Beijing Jiaotong University

SalientSleepNet: Multimodal Salient Wave Detection Network for Sleep Staging

Ziyu Jia, Youfang Lin, Jing Wang, Xuehui Wang, Peiyi Xie
and Yingbin Zhang

Introduction

Sleep

- Sleep takes up nearly a third of our life, and the quality of sleep has a direct influence on our physical and mental health.

Sleep Staging

- Five sleep stages: Wake (W), Non-REM 1 (N1), Non-REM 2 (N2), Non-REM 3 (N3), and REM.
- Recorded signals: polysomnography (PSG) (Include EEG, EOG, and other signal modalities).
- American Academy of Sleep Medicine (AASM) sleep standard[1].
- It is important for assessing sleep quality and diagnosing sleep disorders.

Introduction

Sleep Staging Methods

· ***Manual sleep staging:***

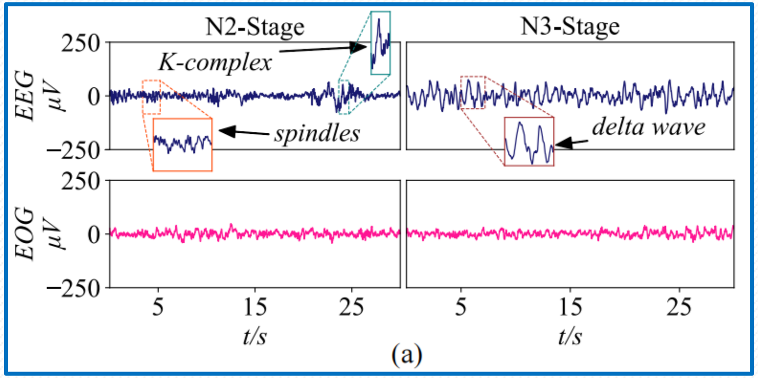
◆ Several sleep experts classify sleep stages.

◆ Labor-intensive and time-consuming.

· ***Automatic sleep staging based on machine learning:***

◆ Machine learning methods (especially deep learning methods).

◆ Improve the efficiency of sleep staging.



Related Work

Automatic Sleep Staging

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

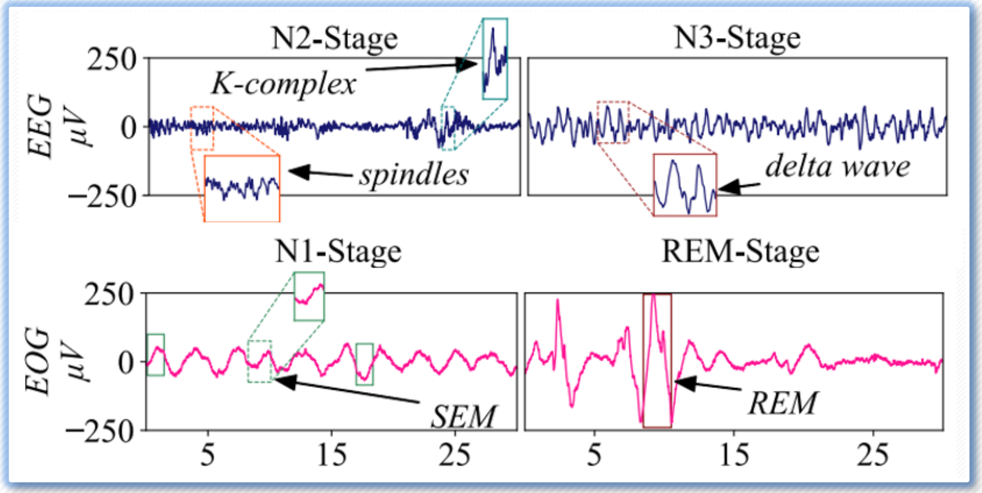
- SVM[2] and RF[3], etc.
- Rely on hand-engineered features that require a lot of prior knowledge.

· ***CNN and RNN:***

- DeepSleepNet [4], XSleepNet[5], etc.
- CNN extracts time-invariant features.
- RNN extracts sleep transition rules among sleep stages.
- Do not make full use of salient wave features and RNN is difficult to tune and optimize.

