Various Attention Mechanism Graph Convolutional Network with Multi-Source Domain Adaptation for Cross-Subject EEG Emotion Recognition

Shuo Shi, Xulei Zheng, Taiyi Wu, and Xiaoke Hao (✉)

Hebei University of Technology
haoxiaoke@hebut.edu.cn

Abstract. EEG-based emotion recognition is vital for patients who are unable to express emotions normally through physical or verbal means.It can provide essential support for their emotional expression and rehabilitation. EEG signals are highly non-stationary, and there is significant variability in emotional expression among individuals. The Graph Convolutional Network (GCN) has shown excellent performance in EEG signal feature extraction, but their accuracy in cross-subject scenarios remains unsatisfactory. In this paper, we propose a Various Attention Mechanism Graph Convolutional Network with Multi-Source Domain Adaptation (VAG-MSDA) model for cross-subject EEG emotion recognition. VAG extracts features through the GCN with various attention mechanism to capture the emotional cognitive attributes of the graph structure in spectral, local, and global spatial domains, ensuring the richness and stability of feature information while reducing redundancy. Additionally, MSDA is used to align the feature distributions and classifiers among different individuals, further enhancing the model's generalization ability. Experiments were conducted on the SEED and SEED-IV datasets. The results demonstrate that the proposed VAG-MSDA model achieves significant performance improvements and reaches state-of-the-art performance levels on the SEED-IV dataset. Our code is open-sourced at https://github.com/e6ut/vag-msda.

Keywords: EEG · Emotion Recognition · Cross-Subject · Attention Mechanism · Domain Adaptation.

1 Introduction

Depression and autism are serious psychological problems, early diagnosis and intervention for them are crucial for recovery and preventing deterioration[26]. EEG-based emotion recognition has broad application prospects such as brain-computer interfaces, affective robotics, mental health assessment. Compared to traditional subjective assessment methods, it can provide objective and quantifiable physiological indicator data, effectively avoiding biases that arise from subjective evaluations. Due to its objectivity and non-invasive characteristics, EEG-based emotion recognition offers reliable diagnostic evidence for clinicians. It significantly enhances the efficiency and effectiveness of diagnosis and treatment for psychological and psychiatric disorders.

In recent years, the academic community has achieved some advances in EEG-based emotion recognition through various methods. Initially, CNNs [12,2] and RNNs [21,11] were used for EEG-based emotion recognition. Due to the non-Euclidean nature of EEG data, these networks often get a low prediction accuracy. Graph Neural Network (GNN) can address this issue effectively, which uses graph structures to capture EEG feature information. Furthermore, GCN combine the advantages of CNN and graph structures, enabling to efficiently extract features with higher discriminative power. The GCN [18] and the DGCNN [17] both achieved high recognition accuracy in EEG emotion recognition tasks. Furthermore, Zhou et al. [25] proposed a Progressive Graph Convolutional Network (PGCN), which combined static and dynamic graph convolutions to extract static spatial proximity information and dynamic functional connectivity information separately. Jin et al. [6] proposed a Pyramidal Graph Convolutional Network (PGCN), aggregating features at three levels: local, mesoscopic, and global and integrating node features with their 3D positions to construct a numerical relational adjacency matrix. These approaches have achieved promising results, demonstrating the effectiveness of GCN in EEG-based emotion feature extraction. However, overly complex networks and excessively high-dimensional feature extraction often lead to difficulties in further processing features and issues of feature redundancy. While these methods perform well in subject-dependent scenarios, redundant feature information and individual differences often lead to the problem of overfitting in cross-subject scenarios.

With the advancement of transfer learning, Domain Adaptation (DA) and Multi-Source Domain Adaptation (MSDA) have been applied on cross-subject scenarios [1,9,20,4,13] and combined with feature extraction networks to solve the issue of individual differences. Researchers also integrated attention mechanisms with DA or MSDA to pursue the extraction of domain-invariant features[5,10,19]. Yang et al. [20] introduced an attention mechanism for EEG-based feature extraction and improved MSDA based on attention alignment methods to learn rich domain-invariant features. Relying solely on attention-based EEG feature extraction may result in insufficient feature information extraction.

