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Phase-Locking Value Based Graph Convolutional Neural Networks for Emotion Recognition

ZHONGMIN WANG[1,2], YUE TONG[2], AND XIA HENG[1,2]
[1]School of Computer Science and Technology, Xi'an University of Posts and Telecommunications, Xi'an 710121, China
[2]Shaanxi Key Laboratory of Network Data Analysis and Intelligent Processing, Xi'an University of Posts and Telecommunications, Xi'an 710121, China

Corresponding author: Yue Tong (tongyue_TY@126.com)

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ABSTRACT Recognition of discriminative neural signatures and regions corresponding to emotions are important in understanding the neuron functional network underlying the human emotion process. Electroencephalogram (EEG) is a spatial discrete signal. In this paper, in order to extract the spatio-temporal characteristics and the inherent information implied by functional connections, a multichannel EEG emotion recognition method based on phase-locking value (PLV) graph convolutional neural networks (P-GCNN) is proposed. The basic idea of the proposed EEG emotion recognition method is using PLV-based brain network to model multi-channel EEG features as graph signals and then perform EEG emotion classification based on this model. Different from the traditional graph convolutional neural networks (GCNN) methods, the proposed P-GCNN method uses the PLV connectivity of EEG signals to determine the mode of emotional-related functional connectivity, which is used to represent the intrinsic relationship between EEG channels in different emotional states. On this basis, the neural network is trained to extract effective EEG emotional features. We conduct extensive experiments on the SJTU emotion EEG dataset (SEED) and DEAP dataset. The experimental results demonstrate that novel framework can improve the classification accuracy on both datasets, but not so effective on DEAP as on SEED, in which with 84.35% classification accuracy for SEED, and the average accuracies of 73.31%, 77.03% and 79.20% are, respectively, obtained for valence, arousal, and dominance classifications on the DEAP database.

INDEX TERMS EEG emotion recognition, phase-locking value, graph convolutional neural networks, brain network, functional connectivity.

I. INTRODUCTION

Emotion computing is the key technology to realize advanced human-computer interaction. Emotion recognition is an important part of emotion computing. Its research purpose is to let the machine perceive the emotional state of human beings and improve the humanization level of the machines [1]. Common emotion recognition methods can be divided into two categories: one is based on non-physiological signals, such as voice [2], facial expression [3] and posture [4], the other is based on physiological signals, mainly including peripheral nervous system and brain signals. Peripheral nervous system recognition method is to identify the corresponding emotional state by measuring physiological signals such as heart rate, skin impedance [5], respiration, etc. Brain signal recognition methods mainly include functional magnetic resonance imaging (FMRI) [6], magnetoencephalography (MEG) [7] and electroencephalogram (EEG) [8]. Among various emotion recognition methods, the brain signal is highly reliable and scientific because it is not affected by human subjective factors [8]. In addition, with the rapid development of wearable devices and dry electrode extraction technology [9], EEG-based emotion recognition technology and EEG-based signal processing methods have become a hot topic in the field of emotion recognition [10], [27].

Different techniques for emotion recognition have been proposed in literature using EEG by either individually engaging the sense of vision, auditory, tactile or by combining both vision and auditory senses. Emotion assessment is a subjective phenomenon and different stimuli evokes different emotions. In [11], [12], frequency and time domain features

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were extracted to classify emotions using EEG by using audio music as a stimuli that engaged only the auditory sense of the listener. In [13], images and audio music were used as a stimuli, thereby engaging only one sense at a time. The emotions have been classified using EEG by extracting frequency domain features. In [14], two human senses were engaged by displaying video clips and emotions were classified using EEG by extracting time domain features. In [15], A user-independent method of emotion recognition using electroencephalography (EEG) in response to traditional and tactile enhanced multimedia (TEM) is presented with an aim of enriching the human experience of viewing digital content. The selected traditional multimedia clips are converted into TEM clips by synchronizing them with an electric fan and a heater to add cold and hot air effect. This would give realistic feel to a viewer by engaging three human senses including vision, auditory, and tactile.

At present, more and more researchers are engaged in the research of emotion recognition. A typical EEG emotion recognition method usually consists of two parts, i.e., EEG emotional feature extraction and emotion recognition [27]. Feature extraction is a crucial part of emotion recognition research. Only by extracting the features that are truly related to emotion can we provide guarantee for subsequent research. Chai *et al.* [16] extracted six time-domain statistical features of EEG signals and used neural networks to identify emotions such as anger, sadness, surprise and pleasure. Hosseini and Naghibi-Sistani [17] extracted the approximate entropy features of EEG signals and used support vector machine for emotion recognition, the accuracy rate reached 73.25%. Although these methods have obtained some research results, the univariate EEG features extracted using these methods lack spatial and functional descriptions. In this paper, a multivariable feature method based on brain network is proposed to solve the problem of how to extract the multivariate features of EEG by utilizing the relationship between multiple scalp EEG channels to fully mine the intrinsic information of EEG signals, and how to select the key channel related to emotion. Since the phase-locking value (PLV) [18] method can separate the phase component from the amplitude component in EEG signal. It is more suitable for EEG data that is affected by synchronous amplitude changes caused by eye movements and other activities. This paper uses PLV to build an emotional correlation model. Multivariate EEG features based on PLV brain network modeling have stable structural and abundant brain activity information compared with univariate features [19], which provides guarantee for EEG classification and recognition.

In the literature [20] proposed a variety of EEG emotion classification and recognition methods. Jirayucharoensak *et al.* [21] used the stacked self-encoder (SAE) method to establish the emotion recognition model, and compared it with traditional classification algorithms such as support vector machine (SVM) [22] and naive Bayes (NB), which verified the superiority of deep network. Deep neural networks (DNN) [23] has been proven to be superior to traditional machine learning methods in applications such as facial recognition and speech recognition. Among them, Convolutional neural network (CNN) has been widely used in spatial continuous data processing such as computer vision [24] and natural language processing. It is worth noting that CNN cannot be used to process spatial discrete data, such as biological molecules, social networks and brain networks, etc. In order to efficiently extract spatial features for machine learning on such data structures (topologies), Graph neural network (GNN) [25] has become the focus of research. In 2009, Scarselli first proposed the concept of graph convolution neural network (GCNN) [26], which is a deep learning method that combines CNN with spectral theory [25], [29]. In the discrete space domain, GCNN provides an effective way to describe the intrinsic relationship between different nodes of the graph, which provides an important clue for exploring the relationship between multiple EEG channels in EEG emotion recognition. In the literatures [27], a method based on GCNN for EEG emotion recognition is proposed. However, only the spatial location of the EEG channel was considered and no functional connection was explored. Because of the working mechanism of division of labor and cooperation among brain regions, the spatial positional relationship and functional connection of EEG channels do not maintain their consistency [28]. In order to solve this problem, this paper proposes a new PLV-based graph convolutional neural network (P-GCNN) emotion recognition method, which determines the emotional-related functional connection mode through the PLV connectivity of EEG signals. Then, the multi-channel EEG emotion recognition problem is studied through graph theory knowledge, where each EEG channel corresponds to one vertex node in the graph, and the connection between two different vertex nodes corresponds to one edge of the graph.

