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Improving EEG-based Emotion Recognition by Fusing Time-Frequency and Spatial Representations

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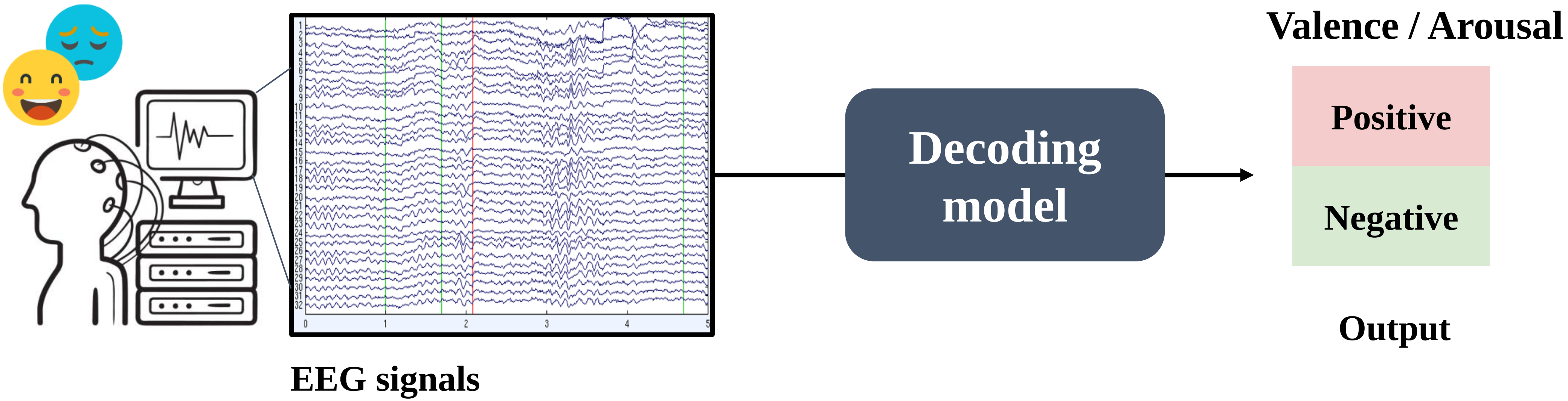
Summary of Key Contributions

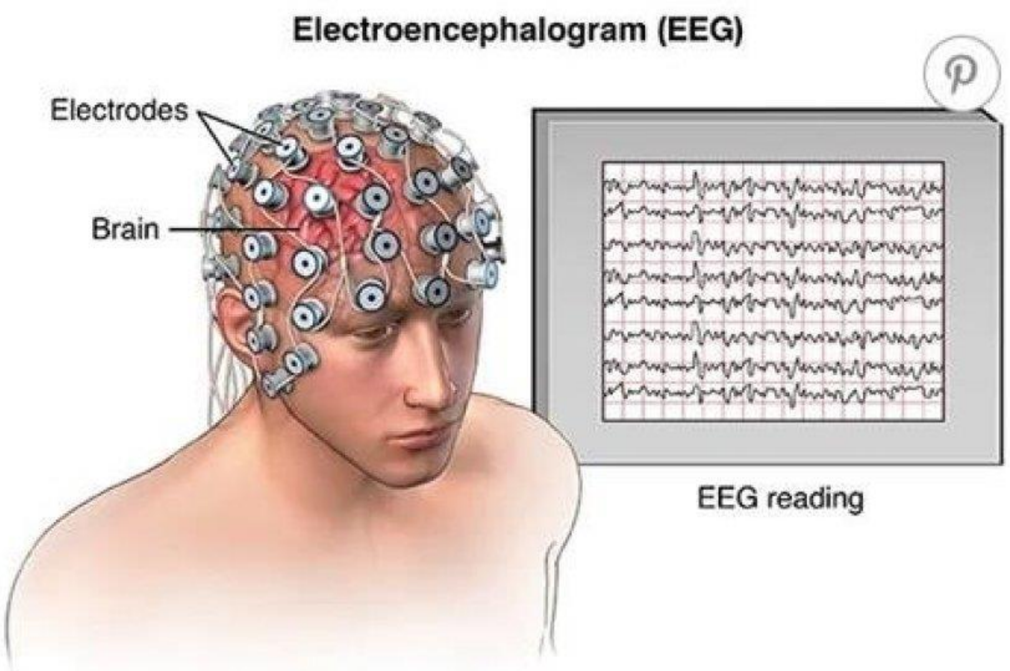
- **EEG Multi-Domain Feature Fusion**
  - Utilize cross-domain attention to fuse spatial representations with time-frequency features for improved feature selection.
  - Developed a two-step fusion method to preserve feature information from both time-frequency and spatial domains.
- **Superior Performance of Subject-independent Emotion Recognition Network**
  - Achieve valence accuracy of 0.859 (with GAT), 0.861 (with GCN)
  - Achieve arousal accuracy of 0.878 (with GAT), 0.884 (with GCN)