In this paper, we propose a model VAG-MSDA for cross-subject EEG emotion recognition. For addressing the overfitting and transfer difficulty caused by the significant impact of individual differences, the insufficient spatial information extraction due to the non-Euclidean nature of EEG signals. Firstly, we design an architecture that integrates GCN, various attention feature extractor (VAFE), and MSDA. The architecture can extract domain-invariant features effectively. Subsequently, we design the MGAFE Module, which expand the module of VAFE to extract features from different local spatial regions to addresses the issue of insufficient feature extraction. Extensive experiments on SEED and SEED-IV datasets demonstrate the superiority of our proposed VAG-MSDA.

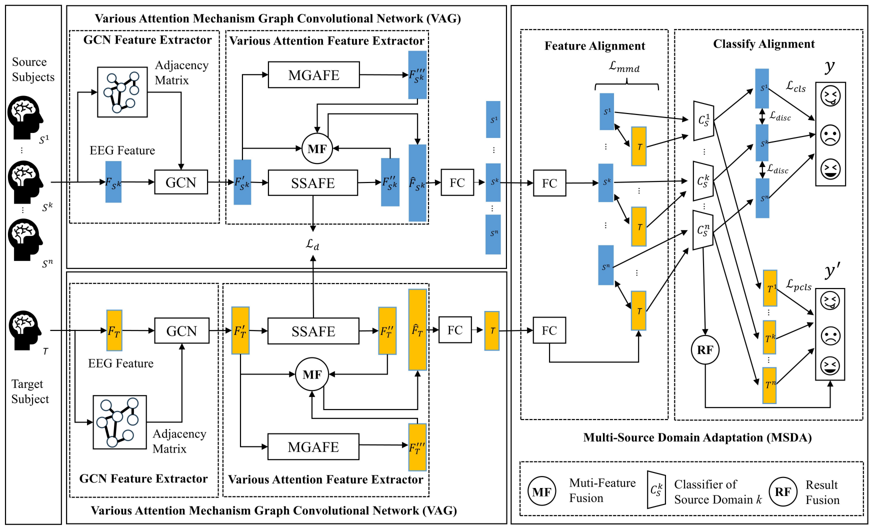


Fig. 1. The overall framework of VAG-MSDA.

2 Methods

The overall framework of the proposed method, as illustrated in Fig. 1. VAG-MSDA comprises two components: 1) the VAG module, which uses a single-layer GCN for feature extraction and constructs various attention mechanisms for secondary feature extraction; and 2) the MSDA module, which includes a feature distribution alignment module to reduce domain discrepancies and a classifier alignment module to align classifiers across source domains, minimizing individual differences' impact on classification.

2.1 Feature extraction

To extract rich and effective features, VAG is employed for feature extraction on both the source and target domains. The feature extraction process is consistent for both the source and target domains, therefore, the feature extraction method described in this section is a general-purpose approach.

Graph Convolutional Feature Extraction (GCFE) Inspired by [6], We based on the inverse of the squared 3D distance d_{ij} between node i and j to compute the element of adjacency matrix $\hat{A}_{ij} = \frac{\delta}{d_{ij}^2}$ ($\hat{A}_{ij} \in [0, 1]$), where δ is the sparsity factor, which is set to 9. $\hat{A}_{ij} \in \hat{A}$, $\hat{A}$ is the adjacency matrix, $\hat{A} \in \mathbb{R}^{n \times n}$ and n is the number of EEG channels. $\hat{A}$ is used to compute the Laplacian matrix $\hat{L}$. The feature H^l extracted by l-layer GCN can be get:

$$H^l = \ LeakyRelu\left(\hat{L}H^{l-1}W^{l-1}\right) \tag{1}$$

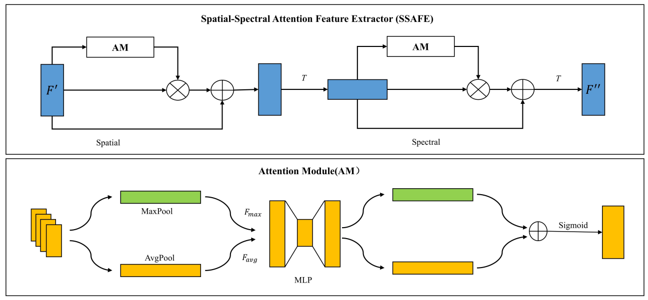


Fig. 2. The overall framework of SSAFE.