Based on the two parts of the feature extraction and classification recognition, this paper proposes a PLV-based graph convolutional neural network emotion recognition method. The univariate EEG feature is modeled as a multivariate feature of the graph signal based on the PLV brain network structure, which restores the spatial and functional intrinsic connection of the data, and provides a new idea for the research of EEG emotion recognition method. At the same time, the PLV-based graph convolutional neural network extracts EEG features that are more able to represent emotions, and the emotion classification recognition rate is improved.

The remainder of this paper is organized as follows: In the second section, a brief introduction of spectral theory and graph convolution. In the third section, the P-GCNN model and the EEG emotion recognition method based on the model are proposed. The fourth part is the EEG emotion recognition experiment. Finally, the fifth section summarizes this paper.

II. GRAPH PRELIMINARY

In this section, the spectral graph theory [29] and the graph convolution [26] are introduced. This is the basis of the P-GCNN method.

A. SPECTRAL GRAPH THEORY

In the traditional convolutional network, convolution essentially uses a filter with shared parameters to extract spatial features by calculating the weighted sum of the central pixel and adjacent pixels. Convolution is the operation between a local filter and a signal on the regular grid and the filtering parameters are obtained by backpropagation. With the generation of discrete data in the spatial domain, a graph representation method is proposed. The eigenvalues and eigenvectors of the Laplacian matrix of the graph are used to study the properties of the graph, and the deep learning technique is extended to the graph domain.

The graph can be defined as G = (V, E, W), where V, E are the vertex and edge sets of the graph. W is the adjacency matrix describing the connection between any two nodes in V, and W_{pq} indicates the importance of the connection of the p-th node to the q-th node. Its Laplacian matrix is defined as L = D − W, Where L is the Laplacian matrix, D is the degree matrix of the graph, and W is the adjacency matrix of the graph. Since L is a symmetric matrix, it can be singular value decomposition (SVD) [29] L = $U \wedge U^T$, Where U = $[u_0, \cdots, u_{N-1}] \in R_{N\times N}$ is the eigenvector matrix, $\bigwedge = \mathrm{diag}([\lambda_0, \cdots, \lambda_N])$ is the diagonal matrix.

The migration of the traditional Fourier Transform and convolution to the graph domain is to change the eigenfunction e^{-iwt} of the Laplacian into the eigenvector of the Laplacian matrix corresponding to the graph.

The graph Fourier transform (GFT) [30] is defined as:

$$F\left(\lambda_l\right) = \hat{f}\left(\lambda_l\right) = \sum\nolimits_{i=1}^{N} f\left(p\right) u_l^*\left(p\right) \tag{1}$$

F is the N-dimensional vector on the graph, f(p) corresponds one-to-one with the vertices in the graph, $u_l(p)$ represents the p-th component of the l-th feature vector, and $u_l^*(p)$ is the conjugate of the feature vector u_l.

Extend the graph Fourier transform to the matrix form is as follows:

$$\begin{pmatrix} \hat{f}(\lambda_1) \\ \hat{f}(\lambda_2) \\ \vdots \\ \hat{f}(\lambda_N) \end{pmatrix} = \begin{pmatrix} u_1(1) & u_1(2) & \cdots & u_1(N) \\ u_2(1) & u_2(2) & \cdots & u_2(N) \\ \vdots & \vdots & \ddots & \vdots \\ u_N(1) & u_N(2) & \cdots & u_N(N) \end{pmatrix} \times \begin{pmatrix} f(1) \\ f(2) \\ \vdots \\ f(N) \end{pmatrix} \tag{2}$$

That is, the matrix form of the graph Fourier Transform of f is:

$$\hat{f} = U^T f \tag{3}$$

B. CONVNETS ON GRAPH

The graph convolutional network can be divided into two types from convolution: spectral convolution and spatial domain convolution. Spectral convolution is to convert the filter of the convolution network and the graph signal to the Fourier domain at the same time, and then process. The spatial domain convolution is that the nodes in the graph are connected in the spatial domain to achieve the hierarchical structure, and then convolute.

The spectral convolution of the graph [29] is defined as the signal x $\in R^N$ multiplied by the filter $g_\theta = diag(\theta)$, and the filter is parameterized by $\theta \in R^N$ of the Fourier domain:

$$g_\theta * x = U g_\theta U^T x \tag{4}$$

where U is composed of the eigenvectors of the normalized Laplacian matrix, defined as:

$$L = I_N - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} = U \bigwedge U^T \tag{5}$$

$\bigwedge$ is the diagonal matrix composed of the eigenvalues of L, and $U^T x$ is the graph Fourier transform of x. g_θ is a function of the eigenvalue of L, i.e., $g_\theta(\wedge)$.

In order to localize the filters in space and reduce their computational complexity, the truncated expansion of the K-order Chebyshev polynomial [26] is used to approximate the filter. The Chebyshev polynomial is defined as $T_k\left(x\right) = 2xT_{K-1}\left(x\right) - T_{K-2}(x)$, where $T_0\left(x\right) = 1$, $T_1\left(x\right) = x$. Then, the signal x is filtered by the k-domain filter, and the expression is as follows:

$$y = g_\theta\left(L\right) * x = \sum\nolimits_{k=0}^{k} \theta_k T_k(\tilde{L}) x \tag{6}$$

where $\tilde{L} = 2L/\lambda_{max} - I_N \lambda_{max}$ represents the maximum eigenvalue of L.

The q-th output feature graph of the sample s in the graph convolution network can be expressed as:

$$y_{s,q} = \sum\nolimits_{p=1}^{F_{in}} g_{\theta_{p,q}}(L) x_{s,p} \in R^R \tag{7}$$

The $F_{in} \times F_{out}$ vector trains the Chebyshev coefficient $\theta_{p,q} \in R^K$, where $x_{s,p}$ represents the input feature map.

III. P-GCNN FOR EMOTION RECOGNITION

In this part, the univariate EEG features were modeled as graph signals using PLV matrices, and then the P-GCNN model is proposed and applied to the EEG emotion recognition problem.

A. EEG PHASE SYNCHRONY ANALYSIS

Phase synchronization phenomena are widely present in EEG data and have been widely used in motion imaging and brain-computer interface research [18]. Compared with other methods to quantify the phase synchronization between signals, PLV [31], [32] represents the absolute value of the average phase difference between any two signals, which can separate the phase component from the amplitude component in EEG signals. The formula definition of PLV [33] is:

$$PLV\left(t\right) = \frac{1}{N} \left| \sum\nolimits_{n=1}^{N} \exp\left(j\left(\Delta\varphi_n\left(t\right)\right)\right) \right| \tag{8}$$

$\Delta\varphi_n(t) = (\varphi_x(t) - \varphi_y(t))$ represents the phase difference between the electrode signal x and the electrode signal y at time t, N is the length of the time series.