Schema of EEG-based Emotion Recognition



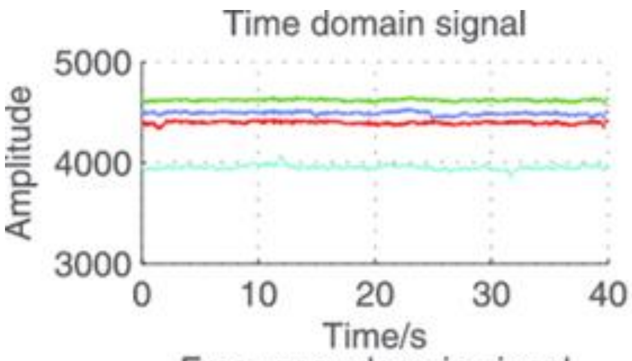
https://eeglab.org/tutorials/06_RejectArtifacts/Scrolling_data.html

Electroencephalography (EEG)

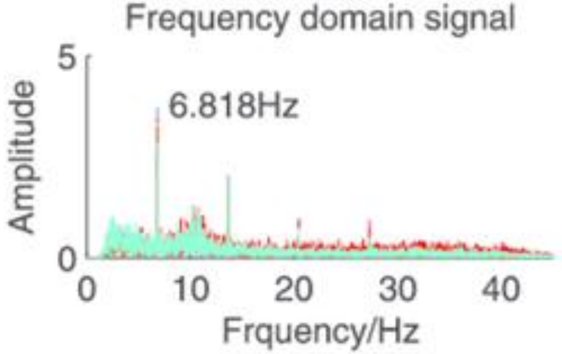


EEG measurement

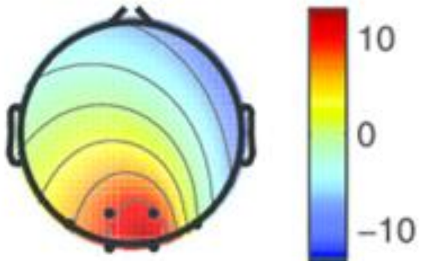
Temporal Domain



Spectral Domain



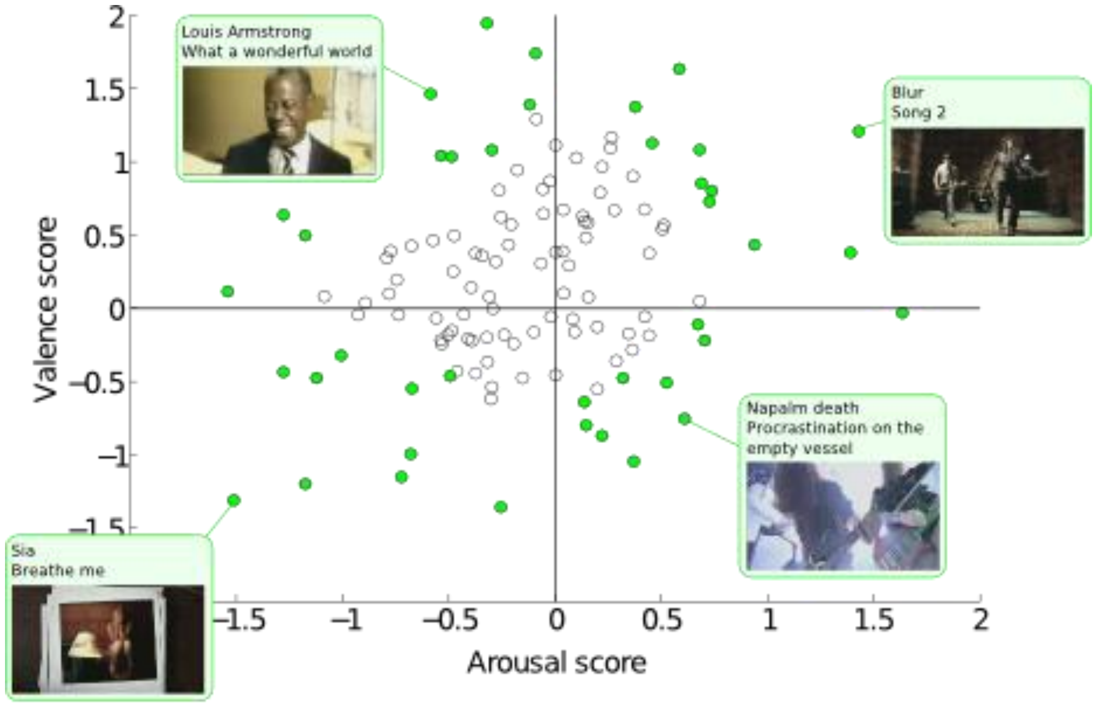
Spatial Domain

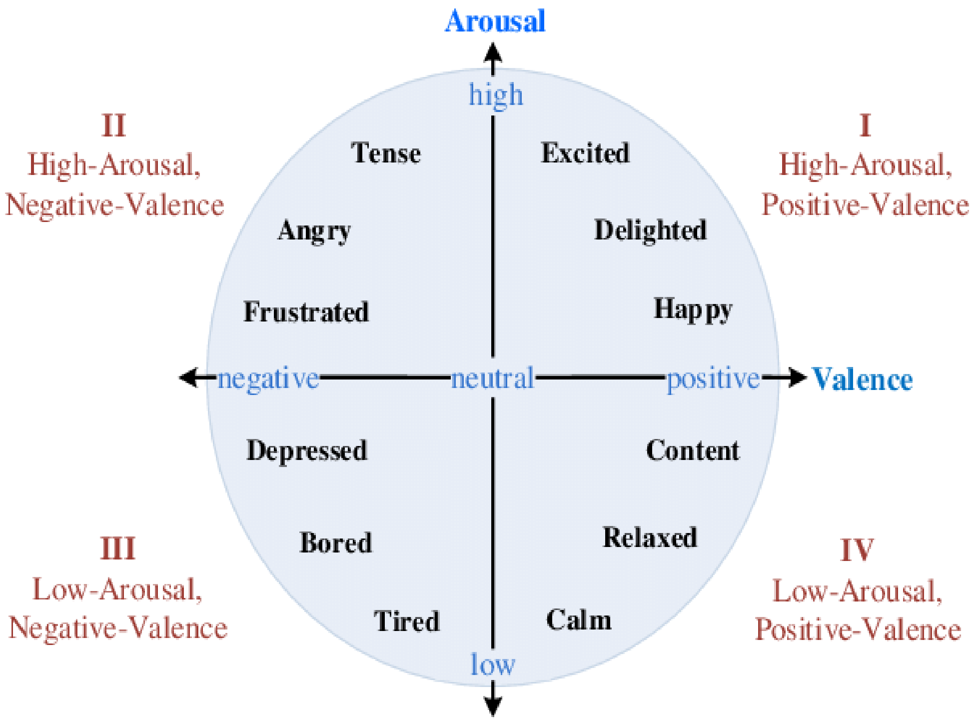


https://www.brightbraincentre.co.uk/electroencephalogram-eeg-brainwaves/
https://www.researchgate.net/publication/298727786_Brain-Computer_Interface_Controlled_Cyborg_Establishing_a_Functional_Information_Transfer_Pathway_from_Human_Brain_to_Cockroach_Brain

Emotional EEG Dataset: DEAP Dataset [16]

- 32 subjects (16 males, 16 females), 40 music videos for each participants
- Rate **valence** and **arousal** scores





Existing Models and Approaches

- In recent years, many EEG classification models based on temporal, frequency, and spatial features have been proposed

