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GraphSleepNet: Adaptive Spatial-Temporal Graph Convolutional Networks for Sleep Stage Classification

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Introduction

Sleep:

- About a third of life is spent in sleep, which directly influences human health;
- Sleep staging is important for assessing sleep quality and diagnosing sleep disorders.

Artificial Sleep Stage Classification:

- Sleep experts identify sleep states based on sleep standard and polysomnography;
- It’s a tedious and time-consuming task;
- The variability and subjectivity of sleep experts affect the classification results.

Automatic sleep stage classification:

- Improve the efficiency of traditional sleep stage classification;
- Have important clinical value.

Related Work

Sleep Stage Classification

· ***Traditional machine learning methods:***

- SVM and RF, etc.
- Need to extract hand-crafted features, which requires a lot of prior knowledge.

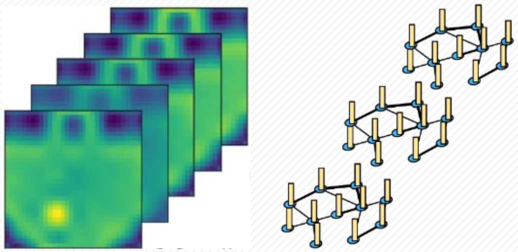
· ***CNN and RNN:***

- FDCCNN[1], SeqSleepNet[2], DeepSleepNet[3], etc.
- Their input must be grid data (image-like).

Motivation & Challenge

· ***Limitations of grid data:***

- Ignore the connections among brain regions.
- Brain regions are in non-Euclidean space, graph is the most appropriate data structure to indicate brain connection.



Grid data　　Graph data

· ***Modeling the functional connections of the brain:***

- GCNs have shown advanced performance in addressing graph structure data[4,5].
- Existing work usually use fixed graph structure, but sleep is a dynamic process.
- Humans' knowledge of the human brain is limited.

C1: **How to determine a suitable graph structure for sleep stage classification.**

Motivation & Challenge

C2: How to effectively extract spatial-temporal features.

- During sleep, the spatial characteristics among brain regions are different.
- In the temporal dimension, there are transition rules between sleep stages.

Sleep Stage Pair	Transition Pattern*	Rule	Differentiating Features
N1-N2	N1-{N1,N2}	5.A.Note.1	Arousal, K-complexes, sleep spindles
	(N2-)N2-{N1,N2}(-N2)	5.B.1 5.C.1.b	K-complexes, sleep spindles Arousal, K-complexes, sleep spindles
	N2-{N1-N1,N2-N2}-N2	5.C.1.c	Alpha, body movement, slow eye movement
N1-R	R-R-{N1,R}-N2	7.B 7.C.1.b 7.C.1.c	Chin EMG tone Chin EMG tone Chin EMG tone, arousal, slow eye movement
	R-{N1-N1-N1,R-R-R}	7.C.1.d	Alpha, body movement, slow eye movement
N2-R	R-R-{N2,R}-N2	7.C.1.e	Sleep spindles
	(N2-)N2-{N2,R}-R(-R)	7.D.1 7.D.2 7.D.3	Chin EMG tone Chin EMG tone, K-complexes, sleep spindles K-complexes, sleep spindles