Challenge

· *C1*： **Directly capture salient waves from raw signals.**



Different sleep stages have different salient waves[1].

N2 stage: Spindle wave, K-complex wave

N3 stage: Delta wave

N1 stage: SEM wave

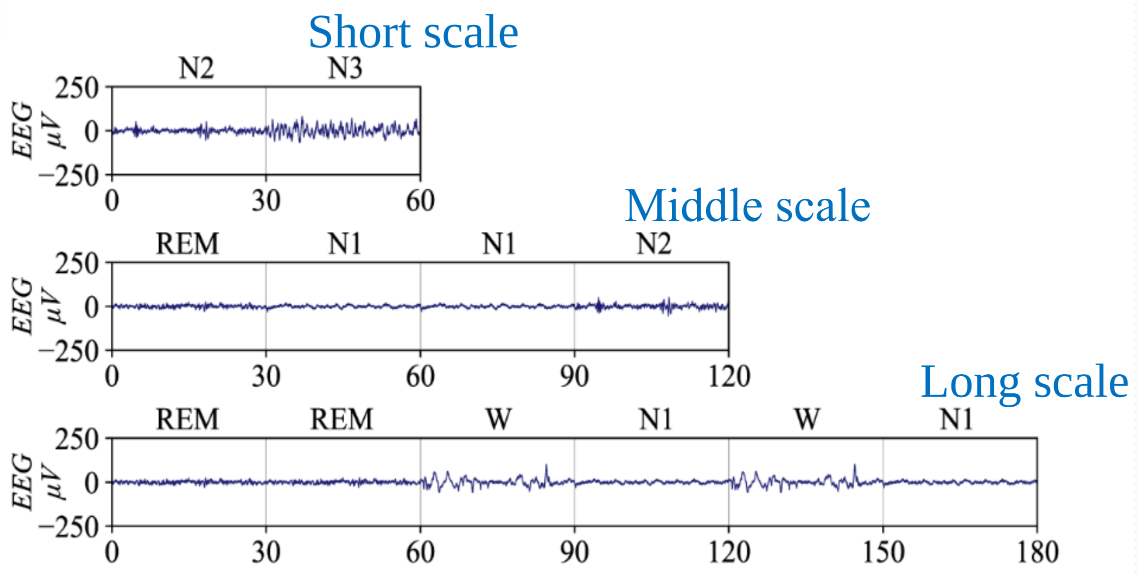
REM stage: REM wave

Some methods use time-frequency images as network input to ***capture salient waves indirectly***[5].

This may cause ***partial information loss***.

Challenge

· *C2*： **Effectively use multi-scale sleep transition rules.**

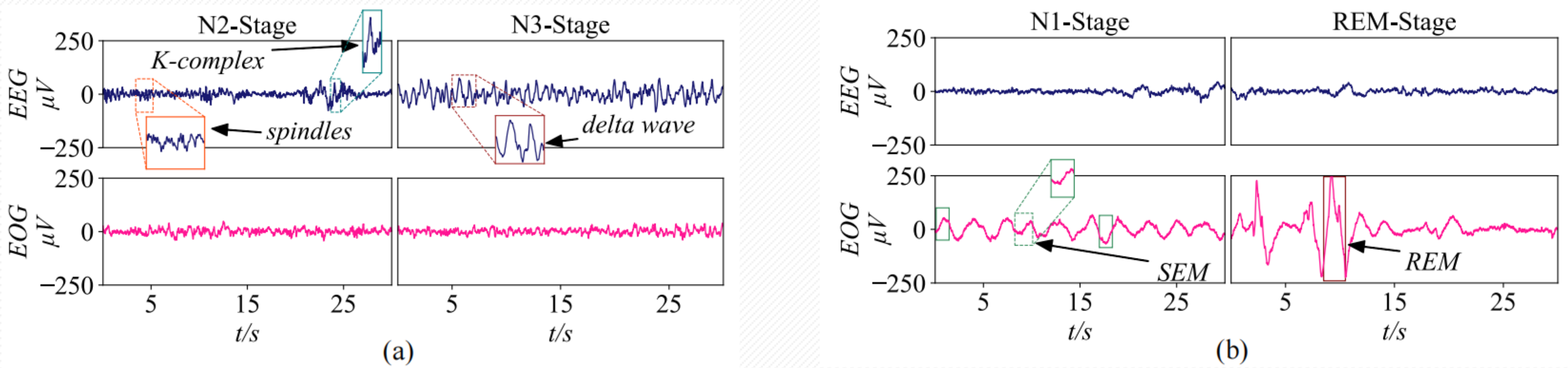


- Changing patterns of different sleep stages are summarized as transition rules in AASM.
- Experts determine the current sleep stage combined with its neighboring sleep stages.
- Transition rules have multi-scale characteristics.