Then the element W_{pq}^* of adjacency matrix W^* is determined based on PLV. The formula can be expressed as:

$$W_{pq}^* = \begin{cases} \frac{1}{N}\left|\sum_{n=1}^{N} \exp\left(j\left(\Delta\varphi_n(t)\right)\right)\right|, & if\ \Delta\varphi_n(t) \leq \tau, \\ 0, & otherwise \end{cases} \tag{9}$$

where τ is a fixed threshold and $\varphi_n(t)$ represents the strength of the functional connection between the p-th node and the q-th node.

Algorithm 1 Procedures of Training Optimal P-GCNN Model for EEG Emotion Recognition

Require: Univariate EEG features associated with multiple frequency bands, multivariable attributes feature based on brain network, the class labels corresponding to the EEG features, the preprocessed EEG timeseries, the numbers of Chebyshev polynomial order k, the learning rate ρ;
Ensure: The desired model parameters of P-GCNN;
1: Initialize model parameters;
2: **repeat**
3: Calculating the PLV adjacency matrix W^* and regularizing the elements of the matrix W^* using Relu operation such that the elements are non-negative;
4: Calculating the Laplacian matrix L^*;
5: Calculating the normalized Laplacian matrix $\tilde{L}^*$;
6: Calculating the Chebyshev polynomial items $T_k(\tilde{L}^*)(k = 0, 1, \cdots, K-1)$;
7: Calculating $\sum_{k=0}^{K-1} \theta_k T_k(\tilde{L}^*)x$;
8: Calculating the convolution results and regularizing the result using the Relu operation;
9: Calculating the results of the full connection layer;
10: Calculating the loss function using (10);
11: Updating model parameter;
12: **until** the iterations satisfies the predefined algorithm convergence condition.

B. P-GCNN MODEL CONSTRUCTION

The P-GCNN model is proposed according to equations (6) and (9) as shown in Figure 1. The model framework consists of two modules, i.e., PLV-based graph signals construction, graph convolution and classification prediction.

The graph signal construction module includes two parts: time-frequency domain feature extraction and PLV-based brain network construction. Among them, the extracted time-frequency domain EEG features include the differential entropy (DE) feature [34], the power spectral density (PSD) feature [35], the differential asymmetry (DASM) feature [36], the rational asymmetry (RASM) feature [37] and the differential caudality (DCAU) feature [41]. The construction of the brain network: We use the formula (9) to achieve brain network construction under different emotional states. The graph convolution and classification prediction modules include a graph convolution layer, two Relu active layers, a graph pooling layer, a fully connected layer, and a softmax layer.

The input of the P-GCNN model is the preprocessed EEG timeseries. The vertices in Figure 1 represent the EEG channels, and the line connecting the vertices indicate the relationship of the brain regions corresponding to the electrode positions in an emotional state. The purpose of the graph convolution operation is to extract more discriminative features. In order to increase the nonlinearity of the neural network model, the Relu function [38] is used to alleviate the occurrence of over-fitting problems. Then there is a fully connected (FC) output layer, which is used to integrate the global information about the graphics from previous localization filters. Finally, the Softmax function [39] is used for classification and identification. we define a cross-entropy loss function to optimize network parameters, which is expressed as follows:

$$Loss = -\sum_{x}(p(x)logq(x) + (1 - p(x))\log(1q(x))) + \lambda R(w) \tag{10}$$

where p(x) and q(x) represent the true and predicted value of the training data, $R(w)$ is an indicator for evaluating the complexity of the model, and $\lambda R(w)$ is intended to prevent over-fitting of the model.

Algorithm 1 summarizes the detailed steps for training the P-GCNN model in EEG emotion recognition.

IV. EXPERIMENTS

In this section, we will conduct extensive experiments on two emotional EEG datasets that are used to evaluate the effectiveness of the proposed P-GCNN method. One is the SEED dataset established by Shanghai Jiao tong University, and the other is the internationally open multimodal DEAP dataset.

A. EMOTIONAL EEG DATABASES

In the SEED dataset [40], 15 subjects (7 males, 8 females) participated in the experiment, and each subject performed 3 experiments with an interval of about one week. Each participant watched 15 videos, which corresponded to the three emotional categories of Positive, Neutral and Negative. They recorded their EEG signals through the electrode cap while the subjects watched the movie clips. The EEG signal sampling frequency is 1000 Hz. According to the international 10-20 system [41], the experiment uses a 62-channel electrode cap. The layout of EEG electrodes on the cap is shown in Figure 2. The four electrodes T7, T8, FT7, and FT8 are distributed in the temporal lobe area above the ear, which is called the conductive electrode. The role of the electrode group is to amplify the collected raw EEG signal and output it to the preprocessing module.

The DEAP dataset [42]– [46] included a total of 40 channels of physiological signals from 32 subjects (16 males

