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EEG-based Emotion Recognition Using Graph Convolutional Network with Learnable Electrode Relations

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Abstract— **Emotion recognition based on electroencephalography (EEG) plays a pivotal role in the field of affective computing, and graph convolutional neural network (GCN) has been proved to be an effective method and made considerable progress. Since the adjacency matrix that can describe the electrode relationships is critical in GCN, it becomes necessary to explore effective electrode relationships for GCN. However, the setting of the adjacency matrix and the corresponding value is empirical and subjective in emotion recognition, and whether it matches the target task remains to be discussed. To solve the problem, we proposed a graph convolutional network with learnable electrode relations (LR-GCN), which learns the adjacency matrix automatically in a goal-driven manner, including using self-attention to forward update the Laplacian matrix and using gradient propagation to backward update the adjacency matrix. Compared with previous works that use simple electrode relationships or only the feature information, LR-GCN achieved higher emotion recognition ability by extracting more reasonable electrode relationships during the training progress. We conducted a subject-dependent experiment on the SEED database and achieved recognition accuracy of 94.72% on the DE feature and 85.24% on the PSD feature. After visualizing the optimized Laplacian matrix, we found that the brain connections related to vision, hearing, and emotion have been enhanced.**

I. INTRODUCTION

Emotion recognition plays an important role for humans to achieve barrier-free human-computer interaction. There are many methods for emotion recognition. For example, preliminary emotion recognition can be achieved by analyzing human behavior, such as gesture language, voice, and facial expressions. But sometimes, people can conceal their true intentions by forging behavior, which makes the above methods misjudgment. Another effective way to recognize human emotion is to analyze physiological signals, such as EEG [1], electrocardiogram (ECG) [2] and electromyogram (EMG) [3]. Compared with behavioral signals, physiological signals can better reflect the true emotional state of human beings. With the rapid development of EEG signal processing, EEG-based emotion recognition has been extensively studied.

Typical EEG-based emotion recognition is consists of EEG signal recording, preprocessing, feature extraction and emotion classification. EEG information is recorded by connecting a certain number of electrodes on the scalp to measure voltage fluctuations in the cerebral cortex of different brain regions. Then the raw data will be preprocessed to remove noise and artifacts. After that, the processed EEG signals are decomposed to five common frequency bands, i.e., δ band (1-3Hz), θ band (4-7Hz), α band (8-13Hz), β band (13-30Hz) and γ band (30-51Hz). Feature extraction methods can be basically categorized into three kinds: frequency domain, time domain and time-frequency domain. The commonly used frequency domain feature extraction method are differential entropy (DE) [4] and power spectral density (PSD) [5]. Finally, emotion recognition is performed on the emotion data after feature extraction. Emotion recognition methods can be divided into traditional methods and methods based on deep learning, and with the development of deep learning, the latter has been widely used in the field of emotion recognition.

There have been many works applying deep learning for EEG-based emotion recognition. Zheng *et al.* [6] first applied a deep belief network (DBN) for EEG-based emotion recognition. Combining the 2D spatial information with the extracted feature of different electrodes, convolutional neural networks (CNN) based and recurrent neural networks (RNN) based emotion recognition are realized [7], [8]. In addition, with the help of transfer learning, fast online emotion recognition was also realized [9]. But in reality, the distribution of brain electrodes is not grid-like, but an irregular connection. To take advantage of the relationship between the irregular electrode connections, Song *et al.* [10] applied graph convolution into the field of emotion recognition and introduced a method that can dynamically update the adjacency matrix. To further utilize the features extracted by a graph structure, Zhang *et al.* [11] designed a graph convolutional broad network (GCB-net) to explore the deeper-level information of emotion data. A regularized graph neural networks (RGNN) [12] based on node-wise domain adversarial training (NodeDAT) and emotion-aware distribution learning (EmotionDL) also achieved good emotion recognition ability. However, the adjacency matrix that can accurately describe the correlations between brain electrodes is unknown, which makes it very important to explore more reasonable electrode relationships for GCN-based EEG emotion recognition.