Some methods use RNN to learn transition rules[4], which is ***difficult to turn and optimize****.*

Challenge

- *C3*： **Effectively utilize multimodal signals**

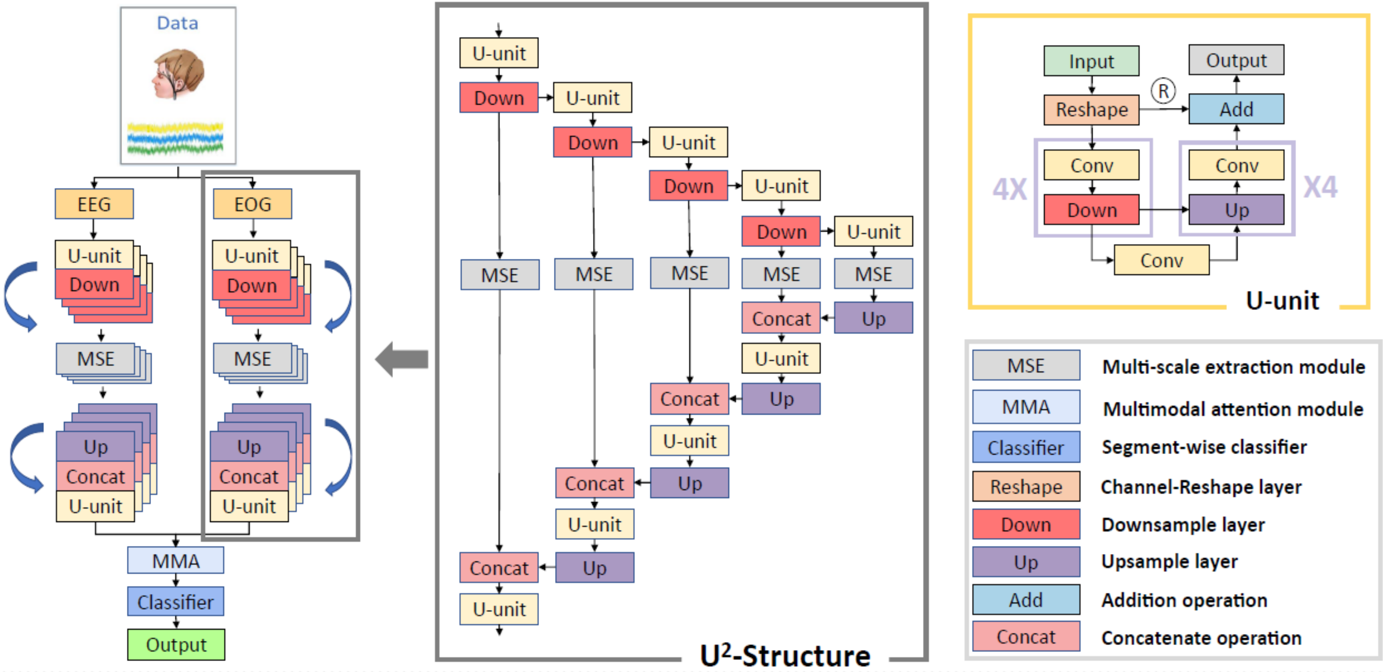


- Different modalities have different contributions to distinguish the sleep stages.
- EEG signals has more contribution to classify N2 and N3 stages. EOG signals contribute more to classify N1 and REM stages.

Existing works ignore that ***the contribution of each modality to the identification of specific sleep stages is different***[5].