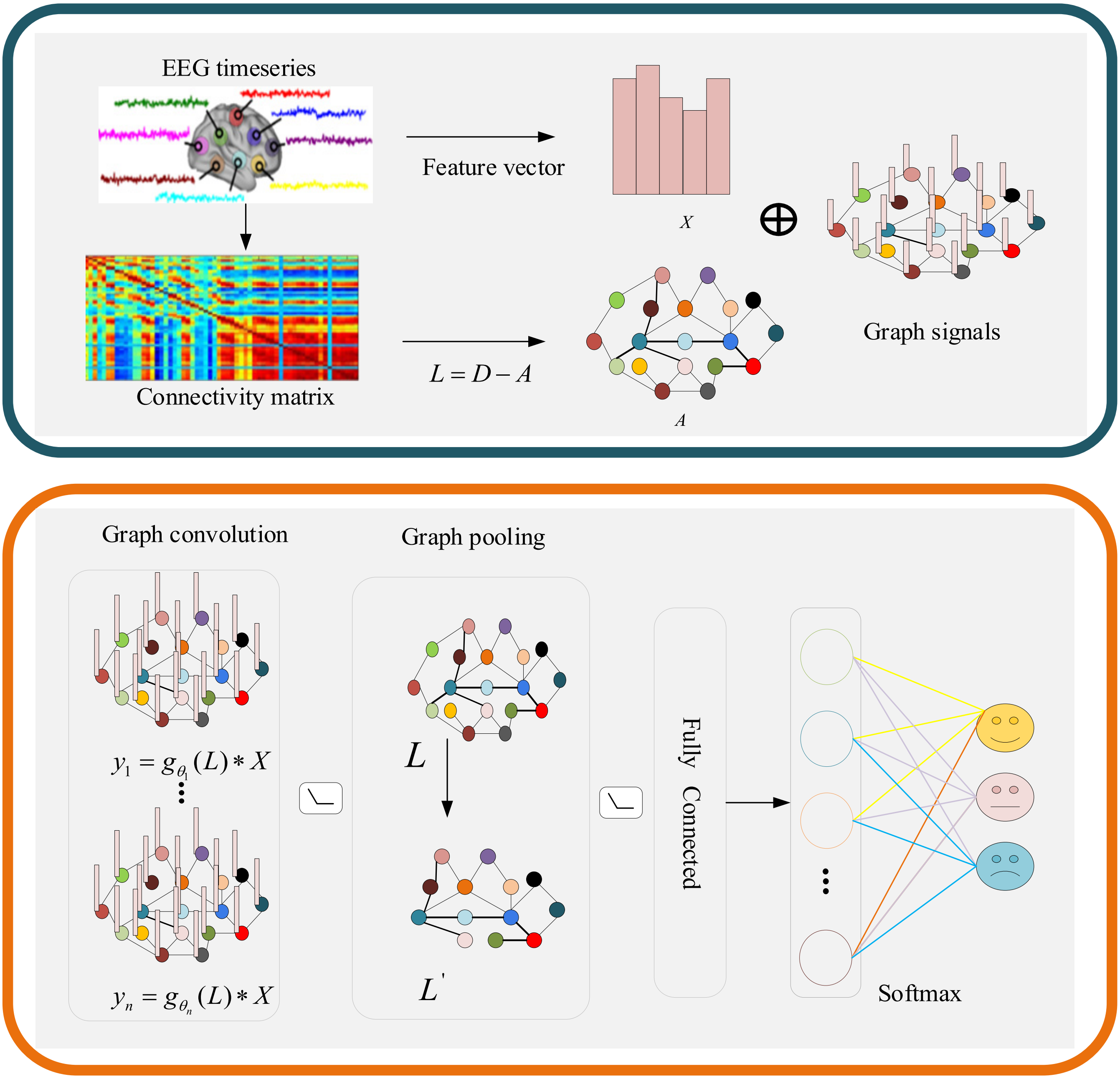

FIGURE 1. **The framework of the P-GCNN model for EEG emotion recognition, which consists of the PLV-based graph signals construction, graph convolutional operation, graph pooling operation, Relu activation and the full connection. The inputs of the model are the preprocessed EEG timeseries. The outputs are the predicted labels through softmax.**

and 16 females) and facial expression videos from the top 22 subjects. Among the physiological signals of 40 channels, the first 32 channels are EEG signals, and the last 8 channels are autonomous physiological signals, including Electro-oculogram (horizontal and vertical Electro-oculogram), myoelectricity, skin electricity, respiratory rhythm, etc. Each participant watched 40 videos. After watching the video, they were asked to mark the valence, arousal, and dominance of the video being watched according to the size relationship from 1 to 9.

B. EEG EMOTION RECOGNITION ON SEED DATABASE

The pre-processed SEED dataset was used for the experiment, and the three experiments of each subject were divided into three groups for research. The EEG data of 11 individuals randomly selected from 15 subjects in each group were the training set, 2 were the verification set, and the remaining 2 were the test sets, and the classification accuracy of each group was obtained. Finally, the average classification accuracy and standard deviation of the three groups are calculated.

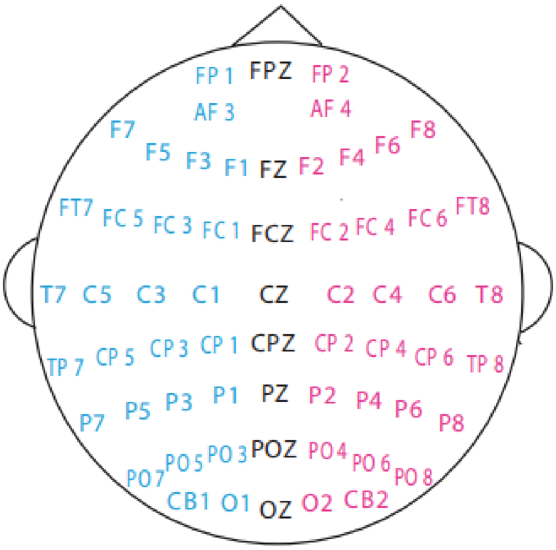

FIGURE 2. The EEG cap layout for 62 channels.

Since the connection mode of the brain network in the initial stage of data collection and the end of the experimental task is difficult to maintain relatively stable (i.e., does not meet the basic assumption of static connection). Therefore, the time series of 4 minutes is equally divided into four parts before calculating the PLV, each segment is 60s, and the time series of the 90s-150s between the cuts is used as the calculated time series. The experiment selects the sliding time window with a step size of 0.12s to calculate the PLV. Figure 3 (a) (b) is the PLV correlation matrix of the first and seventh subjects under the three emotional categories of Positive, Neutral and Negative. (c) is the average PLV matrix of all subjects under three emotions.

It is observed from Fig. 3 that the degree of some electrodes is significantly higher than other electrodes. This shows that some brain parts having higher degree electrodes are more involved and synchronized with other brain parts, which also implies that these brain parts may be responsible for generation of particular emotions.

Analysis of Figure 3, in the same band, the number of electrode pairs with a phase locking value greater than 0.6 in the pleasant state is relatively less than the sad state. so overall, the phase synchronization of different brain regions in the negative state is higher. It is the