Where H^{l-1} and H^l are the input and output features at the l-th layer, W^{l-1} denotes the learnable parameter matrix at the l-th layer, $LeakyRelu$ signifies the activation function, and $\hat{L}$ is the Laplacian matrix. The features extracted through single-layer GCN are denoted as $F' = H^1$.

Various Attention Feature Extraction (VAFE) The VAFE consists of two components: 1) the Spectral-Spatial Attention Feature Extractor (SSAFE), which focuses on extracting domain-invariant features from the spectral domain and global spatial domain [20]; and 2) the Multi -Scale Graph Attention Feature Extractor (MGAFE), which focuses on extracting features from the local spatial domain.

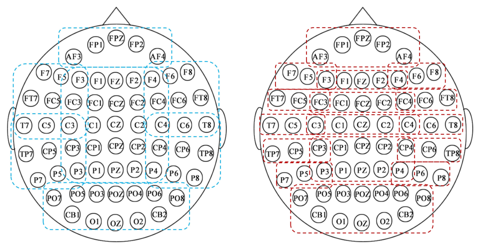
Spectral-Spatial Attention Feature Extractor (SSAFE) As shown in Fig. 2, SSAFE uses an Attention Module (AM) for feature extraction in the spectral and spatial domains, which use avg-pooling and max-pooling to generate two vectors: F_{avg} and F_{max}. And then put them through a shared Multi-Layer Perceptron (MLP), followed by an activation function to generate the attention weights $M(F')$:

$$\begin{aligned} M(F') &= Relu(MLP(Avgpool(F')) + MLP(Maxpool(F'))) \\ &= Relu\left(W^1 W^0 F_{avg} + W^1 W^0 F_{max}\right) \end{aligned} \tag{2}$$

Where W^1 and W^0 denote the learnable parameter matrix, $Relu$ signifies the activation function.

SSAFE extracts features steps as shown in Fig. 2, where T denotes transpose. The extracted features are denoted as F''.

The Multi-Graph Attention Feature Extractor (MGAFE) For better extracting features from local spatial domain, We designed two subgraph partitioning strategies, as illustrated in Fig. 3. Based on the conventional method of dividing brain functional regions, the brain is typically segmented into four main areas: the frontal lobe, parietal lobe, temporal lobe, and occipital lobe. To meet the demands for analyzing finer structures and functional connectivity, we referenced [6] and adopted a partitioning approach that divides the brain into 7



(a) 7 sub-regions (b) 16 sub-regions

Fig. 3. Sub-graph partitioning strategies

sub-regions, as shown Fig. 3(a). Additionally, inspired by [15], we further refined the 7 sub-regions partition by expanding it into 16 sub-regions, as depicted in Fig. 3(b), which not only simplifies the analysis process but also significantly enhances spatial resolution and the interpretability of the results.

Based on these two partitioning strategies, MGAFE performs graph pooling operations separately. For each subgraph, the attention-based connectivity matrix Λ can be represented as:

$$\Lambda = LeakyRelu\left((hW)(hW)^T\right) \tag{3}$$

Where h is the set of features in subgraph region, W denote the learnable parameter matrix, $LeakyRelu$ denote activation function.

Then, we use Λ to aggregate the subgraph features h, which can be get from $m = softmax(\Lambda)h$. By applying the methods to process the subgraphs obtained from the two partitioning strategies, we can derive two local spatial domain features $M^1 \in \mathbb{R}^{7\times K}$ and $M^2 \in \mathbb{R}^{16\times K}$, where K is the number of features in each node. Then fuses M^1 and M^2 as F'''.

