MGHGCN: Boosting EEG-based Emotion Recognition Through Multi-granular Hypergraph Convolutional Networks

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Abstract

Emotion recognition using electroencephalography (EEG) represents a significant area of study in brain-machine interfaces. To address this multifaceted challenge, it is crucial to improve the ability of EEG features to represent emotional states. A hypergraph-based methodology allows for the depiction of higher-order spatial correlations to develop distinguishing emotional features. However, the original hypergraph may lack robustness due to potential interference among local channels. In addition, excessively coarse hypergraph granularity can result in the loss of critical information. To mitigate these issues, we propose hypergraph group learning, which aims to balance robustness with the retention of detailed information. In this study, we model temporal and spatial dependencies across varying granularities using Hypergraph Group Learning to achieve a discriminative representation of emotional features. We used multiple CNN convolutions to map EEG signals from different brain regions and time segments into a unified distribution. The multi-granularity hypergraph convolutional network (MGHGCN) is specifically designed to capture long-term temporal correlations among channels effectively. By integrating multiview fusion, we significantly improved the accuracy and robustness of EEG-based emotion recognition. Experimental results from publicly available datasets, including SEED, SEED-IV, and EMOT, validate the effectiveness of our approach, achieving precisions of 98.51 (2.46) %, 89.20 (6.13) % and 97.79 (1.31) %, respectively. These results demonstrate that our hypergraph effectively maintains both robustness and detailed information.

Keywords: EEG; Emotion recognition; Hypergraph representation; Integrated learning

Introduction

In recent years, Brain-Computer Interface (BCI) technology has garnered significant attention due to the intersection of neuroscience and computer science. Among the various applications, emotion recognition based on electroencephalogram (EEG) has attracted considerable interest and scrutiny (Duan, Zhu, & Lu, 2013).

Although traditional emotion assessment lacks objectivity, emotion decoding techniques based on EEG offer an objective, real-time, and noninvasive way to acquire and analyze emotional states. However, the inherent low signal-to-noise ratio of EEG can hinder the accuracy of emotion recognition.

Past approaches often rely on predefined signal features, which may not adequately capture intricate patterns within EEG and result in suboptimal performance (Moon, Jang, & Lee, 2018; Gao, Yang, Kang, Tian, & Song, 2022; Yin, Zheng, Hu, Zhang, & Cui, 2021). However, many graph-based studies have intended to utilize the topological structure of EEG channels to extract discriminative emotional features (Zhang et al., 2021; Zeng et al., 2022; J. Li & Pan, 2023). However, interactions between channels may exhibit multi-transitional patterns over time (Luppi et al., 2022). Graph-based methods are limited to modeling pairwise relationships, restricting their scalability to EEG with complex and high-dimensional features, and are susceptible to local interference of EEG channels.

Compared to simple graphs, hypergraphs provide a more flexible modeling approach by capturing higher-order dependencies involving multiple nodes (Zhou, Huang, & Schölkopf, 2006). Thus, this paper presents a method to boost EEG emotion recognition based on a multi-granularity hypergraph network (MGHGCN) to overcome those limitations. MGHGCN exhibits the potential to capture intricate spatio-temporal relationships in EEG by modeling high-order interactions based on hypergraph learning. First, we design a temporal encoder based on an attention mechanism to address to capture both local and global dependencies between features inherent in EEG. By constructing a multi-granularity hypergraph group, we intend to address the problem of the low robustness of graph-based methods. A strengthening technique is introduced to capture and fuse complex correlation patterns to improve the discriminative capability of emotional characteristics and the precision of recognition.

The key contributions of this paper are summarized below.

- We have introduced an enhanced EEG emotion recognition method utilizing a multi-granularity hypergraph network. This approach effectively captures intricate spatio-temporal relationships in EEG data through hypergraph group learning.
- We have introduced an innovative feature extraction method that hierarchically integrates temporal and spatial features. This approach creates a hypergraph representation that effectively captures local and global dependencies within EEG data.
- We have introduced hypergraph group learning, which facilitates both inter-hypergraph and intra-hypergraph learning. This approach allows for the simultaneous modeling of various relationships within EEG signals, thereby improving the ability to discriminate emotional features.