Inspired by the work of DGCNN, we further explore the role of learnable graph structure for emotion recognition and proposed LR-GCN, which combined attention-based forward update the Laplacian matrix with backward update the adjacency matrix and obtained the best recognition accuracy. The experiment results proved that introducing an attention mechanism to update the Laplacian matrix can improve the

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accuracy of emotion recognition from 92.34% to 94.72% on the DE features, and the emotion recognition accuracy on the PSD features is 85.24%. Besides, we visualized the optimized Laplacian matrix and found that some key connections were strengthened in the frontal, occipital, and temporal lobes. The above-mentioned brain regions are highly correlated with emotions caused by vision and hearing, which indicates that our proposed LR-GCN improves the emotion recognition accuracy by obtaining more reasonable electrode relations.

II. METHOD

In this section, we will introduce the preliminaries of the spectral graph convolution and graph attention networks (GAT) [13], which are the basis of our proposed LR-GCN. After that, we will introduce more details of LR-GCN and its two paths to update the electrode relationships.

An undirected graph can be expressed as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, in which $\mathcal{V}$ is the set of nodes and $\mathcal{E}$ represents the set of edges that connect different nodes in $\mathcal{V}$. Combining all the connections in $\mathcal{E}$ into a matrix, it was adjacency matrix $\mathbf{A} \in \mathbb{R}^{n\times n}$, and data on $\mathcal{V}$ can be represented as a feature matrix $\mathbf{X} \in \mathbb{R}^{n\times d}$, where n denotes the number of nodes and d is the dimension of input features.

A. Spectral Graph Convolutional Network

The spectral graph theory is an effective method for processing structured data and has achieved great success in the field of social networks, knowledge graphs, etc. Spectral graph convolution relies on the Laplacian matrix $\mathbf{L} = \mathbf{D} - \mathbf{A}$ or the normalized Laplacian matrix $\hat{\mathbf{L}} = \mathbf{I} - \mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}} = \hat{\mathbf{D}}^{-\frac{1}{2}}\hat{\mathbf{A}}\hat{\mathbf{D}}^{-\frac{1}{2}}$ to represent the node connection relationships. where $\mathbf{I}$ is the n-th order identity matrix and $\mathbf{D}$ denotes the diagonal degree matrix of $\mathbf{A}$, i.e., $\mathbf{D}_{ii} = \sum_j \mathbf{A}_{ij}$. $\hat{\mathbf{D}}$ and $\hat{\mathbf{A}}$ are the normalization of $\mathbf{D}$ and $\mathbf{A}$, respectively. Since $\hat{\mathbf{L}}$ is a symmetric positive semi-definite matrix, it can be decomposed as $\hat{\mathbf{L}} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^{\mathrm{T}}$, in which $\mathbf{U}$ is the orthonormal eigenvector matrix of $\hat{\mathbf{L}}$, $\mathbf{U}^{\mathrm{T}}$ is the transposition of $\mathbf{U}$, and $\mathbf{\Lambda} = \mathrm{diag}(\lambda_1, \cdots, \lambda_n)$ is a diagonal matrix.

For a given feature matrix $\mathbf{X}$, its graph fourier transform is $\hat{\mathbf{X}} = \mathbf{U}^{\mathrm{T}}\mathbf{X}$, and the corresponding inverse fourier transform is $\mathbf{X} = \mathbf{U}\hat{\mathbf{X}}$. The graph convolution between the input $\mathbf{X}$ and the filter $\mathbf{G}$ can be expressed as

$$\mathbf{Y} = \mathbf{X} *_{\mathcal{G}} \mathbf{G} = \mathbf{U}\left((\mathbf{U}^{\mathrm{T}}\mathbf{X}) \odot (\mathbf{U}^{\mathrm{T}}\mathbf{G})\right) = \mathbf{U}\hat{\mathbf{G}}\mathbf{U}^{\mathrm{T}}\mathbf{X}, \quad (1)$$

where $\odot$ is the element-wise Hadamard product, and $\hat{\mathbf{G}} = \mathrm{g}(\mathbf{\Lambda}) = \mathrm{diag}(g(\lambda_1), \cdots, g(\lambda_n))$.