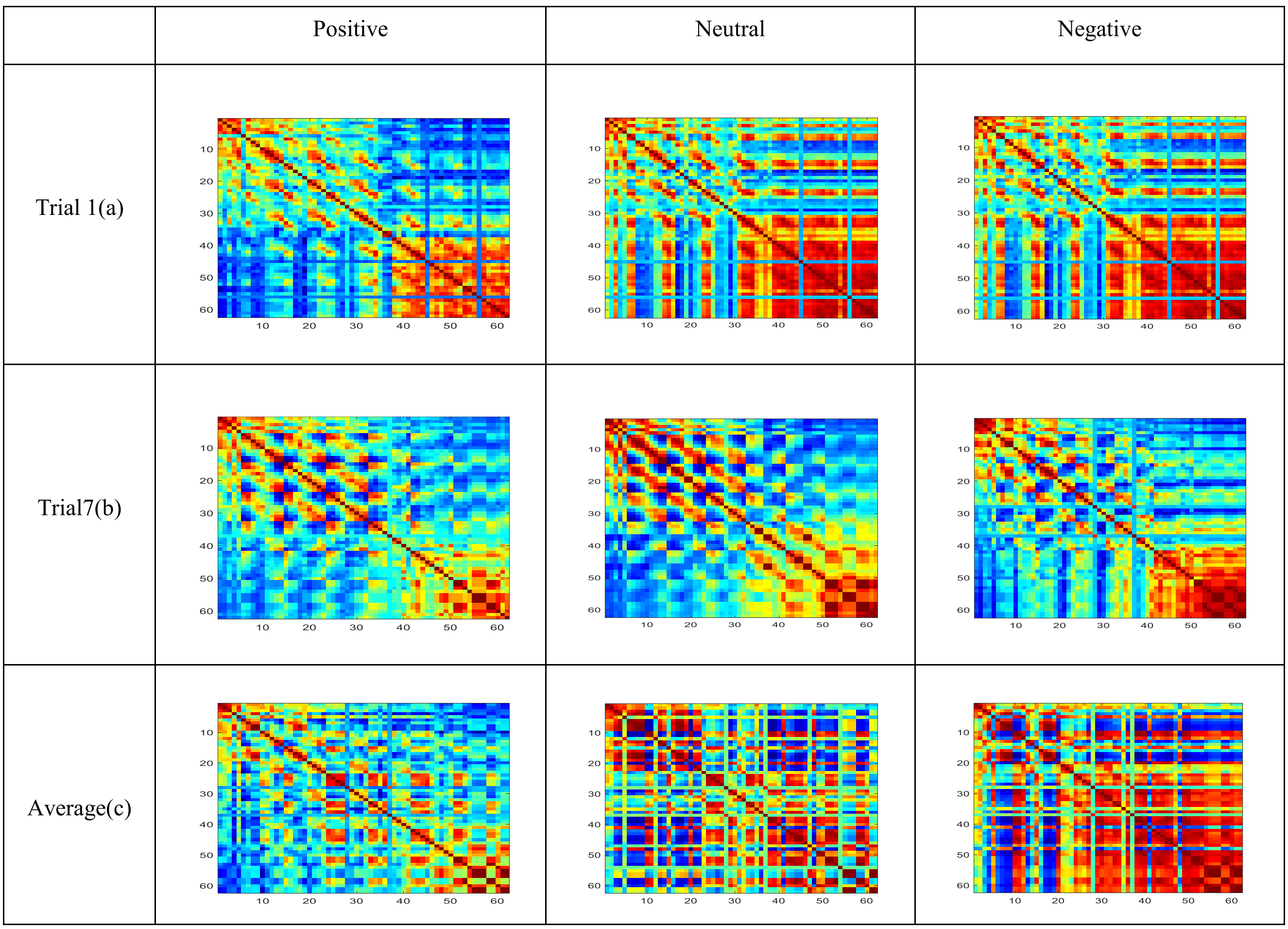

FIGURE 3. (a) (b) is the PLV correlation matrix of the first and seventh subjects under the three emotional categories of Positive, Neutral and Negative. (c) is the case of taking the average of all the subjects.

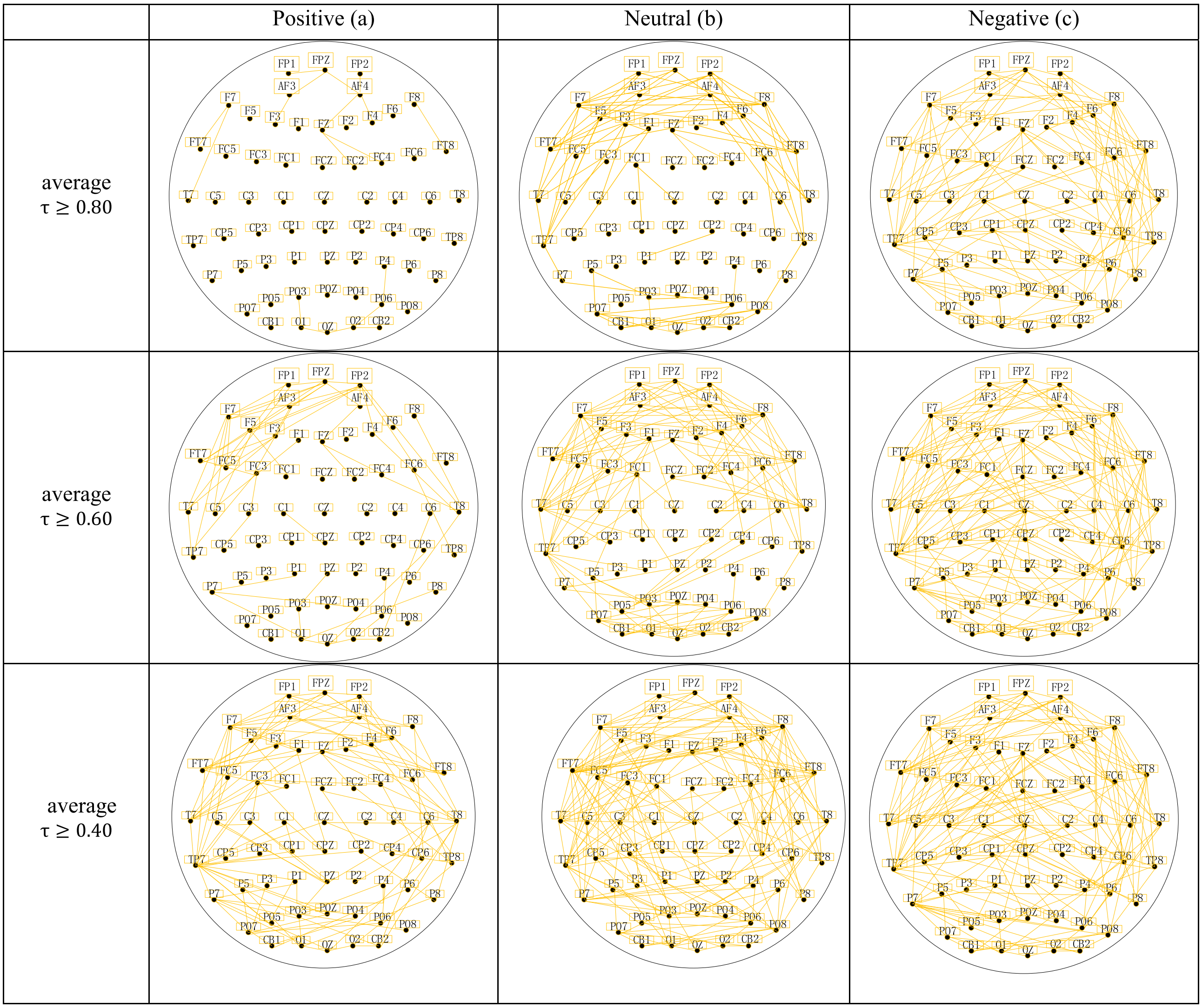

FIGURE 4. Brain connectivity plots of there synchrostates from multiple subject EEG.

range of activated brain regions wider and forms a large range of intraceramic phase synchronization. The state of pleasure is relatively less active and concentrated in the brain area. It is thus assumed that in the negative state, the human brain pays more attention to details than pleasure, thereby activating more relevant brain regions for information processing.