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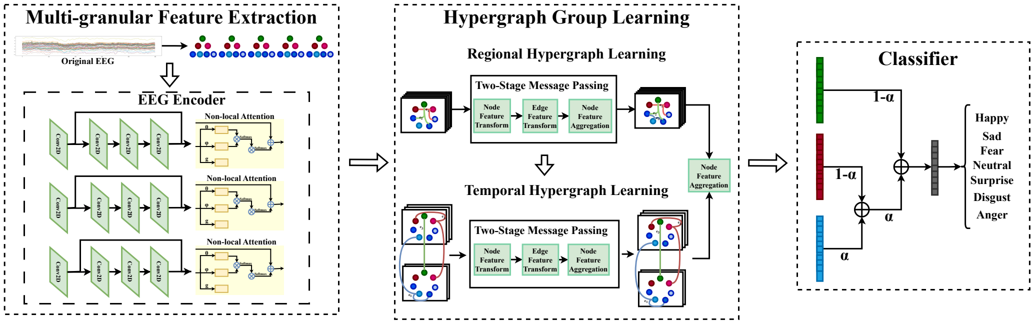


Figure 1: The overall frame of the hypergraph boosting network. From left to right: feature extraction module, hypergraph group learning module, emotion prediction module. Nodes in different colors represent different granularity. Hyperedges in different colors show different connections among nodes.

- Experiments carried out on three standard benchmark datasets showcase its exceptional ability to recognize emotions. These results also enhance our understanding of the spatiotemporal relationships among the activities of various regions of the brain.

Method

Figure 1 illustrates the general architecture of our proposed multi-granularity hypergraph convolutional network (MGHGCN), which comprises three crucial modules: 1) the generation of hierarchical emotion features of EEG for multi-granularity hypergraph representation. 2) constructing a spatiotemporal hypergraph group and engaging in inter-hypergraph learning and intra-hypergraph learning to boost hypergraph representation, and 3) integrated learning of enhanced EEG emotion representation by hypergraphs.

Generating Multi-granularity hypergraph representation of EEG emotion

Given an EEG $S = \{S_1, S_2, ..., S_T\}$, it is divided into T time segments with C channels and W time points. We then partition the channels into subsets $p \in P, P = \{1, 2, 4, C\}$ and explore discriminative representations of the EEG signal in different spatial scopes, including the entire brain, the left and right hemispheres, four regions of the brain and C EEG electrodes. The diagram is illustrated in Figure 2.

We design a multi-granularity spatio-temporal encoder based on attention mechanisms to extract emotion features and capture the multi-granularity interaction dynamics of the preprocessed EEG S primarily. Each single granularity encoder has the same architecture, which is composed of four CNN layers with a skip connection and an attention block.

First, the pre-processed EEG is input into CNN layers to obtain latent representations. Subsequently, we feed the representations specific to the perceived granularity $H_p^l \in R^{T \times P \times D}$ into a non-local attention layer to encode granularity-specific temporal interaction patterns, as follows:

$$H_p^{(l+1)} = softmax(\frac{H_p^l \cdot W_p^Q (H_p^l \cdot W_p^K)^T}{\sqrt{d}}) \cdot H_p^l \cdot W_p^V. \qquad (1)$$

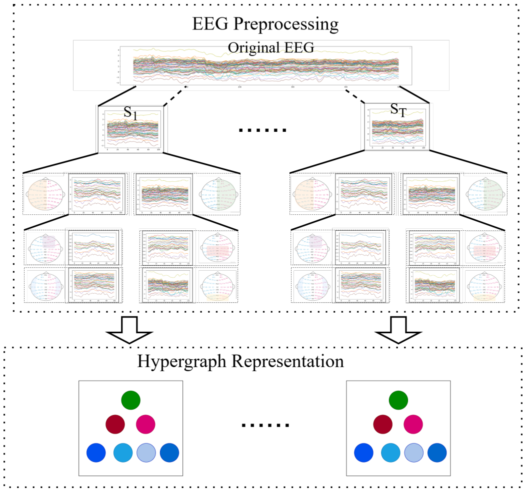


Figure 2: The Process of representing EEG as a multi-granularity hypergraph group. Nodes in different colors represent different granularity. Different hypergraphs mean different time intervals.