Finally, fused the extracted features F', F'' and F''', as $\hat{F}$:

$$\hat{F} = concat\left(F',\ F'', F'''\right) \tag{4}$$

2.2 Multi-Source Domain Adaptation

To effectively mitigate the interference of individual differences on experimental results, we employ the MSDA method. MSDA is divided into two stages: the feature alignment stage and the classifier alignment stage.

Feature Alignment Stage To align the feature distributions from a global perspective, the Maximum Mean Discrepancy (MMD) function is employed to constrain and reduce the feature distribution differences between the source and target domains:

$$\mathcal{L}_{mmd} = \left\| \frac{1}{n_s} \sum_{k=1}^{n_s} \Phi\left(x^{s_k}\right) - \frac{1}{n_t} \sum_{j=1}^{n_t} \Phi\left(x^{t_j}\right) \right\|_{\mathcal{H}}^2 \tag{5}$$

Where x^{s_k} represents the features of k-th source domain, x^{t_j} represents the features of j-th target domain. n_s and n_t are the numbers of source domain and target domain. Φ is a kernel function.

To better extract domain-consistent features using the SSAFE module, inspired by [20], We use an attention alignment loss $\mathcal{L}_d$ to reduces the discrepancies between the features extracted from each source domain and target domain by SSAFE:

$$\mathcal{L}_d = \frac{1}{n_s}\sum_{k=1}^{n_s} |M_{s_k} - M_t| \tag{6}$$

Where M_{s_k} and M_t represents the attention weight of the k-th source domain and the target domain, which get from exponential moving average [3].

Classifier Alignment Stage We use the cross-entropy loss as the classification loss:

$$\mathcal{L}_{cls} = -\frac{1}{N_s}\sum_{i=1}^{N_s} y_i log P_\theta(\hat{y}_i|X_i) \tag{7}$$

Where y_i represents the label of the source domains data, N_s denotes the number of samples, and $P_\theta\left(\hat{y}_i|X_i\right)$ signifies the probability distribution of the predicted label $\hat{y}_i$.

Inspired by [20], we average the predict result of target domain from each sub-classifiers as pseudo-labels of the target domain and compute the pseudo-labels cross-entropy loss for the target domain:

$$\mathcal{L}_{pcls} = -\frac{1}{N_t}\sum_{j=1}^{N_t} y_j \log(P_\theta(\hat{y}_j|X_j) > \tau) \tag{8}$$

Where y_j represents the pseudo-label, N_t denotes the number of target domain samples, and τ is the predefined confidence threshold for filtering labels, which we set to 0.95. $P_\theta\left(\hat{y}_j|X_j\right)$ represents the probability distribution of the predicted label $\hat{y}_j$ that exceeds the confidence threshold τ.

To reduce minimizes the differences between all classifiers. We use a discrepancy loss to constrain each classifier, which helps to minimize the impact of individual differences on the training effectiveness of the classifiers:

$$\mathcal{L}_{disc} = \frac{2}{n_s \times (n_s-1)}\sum_{j=1}^{n_s-1}\sum_{i=j+1}^{n_s} \left|C_i(F(x_i^t)) - C_j\left(F(x_i^t)\right)\right| \tag{9}$$

Where C_i and C_j denote the classifiers belonging to the i-th and j-th source domain, $F(x_i^t)$ denotes extracted reduced-dimensional target-domain features.

In summary, the overall loss $\mathcal{L}$ is defined as:

$$\mathcal{L} = \mathcal{L}_{cls} + \lambda_1\mathcal{L}_d + \lambda_2\mathcal{L}_{mmd} + \lambda_3\mathcal{L}_{disc} + \lambda_4\mathcal{L}_{pcls} \tag{10}$$

Where λ_1, λ_2, λ_3 and λ_4 are the trade-offs to balance the collaborative effect of constraints terms.

