BodySleep: Estimating sleep states from respiration and body movements

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Abstract

We propose a method for automatically estimating sleep states from polygraphy (PG) sleep recordings by extracting features from actigraphy and respiratory inductance plethysmography (RIP) belts. These features are fed into a Recurrent Neural Network (RNN) for prediction. The method was developed on two different datasets, a private polysomnography (PSG) dataset, and a private self-applied somnography (SAS) dataset. Validation against a clinical PSG dataset shows that the method performs on par with human scorers.

Introduction

Being able to estimate sleep states from PG recordings, and thus provide a more detailed diagnosis in home sleep studies, is valuable. This is a challenging task since there are no guidelines on scoring sleep states in the absence of electroencephalograms (EEG). However, studies have shown that various changes occur in the body during sleep [1]. We present a novel automatic sleep state estimator which relies only on the RIP belts and actigraphy.

Results

Our method was evaluated on the clinical PSG dataset, using a five-fold cross-validation and a hidden test set.

The average F1-score is 0.88, compared to state-of-the-art score of 0.80 [2].

The Cohen's Kappa for the test set is 0.74 and 0.75 for cross-validation. As a reference, the range between human scorers on PSG recordings is 0.61-0.8 [3].

	F1-score	
	Test set	Crossval
Wake	0.71	0.73
REM	0.83	0.83
NREM	0.93	0.92
AVG	0.88	0.88

Conclusion

Our method is able to estimate sleep states in a PG study comparable to a human scored PSG study. This will enable sleep clinicians to provide a more detailed diagnoses when doing at-home PG studies, including estimating patient's sleep structure, identifying rem-related sleep apnea and improving sleep time estimation.

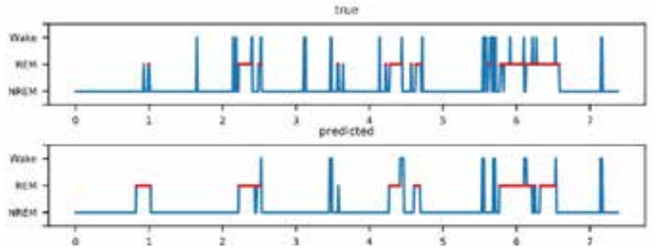
Methods

For each subject the movement of the abdomen and thorax was recorded using RIP belts (true DC-coupled signals). The signals were preprocessed and meaningful physiological features extracted. Deep learning was then trained and applied to map the features to sleep states.

Feature Extraction

Features were extracted from each 30 second epoch. These features were engineered to capture physiological changes which are known to occur during different sleep states [4, 5], as well as features indicating various statistical properties of respiration and respiratory rate.

- Respiratory rate variability
- Abdomen and thorax contributions
- Flow rate
- Tidal volume
- Movement from accelerometer

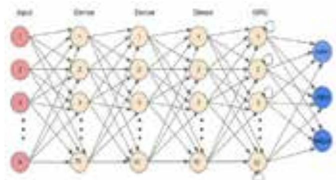


In the example above it is clear that our method successfully estimates the sleep stages

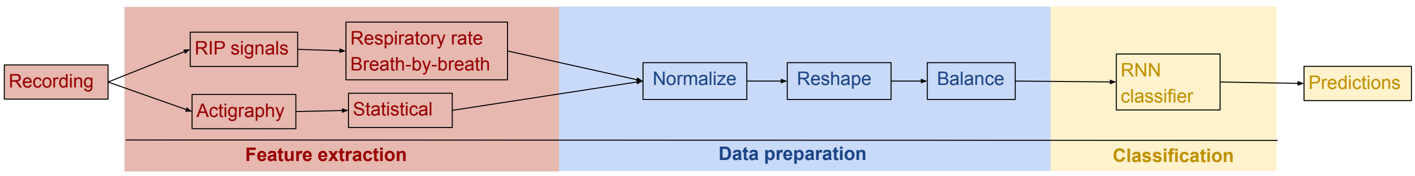
Classification

We implemented a 5 layer neural network with the following layers

- 3 dense layers, 70 nodes, ReLU activation
- 1 recurrent layer, 50 GRU blocks, ReLU activation
- 1 dense output layer, 3 nodes, Softmax activation



Before training, the input data was normalized, reshaped and balanced. The model was trained with Adam optimizer using a Cross-Entropy loss function.



Datasets

The PSG dataset consists of 176 PSG recordings recorded with NOX A1 and provided by the National University Hospital of Iceland. The training set contains 149 recordings and the test set contains 27 recordings.

The SAS dataset consists of 186 SAS recordings recorded with NOX A1. The training set contains 158 recordings and the test set contains 28 recordings.

References

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