Authors	Methods	Key Features
Hou and Jia et al. [6]	LSTM for temporal feature extraction GCN for topological structure modeling	Combines temporal and spatial features
He et al. [7]	Channel attention in MLP	Adaptive learning of channel importance
Yin et al. [8]	GCN for spatial feature extraction LSTM for temporal relationship memorization	Integrates spatial and temporal features
He and Zhong et al. [9]	Temporal convolution networks Adversarial discriminative domain adaptation	Addresses domain drift in cross-subject emotion recognition

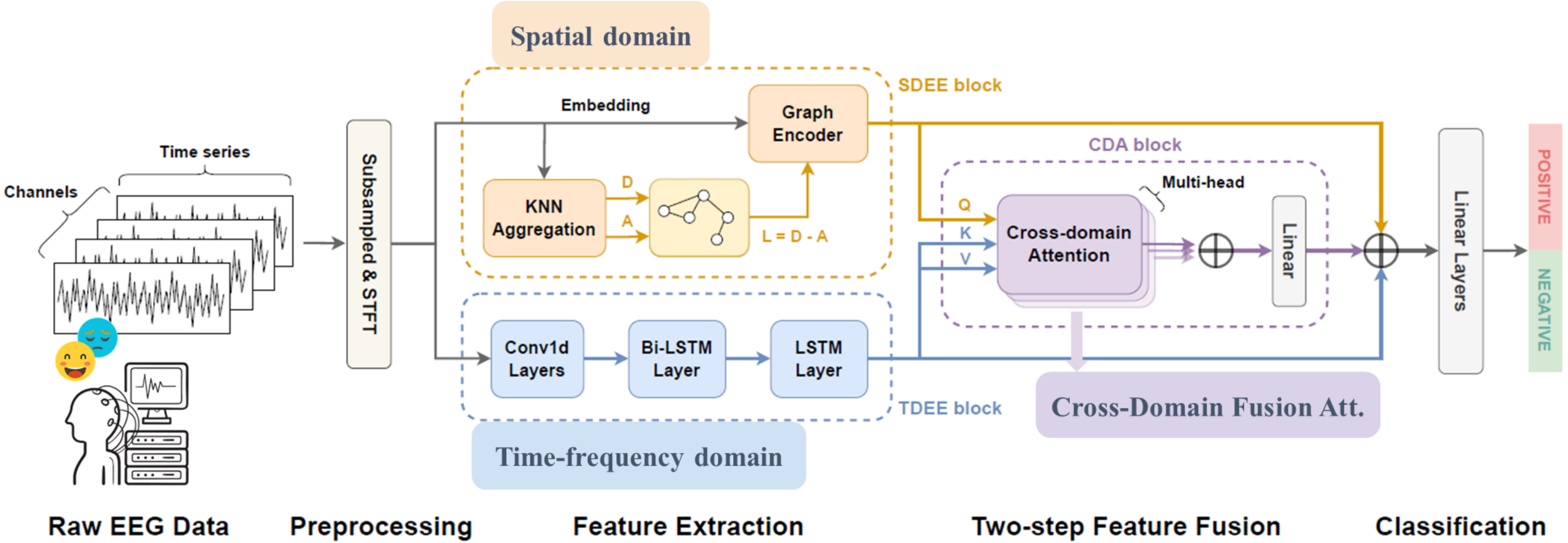
Research Gaps

- **Representation Limitations**
  - Some of the existing works focus on the representations of different domains, lacking the **mapping process of features between representations.**

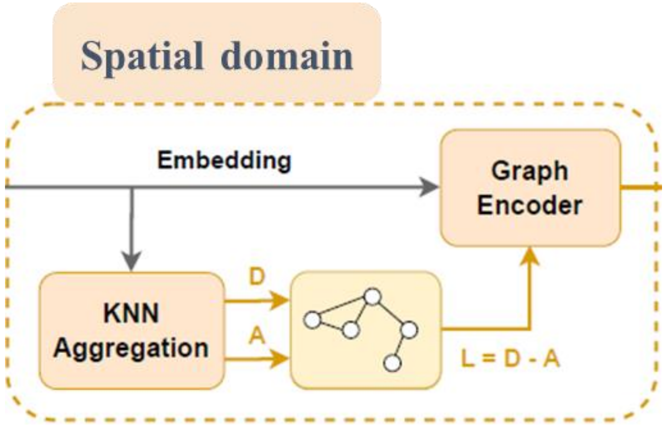
- **Fusion Challenges**
  - Some fusion methods are difficult to **combine different levels of feature information** to comprehensively model EEG signals.

