Beijing Jiaotong University

SST-EmotionNet: Spatial-Spectral-Temporal based Attention 3D Dense Network for EEG Emotion Recognition

Introduction

Emotion:

Related to many mental diseases, such as autism and depression[1, 2];
Used as a reference for assessing patients' mental disorders[3].

Emotion Recognition based on EEG:

EEG signals can objectively reflect different emotions and become a reliable way to identify real emotions in comparison with other external appearance clues like facial expression and gesture [4].

[1] Al-Kaysi, et al. (2017). Predicting tDCS treatment outcomes of patients with major depressive disorder using automated EEG classification. Journal of affective disorders, 208, 597-603.
[2] Bocharov, et al. (2017). Depression and implicit emotion processing: An EEG study. Neurophysiologie Clinique/Clinical Neurophysiology, 47(3), 225-230.
[3] Zhong, et al. (2020). EEG-Based Emotion Recognition Using Regularized Graph Neural Networks. IEEE Transactions on Affective Computing.
[4] Zheng, et al. (2015). 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.

Related Work

· *Frequency Features:*

◆ DE [5, 6], PSD [7, 8], DASM [9], RASM [10], DCAU [4] , etc.

· *Temporal Features:*

◆ LSTM [11], MMResLSTM [12] , etc.

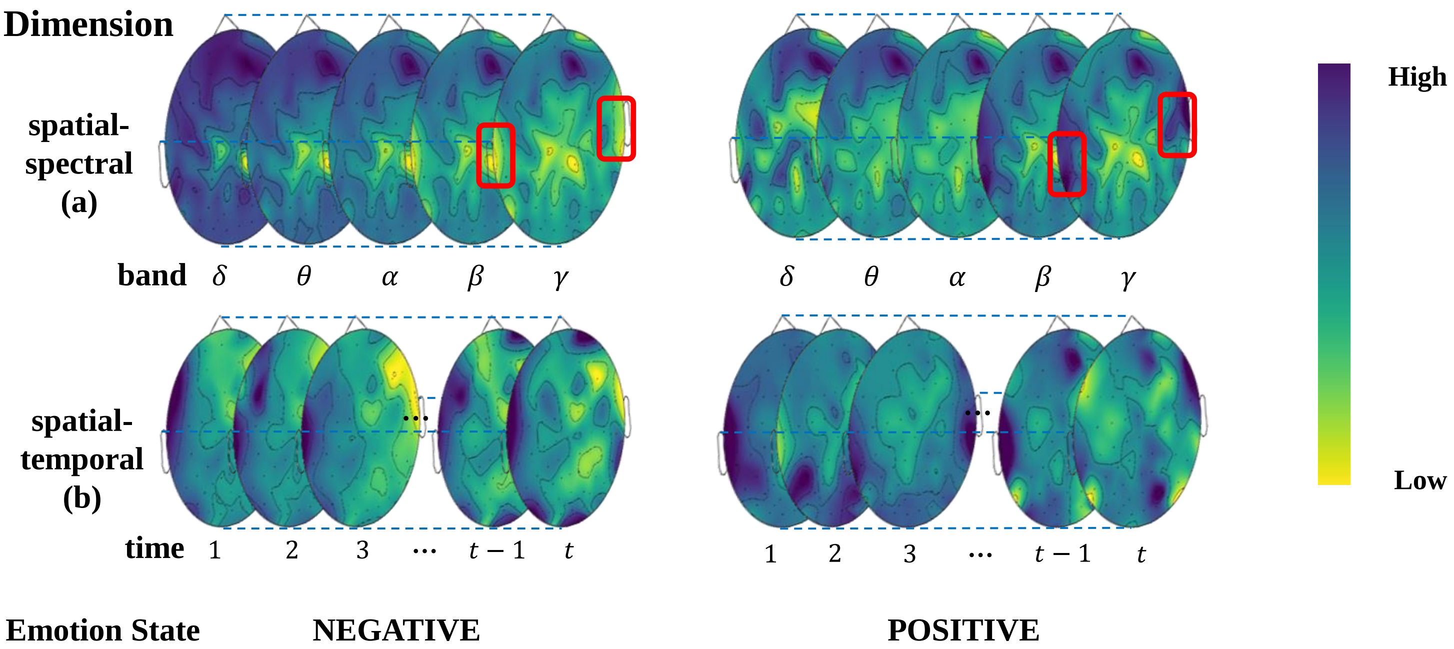
· *Spatial Features:*

◆ CNN [13, 14], GCN [15, 16] , etc.

