SalientSleepNet: Multimodal Salient Wave Detection Network for Sleep Staging

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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\textsuperscript{[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\textsuperscript{[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.

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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 $U^2$-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.
**Methods**

**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

- **Multi-Scale Extraction 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

- **MultiModal Attention 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.

![Diagram showing the process of mapping feature maps](image)

- 1D Average Pooling (pooling size = n)
- 1D Convolution (channel number = 5, activation = Softmax)

**Output**

- Channel Number
- Dimension of a Feature Map: $\mathbb{R}^{L'} (L' = L \times n)$
- Pooling
- Channel reduction & Map to label sequence

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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.
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 U²-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.
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 U²-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!