EEG Scalp Connectivity networks: Also known as functional connectivity networks which aim to identify the changing pattern of functional interconnections among different lobes and parts of the brain. These lobes and parts are represented by EEG electrode, placed according to 10-20 electrode placement system. To generate functional connectivity network corresponding to particular state or stimulation. To the correlation analysis between EEG channels, three different threshold ranges are set $\tau \geq 0.80$, $\tau \geq 0.60$, and $\tau \geq 0.40$, respectively. For more accurate and easy visualization connectivity network between channel locations has been shown for the average theme selected.

Fig 4. shows the brain connection relationship in the three emotional states obtained by setting different thresholds under the average experiment. When the state of pleasure $\tau \geq 0.80$, we see 18 related pairs ('AF3-FPZ', 'FPZ-FP1', 'AF3-F3', 'F8-PT8', 'FP2-AP4', 'AP4-F4 ', 'AP4-FZ', 'AF4-FPZ', 'FC2-FZ', 'FC4-FZ', 'O2-PO6', 'PO6-P4', 'PO3-O1', 'O2 -OZ', 'OZ-O1', 'O2-CB2', 'F7-T7', 'F7-FT7',). When $\tau \geq 0.60$ and $\tau \geq 0.40$, there are 56 and 148 related pairs respectively. Similarly, Figure 4. (b) (c) shows a connectivity network with different thresholds set in neutral and sad states. (b) For different τ values in the figure, the number of related pairs is 103, 168 and 247, respectively. (c) For different τ values in the figure, the number of related pairs is 181, 253and 269, respectively.

From the above findings, we can draw an intermediate conclusion: emotions are mainly related to the brain regions of the human brain and temporal lobe. Through research, it is found that when watching videos of positive emotions, the left forebrain produces strong EEG activity, while when listening

TABLE 1. Comparisons of the average accuracies and standard deviations (%) of subject dependent EEG-based emotion recognition experiments on seed database among the various methods.

Feature	Classifier	Delta	Theta	Alpha	Beta	Gamma	Total
DE	SVM [23]	60.50/14.14	60.95/10.20	66.64/14.41	80.76/11.56	79.56/11.38	83.99/9.72
	DNN [23]	64.32/12.45	60.77/10.42	64.01/15.97	78.92/12.48	79.19/14.58	86.08/8.34
	GCNN [28]	72.75/10.85	74.40/8.23	73.46/12.17	**83.24/9.93**	83.36/9.43	**87.40/9.20**
	P-GCNN	**73.05/11.36**	**75.49/8.41**	**75.66//13.3**	82.32/10.96	**83.55/10.18**	84.08/8.50
PSD	SVM [23]	58.03/15.39	57.26/15.09	59.04/15.75	73.34/15.20	71.24/16.38	59.60/15.93
	DNN [23]	60.05/16.66	55.03/13.88	52.79/15.38	60.68/21.31	63.42/19.66	61.90/16.65
	GCNN [28]	69.89/13.83	**70.92/9.18**	73.18/12.74	76.21/10.76	**76.15/10.09**	81.31/11.26
	P-GCNN	**70.24/12.23**	70.11/9.14	**73.36/12.53**	**77.35/10.43**	76.08/10.38	**81.62/10.82**
DASM	SVM [23]	48.87/10.49	53.02/12.76	59.81/14.67	75.03/15.72	73.59/16.57	72.81/16.57
	DNN [23]	48.79/9.62	51.59/13.98	54.03/17.05	69.51/15.22	70.06/18.14	72.73/15.93
	GCNN [28]	**57.07/6.75**	54.80/9.09	62.97/13.43	**74.97/13.40**	73.28/13.67	76.00/13.32
	P-GCNN	56.19/8.35	**55.17/10.02**	**64.36/15.67**	73.29/13.22	**73.78/13.56**	**78.63/13.02**
RASM	SVM [23]	47.75/10.59	51.40/12.53	60.71/14.57	74.59/16.18	74.61/15.57	74.74/14.79
	DNN [23]	48.05/10.37	50.62/14.02	56.15/15.28	70.31/15.62	68.22/18.09	71.30/16.16
	GCNN [28]	**59.70/5.65**	55.91/8.82	59.97/14.27	79.45/13.32	79.73/13.22	84.06/12.86
	P-GCNN	57.32/6.39	**57.09/8.37**	**61.62/13.30**	**79.58/13.24**	**80.43/13.45**	**84.35/10.28**
DCAU	SVM [23]	55.92/14.62	57.16/10.77	61.37/15.97	75.17/15.58	76.44/15.41	77.38/11.98
	DNN [23]	54.58/12.81	56.94/12.54	57.62/13.58	70.70/16.33	72.27/16.12	77.20/14.24
	GCNN [28]	62.60/12.88	**65.05/8.35**	66.41/11.06	77.28/11.55	78.68/13.00	79.02/11.27
	P-GCNN	**63.28/13.07**	63.53/9.61	**67.62/10.78**	**78.21/11.04**	**79.36/12.38**	**79.86/11.09**

to videos watching negative emotions, the right forebrain produces strong EEG activity. This shows that the forebrain has a great correlation with emotions.

In order to verify that the EEG features extracted based on the PLV relationship between scalp EEG pairs are more representative of emotions, Experiments were carried out on the P-GCNN method and compared with other emotion recognition methods. In this paper, five kinds of EEG features in different frequency bands are used to evaluate the performance of EEG emotion recognition methods. The five EEG features are the differential entropy (DE) feature, the power spectral density (PSD) feature, the differential asymmetry (DASM) feature, the rational asymmetry (RASM) feature, and the differential caudality (DCAU) feature.

Table 1 summarizes the experimental results of the average accuracy and standard deviation (%) of different EEG emotion recognition methods under five different EEG features. For comparison, the experimental results of the DBN and SVM methods in the literature [23] and GCNN in the literature [27] are cited.

From Table 1, we can observe the following points:

- In terms of features, the average recognition rate of RASM features under the P-GCNN method is up to 84.35%. This indicates that RASM features are more relevant to the emotions of the human brain.
- In terms of frequency bands, the average recognition rate of the β and γ bands in each emotion recognition method is higher than the δ, θ, and α bands, and the average recognition accuracy is the highest when all five bands are used simultaneously. This suggests that the higher frequency bands may be more closely related with the emotion activities whereas the lower frequency bands are less related with the emotion activities, which is consistent with the findings of related biology [47], [48].
- Among the four EEG emotion recognition methods, the average recognition rate based on GCNN and P-GCNN methods is higher than the traditional machine learning algorithm SVM and deep learning algorithm DBN. This is probably due to the fact that GCN-based method takes into account the functional relationship between the various channels of EEG signals, which makes the feature extraction more effective.
- Among the GCN-based emotion recognition methods, the recognition rate of the P-GCNN method is higher than that of the GCNN method, which indicates that the phase synchronization phenomenon of EEG signals can mine the intrinsic information of EEG signals, and it is beneficial to emotional feature extraction and classification recognition.

TABLE 2. Classification accuracy with different adjacency matrix.