3 Experiments

3.1 Datasets and Implementation

SEED The SEED dataset [22] includes EEG data from 15 participants (seven males and eight females) who watched 15 movie clips designed to elicit three emotional states: negative, neutral, and positive. For each participant, EEG data were collected across three distinct sessions, each session comprising 15 trials. The data were captured using 62 EEG channels and preprocessed across five frequency bands: δ, θ, α, β and γ for each channel. We use the Differential Entropy (DE) features as the original input features.

SEED-IV The SEED-IV [23] dataset includes EEG data from 15 participants (seven males and eight females) who watched 24 movie clips designed to elicit four emotional states: neutral, sad, fear, and happy. For each participant, EEG data were collected across three distinct sessions, each session comprising 24 trials. Similarly, the differential entropy (DE) feature extract from five frequency bands as the original input features.

Implementation details In cross-subject EEG emotion recognition experiments, we employ the Leave-One-Out (LOO) method to partition the dataset. For the SEED dataset, the batch size is 256, and for SEED-IV, it is 64. The trade-off parameters λ_1, λ_2, λ_3, and λ_4 are set to 0.2, 0.3, 0.3, and 0.5 [20], respectively. During training, the learning rate is set to 0.01, and the number of epochs is set to 200, with L2 regularization and dropout (rate 0.1) to prevent overfitting. All experiments are done on Linux 64-bit operating system, the experimental handware device GPU is NVIDIA A30, which driver version is 525.60.13 and the CUDA version is 12.0.

Table 1. Ablation study for different modules on SEED and SEED-IV datasets.

Dataset	Methods	Mean / Std(%)
SEED	VAG-MSDA	92.06 / 6.72
	w/o MGAFE	90.68 / 6.98
	SSAFE-MSDA	90.11 / 7.32
	GCN-MSDA	89.24 / 8.58
SEED-IV	VAG-MSDA	80.41 / 10.06
	w/o MGAFE	80.18 / 10.36
	GCN-MSDA	79.31 / 11.29
	SSAFE-MSDA	76.23 / 9.02

3.2 Ablation Study

Ablation studies were conducted on two datasets to demonstrate the impact of each fundamental component of VAG-MSDA, as shown in Table 1. In Table 1, VAG-MSDA was the model proposed in this paper, "w/o MGAFE " indicates the removal of MGAFE module from VAG-MSDA, and " GCN-MSDA " signifies the model of GCN combined with MSDA, " SSAFE-MSDA " signifies the model of SSAFE combined with MSDA.

Through the ablation experiments in Table 1, GCN-MSDA achieved excellent results in the SEED-IV dataset, but due to the limited feature extraction capacity of single-layer GCN, the results in the SEED dataset were lower than the SSAFE-MSDA. w/o MGAFE use GCN with SSAFE to extract and fused features, which preserve feature information richness and low redundancy, so w/o MGAFE can extract better domain-invariant features. The ablation experiments demonstrated the effectiveness of structural design. Additionally, in order to extract richer and low redundancy information, the MGAFE module is designed, and combined with the w/o MGAFE model to form the AVG-MSDA model proposed in this paper. Performance improvement demonstrates the effectiveness of the MGAFE module. The VAG-MSDA improves the accuracy from 89.24% to 92.06% in the SEED dataset; and from 76.23% to 80.41% in the SEED-IV dataset.

3.3 Comparison with SOTA Methods

The proposed VAG-MSDA model is compared with six classical supervised learning methods and six transfer learning methods using the SEED and SEED-IV datasets, as shown in Table 2. Compared to supervised learning methods, our approach employs MSDA to mitigate the impact of individual variability; whereas compared to transfer learning methods, our designed architecture enables more comprehensive extraction of domain-invariant features, so the accuracies on both datasets are significantly improved.

Table 2. Compare with other methods on the SEED and SEED-IV datasets.