To meet the intention of reducing the learning complexity, it can be predigest with K-order Chebyshev polynomials [14], then we obtained

$$\mathbf{Y} = \sum_{i=0}^{K-1} \theta_i T_i(\hat{\mathbf{L}}')\mathbf{X}, \quad (2)$$

where $\hat{\mathbf{L}}' = 2\hat{\mathbf{L}}/\lambda_{max} - \mathbf{I}$, θ_i is the parameters to trained, and $T_i(x)$ can be recursively calculated with $T_i(x) = 2xT_{i-1}(x) - T_{i-2}(x)$, $T_0(x) = 1$ and $T_1(x) = x$.

Kipf *et al.* [15] present an efficient variant of convolutional neural networks which operate directly on graphs. They made a localized first-order approximation to (2) with: 1) use $K = 1$; 2) $\lambda_{max} = 2$; and 3) $\theta_1 = -\theta_0$, then we acquired

$$\mathbf{Y} = \sigma\left(\hat{\mathbf{D}}^{-\frac{1}{2}}\hat{\mathbf{A}}\hat{\mathbf{D}}^{-\frac{1}{2}}\mathbf{X}\mathbf{W}\right) = \sigma\left(\hat{\mathbf{L}}\mathbf{X}\mathbf{W}\right), \quad (3)$$

the normalized laplacian matrix $\hat{\mathbf{L}}$ prevents the values in the feature matrix $\mathbf{X}$ grows too large, $\mathbf{W}$ is a linear transformer matrix and σ is the activation function.

B. Forward Update Laplacian Matrix

GAT overcame the shortcomings of prior methods based on graph convolutions or their approximations and provided a new approach to focus on neighbor nodes relationship. To meet the requirements of transforming the input features into higher-level features, $\mathbf{X}$ is augmented by multiplying a shared weight matrix $\mathbf{W}' \in \mathbb{R}^{d\times d'}$, and the extended feature matrix can be expressed as $\mathbf{X}' = \mathbf{X}\mathbf{W}' = \{\mathbf{x}'_1, \cdots, \mathbf{x}'_n\}$.

For a pair of neighbor nodes j and i, the normalized attention coefficient of j to i can be calculated with a shared self-attention mechanism $\mathbf{a} \in \mathbb{R}^{2d'}$:

$$\begin{aligned}\phi_{ij} &= \frac{\exp(\vartheta_{ij})}{\sum_{k\in\mathcal{N}_i}\exp(\vartheta_{ik})} \\ &= \frac{\exp\left(\mathrm{LeakyReLU}(\mathbf{a}^{\mathrm{T}}[\mathbf{x}'_i||\mathbf{x}'_j])\right)}{\sum_{k\in\mathcal{N}_i}\exp(\mathrm{LeakyReLU}(\mathbf{a}^{\mathrm{T}}[\mathbf{x}'_i||\mathbf{x}'_k]))},\end{aligned} \quad (4)$$

where $\mathbf{a}^{\mathrm{T}}$ represents the transposition of $\mathbf{a}$, $\mathcal{N}_i$ means the neighbor of node i and $||$ is concatenation. Since ϑ_{ij} characterizes the correlation of node i and its neighborhood node j, ϕ_{ij} represents the normalized weight of j in all the neighbor nodes of i.

Based on the above calculation, we get the attention-based matrix related to the features collected by different electrodes

$$\mathbf{\Phi} = \left\{\begin{matrix}\phi_{11} & \cdots & \phi_{1n} \\ \vdots & \ddots & \vdots \\ \phi_{n1} & \cdots & \phi_{nn}\end{matrix}\right\}, \quad (5)$$

and if j is not a neighbor of i, we get $\phi_{ij} = 0$.

