You Are How You Sleep: Personalized Sleep Monitoring Based on Wrist Temperature and Accelerometer Data

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ABSTRACT

Good sleep is a key component of good health, and as such, how to obtain quality sleep is of concern to many people. Circadian rhythms vary between individuals and play an important role in regulating sleep, however, they are currently not monitored by commercially available wearables. Previous work has shown that circadian rhythm is reflected in changes of wrist temperature. In this work, we present a prototype wristband that measures motion and temperature at the wrist. We developed an algorithm to detect wrist temperature increase onset, which is an indicator of the body preparing for sleep. Our results demonstrate that our algorithm is able to detect wrist temperature increase onset, which appears to occur at the same time for the same person. We also show that temperature increase onset varies between people as does overall temperature patterns between people. The detection of wrist temperature patterns gives us a deeper understanding of the mechanisms underlying sleep and could be a valuable component of a personalized sleep monitoring algorithm.

CCS CONCEPTS

• **Applied computing → Health informatics**.

KEYWORDS

Sleep, wrist temperature, circadian rhythms, wearables

1 INTRODUCTION

While most people know they have an internal biological clock, few are aware of the endogenous circadian rhythm within our body. Circadian rhythm is like a clock that regulates many biological processes including sleep/wake patterns over 24-hour cycles. For example, the secretion of melatonin, a hormone that regulates wakefulness and sleepiness, is controlled by circadian processes. While we can use willpower to stay awake all night, our circadian rhythms still cause us to feel sleepy. It has been shown that following a sleep/wake cycle that aligns with our circadian rhythm can result in better sleep [17]. Many people believe in the proverb "Early to bed and early to rise, makes a man healthy, wealthy, and wise". However, according to chronobiology [12], not everyone is genetically suited to the "early to bed and early to rise" lifestyle. In fact, the definition of "early" varies between person to person due to different circadian rhythms. Therefore, it follows that a better sense of our own circadian rhythms could help us manage our sleep/wake times accordingly to get better sleep.

Recently, wrist temperature has been shown to be an effective alternative to measuring Core Body Temperature (CBT), which is the current circadian rhythm phase marker gold standard. Wrist temperature has been shown to increase at night before people fall asleep and drop drastically when people wake up [14]. Wrist temperature increase onset (i.e., where the body starts preparing for sleep) has also been shown to be highly correlative to Dim Light Melatonin Onset (DLMO), another circadian phase marker gold standard [11]. Compared to CBT and DLMO, which are done with rectal measurements and saliva analysis respectively, measuring wrist temperature is unobtrusive, convenient, and can be done continuously.

With the rapid development of mobile technology, many commercial smart wristbands or smart watches have developed some form of sleep monitoring. Fitbit and Apple Watch estimate users' sleep quality based on body movement and heart rate. While these biometrics are useful in evaluating sleep duration, they are an "external observation" of sleep; they can only tell you about how you slept. In other words, current wearables can tell you that you had a bad sleep but as they cannot monitor circadian rhythms, therefore cannot help align your sleep/wake times to match your body's ideal times with respect to biological processes. In addition, as most sleep detection is based on accelerometer sensors and supervised learning algorithms, existing works [6] suggest that sleep/wake status can be better detected with a personalized algorithm that aligns with our own sleep habits and needs.

This paper presents the development of a wearable wristband that consists of a temperature sensor and a 3-axis accelerometer to investigate the integration of circadian rhythms into sleep evaluation. Specifically, we focus on extracting circadian rhythms from wrist temperature patterns and compared the extracted circadian markers among all participants. This information helps to evaluate and improve our understanding of personalized sleep. We present our work in following stages:

- Development of a novel algorithm to estimate robust wrist temperature increase onset.
- Comparison of wrist temperature patterns of different people, including an analysis of how wrist temperature trends behave if an early sleeper and a late sleeper sleep at the same time.

2 RELATED WORK

The use of 3-axis accelerometers or actigraphy has already been shown to accurately detect sleep onset and offset [13]; most commercial smartwatches or smart wristbands measure and evaluate sleep quality based on accemetry data. Some wearables (e.g., Fitbit and Apple Watch) also integrate heart rate into their sleep analysis, which tends to make their algorithm more accurate. Recently, researchers built their own sleep monitoring systems based on programmable commercial Android Wear wristbands [5, 15]by using

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sensors such as microphones and light sensors to fuse data together and determine light/deep sleep stages. However, there is still little research (e.g., [2, 8]) that have tried to use an integrated single wearable to measure circadian phase indicators and no commercially available wearables exist.