Methods

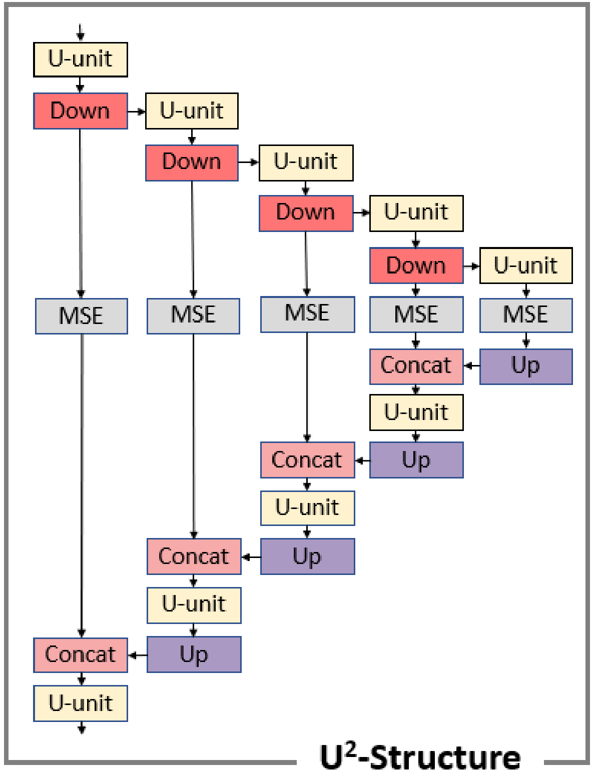
SalientSleepNet: Multimodal Salient Wave Detection Network for Sleep Staging



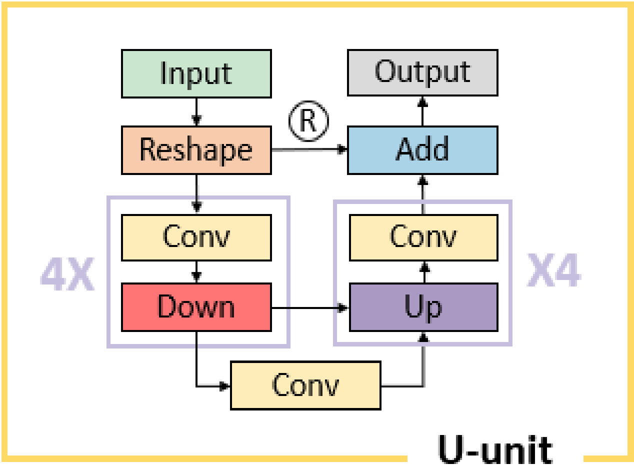
Contribution:

- Develop U²-structure to detect *salient waves*.
- Design a multi-scale extraction module to capture *sleep transition rules*.
- Propose a multimodal attention module to *utilize multimodal data effectively*.
- Achieve *SOTA performance* in sleep staging.

S1: U²-structure for salient wave detection

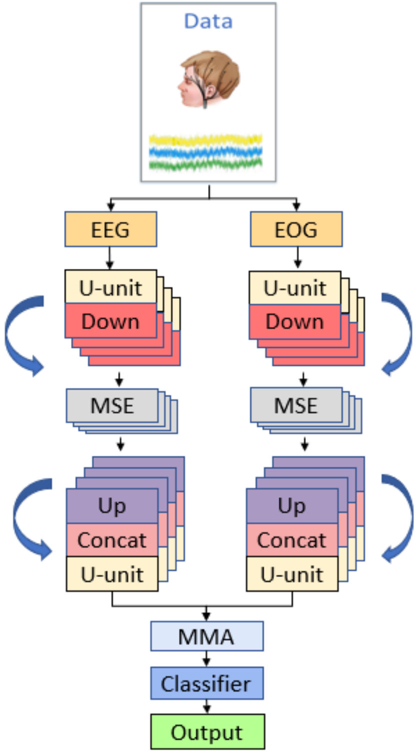


- 1D encoder-decoder structure
- Composed of multiple nested U-units.
- Inspired by U²-Net in salient object detection of images[6].



