End Sem Seminar

Sem 3 MTech AI

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Jumping Knowledge Based Spatial-Temporal Graph Convolutional Networks for Automatic Sleep Stage Classification

Publisher: IEEE
Journal Name: IEEE Transactions on Neural Systems and Rehabilitation Engineering
Impact Factor (2022): 5.26
Authors: Xiaopeng Ji, Yan Li, Peng Wen
Journal Publication: IEEE Xplore Digital Library (online publication)
Year of publication: 2022

Jumping Knowledge Based Spatial-Temporal Graph Convolutional Networks for Automatic Sleep Stage Classification

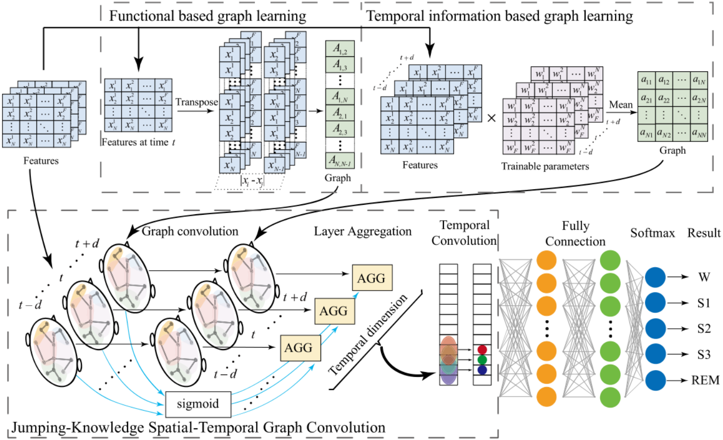

Figure: Architecture of the Proposed Solution

Key Problem Addressed

Key Problem:
Accurate classification of sleep stages from multi-channel bio-signals, such as EEG, EMG, EOG, and ECG, remains a complex task due to the spatial-temporal dependencies among different bio-signals. Existing models do not fully capture these interdependencies, resulting in suboptimal performance in automatic sleep stage classification. There is a need for a model that can effectively extract and learn both spatial and temporal features from these diverse bio-signals.

Proposed Solution

Proposed Solution:
The paper proposes a Jumping Knowledge Spatial-Temporal Graph Convolutional Network (JK-STGCN) to classify sleep stages. The model uses multi-channel bio-signals (EEG, EMG, EOG, and ECG) and extracts features through a CNN called FeatureNet. JK-STGCN utilizes adaptive adjacency matrices to capture spatial dependencies between different bio-signals from the same and neighboring epochs. A ”jumping knowledge” spatial-temporal graph convolution module is used to efficiently extract spatial features from the graph convolutions and temporal features from the standard convolutions, enabling the model to learn transition rules among sleep stages.

Dataset and Accuracy

Dataset:
The model was evaluated on the ISRUC-S3 dataset, which contains multi-channel bio-signals for sleep stage classification. Additionally, experiments were conducted on the ISRUC-S1 dataset to assess the generality of the model.

Accuracy:

Dataset	Accuracy	F1-Score	Cohen's Kappa
ISRUC-S3	0.831	0.814	0.782
ISRUC-S1	0.820	0.798	0.767

Table: Accuracy Results of JK-STGCN Model on ISRUC Datasets

Limitations and Justifications

Limitations:
While the JK-STGCN model shows promising results, its performance is constrained by the limited generalizability across diverse EEG datasets and sensitivity to noise in real-world EEG recordings. Furthermore, the model requires computational resources that may challenge real-time deployment in resource-limited devices.

Justification:
To address these limitations, future work will focus on enhancing model robustness to noisy signals, testing across larger, diverse datasets, and optimizing computational efficiency for real-time applications.

Conclusion

Conclusion:
The JK-STGCN model efficiently classifies sleep stages by leveraging multi-channel bio-signals and capturing spatial-temporal dependencies. Experimental results on ISRUC-S3 and ISRUC-S1 datasets show high accuracy and F1-scores, with significant improvements in computational efficiency. This model offers a promising solution for real-time sleep stage classification.