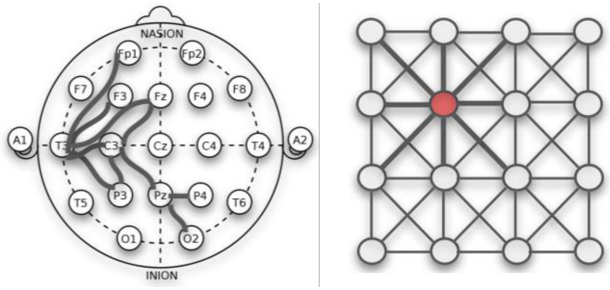
➢ The authors proposed a method for **EEG multi-domain feature fusion** using cross-domain attention, which utilizes information from spatial representations to assist in selecting time-frequency features.

Overview of the proposed model: Multi-domain Feature Fusion Architecture



Spatial-domain Embedding & Encoding Block (SDEE Block)





Graph encoder: Introduce the connection between each channel

1. Mapping brain networks to graph structures
2. Using **KNN** to construct flexible adjacency and degree matrix
3. Graph convolution operations: **GCN [11] & GAT [12]**

GAT [12] improves the normalization constant in the GCN layer into the neighbor node feature aggregation function using attention weight

Spatial-domain Embedding & Encoding Block (SDEE Block)

- **Graph convolution operations**

GCN [11]

$$h_i^{l+1} = \sigma(\sum_j \frac{h_i^l W^l}{c_{ij}}) \tag{1}$$

$$c_{ij} = \sqrt{d_i d_j} \tag{2}$$

h: feature representation vector
i: node
j: neighboring node
W: trainable parameter matrix
d: degree of node
$\vec{a}$: attentional weight vector

GAT [12]

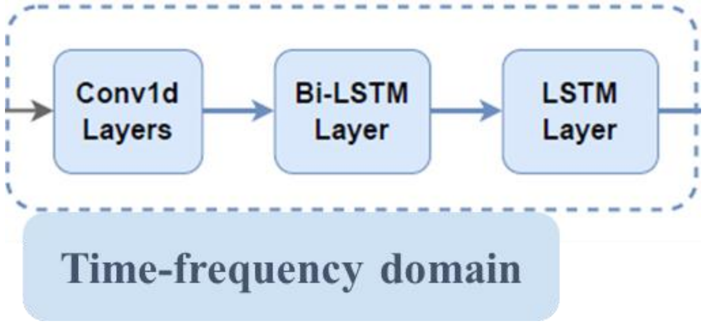
$$h_i^{l+1} = \sigma(\sum_j \alpha_{ij}^l z_j^l) \tag{3}$$

