Accelerometer-based Sleep/Wake Detection in an Ambulatory Environment

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Abstract: It has been shown that poor sleep quality and stress are major causes for mental and physical health problems in developed countries. Thanks to advancements in wearable technology, remote patient monitoring has become possible, without the need of cumbersome and expensive equipment. A method for sleep/wake detection is proposed, using chest-worn accelerometer sensors. A total of 1727 nights from 580 individuals were analysed, resulting on the identification of an average sleep time of 463 min (SD=±80 min) per day. Our algorithm was able to automatically detect 483 min (SD=±97 min) of sleep. Results show that actigraphy with an accelerometer located at the chest has potential for sleep monitoring, though further research is required for further validation, preferably using polysomnography as a benchmark.

1 INTRODUCTION

Stress is regarded as one of the elementary factors for primary insomnia (Morin, et al., 2003). It has been shown that insomnia can have a significant negative impact on the life quality of an individual, including reduced work and cognitive performance (Léger, et al., 2002), (Durmer and Dinges, 2005) and an increased risk of developing obesity (Phillips, 2006), cardiovascular diseases (Li, et al., 2014) and depression (Morawetz, 2003). To date, the golden standard for investigating human sleep patterns is polysomnography. However, this procedure can be experienced as cumbersome, is expensive, and usually deprives the subjects from their familiar environment, which can lead to changes in their sleeping patterns. (Le Bon, et al., 2001). Over the past 30 years, the use of wearable technology has significantly improved, allowing ambulatory sleep investigation. Therefore, researchers are able to conduct experiments on a larger scale, outside a controlled laboratory environment, possibly resulting in more viable data as the first night effect could be reduced (Le Bon, et al., 2001). Actigraphy is considered to be a reliable method for sleep/wake detection (Littner, et al., 2003). Most actigraphy units are constructed in a watch like band shape that is either worn at the wrist or at the ankle. Sleep and wake patterns are estimated from periods of activity and inactivity based on registered movement in the device. (Littner, et al., 2003) Typically, actigraphy shows an accuracy for detecting sleep epochs between 87 and 90 percent compared to a polysomnography. (Meltzer, et al., 2012). This paper investigates the possibility for sleep classification using a chest-worn health device rather than a wrist or ankle-worn device, based on accelerometer data (ACC). The advantage of using such device, is that it is also capable of registering electrocardiogram (ECG) signals besides registering ACC data, which at a later stage, could provide more insight into physiology correlated issues with insomnia and sleep stages. A new method for sleep detection is required, since the chest oscillation during breathing is registered in the ACC data, causing false wake labelled positives, an issue that does not occur in traditional wrist worn devices. The aim of the study is to achieve a sleep detection accuracy equal to traditional actigraphy for the chest worn device. Data from 1002 volunteers over a 5 day consecutive period was used. The outcome of the algorithm was compared to diary input from the volunteers.

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2 METHODS

2.1 Subject Recruitment

Volunteers (n=1,002) were recruited from the active working population from 11 technology, banking, and public sector companies located in Belgium and the Netherlands. People were encouraged to participate through means of internal company communication and the distribution of flyers. Participants had a chance to win a dinner or travel voucher (11 vouchers for every 200 participants). The collected sample contained 481 males (48%) and 446 females (45%).75 participants (7.5%) did not report their gender. The participants were between the age of 21 and 65 ($\bar{x}$=39.5 ± 9.8). An informed consent was obtained from the participants prior to their participation in the experiment.

2.2 Data Collection Protocol

The data was collected over a period of two years, from 2015 till 2017. Prior to the start of the experiment, a survey had to be filled out containing personal information such as gender, age, health information, work related conditions and lifestyle. The experiment lasted over a period of five days, starting on Thursday and ending on Monday. During the experiment, participants were requested to fill in a diary using Ecological Momentary Assessments (EMAs) on a smartphone application. EMAs allow researchers to do frequent sampling of the behaviors of the participant in real-time. (Shiffman, et al., 2008) The application asked the participants 12 times per day, at random times, to rate their perceived stress level from the past hour on a 5-point Likert scale. Additionally, each morning, the participants were asked to fill in a sleep diary in which they had to annotate the time they went to bed, how long it took to fall asleep, the number of times they woke up and the time at which they woke up in the morning. The participants were able to fill in their sleep times freely, by using the smartphone keyboard. The time it took to fall asleep was a multiple-choice: 0-10 minutes, 11-30 minutes, 31-60 minutes or >60 minutes. If they reported it took more than 60 minutes to fall asleep or if they woke up at least once during the night, additionally the reason for not being able to fall asleep or waking up was asked.

Figure 1: A health device used in the experiment.