Since $\mathbf{\Phi}$ in (5) contains the node weight relationships acquired with self-attention, we believe that $\mathbf{\Phi}$ is beneficial to improve the representation ability of the Laplacian matrix $\hat{\mathbf{L}}$. We introduced

$$\hat{\mathbf{L}} = (1-\eta)\hat{\mathbf{L}} + \eta\mathbf{\Phi} \quad (6)$$

to forward update $\hat{\mathbf{L}}$ before model training, where η is a hyperparameter.

C. Backward Update Adjacency Matrix

Song $et\ al.$ [10] proposed DGCNN to update the adjacency matrix $\mathbf{A}$ through a backward propagation. The partial derivative of the loss function with respect to $\mathbf{A}$ can be calculated with

$$\frac{\partial Loss}{\partial \mathbf{A}} = \frac{\partial \mathrm{cross\_entropy}(\mathbf{y}, \mathbf{y}')}{\partial \hat{\mathbf{L}}} \cdot \frac{\partial \hat{\mathbf{L}}}{\partial \mathbf{A}} + \xi\frac{\partial ||\mathbf{\Theta}||}{\partial \mathbf{A}}, \quad (7)$$

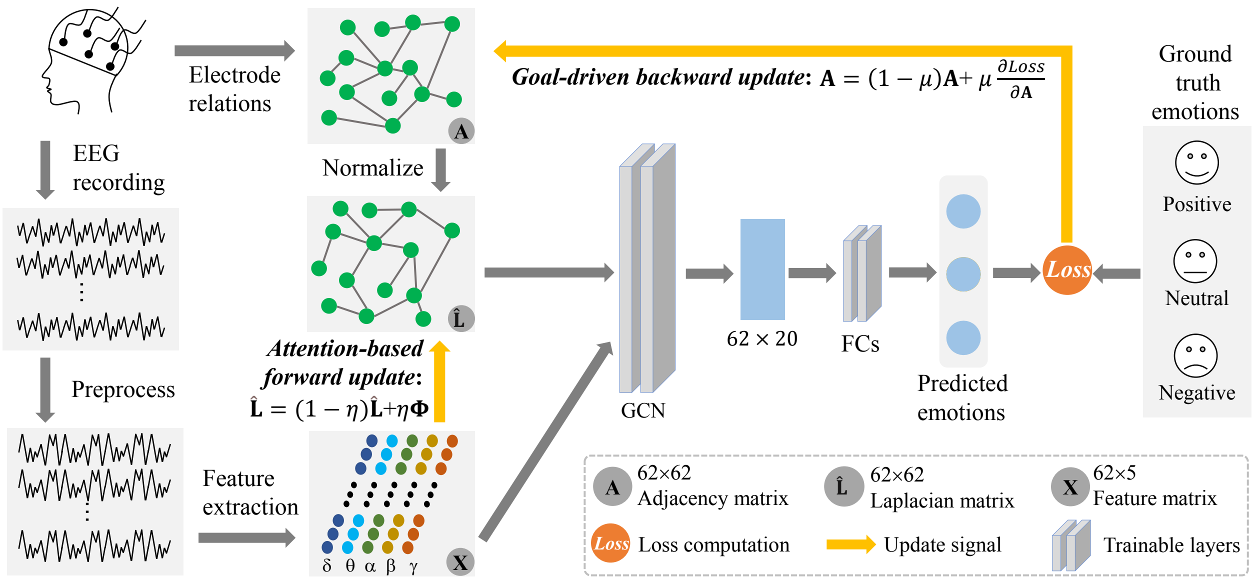


Fig. 1. The framework of the proposed LR-GCN for EEG emotion recognition.

where $\mathbf{y}$ and $\mathbf{y}'$ are the true labels and the predicted labels, respectively. $\xi||\mathbf{\Theta}||$is the regularization to prevent overfitting.