Graph	Accuracy			
	Alpha	Beta	Gamma	Total
PLV	61.62/13.30	79.58/13.24	80.43/13.45	84.35/10.28
Identity	57.43/12.34	72.61/10.69	74.32/15.49	80.89/14.55
Random	51.22/14.81	63.30/11.36	67.28/12.77	74.48/12.67
MI	62.05/10.40	75.66/10.27	78.75/12.61	82.67/13.21

In order to better understand the importance and necessity of incorporating the graph information in the neural networks, we replace the PLV-based adjacency matrix with an identity matrix, a random symmetric matrix, and a mutual information matrix and train the model. Table 1 shows that the recognition accuracy of RASM features is highest under the P-GCNN method, so this experiment was carried out on different frequency bands of RASM features. The results are shown in Table 2:

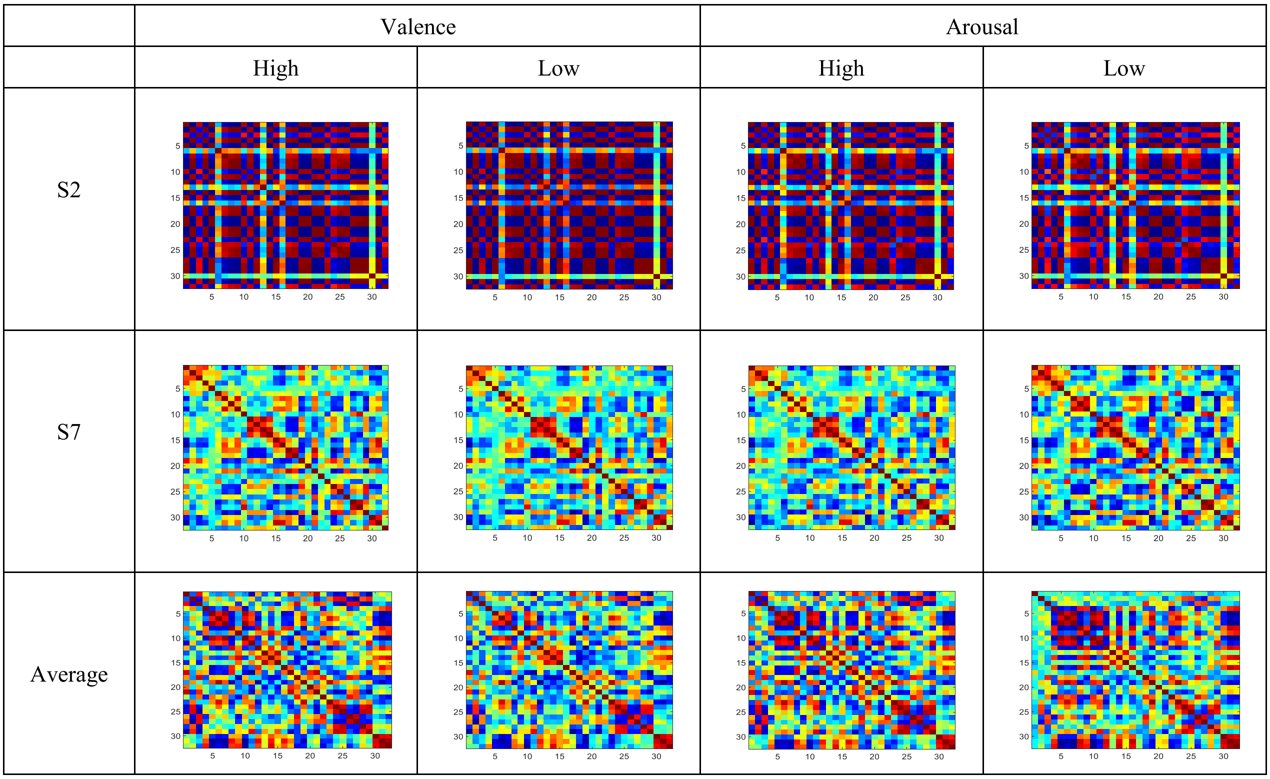

FIGURE 5. **The PLV relationship matrix of the two subjects in S2 and S7 and the average PLV matrix of all subjects in different states.**

Table 2 shows that the network recognition rate based on PLV adjacency matrix is higher than the identity matrix and the random matrix. This may be due to the fact that the EEG features modeled on the PLV matrix take into account the correlation between the emotional features, while the identity matrix and the random matrix ignore the correlation between the features. The network recognition rate of the PLV adjacency matrix is higher than the mutual information matrix. This is because the PLV method can separate the phase and amplitude components in the signal, which can better measure the synchronism between signals.

C. EEG EMOTION RECOGNITION ON DEAP DATABASE

In this part, the pre-processed DEAP dataset was used for the experiment. The sampling frequency of the pretreated EEG data is reduced from 512 Hz to 128 Hz, and the length of each sample data is 63 seconds.

In order to test the recognition performance of P-GCNN method for multivariate and univariate features of EEG signals, We experimented with five univariate features and three multivariate brain network attribute features in different frequency bands on the valence dimension. The extracted five univariate features are the differential entropy (DE) feature, the power spectral density (PSD) feature, the differential asymmetry (DASM) feature, the rational asymmetry (RASM) feature, and the differential caudality (DCAU) feature. The three multivariate features are the average clustering coefficient (ACC), the character path length (CPL) and the global efficiency (GE) of the brain network.

Average cluster coefficient: used to measure the extent to which points in a graph are clustered together.

$$ACC = \frac{1}{n}\sum\nolimits_{i\in N}\frac{2t_i^w}{k_i(K_i-1)} \tag{11}$$

n represents the number of nodes in the network, t_i^w represents the total number of triangle structures around the i-th node of the network, and k_i represents the degree of the i-th node of the network.

Character path length: used to measure the robustness of the network topology.

$$CPL = \frac{1}{n}\sum\nolimits_{i\in N}\frac{\sum_{j\in N, j\neq i} d_{ij}^w}{n-1} \tag{12}$$

n represents the number of nodes in the network, i and j are two different nodes in the network, d_{ij}^w is the distance between two points i and j.

Global efficiency: A measure of the efficiency of information exchange in a network.

$$GE = \frac{1}{n}\sum\nolimits_{i\in N}\frac{\sum_{j\in N, j\neq i}(d_{ij}^w)^{-1}}{n-1} \tag{13}$$

Global efficiency is the reciprocal of the distance between any two points in the network.

