

Characterizing Sleeping Trends from Postures

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Abstract

We present an approach to model sleeping trends, using a light-weight setup to be deployed over longer time-spans and with a minimum of maintenance by the user. Instead of characterizing sleep with traditional signals such as EEG and EMG, we propose to use sensor data that is a lot weaker, but also less invasive and that can be deployed unobtrusively for longer periods. By recording wrist-worn accelerometer data during a 4-week-long study, we explore in this poster how sleeping trends can be characterized over long periods of time by using sleeping postures only.

1 Monitoring Sleeping Postures

The traditional method of observing one’s sleep in a sleeping lab is despite fast-moving technological advances still cumbersome. Patients have to spend a few nights in the lab to get their sleeping behavior evaluated, and certain users such as children do not tend to feel comfortable with the many wired and body-worn sensors. Less accurate, but easier to wear over long periods, are actigraphy devices that have successfully been deployed outside sleeping labs to monitor trends over long-term periods, including proposed sensors that are worn each night [3] or continuously [5].

Early research has shown that sleeping quality manifests itself in a low amount of motion (i.e., few awakenings) during the nights [4], [1]. When regarded over a longer timespan, these motion models can be used to identify changes and abnormalities in sleeping behaviors. As an alternative (but complementary) approach, this poster suggests the use of sleeping postures and their sequences to describe sleep patterns, as they are a especially easy to record over longer time periods. Apart from using postures as basic descriptors for sleep trends, more information about the patient might be embedded in this information, as sleep specialists also study sleeping postures for monitoring disorders and revealing subjects’ personalities [2]. This poster will show a one month-long example to illustrate how such a monitoring system can be trained to estimate posture from a wrist-worn sensor, and use this to analyze sleep trends.

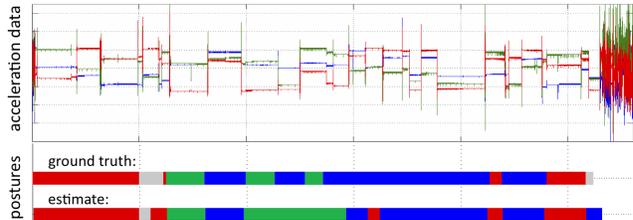


Figure 1. Accelerometer readings from a wrist-worn device (top) are used to estimate sleeping postures (bottom), for each night.

2 Estimating Sleep Posture from the Wrist

In a preliminary study, we reproduced work in [5] with accelerometers: two test subjects (one male of 29, one female of 32) were observed during five nights each, neither of the subjects suffering from a sleeping disorder and an accelerometer sensor being worn on the dominant wrist. Data is sampled at 100Hz and stored locally with time annotations. To obtain ground truth, a commercial IR night vision camera was chosen that can be easily deployed at home, storing an image each minute with the corresponding timestamp (with an average night resulting in 400-500 pictures).

After a nights’ recording, the subject was able to browse the recorded images from a bedside laptop and annotate them with the postures (using the postures from [5]). To minimize the annotation effort, a routine first analyzed consecutive gaussian filtered images for differences to present only unique ones. The threshold for this was recalculated each night, and compared against the differences between images. The final set presented to the subject contained 10 to 15 different posture images. The timestamps then allow relating the postures to the sensor data.

A sleeping posture manifests itself as a steady value over longer time window, whereas transitions are associated with high variance over a small window. An illustration is given in fig. 1 of the sensor values for one night, the filtered data after thresholding, and the according classification of postures. Our study confirmed earlier findings [5], showing sleep posture accuracy of 88% (using KNN, and 5-fold cross-validation: 86-88% precision and 80-86% recall).

