Sleep Arousal Detection from Polysomnography using the Scattering Transform and Recurrent Neural Networks

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Aims

Sleep Apnea Syndrome (SAS) is a serious sleep disorder that arises when breathing is interrupted during sleep. Interruptions may last from a few seconds to a few minutes. Untreated SAS can result in a growing number of health problems, including high blood pressure, stroke, heart failure, diabetes, depression. In this paper, we present a signal-processing/machine learning approach to detecting arousals in the thirteen-channel polysomnographic recordings of the Physionet/CinC Challenge2018 dataset.

Methods

Our network architecture consists of two components. Inputs were presented to a translation-invariant Scattering Transform (ST) representation layer which fed a recurrent neural network for sequence learning using three layers of Long Short-Term Memory (LSTM). The STs were calculated for each signal with an averaging window of 512 samples and half-overlapping frames, reducing the sampling rate to f_{out}=200 Hz/256=0.781 Hz (chosen to give approximately 1 s time resolution). The first two orders of the ST were retained, generating 42 coefficients per signal, a six-fold (256/42) data reduction. The LSTM layers operated at f_{out} with correspondingly downsampled arousal targets. We used ScatNet for the ST and Keras/Tensorflow for network training.

Results

To reduce computational load, we selected 200 subjects at a time from the training set. The network was trained on 80% and tested on 20% of the selected dataset, and we repeated this 4 times. The proposed approach detected arousal regions on the selected test set with an AUROC of 0.776±0.010 and an AUPRC of 0.184±0.055 (see Table 1 for full training and test results).

Conclusions

This large dataset presents computational challenges that we partially mitigated with ST and data partitioning. Our results show promising detection, but elevated false positives. More work is required to determine the most appropriate sampling rates, the most discriminating input signals and to adjust the network architecture and computational framework accordingly.

Table 1. Training and test results.

File selection	Training AUROC	Training AUPRC	Test AUROC	Test AUPRC
0-199	0.852	0.361	0.784	0.242
200-399	0.893	0.393	0.782	0.226
400-599	0.836	0.261	0.765	0.179
600-799	0.867	0.324	0.779	0.133
Overall (mean±std)	0.862±0.024	0.335±0.057	0.777±0.009	0.195±0.050