Ortiz et. al. (2014) proposed a method that integrates temperature and accelerometer sensor data together to determine circadian phase. They calculated several phase markers by combining accemetry data and wrist temperature data using non-parametric methods. Specifically, by comparing the phase calculated from wrist temperature and the phase of DLMO, they found that wrist temperature can effectively predict circadian phase. However, they estimated the temperature increase onset based on wrist temperature patterns averaged over 10 days for 13 participants and did not consider the day/night temperature difference among different participants; their approach looked for changes in temperature as a percentage of an aggregated average temperature. In [10], wrist temperature and accemetry data was compared with polysomnography and found to be effective in sleep status estimation. Compared to their work, which focused more on validation of correlation between wrist temperature and circadian rhythms, our study aims to develop an integrated wristband that uses machine learning to evaluate sleep based on each individual's circadian rhythms.

3 METHOD

3.1 Wristband Design and Data Collection

As there are no available open-data wristbands with a temperature sensor that can measure the temperature of radial artery location, we built our own wristband by modifying a off-the-shelf accelerometer data logger Axivity AX3 sensor (Axivity, York, UK; 100Hz, $\pm 8g$, weight: 9g) to include an iButton DS1922L temperature sensor (Maxim, Dallas, US), as can be seen in Figure 1. We 3D printed a holder for the iButton and attached the sensor to the inside of the Axivity wristband. The DS1922L samples data every 5 minutes with resolution of 0.0625℃and sensitivity of 0.5℃. When the participant is wearing the wristband, the temperature sensor stays on the underside of the participant's wrist and therefore measures the temperature near the radial artery of the wrist.

Data was collected from 10 participants. After obtaining informed consent, participants were asked to fill out the Pittsburgh Sleep Quality Index (PSQI), which is a commonly used questionnaire to collect subjective sleep quality [3]. During the experiment, all participants wore the wristband 24-hours a day for 14 days (except showering) and kept a sleep journal noting when they slept and woke up every day and their subjective evaluation of their sleep quality, which was adopted from [9]. All the data collected by the wristband were stored in the built-in memory of each sensor during the experiment. At the end of 14 days, data were downloaded for offline processing.

The sleep/wake time from the sleep journal was used as ground truth; however, when participants reported that they forgot to record their sleep/wake time or experienced insomnia, sleep/wake times were extracted from accelerometer data. Based on observations of people's sleep data (see Figure 2), we calculated the average wrist temperature at daytime and nighttime and estimated

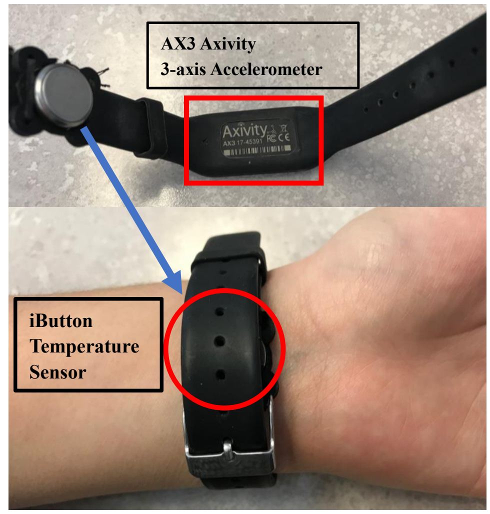

Figure 1: Custom-built temperature and accelerometry wristband

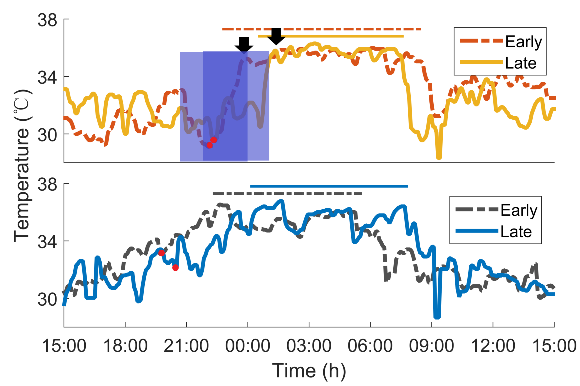

Figure 2: Wrist temperature patterns for (top) early sleeper and (bottom) late sleeper. For both, temperature plots are shown for an early-sleep day and a late-sleep day. The red dots denote the first wrist temperature increase onset time.The horizontal lines above the graphs denote when the person was asleep. The black arrows denote the beginning of elevated wrist temperature period while the boxes show a 3-hour period.

the increase onset for each participant. The methods we used are described below.