MixSleepNet: A Multi-Type Convolution Combined Sleep Stage Classification Model

Publisher: Elsevier
Journal Name: Computers in Biology and Medicine
Impact Factor: 7.7 (2023)
Authors: Xiaopeng Ji, Yan Li, Peng Wen, Prabal Barua, U Rajendra Acharya
Journal Publication: Elsevier's Computers in Biology and Medicine journal
Year of publication: 2024

MixSleepNet: A Multi-Type Convolution Combined Sleep Stage Classification Model

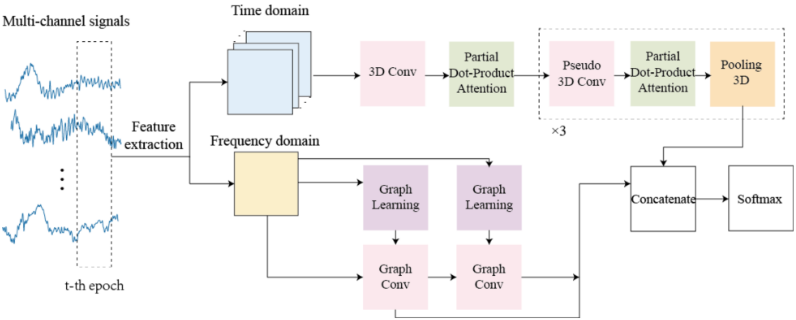

Figure: Architecture of the Proposed Solution

Key Problem Addressed

Problem:
Sleep stage classification is a critical step for sleep disorder diagnosis. Manual classification is labor-intensive and time-consuming for experts. There is a need for automated methods that enhance accuracy and efficiency while relieving experts from these demanding tasks.

Proposed Solution

Solution:
The paper proposes MixSleepNet, a novel multi-channel biosignal-based model combining 3D convolutional and graph convolutional operations. It processes EEG, EMG, EOG, and ECG signals to extract both time-domain and frequency-domain features. The 3D convolution branch explores correlations in time, while the graph convolution branch identifies connections between channels and frequency bands. This combination helps improve the performance of sleep stage classification.

Dataset and Accuracy

Dataset:
The model was evaluated on ISRUC datasets (Subgroup 3 and 50 random samples from Subgroup 1).

Accuracy Results:

Dataset	Accuracy	F1-Score	Cohen Kappa
ISRUC-S3 (Expert 1)	0.830	0.821	0.782
ISRUC-S1 (Expert 1)	0.812	0.786	0.756
ISRUC-S3 (Expert 2)	0.837	0.820	0.789
ISRUC-S1 (Expert 2)	0.829	0.791	0.775

Table: Accuracy Results on ISRUC Datasets

Limitations and Justifications

Limitations:
While MixSleepNet achieves high accuracy and F1-scores, its reliance on multiple biosignals (EEG, EMG, EOG, ECG) increases data acquisition complexity. Additionally, the model requires significant computational resources for training and testing, limiting its scalability for real-world, low-resource scenarios.

Justification:
Future work will focus on reducing dependency on multiple biosignals by enhancing the efficiency of single-signal processing. Further optimizations will aim to reduce computational demands for deployment in real-time sleep monitoring systems.

Conclusion

Conclusion:
MixSleepNet outperforms all compared models in sleep stage classification, demonstrating higher accuracy and F1-scores. The contributions of each module, including 3D convolution and graph convolution, were validated, showing their significance in achieving superior performance. The model provides a promising solution for automated and efficient sleep stage classification.