Then we develop a spatial granularity-aware aggregator that generates factors to weight specific spatial granularity representations while preserving the dynamics of short-term interactions. Given $h^{(l+1)} = \{h_{t \times p}^{(l+1)}\}, t \in 1, 2, ..., T, p \in P$, we define N_p as the length of sub-sequences specific to a particular spatial granularity. The process is as follows:

$$\begin{aligned} \Gamma_{N_p} &= \{\gamma_1, ..., \gamma_p\}, \\ \gamma_p &= Agg(h_{N_p - T + 1}^{(l+1)}, ..., h_{N_p}^{(l+1)}) \end{aligned} \qquad (2)$$

The aggregator $Agg(\cdot)$ is realized by 1D average pooling, which captures the dynamics of short-term behavioral perception. In this subprocess, we design a hierarchical attention-based encoder with multiple views. It can generate latent features for EEG at different granularities in time and space.

Learning Hypergraph Group Representations

Hypergraph Group Construction To capture spatial and temporal dependencies in EEG, we construct a set of hypergraphs $G = \{G_t\}, t \in \{1, ..., T\}$ to represent EEG S, where each hypergraph G_t corresponds to EEG in a specific temporal granularity S_t. The hypergraph nodes in G_t embody multi-spatial granularity EEG derived from $|P|$ spatial scopes, each spatial granularity denoted as G_t^p, containing $|p|$ nodes.

Thus, each hypergraph $G_t = \{V_t, E_p\}$ consists of $N_t = \sum_{p \in P} p$ vertices V_t and a set of hyperedges E_p connecting various spatial scopes. For each hypergraph node in a hypergraph $v_i \in V_t$, we identify its nearest neighbors K within a specific time granularity based on characteristic correlations between nodes. We then use hyperedges $e_{k_i} \in Adj(v_i), k_i \in 1, 2, 3, ...$ to connect $K+1$ graph nodes. Here, $Adj(v_i)$ represents all hyperedges that contain the node and connect it to the nodes with the highest relevance. In addition, Γ_{N_P} and attention weights are introduced here to the weight nodes and hyperedges, respectively.

Construct hyperedges E_T among those specific temporal granularity, allowing us to learn short-term and long-term correlations of the hypergraphs. In this study, we model short-term, medium-term, and long-term dependencies by imposing time thresholds T_t that limit the temporal distance between vertices within a hyperedge e_{t_j}, $j \in \{1, ..., u\}$, $u \in U$ representing short-term, medium-term, and long-term connections. To learn short-term correlations, hyperedges connect only temporally adjacent hypergraph nodes. The medium- and long-term correlations are modeled by connecting hyperedges that involve different periods of characteristics. By treating the multi-temporal granularity EEG obtained at the same spatial granularity p as super nodes and using the similarity of node features (cosine similarity) as the measure of node neighbors, we initialize the interconnections of hypergraphs. Following expert guidance for initialization, building associations between nodes that exhibit similar behaviors but do not have a direct connection, we derived a hypergraph group $G = (V, E_p, E_T, H, W_e, W_v, X, M)$, where H is the incidence matrix, W_e, W_v are the weight of the hyperedge and hypernode, X and M are features of hyperedge and hypernode.

Multi-granularity Hypergraph Group Network Based on the initialized hypergraph, we design a regionalhypergraph neural network to propagate the hypergraph information and update the features of the nodes, as shown in Figure 1. Given a node v_i, we compute the characteristic $m_{k_i} \in M_e$ of the hyperedge e_{k_i} on the node v_i by taking the average of the characteristics of all neighboring nodes except the node v_i itself. The importance of each hyperedge is calculated by measuring the correlation (cosine similarity) between the hyperedge feature $m_{k_i}^{(0)}$ and the corresponding node feature $x_i^0 = h_i^{(l+1)}$. Subsequently, we normalize the importance weights of the hyperedges using the softmax function and aggregate the hyperedge information I_i. We obtain the updated node features by integrating the previous node features x_i^0 with the aggregated hyperedge messages I_i through a skip connection. By iterating this feature update step for L times, we obtain the output features $h_i^{(L)}$ of the nodes v_i. This summarizes the hypergraph propagation process using node v_i as an example.The propagation for each layer of the network is as follows:

$$\mathbf{X}^{(l+1)} = \sigma\left(\mathbf{D}_v^{-1/2}\mathbf{H}\mathbf{D}_e^{-1}\mathbf{H}^\top\mathbf{D}_v^{-1/2}\mathbf{M}\mathbf{X}^{(l)}\Theta^{(l)}\right) + \mathbf{X}^{(l)}. \quad (3)$$

In this subprocess, (E_p, H, X, M) of the hypergraph group is iteratively updated.