3.2 Wrist Temperature Analysis

3.2.1 Average Daytime/Nighttime Temperature Calculation. Using the sleep/wake time provided by sleep journal, we categorized wrist temperature to be daytime and nighttime temperatures by finding the timestamp of sleep onset and offset. Then we calculated the average daytime/nighttime temperature for each day as well as calculating the average temperature over 14 days. This was done to observe the temperature difference among the participants and

Table 1: Participant Demographics.

ID	Age	Gender	PSQI	Avg. SP (℃)	Avg. WK (℃)	Avg. Diff (℃)
001	23	M	4	35.072	33.001	2.071
002	25	M	5	35.091	32.342	2.749
003	23	F	7	34.049	31.705	2.344
004	22	F	5	35.487	31.707	3.780
005	21	M	4	35.157	33.124	2.034
006	26	F	4	34.873	32.859	2.014
007	25	F	11	35.611	32.342	3.269
008	26	M	6	35.043	30.247	4.796
009	26	F	3	35.951	32.587	3.364
010	21	F	3	35.278	32.616	2.662
Avg. SD	-	-	-	0.247	0.610	0.595

to help us determine how to better normalize wrist temperature in algorithm development.

3.2.2 Algorithm for Identifying the Onset of Wrist Temperature Increase. While wrist temperature trends are influenced by circadian rhythms, the wrist region is also exposed to many external factors. For example, the ambient temperature will influence the skin temperature; entering from outside to inside can cause substantial changes in wrist temperature. Factors such as these can "mask" circadian-driven trends of the wrist temperature. Therefore, we needed to create an algorithm that can use a person's past data to estimate the time of onset of rising wrist temperature, as this mitigates changes from extraneous factors.

To achieve this, we averaged wrist temperature for 24-hours (from 3PM to 3PM) for every three days based on timestamps provided by the sensor. Then, we extracted the elevated temperature period (i.e., the person's sleep period) using the algorithm described in [16] and identified the dip point from the beginning of that period. As shown in our previous work [16], when people delay their sleep, a second and sometimes third dip appears in the rising temperature before sleep onset. In order to identify the first dip point (i.e., the initial rising wrist temperature indicating the body preparing for sleep), we searched for the dip point at one hour, two hours and three hours prior to the onset of sleep, which was taken as the beginning of the stable high-temperature that indicates when a person is asleep. We used **findpeaks()** in Matlab 2015a to find the dip that had the lowest temperature within each time range. This enabled us to find up to three different dips within one to three hours for the averaged temperature pattern for every three days. For each participant we found the dips for the 14 days of data, after which we calculated the average dip time for the first dip. This average time was considered to be the wrist temperature increase onset for each individual; namely, the start of temperature increase caused by circadian rhythm that indicates the body preparing for sleep.

4 RESULTS

The demographics of the 10 study participants are presented in Table 1, as well as their average sleep/wake temperature. It can be noticed that participants' average temperature differences range

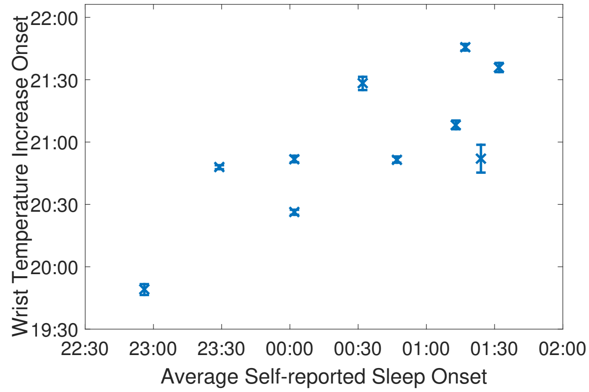

Figure 3: Estimated sleep onset from the first dip in wrist temperature prior to increasing temperature plotted against average time of sleep onset from sleep journals. Bars on the graph denote the variance of all the estimated temperature increase onsets for each participant.

from 2℃ to 4.8℃. This finding is in accordance with [14] and demonstrates that average changes in wrist temperature varies a good deal between participants.