Then we can update the adjacency matrix $\mathbf{A}$ with

$$\mathbf{A} = (1-\mu)\mathbf{A} + \mu\frac{\partial Loss}{\partial \mathbf{A}}, \tag{8}$$

where μ is the learning rate of $\mathbf{A}$.

D. Dynamics of proposed LR-GCN

The diagram of the LR-GCN is shown in Fig. 1. After data collecting, preprocessing and feature extraction, the EEG data are converted into a 62×5 feature matrix $\mathbf{X}$. At the same time, the initial adjacency matrix $\mathbf{A}$ was constructed through the 2D spatial electrode relationships, and then we calculated the corresponding initial Laplacian matrix $\hat{\mathbf{L}}$. After obtaining the feature matrix $\mathbf{X}$ and the graph Laplacian matrix $\hat{\mathbf{L}}$, we began to perform graph convolution in (3) and got the output of 62×20, followed by flattening and two layers of full connection with results of 128 and 3 respectively, we finally got the emotion recognition results. During the experiment, we used LeakyReLU with a coefficient of 0.15 as the activation function and performed batch normalization before the second full connection.

There are two paths to update the electrode relationships during model training. One is forward updating the Laplacian matrix based on self-attention, and the other is backward updating the adjacency matrix based on gradient propagation.

The first is to update the Laplacian matrix with feedforward. Before each model training, we employed (6) to update the Laplacian matrix $\hat{\mathbf{L}}$, so we get the Laplacian matrix of electrode relationships related to the feature. During the training process, we tried to set the value of η to 0.1, 0.3, 0.5, and finally found that the best result was obtained when η is set to 0.5. Therefore, the value of η is fixed at 0.5 in the experiment.

The other is to update the adjacency matrix with feedback. After calculating the gradient of the adjacency matrix $\mathbf{A}$ from (7), we employed (8) to backward update $\mathbf{A}$, where the value of μ is 5e-5. Before the next epoch of training, we recalculated the normalized Laplacian matrix with $\hat{\mathbf{L}} = \mathbf{I} - \mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}}$.

Algorithm 1 summarizes the training procedures of the proposed LR-GCN in EEG-based emotion recognition.

Algorithm 1 The Training Procedure of LR-GCN.

Input: $\mathbf{X}$, $\mathbf{y}$: EEG features associated with multiple frequency bands and the corresponding labels; $\mathbf{A}$: The adjacency matrix that characterizes the initial electrode relationship; η, μ: The learning rate for forward updating Laplacian matrix and backward updating adjacency matrix;

Output: The learned model parameters in LR-GCN;

for i = 1:T **do**
  repeat
    Draw one batch of training samples;
    Calculate the attention matrix $\mathbf{\Phi}$ using (4) and (5);
    Feed-forward update $\hat{\mathbf{L}}$ with

$$\hat{\mathbf{L}} = (1-\eta)\hat{\mathbf{L}} + \eta\mathbf{\Phi};$$

    Calculate GCN using (3);
    Calculate the results of full connection layers;
    Feedback update the adjacency matrix using

$$\mathbf{A} = (1-\mu)\mathbf{A} + \mu\frac{\partial Loss}{\partial \mathbf{A}}$$

    and other model parameters;
  until The iterations satisfies the convergence condition;

III. EXPERIMENTS AND RESULTS

In this section, we will introduce the SJTU Emotion EEG database (SEED) [6] and reveal the subject-dependent emotion recognition ability of our proposed LR-GCN on this database. Furthermore, we showed that the proposed method can obtain more reasonable electrode relationships.

A. Database

The SEED database collects three types of EEG-based emotion data, i.e., negative, positive, and neutral when 15 subjects (7 males and 8 females) watching 15 different movie clips, and the EEG data was recorded by a ESI NeuroScan System with 62 electrodes. The whole database contains 3 sessions, each session contains data of 15 different subjects, and each subject's data could be divided into 15 trials, which corresponds to 15 movie clips. In each trial, there is a 5-second hint, 4 minutes of the movie clip, 45s for self-assessment, and 15s for rest. The experimental procedures involving human subjects described in this paper were approved by the Institutional Review Board.

