Automated Detection of Sleep Disorder-Related Events from Polysomnographic Data

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Abstract

This work presents our effort in analyzing human biosignals collected during sleep studies, to automatically detect events related to sleep disorders. We experiment with real sleep data collected using standard Polysomnography (PSG), and our preliminary experimental results show that the event detection goal can be successfully achieved, while our methods can also be directly applied to sleep data collected using in-home non-invasive sensors.

Introduction

Problem: The National Heart, Lung, and Blood Institute estimates between 50 to 70 million Americans are currently suffering from some type of chronic sleep disorder (Fig. 1), the vast majority of which remain undiagnosed and untreated due to the inconvenience and high costs associated with sleep studies, using Polysomnograms (Fig. 2).

Goal: Our goal is to develop an alternative solution that allows in-home, non-invasive sleep monitoring and automated analysis of the collected data to detect, assess and monitor the progression of sleep disorders.

Findings: Our preliminary results using machine learning methods show that it is possible to automatically detect sleep disorder-related events with high accuracy. This is the first step towards sleep disorder assessment.

1. Insomnia
2. Sleep-related breathing disorders
   (a) Obstructive sleep apnea disorders
   (b) Central sleep apnea syndrome
   (c) Sleep-related hypoventilation disorders
3. Central disorders of hypersomnolence
4. Circadian rhythm sleep-wake disorders
5. Parasomnias
   (a) NREM-related parasomnias
   (b) REM-related parasomnias
   (c) Other parasomnias
6. Sleep-related movement disorders
   (a) Restless legs syndrome
   (b) Periodic limb movement disorder
   (c) Sleep-related Bruxism
   (d) etc.

Figure 1: ISCD-3 Classification of Sleep Disorders

Figure 2: Photo of a subject wired for a PSG study.

Background

Related research in sleep studies has focused on detecting various parameters of sleep for humans and animals as well as sleep quality and body posture recognition.[3] uses EEG and other signals and Markov modeling techniques to classify normal and abnormal human sleeping patterns. The authors in [5] evaluate classification results using spectral and non-linear analysis for feature extraction and Quadratic Discriminant Analysis (QDA), Linear Discriminant Analysis (LDA), k-NN and Linear Regression (LR) for classification. In [4] the authors try to assess sleep quality using near-infrared video only. The authors apply a homomorphic filtering technique to tackle the problem of over exposure in the center, common in near-infrared cameras.

Data

PSG Data were collected from real patients during sleep study sessions at the Texas State Slep Center are used for research purposes in anonymized format. 28 different signals with varying sampling frequencies were recorded by Profusion PSG 3 software (Fig 3).

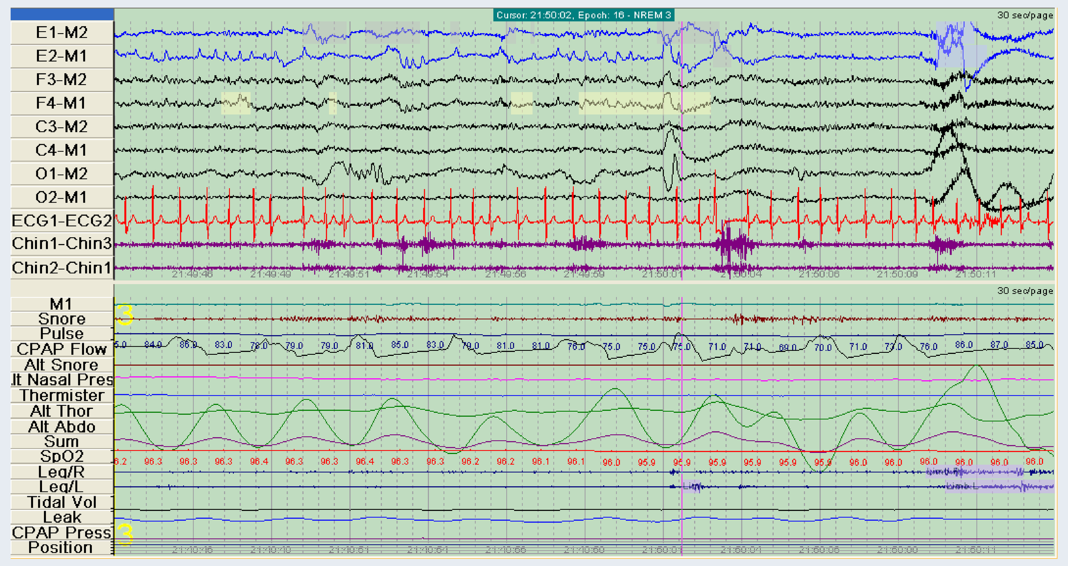

Figure 3: A 30-second epoch visualization of the signals recorded by Profusion PSG 3 software.

Signal features extracted (used for classification):

- Average and standard deviation of amplitude
- Power spectral density estimate peaks
- Energy/Power
- Energy entropy
- Zero crossing rate

Methods

Unsupervised Signal Segmentation: The adaptive signal segmentation technique described in [1] was implemented for better classification results than a fixed window segmentation. The signal is filtered to attenuate short-term variations and to allow for a more reliable segmentation. The filtered signal is then segmented based on changes of the amplitude and frequency using the Modified Varri method (Fig. 4).