Method	Mean / STD(%)		Method	Mean / STD(%)	
	SEED	SEED-IV		SEED	SEED-IV
Supervised Learning					
DGCNN [17]	79.95 / 9.02	52.82 / 9.23	V-IAG [15]	88.38 / 4.80	- / -
A-LSTM [16]	- / -	55.03 / 9.28	PGCN [6]	84.59 / 8.68	73.69 / 7.16
IAG [14]	86.30 / 6.91	62.64 / 10.25	GMSS [7]	86.52 / 6.22	73.48 / 7.41
Transfer Learning					
BiDANN [8]	84.14 / 6.87	69.03 / 8.66	UDDA [9]	88.10 / 6.54	73.14 / 9.43
RGNN [24]	85.30 / 6.72	73.84 / 8.02	MSDA-SFE[4]	91.65 / 2.91	73.92 / 6.04
IDDA [1]	85.75 / 8.11	72.36 / 9.43	S2A2-MSDA [20]	90.11 / 7.32	76.23 / 9.02
VAG-MSDA				**92.06 / 6.72**	**80.41 / 10.06**

4 Conclusion

In this paper, we propose a novel network architecture called VAG-MSDA. The main idea of VAG-MSDA is to use graph convolution combined with various attention mechanism to extract domain-invariant features focused on the spectral domain, global and local spatial domain under the constraints of MSDA. The design of this architecture enabling effectively extract domain-invariant features. Extensive experiments on the SEED and SEED-IV datasets have demonstrated the effectiveness of the model. The ablation studies are conducted to verify the effectiveness of both the overall architectural design and the MGAFE module.

Acknowledgments. This work is supported by the National Natural Science Foundation of China (No.62276088, No.62102129), the Natural Science Foundation of Hebei Province (No.F2023202072, No.F2024202017), The Basic Research Project of Hebei Universities in Shijiazhuang (No.241790817A), The Central Guiding Local Technology Development Fund Project (No.246Z0106G). The Beijing-Tianjin-Hebei Basic Research Cooperation Project (No.J230040).

Disclosure of Interests. The authors declare that they have no competing interests[1].

References

1. An, Y., Hu, S., Liu, S., Wang, Z., Wang, X., Ma, X.: Cross-subject eeg emotion recognition based on interconnected dynamic domain adaptation. In: ICASSP 2024-2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). pp. 12981–12985. IEEE (2024)
2. Baradaran, F., Farzan, A., Danishvar, S., Sheykhivand, S.: Customized 2d cnn model for the automatic emotion recognition based on eeg signals. Electronics **12**(10), 2232 (2023)
3. Deng, Z., Zhou, K., Yang, Y., Xiang, T.: Domain attention consistency for multi-source domain adaptation. arXiv preprint arXiv:2111.03911 (2021)
4. Guo, W., Xu, G., Wang, Y.: Multi-source domain adaptation with spatio-temporal feature extractor for eeg emotion recognition. Biomedical Signal Processing and Control **84**, 104998 (2023)
5. Huang, L., Fan, J., Wang, S., Liew, A.W.C.: Multi-source multi-target domain adaptation based on evidence theory. IEEE Transactions on Instrumentation and Measurement (2025)
6. Jin, M., Du, C., He, H., Cai, T., Li, J.: Pgcn: Pyramidal graph convolutional network for eeg emotion recognition. IEEE Transactions on Multimedia (2024)
7. Li, Y., Chen, J., Li, F., Fu, B., Wu, H., Ji, Y., Zhou, Y., Niu, Y., Shi, G., Zheng, W.: Gmss: Graph-based multi-task self-supervised learning for eeg emotion recognition. IEEE Transactions on Affective Computing **14**(3), 2512–2525 (2022)
8. Li, Y., Zheng, W., Zong, Y., Cui, Z., Zhang, T., Zhou, X.: A bi-hemisphere domain adversarial neural network model for eeg emotion recognition. IEEE Transactions on Affective Computing **12**(2), 494–504 (2018)
9. Li, Z., Zhu, E., Jin, M., Fan, C., He, H., Cai, T., Li, J.: Dynamic domain adaptation for class-aware cross-subject and cross-session eeg emotion recognition. IEEE Journal of Biomedical and Health Informatics **26**(12), 5964–5973 (2022)

[1] The authors declare that they have no competing interests.