$$\alpha_{ij}^l = \frac{exp(e_{ij}^l)}{\sum_k exp(e_{ik}^l)} \tag{4}$$

$$e_{ij}^l = LeakyReLU((\vec{a}^l)^T (z_i^l || z_j^l)) \tag{5}$$

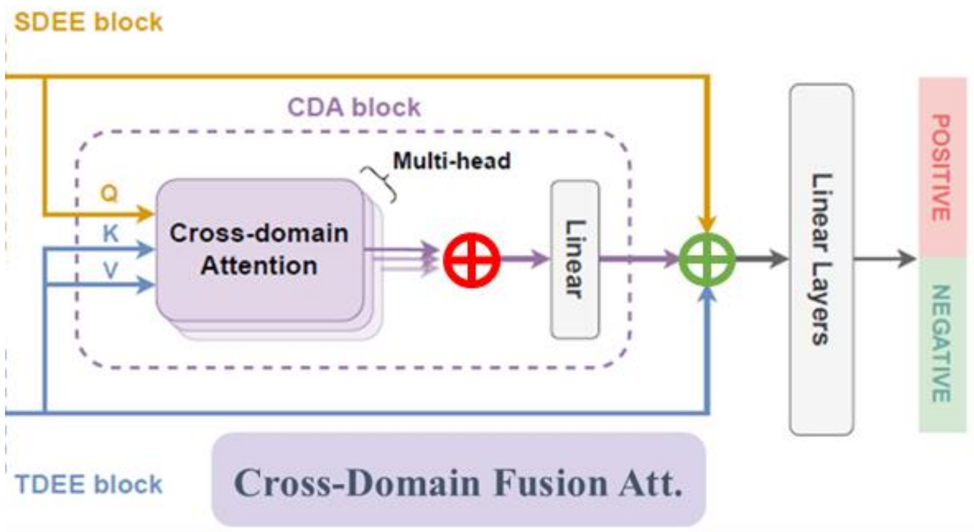
$$z_i^l = h_i^l W^l \tag{6}$$

Time-domain Embedding & Encoding Block (TDEE Block)



- **CRNN [10]**
  1. **Three 1-dimension convolution**: Extract channel correlation information by convolution operation between channels
  2. **Bi-LSTM & LSTM**: Encode the context relationship by LSTM layers

Cross-domain Attention Block (CDA Block)



- **Two-step fusion**

  ⊕ $$X_{CM} = MultiHead(X_\alpha, X_\beta) \quad (13)$$

  ⊕ $$X_{FC} = Concat(X_\alpha, X_\beta, X_{CM}) \quad (14)$$

- **Multi-head cross-domain attention [13, 14]**

$$Attention(Q_\alpha, K_\beta, V_\beta) = Softmax(\frac{Q_\alpha (K_\beta)^T}{\sqrt{d}})V_\beta \quad (10)$$

α : SDEE block output feature vector (i.e. spatial domain)
β : TDEE block output feature vector (i.e. time frequency domain)

Experimental setup

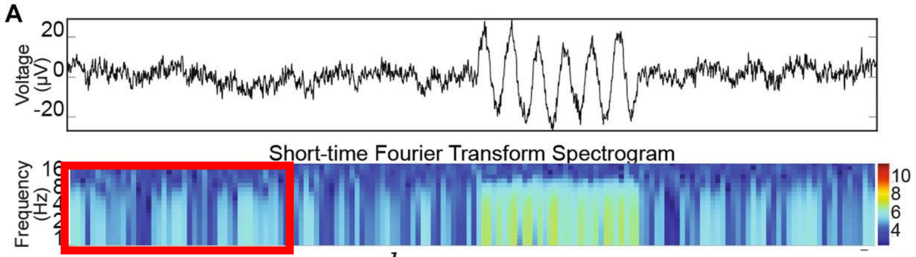
1. Dataset: DEAP Dataset [16] (32 subjects, 32 EEG channels, 40 videos, 60 sec/video)

2. Subject-independent Model: Leave-one-subject-out (LOSO) cross validation

3. Data Preprocessing:

a. **Epoch** with sliding window of a 2 second-width in steps of 0.125 seconds (480 epochs/video).

b. **Short-time Fourier transform (STFT)** is used to calculate differential entropy (DE) as the frequency domain features in five bands, including Delta, Theta, Alpha, Beta, and Gamma.



$$DE = -\int_a^b p(x)\, log(p(x))\, dx$$

32 (channels) × 5 (frequency band) — **SDEE Block**

32 (channels) × 5 (frequency band) × ~512 (time sample) — **TDEE Block**

Classification performance of emotion recognition

Table 1. Comparison between our proposed method and other methods

Study	Feature(s)	Accuracy	
		Valence	Arousal
Li et al. [17]	T-F	0.691	0.710
Wang et al. [5]	SFM	0.712	0.713
Atkinson et al. [18]	mRMR	0.731	0.730
Guo et al. [19]	T-F, FuzzyEn	0.844	0.856
Ours (with GAT)	T-F, Graph	0.859	0.878
Ours (with GCN)	**T-F, Graph**	**0.861**	**0.884**

Note: **GAT has higher computational efficiency** where T-F represents the time-frequency feature, SFM represents spatial-frequency matrices, and mRNR represents minimum-Redundancy-Maximum-Relevance.

Ablation study of blocks

Table 2. Ablation study in proposed method (with GCN) and comparison experiment of different fusion methods.