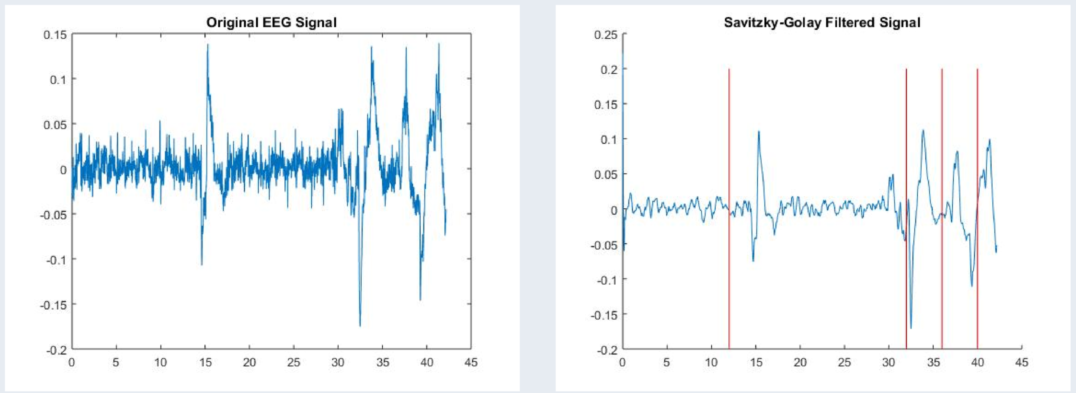

Figure 4: **Left:** Original signal. **Right:** Filtered and segmented signal.

Event recognition: The following sleep events were recognized using classification algorithms.

- Arousal Event *(Biosignals used: 8 EEG signals)*
- Left and Right Leg Movement *(Biosignals used: 8 EEG signals)*

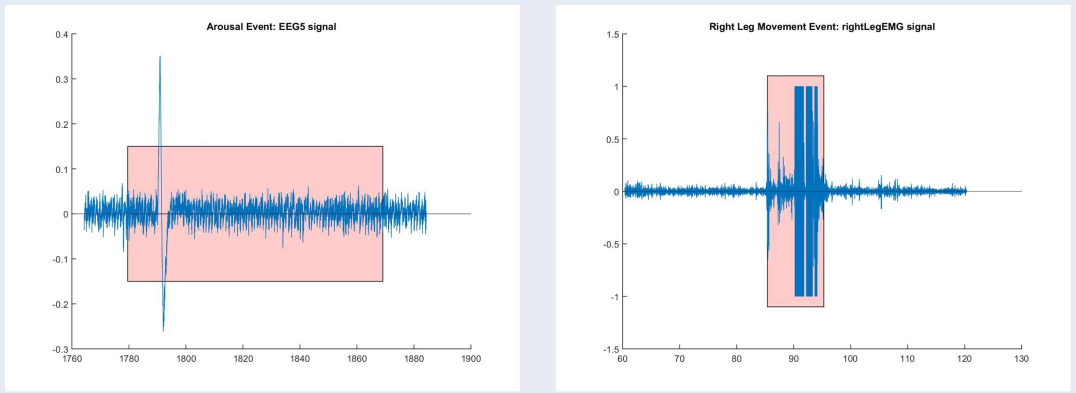

Figure 5: **Left:** Example of an arousal event (EEG signal). **Right:** Example of a leg movement event (EMG signal).

Classification Techniques [2]: We experimented with the following supervised learning algorithms, to assess their performance in detecting events of interest.

- Decision Tree
- Logistic Regression
- Naive Bayes

Event recognition is achieved by classifying each segment as containing or not containing an event of interest, thus reducing the detection problem to a binary classification problem.

Results

This section presents the event detection performance results by comparing the *Accuracy*, *Recall* and *Precision* values for each combination of classification algorithm and segmentation technique used.

Arousal Event

Fixed Window Segmentation			
Classifier	Accuracy	Recall	Precision
DT	85%	95%	88%
LR	78%	86%	88%
NB	78%	83%	91%
Adaptive Segmentation			
Classifier	Accuracy	Recall	Precision
DT	91%	99%	91%
LR	90%	97%	92%
NB	66%	67%	93%

Left Leg Movement Event

Fixed Window Segmentation			
Classifier	Accuracy	Recall	Precision
DT	75%	90%	80%
LR	74%	86%	82%
NB	68%	68%	89%
Adaptive Segmentation			
Classifier	Accuracy	Recall	Precision
DT	88%	98%	90%
LR	87%	96%	90%
NB	58%	58%	93%

Right Leg Movement Event

Fixed Window Segmentation			
Classifier	Accuracy	Recall	Precision
DT	75%	90%	80%
LR	74%	86%	82%
NB	67%	67%	89%
Adaptive Segmentation			
Classifier	Accuracy	Recall	Precision
DT	90%	99%	91%
LR	87%	95%	91%
NB	57%	57%	93%

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