◆ Most existing emotion recognition methods only consider a single feature or a combination of two features.

Introduction

Spatial-Spectral-Temporal features of EEG in different emotion states:



Challenges

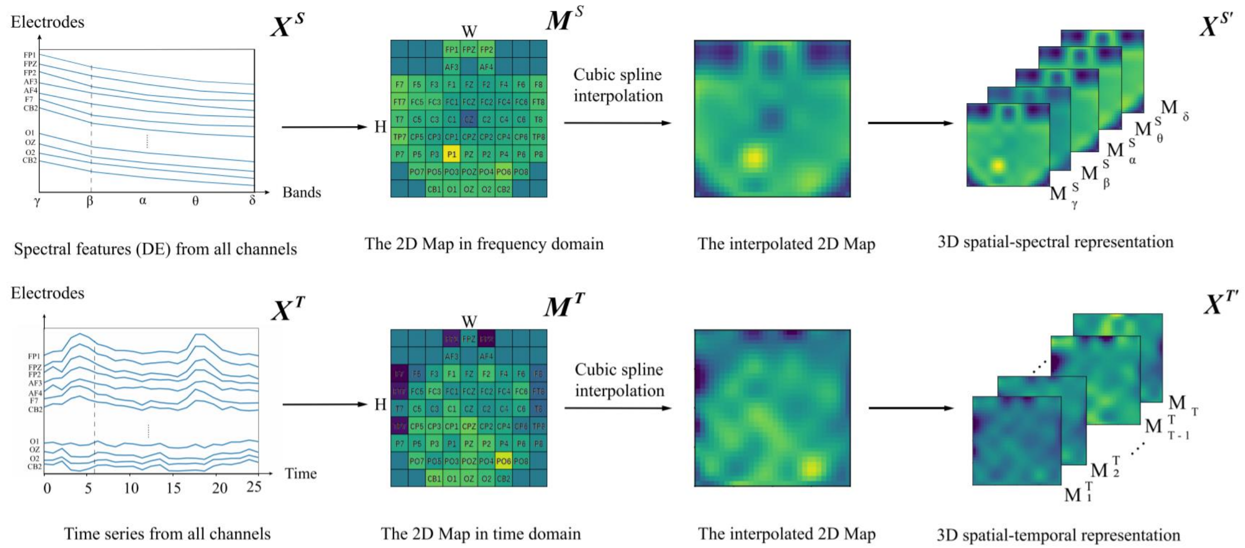
C1: **Existing methods ignore the complementarity among the spatial-spectral-temporal features.**

C2: **How to capture local patterns in spatial-spectral-temporal features for emotion recognition.**

Methods

C1: How to utilize the complementarity among different features?

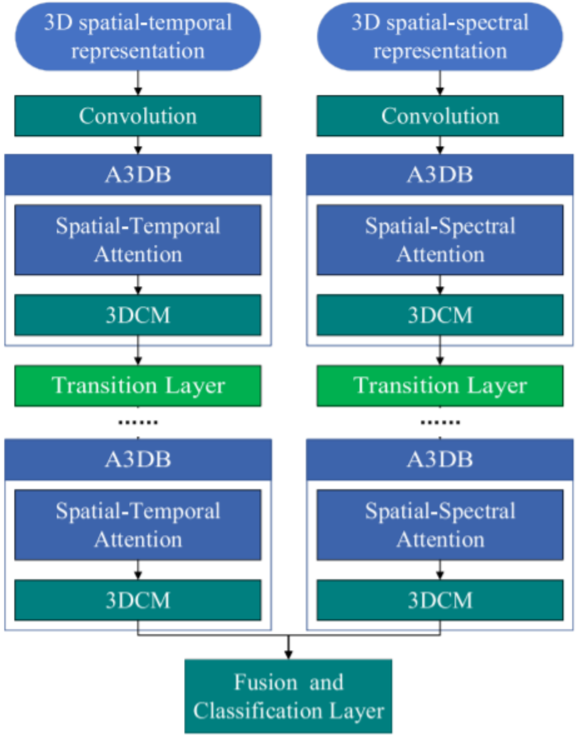
S1.1: Constructed 3D spatial-spectral-temporal EEG representation.