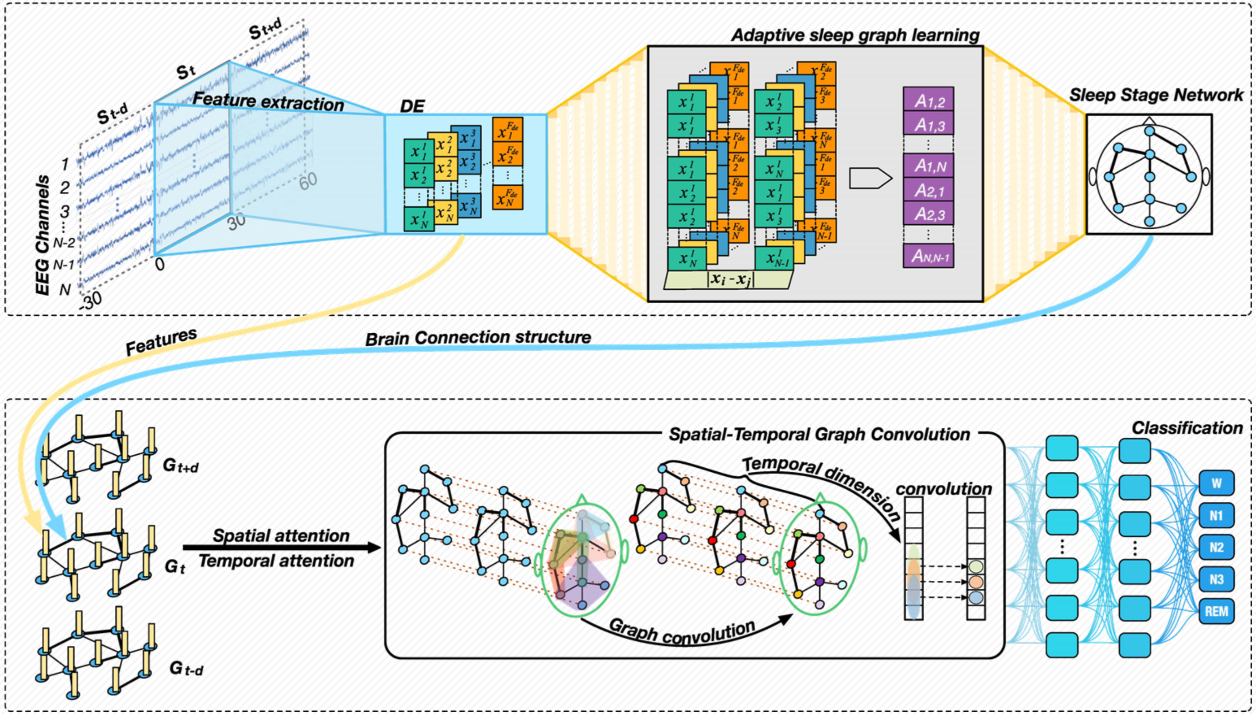
*Curly braces indicate choice between the stages or stage progressions in the set, and parentheses indicate optional epochs.

The transition rules summarized from the AASM sleep scoring manual[6]

- *C2.1*: How to effectively apply graph convolution to sleep stage classification.
- *C2.2*: How to exploit the sleep transition rules between neighboring stages.

Methods

GraphSleepNet: Adaptive Spatial-Temporal Graph Convolutional Networks

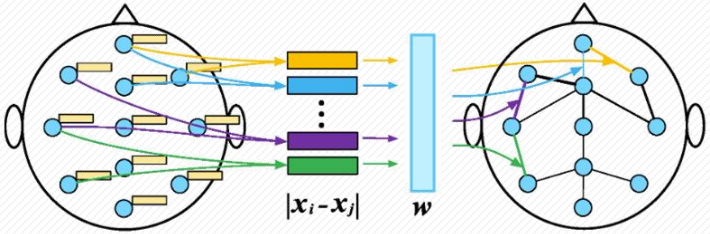


Contribution:

- The *first attempt* to apply *ST-GCN* for sleep stage classification.
- A novel *adaptive sleep graph learning mechanism*.
- We design a *spatial-temporal convolution*.
- Achieves *SOTA performance* in sleep stage classification.

Methods

C1: **How to determine a suitable graph structure for sleep stage classification?**



S1: **We propose a novel adaptive sleep graph learning mechanism.**

- Integrated with ST-GCN simultaneously in a unified network architecture.
- Dynamically construct adjacency matrix ***A***.
- Utilize the second term in the loss function to control the sparsity of graph ***A***.

$$A_{mn} = g(\boldsymbol{x}_m, \boldsymbol{x}_n) = \frac{\exp(\mathrm{ReLU}(\boldsymbol{w}^T |\boldsymbol{x}_m - \boldsymbol{x}_n|))}{\sum_{n=1}^{N} \exp(\mathrm{ReLU}(\boldsymbol{w}^T |\boldsymbol{x}_m - \boldsymbol{x}_n|))}$$

$$\mathcal{L}_{\text{graph\_learning}} = \sum_{m,n=1}^{N} \|\boldsymbol{x}_m - \boldsymbol{x}_n\|_2^2 A_{mn} + \lambda \|\boldsymbol{A}\|_F^2$$