In the process of calculating the phase synchronism between the signals of each channel, considering the characteristics of emotional excitation and the smoothness of the

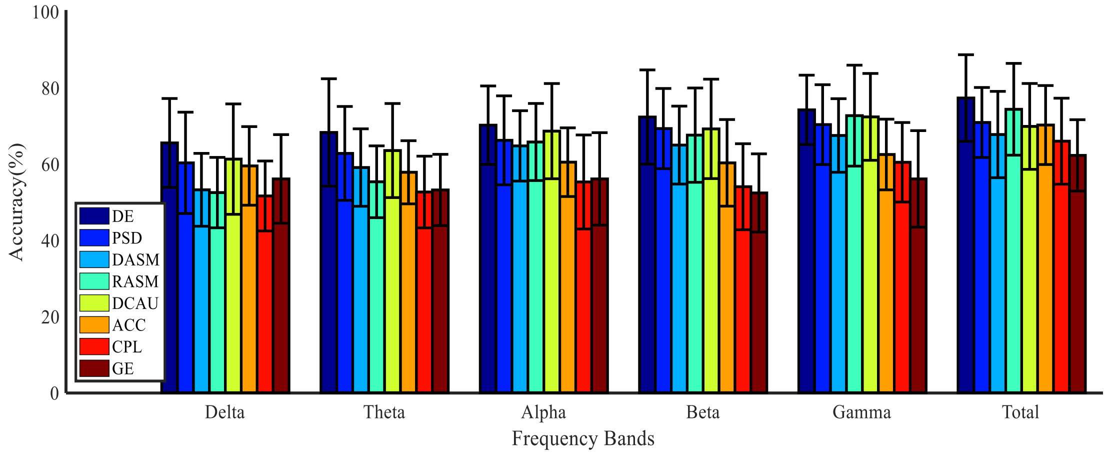

FIGURE 6. The average accuracies of P-GCNN using different features obtained from five frequency bands in the valence dimension.

TABLE 3. The average classification accuracies and standard deviations (%) of EEG emotion recognition on DEAP database using de feature.

	Valence		Arousal		Dominance	
	p_{acc}	p_{std}	p_{acc}	p_{std}	p_{acc}	p_{std}
SVM	0.6200	0.1256	0.7060	0.1504	0.7440	0.1320
DBN	0.6730	0.1409	0.7273	0.1649	0.7299	0.1420
GCNN	0.7014	0.1560	0.7441	0.1850	0.7631	0.1234
P-GCNN	0.7331	0.1166	0.7703	0.1149	0.7920	0.1046

signal, the experiment selected 30s in the middle of each trial as the research object. Figure 5 shows the PLV relationship matrix of the two subjects in S2 and S7 and the average PLV matrix of all subjects in different states. In the DEAP database, S2 is a female subject, and S7 is a male subject. It can be observed from the figure 5 that there are great differences among different individuals and between female and male. Female are more sensitive to emotional stimuli than male.

In the experiment, the EEG data of all 32 individuals were regarded as a group, 22 EEG data were randomly selected as the training sets, and the remaining 10 were used as test sets to calculate the average classification accuracy and standard deviation. The experimental results are shown in Figure 6:

Figure 6. shows that the recognition accuracy of univariate features is higher than that of multivariate features when the P-GCNN method is used for emotion recognition, which may be due to the fact that the selected multivariate features are global attribute features, while the main advantage of P-GCNN method is to discover the correlation between univariate features in different channels.

At the same time, in order to verify the effectiveness of the proposed P-GCNN method in the three emotional dimensions (i.e., valence, arousal, dominance), we set up the same experiment using DBN, SVM and GCNN methods to compare. It can be seen from Figure 4 that the recognition accuracy of the DE feature is the highest under the P-GCNN method, so the experiment is studied on the DE feature, and the experimental results are shown in table3.

From Table 3, we can obtain the following major points:

- The proposed P-GCNN method achieves much higher classification accuracies than the other three state-of-the-art methods, in which the classification accuracies could be as high as 73.31% for valence classification, 77.03% for arousal classification, and 79.20% for dominance classification, respectively.
- Among the four recognition methods, the recognition rate based on dominance in the same emotional state is higher than the other two dimensions, which may be more likely to stimulate emotion when the subject is more familiar with the video being watched.

V. CONCLUSION

In this paper, we have proposed a deep learning model, P-GCNN, which integrates PLV and GCNN, for emotion recognition based on multi-channel EEG signals. Specifically, the PLV component has the ability to separate phase and amplitude components in the EEG signal and to mine inter-channel correlation information. On the other hand, the model structure based on GCNN can integrate graphical information such as brain connections with fully-connected layers, and can learn surrounding node information from the modeled graphic signals. We propose the P-GCNN method by combining PLV and GCNN. The method can extract the emotional information implicit in the brain network graph more effectively, and provides protection for classification identification. This method utilizes a PLV matrix to represent the inter-channel relationships. Then based on the constructed brain network, the EEG features are modeled as graph data, and finally the proposed model is used for classification and recognition. Experiments were carried out on two public datasets. On the SEED dataset, when the RASM features of five frequency bands are combined together, the average recognition accuracy of the P-GCNN method can be as high as 84.35%. On DEAP dataset, the average accuracies of valence, arousal, and dominance using the proposed P-GCNN are 73.31%, 77.03% and 79.20% respectively, which are higher than SVM, DBN and GCNN. The better recognition performance of P-GCNN is most likely due to the following major points:

- The P-GCNN method models the spatially discrete EEG signals using the intrinsic relationship between the channels as the data of the network structure, which restores the spatial and functional connection of the data.
- Compared with the GCNN method, P-GCNN is based on the functional connection of EEG signals, and is not limited to the spatial position of EEG signals in each channel. Therefore, the relationship between EEG channels described by the P-GCNN method is more accurate than the GCNN method, and the extracted EEG features are more representative of emotions.

At present, EEG-based emotional recognition research is mostly based on full-channel EEG signals, but the acquisition of full-channel EEG signals is not convenient for the development of wearable devices. For this problem, we can eliminate some useless electrodes according to the synchronization phase lock value between the EEG signals of each channel, so as to reduce the number of channels. We leave this interesting topic as our future work.

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ZHONGMIN WANG received the M.S. degree in mechatronic engineering and the Ph.D. degree in mechanical manufacture and automation from Beijing Institute of Technology, Beijing, China, in 1993 and 2000, respectively. He was with Xidian University from 1993 to 1997. From 2004 to 2005, he was a Visiting Scholar with the Robotics Laboratory, Australian National University, Canberra, Australia. Since 2000, he has been a Full Professor with the School of Computer Science and Technology, Xi'an University of Posts and Telecommunications. His current research interests include embedded intelligent perception, intelligent information processing, machine learning, brain–computer interface and affective computing.

YUE TONG was born in Shaanxi Province, China, in 1994. She received the B.S. degree from the Xi'an University of Posts and Telecommunications, in 2017, where she studied from 2013 to 2017, and her major is artificial intelligence. She is currently pursuing the master's degree with Xi'an University of Posts and Telecommunications, since 2017. Her current research interests include artificial intelligence, big data processing, brain–computer interface, and emotional computing.

XIA HENG received the M.S. degree in computer science from Xidian University, in 2004. She is currently an Associate Professor with Xi'an University of Posts and Telecommunications. Her research interests include multimedia telecommunications, intelligent information process, and pattern recognition.