2.3 Sensor Information

Each participant was asked to wear a health device at the chest, for the duration of the experiment, i.e. five days continuously (fig1). This is a regulatory approved device, for recording ECG (256Hz) and triaxial accelerometer (ACC) (32Hz) signals. The data was stored on an SD card, and read out after the experiment was concluded. Before the start of the experiment, the internal clock of the device was synchronised to UTC. Participants were asked to remove the sensor in case they participated in a vigorous physical activity, in order to prevent potential damage from sweating.

2.4 Sleep Wake Classification

The most commonly referred sleep/wake detection methods for wrist actigraphy are those of Cole *et al* (Cole, et al., 1992) and Sadeh *et al* (Sadeh, et al., 1994) The findings of Cole *et al* are based on previous findings of Webster *et al*, who used equation eq. 1. (Webster, et al., 1982)

$$A = 0.025(0.15\ X_{t-4} + 0.15\ X_{t-3} + 0.15\ X_{t-2} + 0.08\ X_{t-1} + 0.21\ X_t + 0.12 X_{t+1} + 0.13\ X_{t+2} \quad (1)$$

In this equation, X(t) represents the sum of the digital activity values of the Medilog1 recorder for all 30 2-s data epochs in 1 min at time t. (Webster, et al., 1982). Activity indicator A is considered sleep if A<1. (Webster, et al., 1982). However, above stated activity recognition methods are all based on wrist-based activity. When the activity is measured from the chest, there is a natural oscillation due to the breathing pattern. Therefore, there was a need for a modified sleep/wake detection, with a lower sensitivity. The analysis was performed in MATLAB and the classification is determined by the ACC recordings of the health device. Each 60 seconds the ACC signal was scored for activity (A). For each axis, the difference between the minimal and maximal g value was calculated, and the activity was determined by eq. 2.

$$A = 0.025(0.2X_{t-3}+0.2X_{t-2}+0.2X_{t-1}+0.2X_{t0}+0.2X_{t+1}) \quad (2)$$

Activity indicator A is considered sleep if A<1. X is the average maximal difference in g for each axis. t represents the time epoch in minutes of the signal, with t0 as the current minute. The sleep/wake state was evaluated based on activity indicator A (eq1), and stored as a Boolean true/false. From the moment the first 30 minutes of the Boolean stored sleep/wake indicator where label as sleep, the participant was considered asleep until the data indicated that the participant was up for at least 30 minutes, with a minimum of 120 minutes of registered sleep, in order to exclude potential daytime naps from the dataset. If participants did not fill in the sleep diary correctly in the morning, the data of the previous night was removed. In total 1727 nights were included for analysis.

2.5 Validation

The outcome of the sleep-wake classification algorithm is compared with the diary entries from the EMAs. The maximum falling asleep times were added to the reported time to bed, e.g. if the participant indicated it took 0-10 minutes to fall asleep, 10 minutes were added to the time to bed to find the time the participant actually fell asleep. We investigated for which percentage of the nights the reported sleep and wake times matched with the detected sleep and wake times based on the accelerometer data. Since self-reporting is not always accurate, a tolerance of 0, 10, 30 and 60 minutes was introduced, allowing the classification to differ 0, 10, 30 or 60 min respectively from the self-reported wake and sleep times.

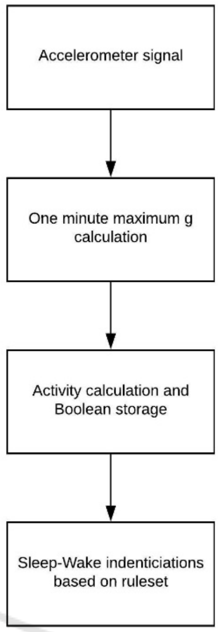

Figure 2: Flowchart for the sleep identification.

3 RESULTS

The tolerance scores of the algorithm are shown in table 1. A total of 1727 nights of 580 unique participants were analysed, and 81% of the nights fell within a 60 minute range in wake up and sleep time

Table 1: Population within tolerance.

Tolerance (minutes)	Population within tolerance for sleep time(%)	Population within tolerance for wake up time(%)	Population within tolerance for sleep time and wake up time(%)
0	49	23	13
10	70	51	37
30	82	80	67
60	90	91	83