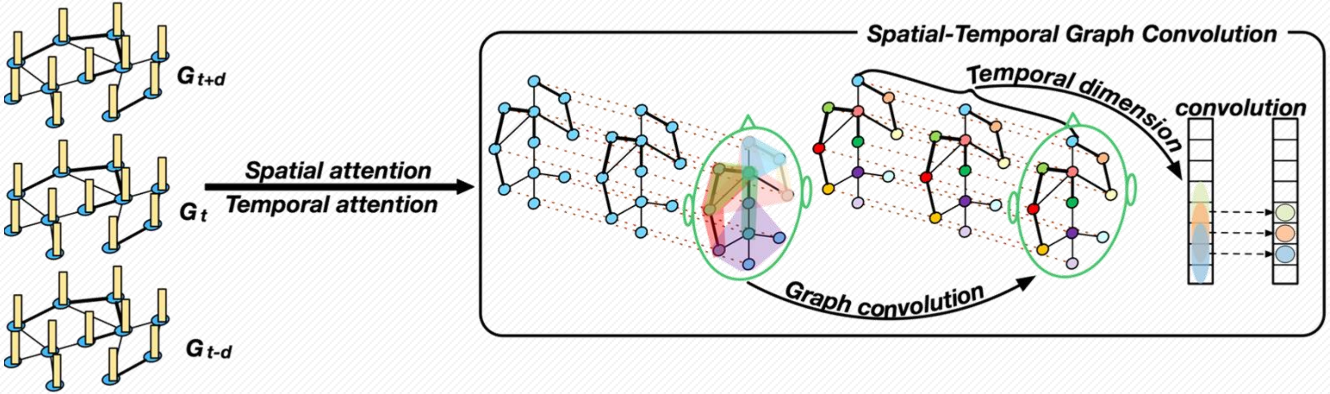
Methods

C2: **How to extract spatial-temporal features?**

S2: **We design a Spatial-Temporal Graph Convolution architecture.**

a) *Spatial dimension*: use graph convolution to extract spatial features.

- Use graph convolution based on spectral graph theory.
- Employ the Chebyshev expansion of graph Laplacian to reduce computational complexity.



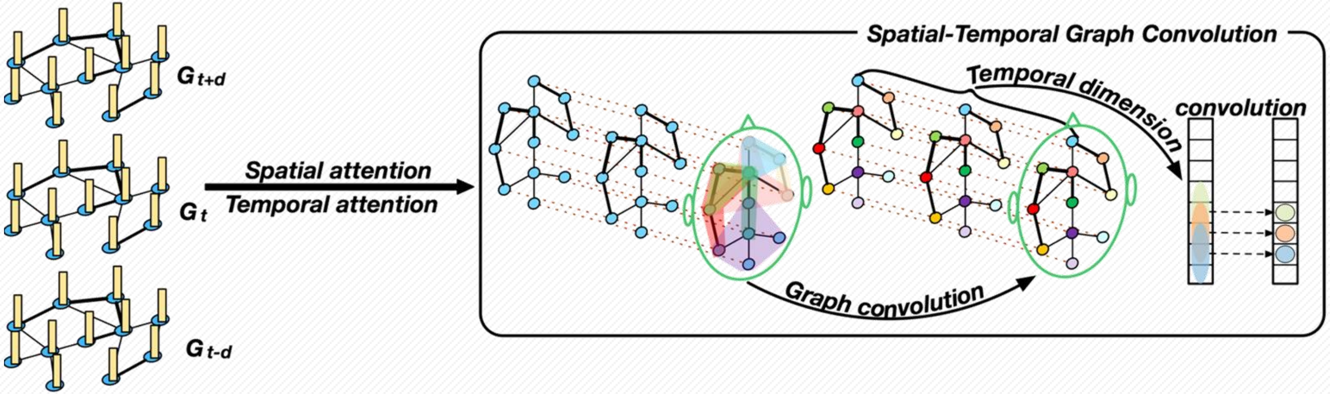
Methods

C2: **How to extract spatial-temporal features?**

S2: **We design a Spatial-Temporal Graph Convolution architecture.**

b) *Temporal dimension*: employ CNN to perform convolution operation to capture the sleep transition rules.

c) *Spatial-Temporal Attention*: automatically extract valuable information.



Experiments

Dataset:

Montreal Archive of Sleep Studies (MASS)-SS3 dataset [7]

- PSG recordings from 62 healthy subjects (28 male and 34 female).
- Experts classify these PSG recordings into five sleep stages (W, N1, N2, N3, and REM) according to AASM standard.
- We extract DE features from the raw signal.

