig. 7, the features of the brain functional connectivity networks and eye gaze signals are feature fused based on FLF, and the fused features are input into the SVM to obtain the classification results of seven frequency bands in two dimensions. The analysis shows that the classification effect of FLF in the valence dimension is better than the classification results in the arousal dimension.

To further explore the effect of randomized feature space on emotion classification, we compared single-modal and multimodal feature-level fusion methods. First, the classification effect on single modal features is compared. By comparing the emotion classification effects of brain functional connectivity network features based on PLI and PLV and eye gaze features, it is concluded that the emotion classification accuracy of the valence dimension is better than that of the arousal dimension. Second, the shallow feature level fusion algorithms are compared, and the eye gaze features are fused with brain functional connectivity networks. It is concluded that the features and fusion algorithm based on the PLI brain functional connectivity network are better than those based on PLV in both the valence dimension and the arousal dimension.

TABLE III
THE AVERAGE ACCURACY (%) AND STANDARD DEVIATION (%) OF SINGLE MODAL AND MULTIMODAL ARE USED TO CLASSIFY EMOTIONS OF THE MAHNOB-HCI DATASET

Method		Accuracy			
		Valence		Arousal	
		Mean	Std.	Mean	Std.
Single Modal	EEG-PLI	66.36	3.2	62.19	0.99
	EEG-PLV	66.26	1.41	63.03	1.83
	Eye Gaze	77.09	3.15	72.97	1.61
Multimodal	FLF-PLI	86.09	1.35	84.96	1.63
	FLF-PLV	84.95	2.38	83.57	2.19
	F-CCA-PLI	80.98	3.27	78.33	7.58
	F-CCA-PLV	80.59	3.52	79.12	5.93
	F-KCCA-PLI	85.78	3.07	85.76	4.25
	F-KCCA-PLV	85.73	1.16	85.6	2.34
	F-DCCA-PLI	87.26	2.38	85.29	3.56
	F-DCCA-PLV	86.23	2.22	85.29	3.56
	FRKCCA-PLI	**91.32**	**1.81**	**90.16**	**2.61**
	FRKCCA-PLV	**89.08**	**1.36**	**87.86**	**2.42**

TABLE IV
TIME COST(S) COMPARISON OF MULTIMODAL FUSION METHODS

	Dimension	Algorithm running time	Total running time
F-CCA-PLI	Valence	0.039	305.880
	Arousal	0.036	331.350
F-CCA-PLV	Valence	0.035	316.975
	Arousal	0.037	327.715
F-KCCA-PLI	Valence	0.042	482.480
	Arousal	0.046	560.469
F-KCCA-PLV	Valence	0.032	510.165
	Arousal	0.024	548.297
F-DCCA-PLI	Valence	427.768	4420.152
	Arousal	428.253	4436.014
F-DCCA-PLV	Valence	432.202	4418.803
	Arousal	433.323	4382.933
FRKCCA-PLI	Valence	0.128	397.308
	Arousal	0.127	420.522
FRKCCA-PLV	Valence	0.117	405.977
	Arousal	0.119	418.810

Finally, a deeper FLF is performed. We used the canonical correlation analysis (CCA) algorithm of FLF to fuse the eye gaze features with the brain functional connectivity network features. The fusion classification effect is better than the single-modal feature classification, but it does not exceed that of shallow feature level fusion. Moreover, we use the KCCA algorithm for feature level fusion. The effect of FLF based on PLI is better than that of shallow feature level fusion, which is better than that of the CCA algorithm, but the effect based on PLV is weak. We also adopt the deep canonical correlation analysis (DCCA) algorithm of FLF to fuse the eye gaze features with the brain functional connectivity network features, and the sigmoid function is adopted as the activation function, for which the learning rate of DCCA is 0.01. Furthermore, we design a new FLF algorithm to improve and optimize the FLF based on KCCA, and we propose the FRKCCA algorithm to obtain better emotion classification performance than the other multimodal and single modal methods. The results show that our proposed FRKCCA model has good classification performance in emotion classification and achieved a classification accuracy of 91.32±1.81%.

Single modal features and multimodal features that use FLF, F-CCA, F-KCCA, F-DCCA, and FRKCCA fusion methods to combine the features of the brain functional connectivity networks constructed by PLI and PLV and eye gaze features are used in the SVM emotion classification model for emotion classification. The mean and standard deviation of the classification results are shown in Table III. Under the same computing setting, we recalculated the running time of the multimodal fusion algorithm and the total emotion classification algorithms. It is shown that the FRKCCA algorithm can improve the classification accuracy and save calculation time. The results are shown in Table IV.

According to the comprehensive analysis of Tables III and IV, FRKCCA is better than the other three fusion algorithms in classification accuracy. In terms of time cost, it is weaker than the CCA algorithm, but the CCA algorithm is a linear fusion of multimodal features, losing some feature information, and the classification accuracy is lower than that of the other two. The proposed FRKCCA algorithm is better than the KCCA algorithm in terms of the time cost and classification accuracy. Therefore, the FRKCCA algorithm has a certain feasibility and superiority.