Regarding sleep quality, people who might be experiencing sleep disturbance score 8 or higher on the PSQI [4]. A visual comparison of participants' temperature differences and PSQI scores suggests that there is no correlation between sleep/awake temperature difference and sleep quality. For example, participant 007 showed a possible sleep problem by having a score of 11; her temperature difference is 3.269℃. On the other hand, participant 006 has the lowest wrist temperature difference and has a PSQI score of 4. This aligns with results in[7].

In Figure 2, the wrist temperature patterns of two participants on two different days are shown. In the top figure, the orange dashed line represents the day when the participant started sleeping at almost 11:00 PM, while the solid yellow line shows the trend on one day when sleep onset was delayed to 1:30 AM. In the bottom of the figure, the grey dashed line represents an early sleep onset at 10:20 PM and the blue solid line shows a late sleep onset at around 12:15 AM. It can be observed that sleep occurred when temperature was elevated and temperature remains relatively stable throughout sleep. The wrist temperature started to rise at different time for the late and early participants. For the late sleeper, onset was around 10:10 PM, while the onset for the early sleep occurred at around 8:10 PM. In addition, both participants' wrist temperature patterns show a less-smooth temperature increase when they went to sleep late.

The increase onset detection algorithms described above were used to find the temperature increase onset (red dots) and beginning of the elevated temperature denoting sleep (black arrows) in Figure 2. Using these algorithms enabled us to find up to three different dips within one to three hours before the elevated temperature period. We check the accuracy of the algorithm based on a visual analysis was done with 60% of the total data to validate the algorithm's accuracy, the estimated onsets were all the same as manual observations. In addition,the variance of all the detected onsets was calculated - a smaller variance means good estimation as the wrist temperature increases at almost the same time everyday. By applying the wrist temperature increase onset searching algorithm, we extracted 7×3 potential onsets for each participant. Figure 3 shows the estimated dip of wrist temperature plotted against the average sleep onset time from the participant's sleep journal. The error bars which represent the variance of estimated onsets for each participant is also shown.

5 DISCUSSION

Similar to [1, 10], we integrated temperature and accelerometer sensors into a wearable. Our approach differs from the aforementioned studies as their wearable was worn on the participant's arm and has very low sampling rate (1 sample/30 seconds). The low sampling rate might filter out a minor body movement such as rolling over. Moreover, their sleep detection algorithm was not calculated for each participant, rather it was based on a manually optimized threshold across all participants.

As Figure 2 shows, wrist temperature patterns show personalized trends for different people. However, there are some trends that occur for everyone, such as a less-smooth rise in temperature and multiple dip points with delayed sleep. These results speak to some aspects that can be leveraged in developing personalized sleep algorithms. It can be seen in Figure 3 that the estimated onsets have low variance and occur within the same time range for most participants. This supports that people's circadian rhythm causes changes in wrist temperature at the same time everyday. It also indicates that the algorithm is accurately detecting the first dip time that indicates wrist temperature increase onset. Compared to the method used in [16], the algorithm presented here is also able to detect multiple dip times, which is an indicator that a person is delaying sleep. In addition, Figure 3 shows that the later the wrist temperature increase onset, the later the average sleep onset, which supports the detection of people's individual circadian rhythm pattern.

Our approach looks to build a personalized sleep monitoring system by assessing people's individual sleep patterns. In the future work, we will investigate sleep patterns and circadian rhythms of other two groups: (1) healthy older adults (> 65 years old), (2) older adults living with dementia (> 65 years old). We will focus on combining wrist temperature and 3-axis accelerometer features to build a an unsupervised sleep detection algorithm. Features (e.g., root mean squares, standard deviation and angles along each axis) from accelerometer data together with wrist temperature data (e.g., slopes of temperature trends, dip time) will be explored using unsupervised clustering algorithms, such as K-Means, to cluster the data into sleep/wake status. Furthermore, we will investigate whether delaying sleep onset could influence a person's activity the next day by calculating physical activity level based on the accemetry data. Correlations between the estimated wrist temperature increase onsets, wrist temperature trends, variations during sleep, and accemetry data will also be explored.

6 CONCLUSION

In this work, we focused on investigating how we might use wrist temperature patterns and its implied circadian information to support better individualized sleep analysis. To the authors' knowledge, this work is the first to outline a personalized sleep monitoring wristband with the circadian phase sensing. We believe that using a wrist-worn temperature sensor can help to better understand circadian rhythms and sleep patterns. This can then be used to give a better sense of quality of sleep as well as help to plan for better sleep. Future work includes evaluating how detection of one's circadian rhythm can be used to promote better alignment between sleep time and internal rhythms.

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