Predicting Sleeping Behaviors in Long-Term Studies with Wrist-Worn Sensor Data

Marko Borazio and Kristof Van Laerhoven

TU-Darmstadt, Germany
http://www.ess.tu-darmstadt.de

Abstract. This paper conducts a preliminary study in which sleeping behavior is predicted using long-term activity data from a wearable sensor. For this purpose, two scenarios are scrutinized: The first predicts sleeping behavior using a day-of-the-week model. In a second scenario typical sleep patterns for either working or weekend days are modeled. In a continuous experiment over 141 days (6 months), sleeping behavior is characterized by four main features: the amount of motion detected by the sensor during sleep, the duration of sleep, and the falling asleep and waking up times. Prediction of these values can be used in behavioral sleep analysis and beyond, as a component in healthcare systems.

Keywords: sleep behavior, wearable computer, long-term studies.

1 Introduction

Approximately a third of our life is spent sleeping. With sleep researchers steadily discovering new ways in which sleep impacts quality of life, sleep is considered to be equally important to life as nutrition [3], while contributing significantly to regeneration and healing [1][6]. Scientists also analyze sleep to assess its quality and to discover potential irregularities [5]. While the significance of sleep was identified as an important factor in the medical field, it also attracted interest from psychology due to its impact on daytime behavior, and from an increasing group of consumers who want to keep track of their sleeping behavior. Different commercial products are available that estimate the quality of past nights. The Zeo [7], for example, uses a headband for recording brain waves and showing users how well they slept by assigning a sleep score to the data.

This paper contributes with a behavioral sleep model based on actigraphy-like motion data from a wrist-worn sensor collected in a long-term and continuous dataset of 141 days. From the original 100Hz sensor samples, user-specific data from nights is categorized into four different features, which built up the behavioral model. These features are: *amount of motion*, *duration of sleep*, *sleep start time* and *sleep stop time*. In this preliminary study, our model is capable of capturing regularities from working days, weekends, as well as from individual days of the week, enabling it to predict likely future sleeping behavior by observation of past nights, and discover irregularities that deviate from prior observations.

D. Keyson et al. (Eds.): AmI 2011, LNCS 7040, pp. 151–156, 2011.

In section 2 the sleeping features are first described, before focusing in section 3 on the method used to obtain the dataset for this study and performing a first evaluation, while explaining our preliminary results. We conclude this paper in the final section 4, giving an outlook on the tasks that still have to be performed.

2 Sleep Behavior

After multiple discussions with sleep experts in the medical field, we identified several characteristic features based on inertial-only measurements for characterizing sleeping behaviors. We will first describe these features and then discuss their value for current behavioral research.

Sleep Duration. Observing a person's hours slept gives an insight to the usual habits as well as to irregularities whenever a person is not reaching the usual amount of sleeping hours. Health care systems benefit from such information. Although there are different theories on how much a person should sleep, a deviation in the daily routine makes irregularities immediately visible.

Start and Stop Time of Sleep. The second and third descriptors of sleep are the falling asleep and waking up times. Persons tend to have regular habits, especially during working days, and therefore this feature is an important characteristic in a person's sleep behavior. People tend to go to bed earlier on working days in contrast to weekends.

Motion. Movement during the night is an indicator for sleep quality: increased movement is considered as a sign for a qualitatively bad night. Sleep scientists for example assign the amount of posture changes to a normal (15-20 posture changes) or abnormal night (over 30) [4]. Here, motion not only appears while changing postures, but also during spontaneous movements in the same posture. In order to describe a person's night, we use the amount of motion detected between non-motion segments.

Discussion. Sleep quality estimation is an interplay of the previously mentioned features. Extracting these features from long-term and especially continuous motion data is therefore important in such assessments. This work focuses on prediction of sleeping behaviors based on previous nights for following nights.

In interviews with sleeping specialists from the local sleeping lab, the value of the chosen features was discussed. Since sleep is usually investigated in sleeping labs, long-term studies are only conducted to assess a patient's circadian rhythm, which is simply the self-regulation of one's 24-hour cycle, including sleeping behaviors. Sleeping disorders like *Delayed Sleep Phase Syndrome* are usually immediately visible in such long-term observational studies. Although we focus in this work on sleeping behavior for night prediction, the importance in further studies is apparent and strengthens the selection of our features.

3 Night Time Prediction

The main reason for building a sleep model based on past behavior is to first predict a user's upcoming night to discover regularities as well as irregularities and evaluate a person's sleep on a long-term basis. We will illustrate how data is collected and further processed, resulting in a preliminary evaluation on night prediction.

3.1 Method and Dataset

The dataset used for this purpose was obtained from a healthy 30 year old male. An actigraph-like sensor was worn on the non-dominant wrist, recording inertial data at 100Hz from a 3D accelerometer, which resulted in an almost continuous dataset of 141 days. In the beginning of the recordings minor problems were experienced in the hardware, leading to a few gaps in the dataset. The last 105 days were then continuously recorded 24/7.

The data was further processed by extracting night segments with a threshold-based algorithm inspired by [2], which uses motion, light intensity and sleep time for classifying potential night segments. Ground truth is provided by a time diary maintained by the test subject. The resulting night segments are used to calculate the sleep duration given by start and stop time of sleep.

The amount of motion segments are identified as follows: over a window of $2sec$ the variance of the acceleration is calculated. Whenever the variance exceeds a threshold $vthresh$ of 1, a motion segment is being detected, until the variance is above $vthresh$. We experimentally estimated $vtresh$ by video observation.