Consistent with the information propagation method of regional hypergraph convolution conducted intra-hypergraph, we proposed a temporal hypergraph convolution conducted inter-hypergraph. The temporal hypergraph convolutional network has the same structure as the regional hypergraph convolution. It updates (E_T, H, X, M) of hypergraph group G.

To further boost the hypergraph group learning, we fully utilize the dynamic nature of the hypergraph and update the convolution parameters when the structure of the hypergraph changes, dynamically adjusting the weights of hyperedges and updating the impact of each neighboring node on the anchor node. We used the GRU architecture to implement weight update in this study. It updates (W_e, W_v) of hypergraph group G.

After the intra-hypergraph and inter-hypergraph learning, we obtained the final updated node features for each hypergraph at each spatial and temporal granularity. By aggregating the temporal and spatial information of the EEG, we further aggregate node-level features into semantic-level representations for each hypergraph.

Integrating Hypergraph Boosting Representations

To fuse the features obtained from hypergraph convolution at different scales, we design a trainable fusion parameter to automatically adjust the fusion operator, as shown below:

$$X_i^+ = \alpha W_{(j,i)} X_{i+1} + (1-\alpha) X_i \quad (4)$$

where X_i represents the EEG emotion features at a certain scale i, $W_{(j,i)}$ represents the weight matrix for up-adopted features from scale i to scale j, α serves as fusion coefficients, and $'+'$ denotes the feature fusion operation. We would get the final feature of the input EEG X_+ through this step.

Through the steps mentioned above, we perform feature fusion on the EEG emotion representations represented by the hypergraph boosting, resulting in spatiotemporal features of the EEG. After that, an MLP module with softmax activation is adopted to classify these features into different emotion classes.

$$\hat{y}_i = softmax(W_f \times X^+ + b) \quad (5)$$

where W_f and b are learnable parameters.

In this paper, the classification cross-entropy is used as the loss function, which is defined as follows:

$$L = -\sum_{i=1}^{N}\sum_{k=1}^{M} y_i log(p(\hat{y}_i)) \quad (6)$$

where y_i is a binary indicator meaning the label of sample i, $p(\hat{y}_i)$ represents the probability that label prediction of sample i is correct.

Table 1: The performance comparison of the state-of-the-art models on the SEED and SEED-IV dataset to do 3-class, 4-class classification

Model	SEED		SEED-IV	
	Acc.(%)	Std.(%)	Acc.(%)	Std.(%)
DGCNN (Song, Zheng, Song, & Cui, 2018)	90.40	8.49	69.88	16.29
BiDANN (Y. Li, Zheng, Cui, Zhang, & Zong, 2018)	92.38	7.04	70.29	12.63
R2G-STNN (Y. Li, Zheng, Wang, Zong, & Cui, 2019)	93.38	5.96	68.51	12.37
RGNN (Zhong, Wang, & Miao, 2020)	94.28	5.95	80.51	10.54
EEG-SWTNS(Cai, Chen, Hua, Wen, & Fu, 2024)	94.83	7.16	79.45	10.86
SST-EmotionNet (Jia et al., 2020)	96.02	2.17	84.92	**6.66**
EeT (Wang, Wang, Hu, Yin, & Song, 2022)	96.28	4.39	83.27	8.37
PGCN (Jin, Du, He, Cai, & Li, 2024)	96.93	5.11	82.24	14.85
STHGCN (M. Li, Qiu, Zhu, & Kong, 2023)	**97.51**	**2.01**	**85.99**	7.33
MGHGCN(Ours)	**98.51**	**2.46**	**89.20**	**6.13**

Table 2: The performance comparison of the state-of-the-art models on the EMOT dataset for 7-class classification