SleepXAI: An explainable deep learning approach for multi-class sleep stage identification

Publisher: Springer
Journal Name: Applied Intelligence
Authors: Micheal Dutt, Surender Redhu, Morten Goodwin, Christian W. Omlin
Journal Publication: Springer Applied Intelligence Journal
Impact Factor: 5.0 (2022)
Year of publication: December 17, 2022

SleepXAI: An explainable deep learning approach for multi-class sleep stage identification

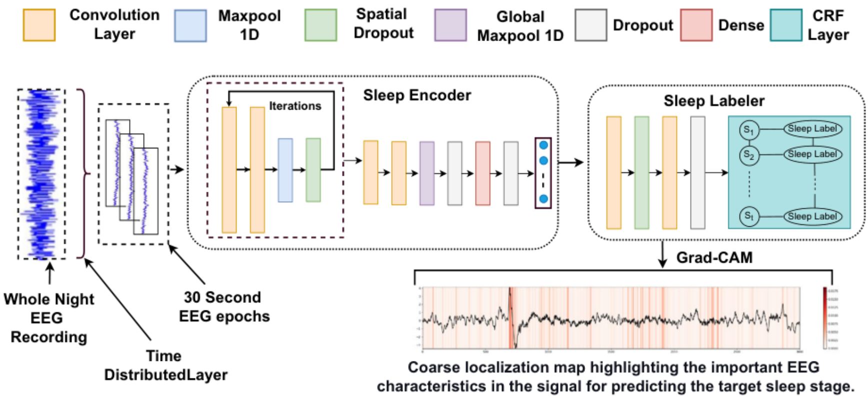

Figure: Architecture of the Proposed Solution

Key Problems Addressed

Key Problem:
Traditional automatic sleep stage classification methods, despite their high accuracy, lack explainability. Sleep specialists need models that not only classify sleep stages but also provide insights into how decisions are made.
Need for Explainability:
The interpretability of the classification process is crucial for clinical applications, ensuring that sleep specialists can trust the model's predictions.

Proposed Solution

Proposed Model:
A unified CNN-CRF model called SleepXAI is proposed for multi-class sleep stage classification using univariate EEG signals.
Explainability Mechanism:
Modified gradient-weighted class activation mapping (Grad-CAM) is utilized to provide insight into the parts of EEG signals that most influence the predicted sleep stages.
Model Benefits:
- Increased classification accuracy
- Clear visual explanation of model decisions

Dataset and Accuracy

Dataset:
The model was evaluated on the sleep-EDF dataset.
Accuracy Results:
- Accuracy = 86.8%
- Outperformed state-of-the-art models by 16.3% in classifying the N1 stage.

Limitations and Justifications

Limitations:
While SleepXAI significantly improves classification accuracy and provides explainability, the model's reliance on univariate EEG signals limits its ability to capture multi-channel interactions. Additionally, the explainability mechanism, while useful, may introduce computational overhead that affects real-time performance.

Justification:
Future work will focus on incorporating multi-channel EEG signals to enhance the model's robustness and reducing the computational complexity of Grad-CAM to improve real-time applicability in clinical settings.

Conclusion

Key Findings:
SleepXAI significantly improves sleep stage classification accuracy, achieving 86.8% on the sleep-EDF dataset. Additionally, it provides explainability through Grad-CAM, enabling clinicians to understand model decisions.

Clinical Relevance:
SleepXAI's ability to offer both accurate and interpretable predictions highlights its potential to support sleep specialists in clinical practice.

References

Ji, X., Li, Y., & Wen, P. (2022). Jumping Knowledge Based Spatial-Temporal Graph Convolutional Networks for Automatic Sleep Stage Classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. IEEE Xplore Digital Library.

Ji, X., Li, Y., Wen, P., Barua, P., & Acharya, U. R. (2024). MixSleepNet: A Multi-Type Convolution Combined Sleep Stage Classification Model. *Computers in Biology and Medicine*. Elsevier.

Dutt, M., Redhu, S., Goodwin, M., & Omlin, C. W. (2022). SleepXAI: An explainable deep learning approach for multi-class sleep stage identification. *Applied Intelligence*. Springer.

Let’s Dive Into Your Questions!

Questions !

Appreciation Time!

Thank You for Your Attention!