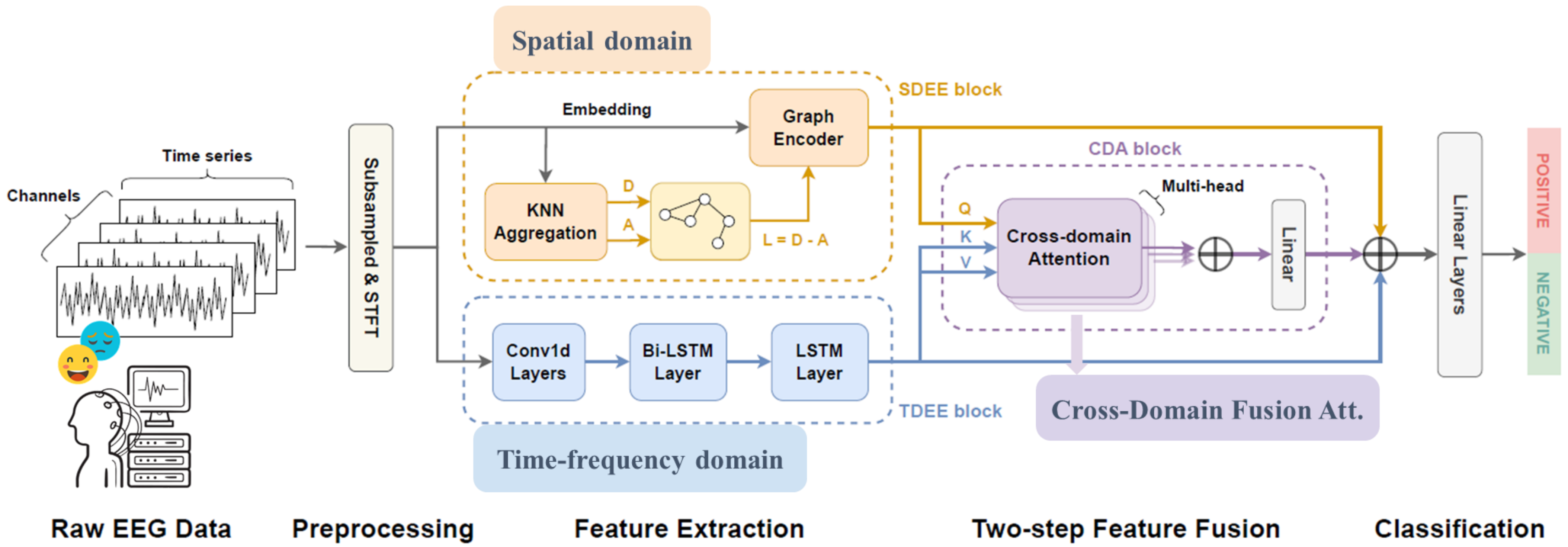
SDEE	TDEE	CDA	Fusion	Accuracy	
				Valence	Arousal
✓			-	0.530	0.512
	✓		-	0.834	0.840
✓	✓		Concat	0.849	0.864
✓	✓	✓	One-step	0.855	0.867
✓	✓	✓	**Two-step**	**0.861**	**0.884**

Summary of the results

- **The proposed multi-domain feature fusion model significantly improves EEG-based emotion recognition.**
  - Achieve valence accuracy of 0.859 (with GAT), 0.861 (with GCN)
  - Achieve arousal accuracy of 0.878 (with GAT), 0.884 (with GCN)
- **The two-step fusion method and cross-domain attention are crucial for achieving high performance.**

Key Ideas Recap

- **EEG Multi-Domain Feature Fusion**
  - Utilize cross-domain attention to fuse spatial representations with time-frequency features for improved feature selection.



Critical questions

- **Generalization to other tasks:**
  - Can the proposed multi-domain feature fusion method be **generalized** to other EEG-based tasks beyond emotion recognition.
- **Data preprocessing:**
  - Preprocessing steps are necessary to prepare the EEG data for input into the proposed model, but **they were not clearly listed in the paper**
- **Parameter usage:**
  - Lack information in TDEE block: Conv1d (kernal size, stride, padding)
  - k value in kNN was not provided

Thanks for your listening

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