Stage	W	N1	N2	N3	REM	Total
Samples	6357	4829	29777	7651	10566	**59180**
Ratio	10.7%	8.2%	50.3%	12.9%	17.9%	**100%**

Number of samples for each sleep stage

Experiments

Baseline:

- **[Dong *et al.*, 2017][8]**: A mixed neural network, which combines multilayer perceptron (MLP) and LSTM, and also compare its performance with RF and SVM.
- **[Supratak *et al.*, 2017][3]**: A model combines CNN and BiLSTM to capture both time-invariant features and transition rules among sleep stages.
- **[Chambon *et al.*, 2018][9]**: A temporal sleep stage classification use multivariate and multimodal time series.
- **[Phan *et al.*, 2019][2]**: SeqSleepNet changes the single sleep stage classification problem into a sequence-to-sequence classification problem by using attention-based bidirectional RNN (ARNN) and RNN.
- **[Sun *et al.*, 2019][10]**: A hierarchical neural network, which learns comprehensive features and sequence respectively.
- **[Jiang *et al.*, 2019][11]**: Robust sleep stage classification which uses multimodal decomposition and Hidden Markov Model (HMM) -based refinement.

Experiments

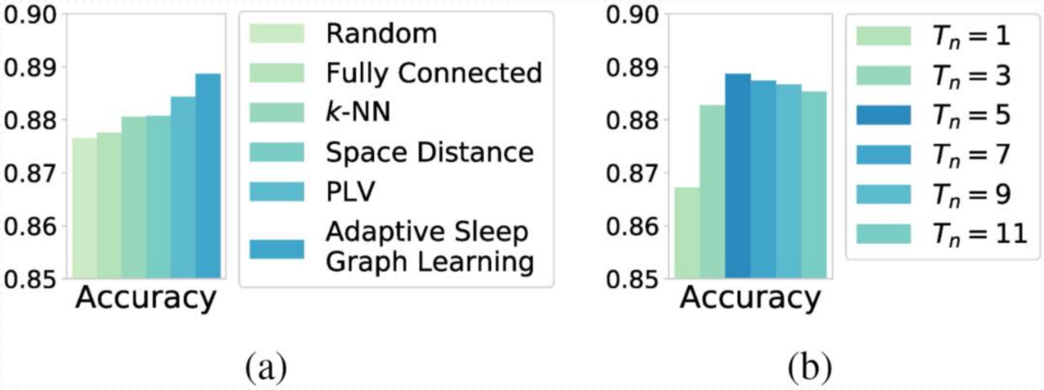
Comparison with the state-of-the-art models:

Method		Overall results			F1-score for each class				
		Accuracy	F1-score	Kappa	Wake	N1	N2	N3	REM
[Dong *et al.*, 2017]	SVM	0.797	0.750	-	0.786	0.487	0.861	0.825	0.792
[Dong *et al.*, 2017]	RF	0.817	0.724	-	0.782	0.351	0.880	0.815	0.794
[Dong *et al.*, 2017]	MLP+LSTM	0.859	0.805	-	0.846	0.563	0.907	0.848	0.861
[Supratak *et al.*, 2017]	CNN+BiLSTM	0.862	0.817	0.800	0.873	0.598	0.903	0.815	0.893
[Chambon *et al.*, 2018]	CNN	0.739	0.673	0.640	0.730	0.294	0.812	0.765	0.764
[Jiang *et al.*, 2019]	RF+HMM	0.808	0.793	0.710	-	-	-	-	-
[Phan *et al.*, 2019]	ARNN+RNN	0.871	0.833	0.815	-	-	-	-	-
[Sun *et al.*, 2019]	CNN+BiLSTM	0.881	0.824	0.819	0.912	0.551	0.916	0.826	0.914
GraphSleepNet	**Adaptive ST-GCN**	**0.889**	**0.841**	**0.834**	**0.913**	**0.603**	**0.921**	**0.851**	**0.919**

Table 2: The performance comparison of the state-of-the-art approaches on the MASS dataset

Experiments

Experimental Analysis:



- **Adjacency matrix**: The proposed adaptive sleep graph learning is superior to all fixed graphs.
- **Number of input sleep stage networks T_n**: The performance improves as T_n increases, and the best accuracy is achieved when $T_n = 5$.

Conclusion

Contribution:

- To the best of our knowledge, it is the first attempt to apply ST-GCN for automatic sleep stage classification. Moreover, we propose a novel adaptive sleep graph learning mechanism, which is integrated with ST-GCN simultaneously in a unified network architecture.
- We design a spatial-temporal convolution, which consists of graph convolutions for capturing spatial features and temporal convolutions for capturing the transition among different sleep stages.
- Experimental results demonstrate that the GraphSleepNet achieves state-of-the-art performance in sleep stage classification.

Prospect:

- The proposed model is a general-framework for multivariate physiological time series.
- It can be applied to time series classification, prediction and other related fields.

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Thanks!