3.2 Evaluation

The obtained features were used in two different scenarios. The first depicts how well the features describe usual sleep habits in the weekend (Friday and Saturday night) and during working days (Sunday to Thursday night). The second scenario displays what sleep habits the same weekdays exhibit.

Weekend vs. Working Days. We state that there is a significant difference between a person's sleeping behavior on weekends and that on working days. The weekends are defined by Friday and Saturday, due to the fact that the person is not working the next day.

In Figure 1, all examined nights (gray = working days, red = weekends) are displayed with the average falling asleep and waking up times depicted as black lines. By visual inspection, differences between weekends and working days are already visible, showing different patterns in both environments.

The features extracted for this scenario are displayed in Table 1. The difference in all features depicts the deviation between both, showing almost none in sleep duration and amount of movements, but a significant one in falling asleep and wake up times. As expected, the person falls asleep later on weekends, exhibiting a completely different pattern in contrast to working days. Interestingly, the user shows an average sleep duration of approximately 430 minutes for both environments, strengthening the theory that a person uses a typical amount of sleep. We conclude that it is possible to detect differences in sleeping behaviors on weekends and working days. In the next section a more fine-grained approach is performed by comparing same weekdays to each other.

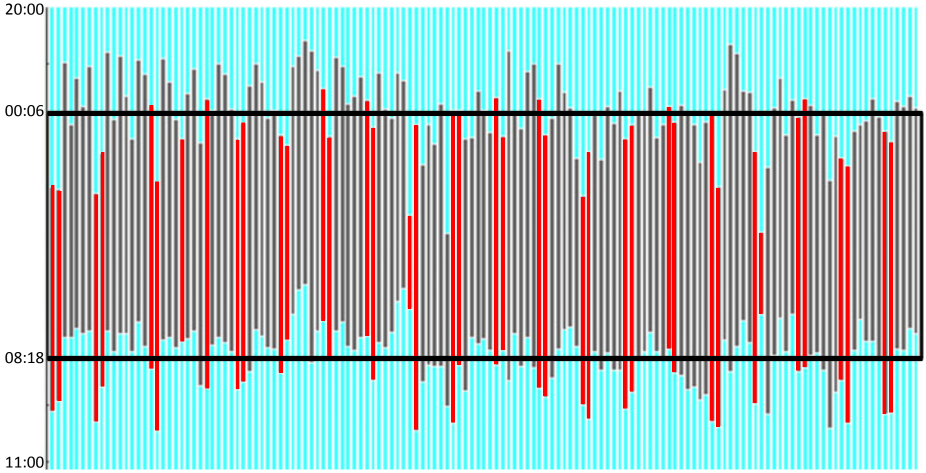

Fig. 1. All 141 nights (gray = working days, red = weekends) are displayed with portions of day data (blue) prior and after sleep. The black lines describes the average falling asleep and waking up times calculated on the whole dataset.

Table 1. Average sleep duration, falling asleep time, waking up time, and amount of movement for all nights, observed during week- and weekend days. The differences in the last row show for this data especially stark differences in the start and stop times.

	sleep duration	**start**	**end**	**#movements**
weekends	428 min	01:55	08:02	61
working days	434 min	23:47	07:01	59
diff	**6 min**	**2hrs 8min**	**1hr 1min**	**2**

Same Weekdays. Only a dataset of about six months makes it possible to gather a sufficient amount of data to observe which sleeping behavior exists on same weekdays. On average we obtained for each weekday 20 days to build the model. In order to examine the features for these days, we performed a leave-one-out cross-validation, by calculating for all other features the average and comparing the results to the day that was left out. For this, we used a threshold for all features, which displays how well the model fits to the night. The thresholds are: duration of sleep (+/-) 45 minutes, wake-up or falling asleep time each (+/-) 45 minutes and amount of motion-detections (+/-) 15.

The results are displayed in Table 2. Due to the limited space, only the final results are listed. The table shows how allocation of the same weekday to the model of the other same weekdays performed. Overall, we can state that crucial parameters for similar nights are *falling asleep* and *waking up times*. These are regular during all scrutinized nights, which strengthens the assumption that a person tends to follow a time-critical sleep habit. Although the sleep duration and the amount of movements vary a lot on same weekdays, these features need

Table 2. Accuracy results for the leave-one-out cross-validation over all weekdays (Sunday, Monday, ..., Saturday). The last row lists how well the four features were captured overall by the prediction model. As the start and stop times of sleep were important in this dataset, it is not surprising that their accuracies are also well predicted.

accuracy for...	sleep duration	start sleep	end sleep	#movements
Sundays	79%	95%	89%	79%
Mondays	62%	86%	90%	76%
Tuesdays	71%	76%	86%	76%
Wednesdays	76%	76%	100%	67%
Thursdays	53%	79%	63%	68%
Fridays	62%	81%	76%	52%
Saturdays	53%	89%	89%	42%
total	65%	83%	85%	66%

more individual analysis in the context of sleep quality. As stated in section 2, movement is an indicator for sleep quality, as well as sleep duration.

4 Conclusion

This paper illustrates how sleep data features can be used to describe sleep trends, on a continuous dataset of 141 days from a 30 year old healthy (not suffering from sleep disorders) male. We designed a model that, with the use of four features, characterizes trends such as weekdays, weekends and individual days. Furthermore, we could assess the test subject's night by our prediction model as a prior, using new nights as input to the model and categorizing them to regular and irregular nights.

We illustrated that our technique is feasible on this particular data set, modeling his normal nights, which can be put into contrast to a model of an irregular night. Further experiments are underway in a sleeping lab, monitoring multiple patients over a 6-month timespan – with nights in and outside a sleep lab, where all information of a patients sleep is gathered and analyzed by sleep scientists.

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