B. Subject-Dependent Classification

In this experiment, we used the 2D distribution of electrodes as the initial adjacency matrix: when two electrodes are adjacent, the corresponding value in the adjacency matrix is 1; when they are not adjacent, the value is 0. Besides, we used the global channel pairs used in RGNN: (FP1, FP2), (AF3, AF4), (F5, F6), (FC5, FC6), (C5, C6), (CP5, CP6), (P5, P6), (PO5, PO6) and (O1, O2) are also set to 1 on the adjacency matrix. After that, we normalized the initialized adjacency matrix, and obtained the corresponding Laplacian matrix. For each feature, we select the values of all 5 frequencies of 62 channels as its feature matrix, so the size of the feature matrix $\mathbf{X}$ in the experiment is 62 $\times$ 5. In the subject-dependent experiment, among the 15 trials of the same subject in a session, the first 9 trials were used for training and the last 6 trials were used for testing. We evaluate the model performance by using the average accuracy of all subjects in the EEG data of all three sessions.

TABLE I

AVERAGE ACCURACIES (%) OF DIFFERENT EEG-BASED EMOTION RECOGNITION METHOD ON SEED DATABASE

Model	Feature	Frequency	avg. / std. (%)
DBN[6]	DE	$\delta, \theta, \alpha, \beta, \gamma$	86.08 / 8.34
DGCNN[10]	PSD	$\delta, \theta, \alpha, \beta, \gamma$	81.73 / 9.94
DGCNN[10]	DE	$\delta, \theta, \alpha, \beta, \gamma$	90.40 / 8.49
GCB-net[11]	PSD	$\delta, \theta, \alpha, \beta, \gamma$	84.32 / 10.61
GCB-net[11]	DE	$\delta, \theta, \alpha, \beta, \gamma$	94.24 / 6.70
RGNN(sota)[12]	DE	$\delta, \theta, \alpha, \beta, \gamma$	94.24 / 5.95
LR-GCN without Attention	DE	$\delta, \theta, \alpha, \beta, \gamma$	92.34 / 7.68
LR-GCN(ours)	PSD	$\delta, \theta, \alpha, \beta, \gamma$	**85.24** / 13.24
LR-GCN(ours)	DE	$\delta, \theta, \alpha, \beta, \gamma$	**94.72** / 5.47

We evaluated the proposed LR-GCN using two different features, DE and PSD. The mean accuracies (avg.) and standard deviations (std.) are shown in Table I. When we used the DE feature for emotion recognition, the average accuracy is 94.72%, and the standard deviation is 5.47%; when the feature was changed to PSD, the accuracy and standard deviation were dropped to 85.24% and 13.24%, respectively. It shows the proposed LR-GCN can obtain the best emotion recognition accuracy and extract more critical features from DE features.

We also compared the performance of LR-GCN with four popular deep learning models. Since the data division of all models is the same: the first 9 trials were used for training and the last 6 trials were used for testing, the accuracy of these four models is extracted from the corresponding papers. As the first deep learning method for emotion recognition, DBN achieved an average accuracy of 86.08%. Compared with DBN, DGCNN has achieved great success by introducing GCN for emotion recognition and achieved an accuracy rate of 90.40%. By combining a broad learning systems and GCN, GCB-net increased the accuracy of emotion recognition to 94.24%. Combining NodeDAT and EmotionDL, RGNN also obtained the state-of-the-art recognition accuracy of 94.24%. Comparing the above four models, LR-GCN improves the accuracy of emotion recognition from 94.24% to 94.72% without increasing the number of model parameters, moreover, compared with GCB-net, the number of parameters of the proposed LR-GCN is reduced.