Methods

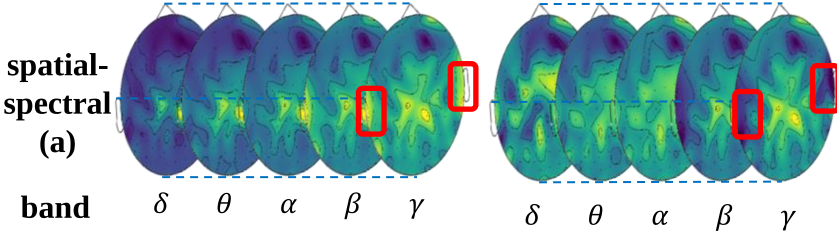
C1: **How to utilize the complementarity among different features?**

S1.2: **We propose a two-stream 3D Dense network, which fuses the spatial-spectral-temporal information of EEG signals in a unified network framework based on the constructed 3D EEG representation.**

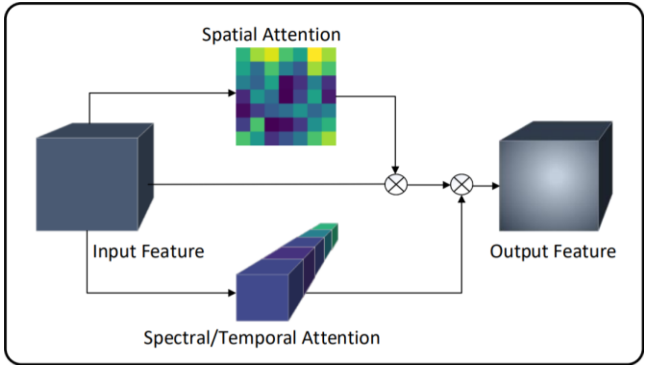


Methods

C2: **How to capture local patterns in spatial-spectral-temporal features for emotion recognition?**



S2: **Develop a parallel Spatial-Spectral/Temporal attention mechanism to adaptively capture discriminative patterns in brain regions, frequency bands and time stamps.**



Experiments

Comparison with the state-of-the-art models:

Table 1: The performance comparison of the state-of-the-art models on the SEED and SEED-IV dataset

Model	SEED		SEED-IV	
	ACC (%)	STD (%)	ACC (%)	STD (%)
SVM [26]	83.99	9.72	56.61	20.05
GSCCA [33]	82.96	9.95	69.08	16.66
DBN [31]	86.08	8.34	66.77	7.38
DGCNN [25]	90.40	8.49	69.88	16.29
BiDANN [17]	92.38	7.04	70.29	12.63
BiHDM [19]	93.12	6.06	74.35	14.09
R2G-STNN [18]	93.38	5.96	-	-
RGNN [34]	94.24	5.95	79.37	10.54
SST-EmotionNet	**96.02**	**2.17**	**84.92**	**6.66**

Conclusion

Contribution:

- We propose a two-stream 3D Dense network, which fuses the spatial-spectral-temporal information of EEG signals in a unified network framework based on the constructed 3D EEG representation.
- We develop a parallel Spatial-Spectral/Temporal attention mechanism to adaptively capture discriminative patterns in brain regions, frequency bands and time stamps.
- We conduct extensive experiments on two benchmark datasets and the experimental results show that our SST-EmotionNet consistently outperforms all state-of-the-art models.

References

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Thanks!