TABLE V
BINARY CLASSIFICATION PERFORMANCE OF DIFFERENT WORKS IN MULTIMODAL EMOTIONS (%) CLASSIFICATION ON THE MAHNOB-HCI DATASET

Method	Multimodal	Accuracy (%)	
		Valence	Arousal
HFCNN + RF [24]	EEG (6 channels) + GSR + RESP + TEMP + PLET	89.00	88.28
LSTM [25]	EEG + Face	86.31	83.70
RBM [26]	EEG + EOG + EMG + GSR + RESP + TEMP + PLET	59.10	65.90
SNN [27]	EEG + Face	72.12	79.39
Proposed method FRKCCA + SVM	**EEG (Brain functional connectivity networks) + Eye gaze**	**93.41**	**91.46**

E. Comparison of Different Studies Related to Emotion Classification

In recent years, multimodal physiological signal fusion for emotion classification methods has attracted much attention. The method of EEG and other modal fusion reveals the neural mechanism of emotion. A comparison of different studies related to emotion classification is shown in Table V.

V. DISCUSSION

We compared and analysed the two types of brain functional connectivity networks in different frequency bands. Generally, the scalp area of the brain is divided into left and right hemispheres (LH and RH); the frontal region is divided into left frontal (LF), right frontal (RF), left temporal (LT) and right temporal (RT) areas; the central region is divided into left central (LC) and right central (RC); and the posterior is divided into left posterior (LP) and right posterior (RP) [49].

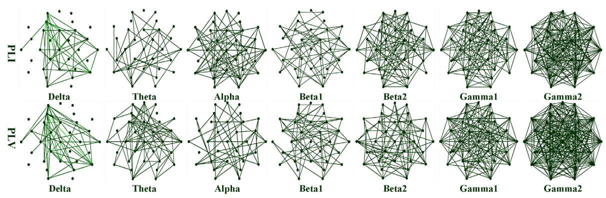
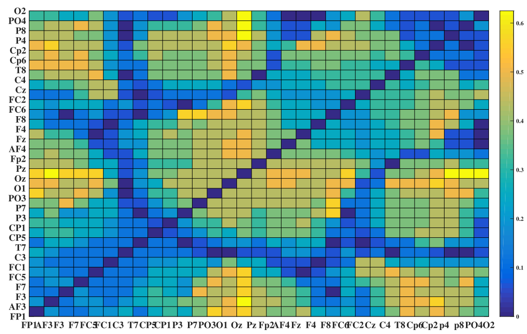
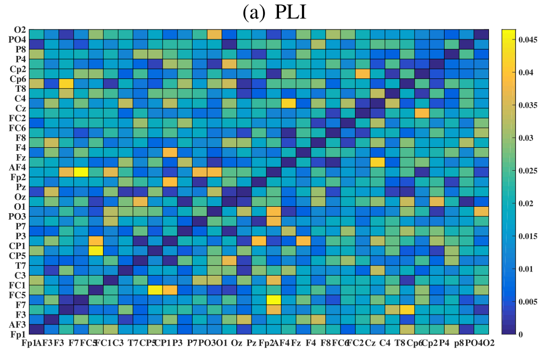


Fig. 8. Comparison of brain functional connectivity networks in seven frequency bands based on PLI and PLV.



(a) PLI



(b) PLV

Fig. 9. Synchronization analysis based on PLI and PLV.

A large number of studies of EEG have found that different brain waves represent different human body states. Furthermore, the original EEG signals are decomposed into seven frequency bands, and different frequency bands correspond to different brain waves and human body states. When people are in infancy or immature intellectual development and adults are in a state of extreme fatigue, drowsiness or anaesthesia, the Delta wave can simulate the EEG signals of the temporal and parietal lobes in this state. The Theta wave is the "subconscious level" – the state of the brain in which memories, perceptions, and emotions are present and usually occur during dreaming and deep meditation. The Alpha wave is gradual, shallow consciousness of the brain, and then the consciousness gradually moves towards the paste; usually, the brain is in a blank state before sleeping. The Beta1 wave indicates thinking and processing of information heard or thought from the outside world when the brain is relaxed but focused. The Beta2 wave indicates heightened awareness of the human body when the person is agitated or anxious. Gamma waves are highly concentrated, usually when people ruminate and are mentally focused but their emotional state is high [50]. Fig. 8 shows the brain functional connectivity networks constructed based on PLI and PLV in the seven frequency bands. The figures are drawn with the help of the HERMES toolbox [51].

As shown in Fig. 8, the brain functional connectivity networks based on PLI and PLV indicate the deficiency of left and right functional connections after emotional stimulation; in particular, there are some differences in functional connections between the RT and RP of the brain functional connectivity networks based on PLI and PLV in the Delta, Theta, Alpha, Beta1, Beta2, Gamma1 and Gamma2 frequency bands. The results further indicate that, when humans cannot be highly concentrated, there are some differences in functional connections in the RT and RP areas of the brain functional connectivity networks, indicating that right brain information processing is weak.

Comparative analysis shows that the brain functional connectivity networks of the right brain are defective after emotional stimulation and in the lower frequency bands, so the information processing ability of the right brain RT and RP regions is weak. In this study, the 32 electrodes are connected in pairs to form a 32 * 32 connection matrix. The stronger that the connection is, the more yellow that the colour is, and the weaker that the connection is, the more blue that the colour is. The electrode itself is not connected by default. As shown in Fig. 9, the phase synchronization of the brain functional connectivity networks based on PLI was stronger than that of the brain functional connectivity networks based on PLV.

VI. Conclusion

In this paper, we propose an ECFCEG method in the field of affective computing. At the same time, the brain functional connectivity networks based on PLI and PLV and eye gaze features were fused using FLF, FRKCCA, and other algorithms. Finally, single modal features and multimodal features were fed into the SVM to classify positive and negative emotions. The experimental results demonstrated that the proposed FRKCCA model had good performance in emotion classification and achieved a classification accuracy of $91.32\pm1.81\%$. These results demonstrate the complementary features between brain functional connectivity networks and eye gaze in the field of affective computing.

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