Different from improving the emotion recognition accuracy by increasing the model complexity, LR-GCN has significantly improved the recognition accuracy by employing a better method to update the electrode relationships. We added an attention structure to update the Laplacian matrix and combined it with the original backward update adjacency matrix, and improved the accuracy of emotion recognition from 92.34% to 94.72% in the DE features, it showed that the added attention structure can improve the accuracy by 2.38%.

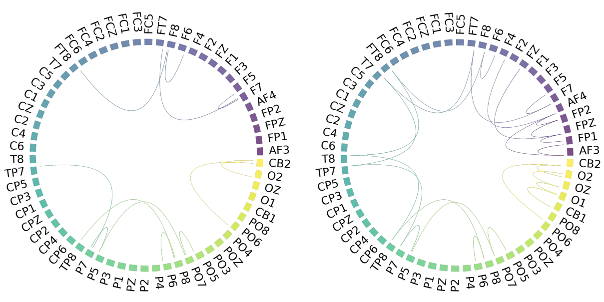
The experimental results proved that our proposed LR-GCN can improve the emotion recognition accuracy by applying the attention mechanism to update the electrode relationships. At the same time, it showed that it is a effective method to improve the learning ability of the GCN by optimizing the connection relationships of different nodes.

C. Electrode Relations Visualization

After the model training is completed, we visualized the Laplacian matrix before and after training and showed it in Fig. 2. Each arc in Fig. 2 indicates that the two connected electrodes have a strong correlation, and the values less than 0.25 are suppressed. It can be found that after optimization, many connections on the Laplacian matrix have been strengthened. They are (AF3, FP1), (FP1, FPZ), (FPZ, FP2), (FP2, AF4), (AF3, AF4), (FPZ, FZ) and (AF4, F4) located in the frontal lobe; (FT7, T7) and (T7, TP7) located in the left temporal lobe; (FT8, T8) and (T8, TP8) located in the right temporal lobe, and (CB1, O1), (O1, OZ) and (OZ, O2) located in the occipital lobe.

With the deepening of research on the human brain, the functions of different brain regions have been continuously revealed. For example, the occipital lobe has been found to have a strong relationship with human vision [16], the temporal lobe is highly related to emotion recognition and social cognition [17], [18], damage to the forehead may cause emotion disorders [19]. These studies have shown that the frontal, temporal and occipital lobes are all involved in audiovisual inspired emotion.

In LR-GCN, the optimized Laplacian matrix significantly strengthened the correlation of electrodes located in the frontal, temporal and occipital lobes. It shows that during the training process, the relationship between different electrodes has been further optimized. At the same time, the optimized electrode relationship further improves the accuracy of emotion recognition.



(a) Chord Diagram of Laplacian Matrix before Optimization (b) Chord Diagram of Laplacian Matrix after Optimization

Fig. 2. Chord diagram of Laplacian matrix depicting electrode relations before and after training. (values less than 0.25 are suppressed).

IV. CONCLUSIONS

We proposed a model employing learnable electrode relations for GCN-based EEG emotion recognition, which combined forward updating the Laplacian matrix based on self-attention and backward updating the adjacency matrix based on gradient propagation. We conducted subject-dependent experiments on the DE and PSD features and achieved an average accuracy of 94.72% and 85.24% respectively. Besides, ablation experiments proved the effectiveness of using attention to update the Laplacian matrix. After visualizing the learned Laplacian matrix, we observed a phenomenon consistent with previous research: the frontal, temporal and occipital lobes are highly related to audiovisual inspired emotion. The results prove that the proposed LR-GCN achieves the best emotion recognition by focusing on optimizing the electrode relations. In future work, we will focus on optimizing the method of updating the adjacency matrix and using a deeper network to further improve the emotion recognition ability.

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REFERENCES

[1] Y.-P. Lin, C.-H. Wang, T.-P. Jung, T.-L. Wu, S.-K. Jeng, J.-R. Duann, and J.-H. Chen, "Eeg-based emotion recognition in music listening," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 7, pp. 1798–1806, 2010.