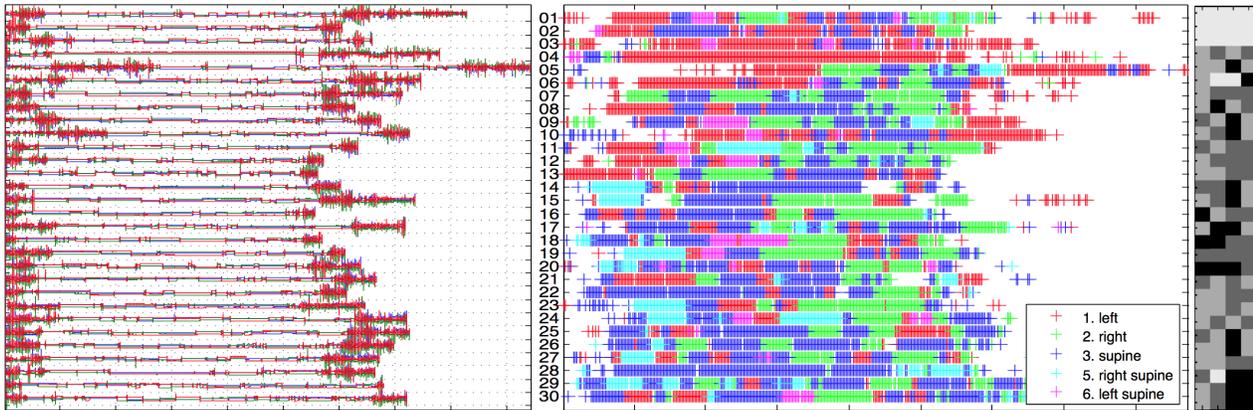


Figure 2. Dataset of a subject's 30 nights of sleep depicted as wrist-worn inertial data (left plot), raw posture classifications (middle plot), and the reported questionnaire scores (right table) per night.

3 Posture-Based Sleep-Modeling

As a scaled-up study of our system, a 30-nights data set was recorded with the aforementioned conditions for the male subject, to study the sequences of sleeping postures in the subject's night segments on a longer time scale and for a larger variety of night segments. For keeping track of sleep quality, a minimal version of a traditional sleep questionnaire was used, asking 8 questions in a subjective evaluation of sleep quality by the test subject before and after each night. All nights and the detected postures of the subject are shown in fig. 2. The left plot contains the raw sensor values obtained in 30 nights, whereas in the middle the detected postures are presented before filtering out those that only last for less than a minute. The right plot displays the results from the questionnaire, color-coded by having darker for higher scores and lighter ones for lower scores.

Although this figure presents a fairly coarse-grained view, with the data of just one subject and one month, certain patterns and observations are encouraging when analyzing fig. 2. Overall patterns can be witnessed, such as the fact that this subject tends to start the night by lying on his left or supine (lying on the back), and gradually is positioned more on his right towards the morning. Also, most nights in the first half of the month tend to start on the subject's left, while the second half (from the 14th day onwards) tend to start from the supine or right-supine posture.

When visually investigating the correlation between the sleep questionnaire and the different postures, it can be noticed that especially nights 29 and 30 are marked as poor in terms of sleeping quality by the subject. As can be expected, a higher number of posture transitions also occurred during these nights; Related to movement, the number of posture transitions is likely a good indicator for sleep quality. Similarly, night 8 was evaluated as better, with less posture transitions and following an overall regular sequence.

4 Conclusions and Future Work

This poster presented two studies on a simple but sustainable sleep posture detection technique with a cost-efficient, wrist-worn sensor. By using an especially non-invasive way of recording sleep information, we argue that this method might be complementary with other approaches to facilitate sleep research on the long term. These first studies have shown that with one 3D accelerometer on the wrist, sleeping postures can be estimated with relatively high accuracies (resp. 88% each for two subjects) given that they are trained on personal data, and that visualizing these postures over multiple days could offer an insight in sleeping trends.

On-going work focuses on how sleep models can be extracted using sleep postures as basic elements. As more data is recorded in our studies, closer collaborations with sleeping labs have been started in order to assess regular sleep and detect abnormalities: expertise will become especially needed during evaluation of further studies.

5 Acknowledgement

This work was sponsored by the project *Long-Term Activity Recognition with Wearable Sensors* (LA 2758/1-1) from the German Research Foundation (DFG).

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