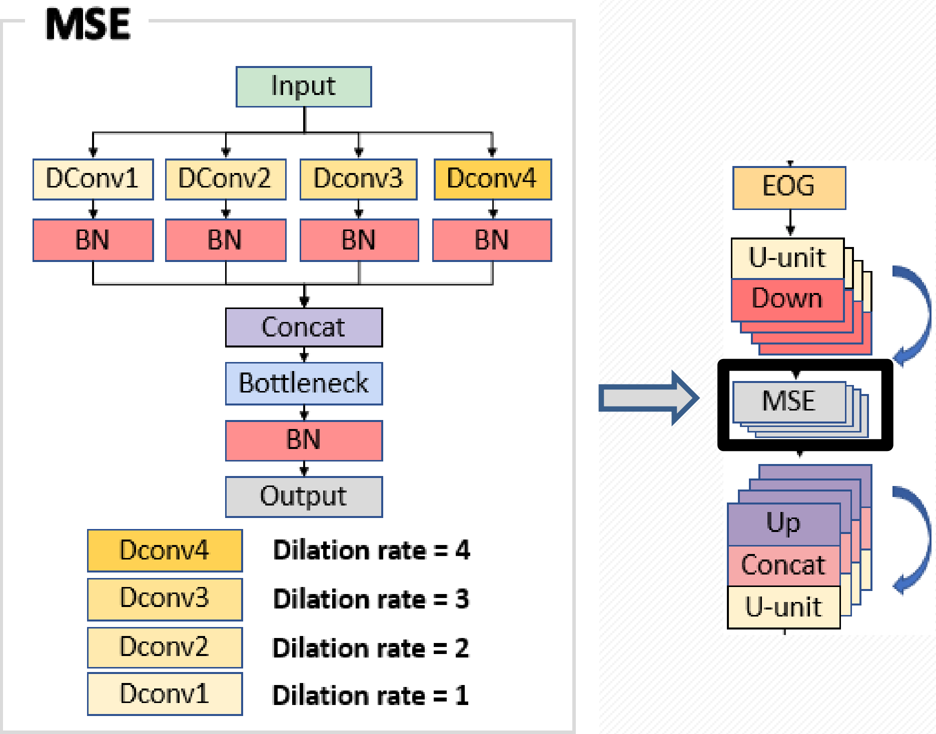
Methods

S1: U²-structure for salient wave detection



- Two-stream U²-structure.
- Raw EEG signals and EOG signals are input into two independent U²-structures.

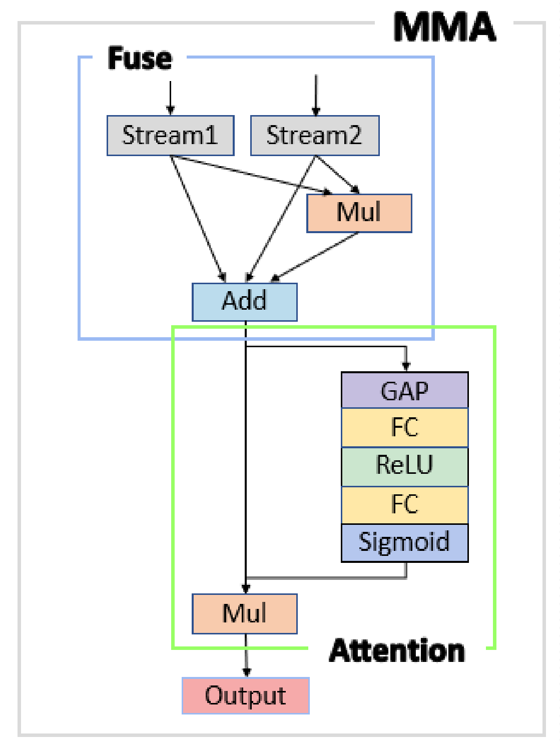
Methods *S2:* MSE for learning multi-scale sleep transition rules

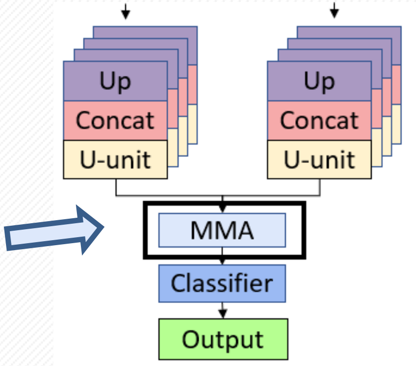


- **M**ulti-**S**cale **E**xtraction module (MSE) for explicit multi-scale sleep transition rules learning.
- Dilated convolutions with different dilation rates to capture features in different scales of receptive fields.
- Bottleneck layer for reducing parameters.
- Each encoder followed by a MSE.