[2] F. Agrafioti, D. Hatzinakos, and A. K. Anderson, "Ecg pattern analysis for emotion detection," *IEEE Transactions on affective computing*, vol. 3, no. 1, pp. 102–115, 2011.

[3] B. Cheng and G. Liu, "Emotion recognition from surface emg signal using wavelet transform and neural network," in *Proceedings of the 2nd international conference on bioinformatics and biomedical engineering (ICBBE)*, 2008, pp. 1363–1366.

[4] L.-C. Shi, Y.-Y. Jiao, and B.-L. Lu, "Differential entropy feature for eeg-based vigilance estimation," in *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2013, pp. 6627–6630.

[5] M. Alsolamy and A. Fattouh, "Emotion estimation from eeg signals during listening to quran using psd features," in *2016 7th International Conference on Computer Science and Information Technology (CSIT)*. IEEE, 2016, pp. 1–5.

[6] W.-L. Zheng and B.-L. Lu, "Investigating critical frequency bands and channels for eeg-based emotion recognition with deep neural networks," *IEEE Transactions on Autonomous Mental Development*, vol. 7, no. 3, pp. 162–175, 2015.

[7] D. Zhang, L. Yao, X. Zhang, S. Wang, W. Chen, R. Boots, and B. Benatallah, "Cascade and parallel convolutional recurrent neural networks on eeg-based intention recognition for brain computer interface," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 32, no. 1, 2018.

[8] T. Zhang, W. Zheng, Z. Cui, Y. Zong, and Y. Li, "Spatial–temporal recurrent neural network for emotion recognition," *IEEE transactions on cybernetics*, vol. 49, no. 3, pp. 839–847, 2018.

[9] J. Li, H. Chen, and T. Cai, "Foit: Fast online instance transfer for improved eeg emotion recognition," pp. 2618–2625, 2020.

[10] T. Song, W. Zheng, P. Song, and Z. Cui, "Eeg emotion recognition using dynamical graph convolutional neural networks," *IEEE Transactions on Affective Computing*, vol. 11, no. 3, pp. 532–541, 2018.

[11] T. Zhang, X. Wang, X. Xu, and C. P. Chen, "Gcb-net: Graph convolutional broad network and its application in emotion recognition," *IEEE Transactions on Affective Computing*, 2019.

[12] P. Zhong, D. Wang, and C. Miao, "Eeg-based emotion recognition using regularized graph neural networks," *IEEE Transactions on Affective Computing*, 2020.

[13] P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Lio, and Y. Bengio, "Graph attention networks," *arXiv preprint arXiv:1710.10903*, 2017.

[14] M. Defferrard, X. Bresson, and P. Vandergheynst, "Convolutional neural networks on graphs with fast localized spectral filtering," *arXiv preprint arXiv:1606.09375*, 2016.

[15] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," *arXiv preprint arXiv:1609.02907*, 2016.

[16] E. Pöppel, R. Brinkmann, D. von Cramon, and W. Singer, "Association and dissociation of visual functions in a case of bilateral occipital lobe infarction," *Archiv für Psychiatrie und Nervenkrankheiten*, vol. 225, no. 1, pp. 1–22, 1978.

[17] G. Monti and S. Meletti, "Emotion recognition in temporal lobe epilepsy: a systematic review," *Neuroscience & Biobehavioral Reviews*, vol. 55, pp. 280–293, 2015.

[18] J. Amlerova, A. E. Cavanna, O. Bradac, A. Javurkova, J. Raudenska, and P. Marusic, "Emotion recognition and social cognition in temporal lobe epilepsy and the effect of epilepsy surgery," *Epilepsy & Behavior*, vol. 36, pp. 86–89, 2014.

[19] E. T. Rolls, J. Hornak, D. Wade, and J. McGrath, "Emotion-related learning in patients with social and emotional changes associated with frontal lobe damage." *Journal of Neurology, Neurosurgery & Psychiatry*, vol. 57, no. 12, pp. 1518–1524, 1994.