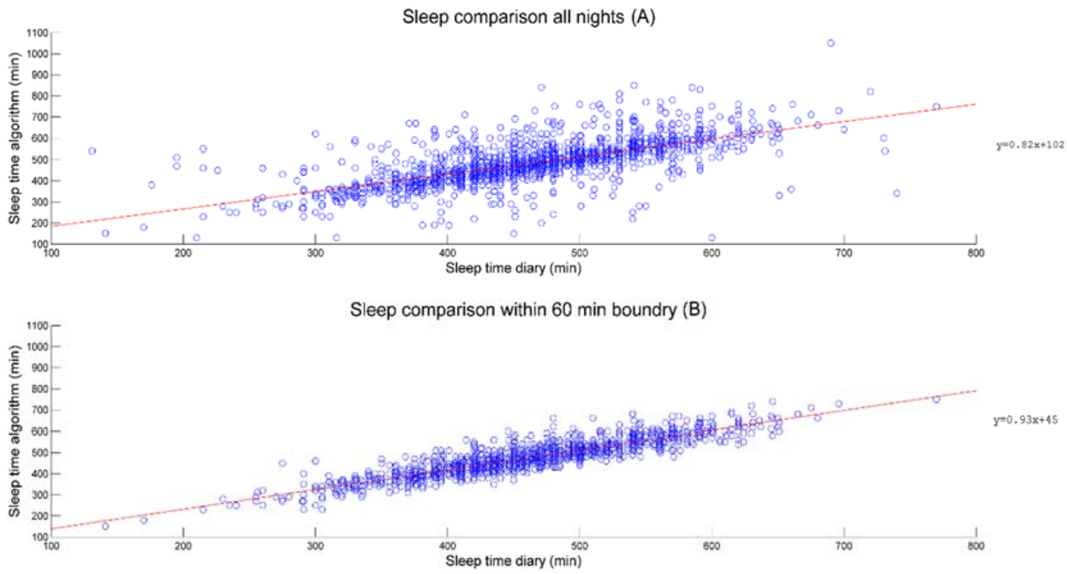

Figure 3: Scatterplot comparing the total sleep time (TST) of the diary and the algorithm for the entire population (A)-(n=1723) and the population within the 60 minute tolerance (B) (n=1427). Regression equation for the entire population is y=0.82x+102 and for the population within the 60 min tolerance y=0.93x+45. The root mean square values (RMSEs) are 75.72 and 38.08 for A and B respectively.

with regards to the diary entry. The average total sleep time (TST) of the population was 462 min for the data reported in the diary, with a SD of ±80 min, and 483 min for the data predicted with the algorithm, with an SD of ±97 min. The population that fell within the one hour tolerance had a TST of 460 min (SD=±76 min) for the diary and 472 min (SD=±78 min) for the algorithm. Reported average falling asleep times for the populations was 22 minutes (SD=±15 min). The RMSEs are 75.72 min and 38.08 min for A and B respectively. The correlation coefficient for the total estimated sleep time based on diary and algorithm was 0.69. For the population that fell within the diary boundary of 60 minutes, the absolute mean difference is 29 minutes (SD=±26 min), and the correlation coefficient between the sleep times is 0.90. A scatterplot comparing the algorithm and the diary TST is presented in figure 3.

4 DISCUSSION

On average, the algorithm overestimated the sleep period by 20 min. The overestimation of the TST is in line with other research. This is a known issue with accelerometer data, as it is difficult to distinguish the sleep onset (SO), wake after sleep onset (WASO) and stage 1 sleep, as activity is generally limited when one is falling asleep (Lockley, et al., 1999). Nevertheless, the agreement rate is within acceptable range, especially considering that the maximum range for falling asleep was subtracted from the TST, which is likely to be an overestimation of the reported SO. The current study has limitations regarding validation of the results, i.e. the lack of a comparison to a golden standard (polysomnography). Further research should investigate how the polysomnography, actimetry and self-reported sleep times are associated. Since the device used in this study also recorded the ECG, this could be used to further enhance the sleep/wake detection of the algorithm. Research has shown that the inclusion of ECG-based analysis can further improve the sleep wake detection, and could enable the differentiation between light sleep (stage 1 and 2), slow wave sleep (stage 3 and 4) and rapid eye movement sleep (Tal, et al., 2017). The data could potentially also be used for the detection of health hazards, opening the path for further usage of wearable sensors in ambulatory healthcare monitoring (Mezick, et al., 2013).

5 CONCLUSION

We have collected ambulatory physiological data of 1,002 subjects during 5 consecutive days and 4 nights, in combination with background information, and smartphone-based self-reports. 580 subjects from this dataset were eligible for this analysis. This paper provides a method to distinguish sleep and non-sleep periods on basis of accelerometer data, which can be used independent from the diary input. The usage of a chest located health device rather than a conventional wristband has the advantage that additional signals such as ECG can be recorded, without the need for additional sensors, which decreases the subject's discomfort during measurements. Our paper presents an important first step for further research in linking continues monitored physiological night-time data with psychological self-reports. This could be used to create a model for individual based feedback, granting personalised health information to the user of the device. The ECG data from this dataset could be used to further enhance the detection of potential health hazards, contributing for increased usage of wearable sensors for healthcare monitoring purposes in the future.

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