Methods

S3: MMA for multimodal data learning



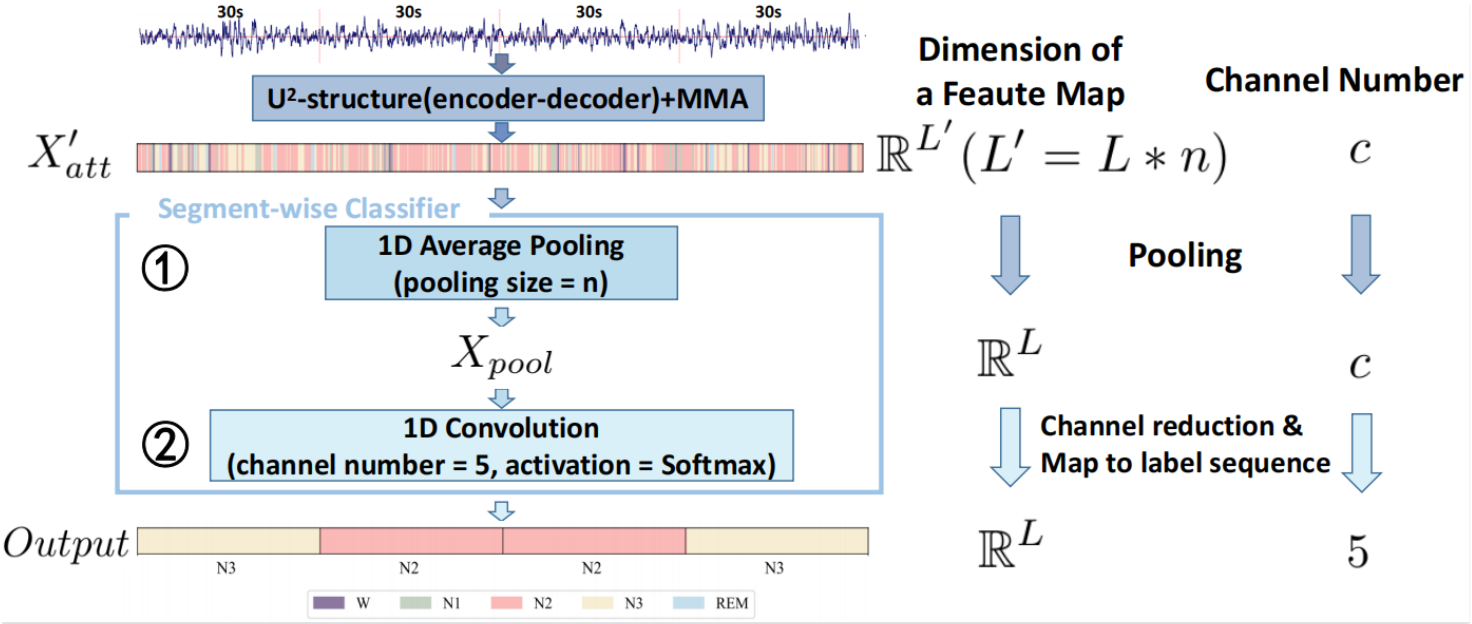


- **M**ulti**M**odal **A**ttention module (MMA) adaptively captures the important features of different modalities for certain sleep stages.
- *Modality fusion component* for fusing the feature maps from two streams.
- *Channel-wise attention component* for strengthening the most important features in an implicit way for certain sleep stages.

Methods

Segment-wise Classifier

- Mapping the pixel-wise feature map to a segment-wise predict label sequence.



Experiments

Dataset:

Sleep-EDF-39 & Sleep-EDF-153[7][8]

- **Sleep-EDF-39** consists of 42308 sleep epochs from 20 healthy subjects (10 males and 10 females) aged 25-34.
- **Sleep-EDF-153** consists of 195479 sleep epochs from 78 healthy subjects aged 25-101.
- Adopt Fpz-Cz EEG and ROC-LOC EOG channels.