Model	Acc.(%)	Std.(%)
Brain-VAE (Long & Kong, 2019)	82.95	7.39
RGNN (Zhong et al., 2020)	89.17	4.71
BMCL (Liu et al., 2023)	95.02	**0.94**
STHGCN (M. Li et al., 2023)	**95.39**	2.04
MGHGCN(Ours)	**97.79**	**1.31**

Experiment Results and Analysis

The experiments are carried out on the SEED (Zheng & Lu, 2015), SEED-IV (Zheng, Liu, Lu, Lu, & Cichocki, 2018), and EMOT dataset (Long & Kong, 2019). SEED contains three different states of emotions: positive, negative, and neutral. SEED-IV contains four different states of emotions: happy, sad, fearful, and neutral. The EEG recordings in both datasets contain 62 channels that were collected from 15 participants while watching stimulus videos. EMOT contains seven different states of emotions: happy, sad, fearful, neutral, surprised, disgusted, and angry. The EEG recordings contain 62 channels, which were collected from six participants while they were watching stimulus photos.

We implemented our network using PyTorch (Paszke et al., 2019) and trained with Adam (Kingma & Ba, 2014) optimizer where the learning rate λ was set to 0.0005. We trained the model in 50 steps on a NVIDIA GeForce RTX 3090 with a batch size of 128.

We have compared the performance of our method with eight state-of-the-art EEG-based emotion recognition methods, as shown in Subsection *Quantitative Analysis*. The effectiveness of each key module in MGHGCN and the impact of different hyperparameters on the model performance are shown in Subsection *Ablation Study*. Then, we analyze the importance captured by MGHGCN regarding different channels, and time stamps as shown in Subsection *Representation Visualization*.

Quantitative Analysis

In our experiments, we strictly followed the settings in (Zheng & Lu, 2015; Zheng et al., 2018; Long & Kong, 2019) to evaluate the performance of the proposed method. To validate the superiority of MGHGCN, it is compared with generic emotion recognition methods , graph-based emotion recognition methods , and image-enhanced emotion recognition methods .

In Table 1 and Table 2, we conducted a detailed performance comparison on different datasets, and the observed results are summarized as follows:

The proposed MGHGCN consistently outperforms the baseline methods in different datasets. By capturing the transitional patterns of emotional states from fine- to coarse-grained temporal resolutions and long-term temporal correlations across channels, MGHGCN has achieved 98. 51% (2. 46%) in SEED, 89. 20% (6. 13%) in SEED-IV, and 97. 79% (1. 31%) in EMOT.

The robustness of emotion recognition methods based on simple graphs on the dataset (acc., std.) is lower than the general baselines. One possible reason is that it is challenging to capture long-term temporal dependencies by propagating messages between time segments based on their direct transformation relationships in the generated graph structure, causing their recognition results to be easily disturbed by local perturbations. However, MGHGCN overcomes the difficulty to some extent and improves its robustness.

By jointly analyzing the results from these benchmark datasets, we can observe that the MGHGCN demonstrates robustness to features of different EEG sets and has the potential to reflect the interaction patterns between single-channel signals of various brainwaves in different emotional stimuli.

Ablation Study

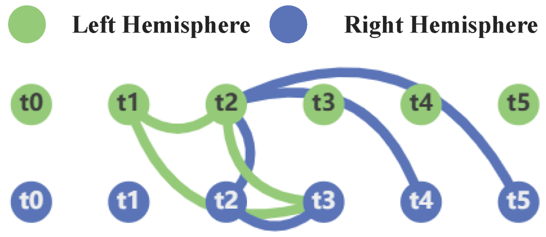
The Effectiveness of Multi-granularity Hypergraph Group We first use a simple graph to replace the hypergraph and then use single granularity to replace the multi-granularity hypergraph group to see the effectiveness of the proposed multi-granularity hypergraph group. The results are

Table 3: The comparison of different graph structures.