10. Lu, Y., Huang, H., Hu, X., Lai, Z., Li, X.: Multiple adaptation network for multi-source and multi-target domain adaptation. IEEE Transactions on Multimedia (2025)
11. Mirzabagherian, H., Menhaj, M.B., Suratgar, A.A., Talebi, N., Sardari, M.R.A., Sajedin, A.: Temporal-spatial convolutional residual network for decoding attempted movement related eeg signals of subjects with spinal cord injury. Computers in Biology and Medicine **164**, 107159 (2023)
12. Schirrmeister, R.T., Springenberg, J.T., Fiederer, L.D.J., Glasstetter, M., Eggensperger, K., Tangermann, M., Hutter, F., Burgard, W., Ball, T.: Deep learning with convolutional neural networks for eeg decoding and visualization. Human brain mapping **38**(11), 5391–5420 (2017)
13. She, Q., Zhang, C., Fang, F., Ma, Y., Zhang, Y.: Multisource associate domain adaptation for cross-subject and cross-session eeg emotion recognition. IEEE Transactions on Instrumentation and Measurement **72**, 1–12 (2023)
14. Song, T., Liu, S., Zheng, W., Zong, Y., Cui, Z.: Instance-adaptive graph for eeg emotion recognition. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 34, pp. 2701–2708 (2020)
15. Song, T., Liu, S., Zheng, W., Zong, Y., Cui, Z., Li, Y., Zhou, X.: Variational instance-adaptive graph for eeg emotion recognition. IEEE Transactions on Affective Computing **14**(1), 343–356 (2021)
16. Song, T., Zheng, W., Lu, C., Zong, Y., Zhang, X., Cui, Z.: Mped: A multi-modal physiological emotion database for discrete emotion recognition. IEEE Access **7**, 12177–12191 (2019)
17. Song, T., Zheng, W., Song, P., Cui, Z.: Eeg emotion recognition using dynamical graph convolutional neural networks. IEEE Transactions on Affective Computing **11**(3), 532–541 (2018)
18. Wang, M., El-Fiqi, H., Hu, J., Abbass, H.A.: Convolutional neural networks using dynamic functional connectivity for eeg-based person identification in diverse human states. IEEE Transactions on Information Forensics and Security **14**(12), 3259–3272 (2019)
19. Wang, Y., Zhang, Z., Hao, W., Song, C.: Attention guided multiple source and target domain adaptation. IEEE Transactions on Image Processing **30**, 892–906 (2020)
20. Yang, Y., Wang, Z., Tao, W., Liu, X., Jia, Z., Wang, B., Wan, F.: Spectral-spatial attention alignment for multi-source domain adaptation in eeg-based emotion recognition. IEEE Transactions on Affective Computing (2024)
21. Zhang, T., Zheng, W., Cui, Z., Zong, Y., Li, Y.: Spatial–temporal recurrent neural network for emotion recognition. IEEE transactions on cybernetics **49**(3), 839–847 (2018)
22. Zheng, W.L., Lu, B.L.: Investigating critical frequency bands and channels for eeg-based emotion recognition with deep neural networks. IEEE Transactions on autonomous mental development **7**(3), 162–175 (2015)
23. Zheng, W.L., Zhu, J.Y., Lu, B.L.: Identifying stable patterns over time for emotion recognition from eeg. IEEE transactions on affective computing **10**(3), 417–429 (2017)
24. Zhong, P., Wang, D., Miao, C.: Eeg-based emotion recognition using regularized graph neural networks. IEEE Transactions on Affective Computing **13**(3), 1290–1301 (2020)
25. Zhou, Y., Li, F., Li, Y., Ji, Y., Shi, G., Zheng, W., Zhang, L., Chen, Y., Cheng, R.: Progressive graph convolution network for eeg emotion recognition. Neurocomputing **544**, 126262 (2023)

26. Zotev, V., Mayeli, A., Misaki, M., Bodurka, J.: Emotion self-regulation training in major depressive disorder using simultaneous real-time fmri and eeg neurofeedback. NeuroImage: Clinical **27**, 102331 (2020)