Experiments

Baseline Methods:

- **SVM[2] & RF[3]:** Traditional machine learning method.
- **DeepSleepNet[4]:** Utilize CNN to extract time-invariant features and BiLSTM to learn the transition rules among sleep stages.
- **SeqSleepNet[9]:** Composed of parallel filterbank layers for preprocessing the time-frequency images and bidirectional RNN to encode sleep sequential information.
- **SleepEEGNet[10]:** Extract time-invariant features from the sleep signals and capture long short-term context dependencies.
- **SleepUtime[11]:** Map sequential inputs of arbitrary length to sequences of class labels on a freely chosen temporal scale.
- **TinySleepNet[12]:** Lightweight mixed model of CNN and unidirectional RNN.

Experiments

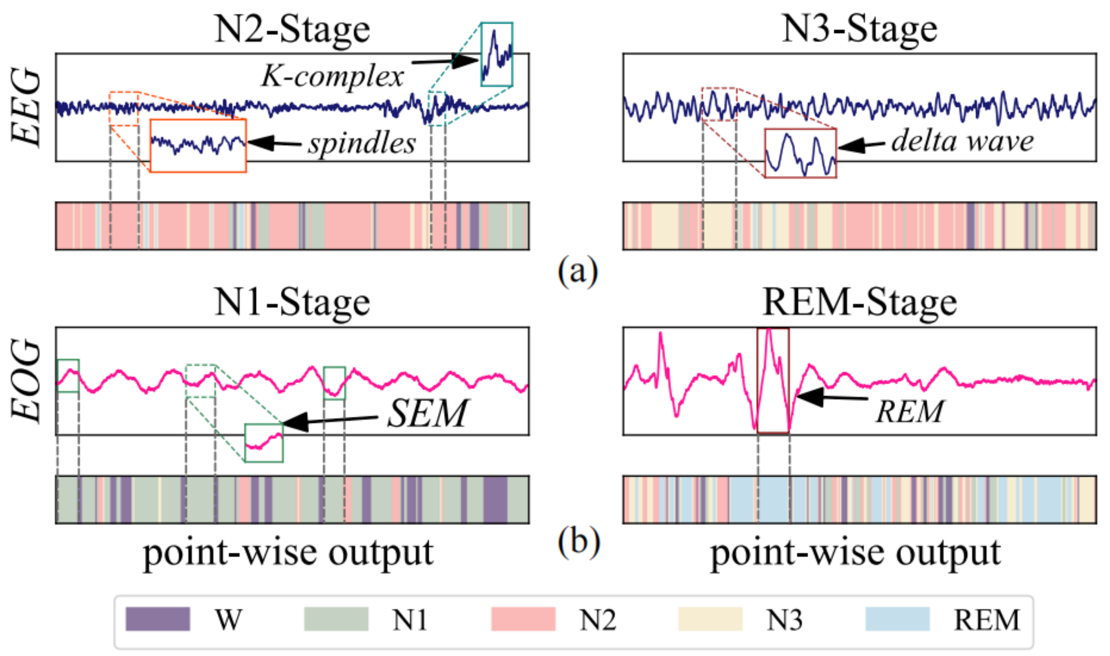
Comparison with the state-of-the-art models:

Method	Parameters	Sleep-EDF-39 dataset							Sleep-EDF-153 dataset						
		Overall results		F1-score for each class					Overall results		F1-score for each class				
		F1-score	Accuracy	Wake	N1	N2	N3	REM	F1-score	Accuracy	Wake	N1	N2	N3	REM
SVM	<0.1M	63.7	76.1	71.6	13.6	85.1	76.5	71.8	57.8	71.2	80.3	13.5	79.5	57.1	58.7
RF	<0.1M	67.6	78.1	74.9	22.5	86.3	80.8	73.3	62.4	72.7	81.6	23.2	80.6	65.8	60.8
DeepSleepNet	21M	76.9	82.0	85.0	47.0	86.0	85.0	82.0	75.3	78.5	91.0	47.0	81.0	69.0	79.0
SeqSleepNet	–	79.7	86.0	91.9	47.8	87.2	85.7	86.2	78.2	83.8	92.8	48.9	85.4	78.6	85.1
SleepEEGNet	2.1M	79.7	84.3	89.2	52.2	86.8	85.1	85.0	77.0	82.8	90.3	44.6	85.7	**81.6**	82.9
SleepUtime	1.1M	79.0	–	87.0	52.0	86.0	85.0	82.0	76.0	–	92.0	51.0	84.0	75.0	80.0
TinySleepNet	1.3M	80.5	85.4	90.1	51.4	88.5	**88.3**	84.3	78.1	83.1	92.8	51.0	85.3	81.1	80.3
SalientSleepNet	**0.9M**	**83.0**	**87.5**	**92.3**	**56.2**	**89.9**	87.2	**89.2**	**79.5**	**84.1**	**93.3**	**54.2**	**85.8**	78.3	**85.8**

Table 1: Performance comparison of the state-of-the-art approaches on Sleep-EDF-39 and Sleep-EDF-153 datasets. ”–” indicates the corresponding value not provided in the baseline models.

Experiments

Visualization: point-wise outputs of U^2-structure



N2 stage: Spindle wave, K-complex wave

N3 stage: Delta wave

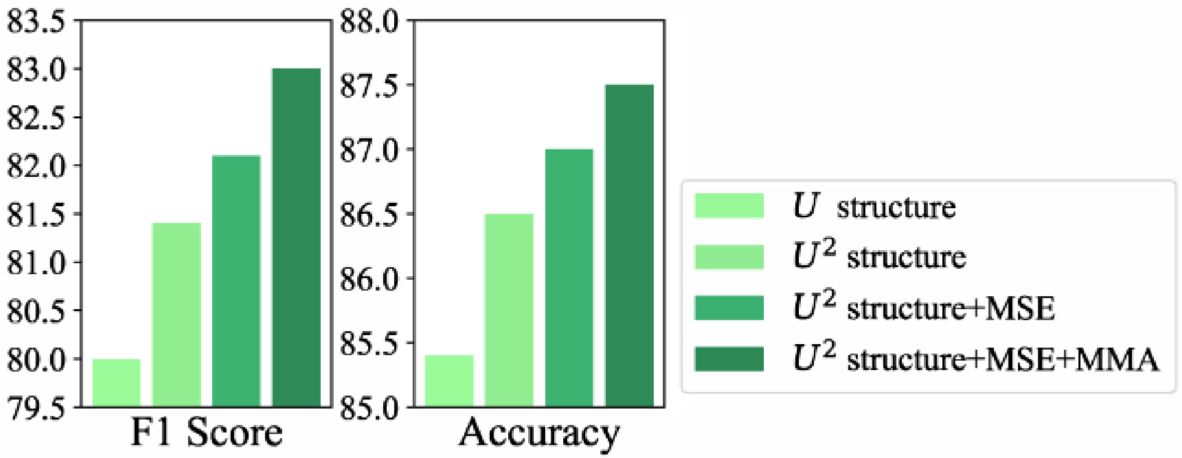
N1 stage: SEM wave

REM stage: REM wave

SalientSleepNet can detect salient waves in multimodal signals to a certain extent.

Experiments

Ablation Experiment:



- **U structure (basic):** A two-stream U structure without nested U-units, MSE, and MMA.
- **U2 structure**: The nested U-units are applied to the basic model.
- **U2 structure+MSE**: Add the multi-scale extraction modules based on U2 structure.
- **U2 structure+MSE+MMA (SalientSleepNet):** Add the multimodal attention module instead of a simple concatenate operation based on U2+MSE model.

Conclusion

Contribution:

- Our work is the first attempt to borrow the U^2-Net from the visual saliency detection domain to sleep staging.
- SalientSleepNet can effectively detect and fuse the salient waves in multimodal data.
- SalientSleepNet can extract multi-scale transition rules among sleep stages.
- Experiment results show that SalientSleepNet achieves state-of-the-art performance.
- The parameters of our model are the least among the existing deep learning models.

Prospect:

- The proposed model is a general-framework for multimodal physiological time series.

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Thanks!