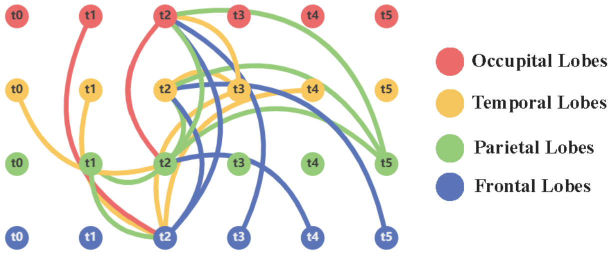
Graph Structures	SEED	SEED-IV	EMOT
MGHGCN(w.o. hypergraph)	95.23	82.41	92.16
MGHGCN(w.o. multi granularity)	97.55	85.25	95.39
MGHGCN(Ours)	**98.51**	**89.20**	**97.79**

Table 4: The comparison of different branches of hypergraph on SEED dataset.

Hypergraph Branches	Temporal Hypergraphs	Spatial Hypergraphs	Acc.(%)
MGHGCN-t	✓		92.85(4.31)
MGHGCN-s		✓	93.80(5.51)
MGHGCN(Ours)	✓	✓	**98.51(2.46)**



(a) The spatiotemporal connections among different hemispheres



(b) The spatiotemporal connections among different lobes

Figure 3: The spatiotemporal connections among different hemispheres and different lobes. Each column represents a time stamp. Lines in different colors show the engagement of different regions.

shown in Table 3. It can be observed that the hypergraph group designed in this paper achieves an increase in prediction accuracy compared to MGHGCN(w.o. hypergraph) and MGHGCN(w.o. multi granularity) by 3.28% and 0.96%, respectively, on SEED. These results indicate the effectiveness of the proposed hypergraph group, which can capture more comprehensive emotional information from EEG.

The Effectiveness of Spatial and Temporal Branches Within A Hypergraph To validate the effectiveness of spatial and temporal branches within a hypergraph, we set the hypergraph as a temporal hypergraph and a spatial hypergraph, respectively. The comparison results are in Table 4.

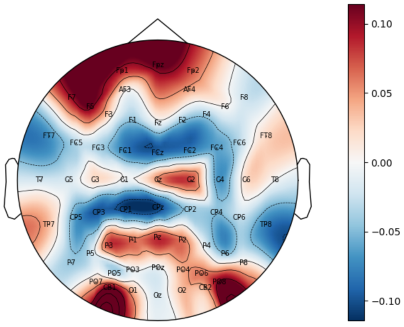


Figure 4: The topographical map of captured semantic features on SEED, where deeper red color denotes a more significant contribution of the corresponding brain region.

It is observed that the hierarchical process of learning temporal information in EEG is more effective than spatial information. By effectively modeling dynamic multi-granularity EEG features from both short-term and long-term perspectives, the MGHGCN performs better than other architectures, confirming the information complementary to the temporal hypergraphs and spatial hypergraphs.

Representation Visualization

To demonstrate the spatio-temporal relationships present in EEG samples, we visualized the average hypergraph at the hemisphere and lobe levels. Figure 3a indicates that emotional information is transmitted from the left hemisphere to the right as time progresses. As depicted in Figure 3b, emotional information flows from the Occipital and Temporal lobes toward the Parietal and Frontal lobes over time, which shows a close connection between emotion and vision. Consistent with the former study of (Zhong et al., 2020; Y. Li et al., 2019), we have observed that the Frontal lobes is important for emotion recognition.

To effectively assess brain engagement, we analyze the average weight of each channel. Figure 4 illustrates that the left frontal lobe and the right occipital lobe exhibit significantly higher levels of activity compared to other brain regions, supporting the concept of cerebral lateralization (Wu et al., 2022).

Due to the high-order characteristics of hypergraphs, it captures dependencies across different ranges of time and space, aiding in understanding the interactions between different regions in the brain over time. This may provide more precise patterns of brain activation for emotion recognition.

Conclusion

In this paper, we have proposed a multi-granularity hypergraph-based EEG emotion recognition framework (MGHGCN) that explicitly captures short- and long-term multichannel interaction patterns. MGHGCN incorporates a hierarchical attention-based encoder to encode temporal features of EEG at both fine- and coarse-grained levels. To capture multi-granularity spatiotemporal interaction patterns of

EEG, we design a hypergraph group learning strategy. Experimental results in several benchmark datasets validate the advantages of the MGHGCN and depict the correlations of different brain region activities.

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