Sleepy Watch – Towards Predicting Daytime Sleepiness based on Body

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ABSTRACT

Daytime sleepiness, the difficulty to maintain an alert waking state during the day, is a serious problem causing vehicle accidents and adverse effects on well-being, health, and productivity. Our research aims at predicting daytime sleepiness using wearable sensing in everyday life to raise awareness and help people to manage their energy better. This study presents a first exploration of comparing body temperature (wrist, forehead, in-ear) with users alertness, measured over a reaction test: Psychomotor vigilance task (PVT) in 7 participants over 2 days in real-life conditions (168 hours in total). The results indicate a weak correlation between some body temperature measures and the PVT scores for certain subjects. This underlines that unobtrusive on-body temperature sensing can be an interesting modality to understand and explore daytime sleepiness.

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INTRODUCTION

Have you ever had a situation where it was hard to keep your eyes open? Then, you have most likely experienced an episode of excessive daytime sleepiness. We define daytime sleepiness as the difficulty of maintaining an alert waking state even during the day. Sleepiness and hours of sleep are inversely associated. In certain activities, such as driving, sleepiness is considered as a significant risk factor that substantially contributes to the increasing number of motor vehicle accidents each year. Besides vehicle accidents, the economic loss caused by sleepiness was reported in recent studies. Additionally, people seem bad in recognizing their level of alertness and sleep deprivation by themselves. Many researchers are working on detecting driver drowsiness. However, similar explorations on daily life's sleepiness are still very limited. So far, the COVID-19 pandemic lock-down has affected people's lives both physically and mentally. Boundaries of work and life were blurred, regular daily routines were forced to change, and stress was accumulated. According to some research, this situation has led the general public, especially female and young people, to poor sleep hygiene habits, such as sleeping hours reduction. From medical research, core body temperature seems to be a good measure for sleepiness. If daytime sleepiness can be detected in a rigorous but unobtrusive way, such as body temperature, it would bring a huge impact on our daily life.

APPROACH AND EXPERIMENTS

There are several methods to detect sleepiness and related cognitive states such as fatigue, alertness in the laboratory. Our research focuses on approaches to detect cognitive activities in real life.
Core temperature performs stable when people are staying in steady environment and changes in the opposite direction of the skin temperature. When sleepy or sleeping, core temperature drops, while skin temperature increases noticeably.
We want to use this effect to monitor sleepiness over the day with unobtrusive devices, measuring temperature on several body locations easily augmented with a wearable device: in-ear (headphones), wrist (smart watch), forehead (glasses).

We gave all participants 20s' trial before the formal test and generally explained sensors used in this study:

(1) An iButton Ds1922L temperature sensor(Maxim, Dallas, US)(See in Figure 1): Participants were asked to wear the iButton temperature sensor on their left wrists for a whole day from waking up till going to bed. Wrist temperature was collected once a minute.
(2) An infrared medical thermometer(Dretec, JP) and(See in Figure 3): Participants were asked to report their forehead temperatures and in-ear temperatures once an hour by using this infrared medical thermometer.
(3) A Mi Band 4: Mi Band 4 was used to record participants' sleep length before the test day.

Besides data collection from sensors, all participants were asked to do a PVT task lasting for one minute once an hour during the test period. After they completed PVT, participants were requested to measure and record their forehead temperature and in-ear temperature at this time by themselves. We also asked them to track their activities such as having a meal, taking a nap, and even drinking a cup of coffee.

RESULTS

In this study, we use the mean value of PVT in each session as its PVT score to evaluate the subject's sleepiness. Among the three types of body temperatures, we focused on exploring wrist temperature change because it can be tracked precisely without subject interaction. Also, different operations of the infrared thermometer, such as measuring angles, seem to affect the accuracy of in-ear temperatures and forehead temperatures. Therefore, we only use in-ear temperatures and forehead temperatures as supplementary data. We also recorded room temperatures of some participants data during the test period. Most room temperatures fluctuated within 0.5◦C to 1.4◦C which has larger fluctuation than in-ear and forehead range.

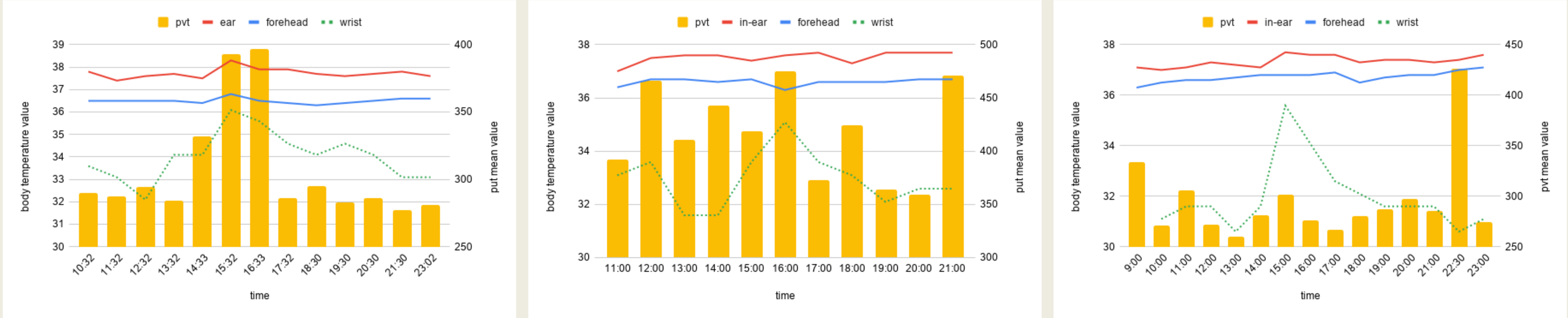

Figure2. Three types of body temperatures and PVT data in a day from 3 subjects whose wrist data were proved to correlate with corresponding mean value PVT scores.Subject f2 and subject f3 are females, while subject m1 is male.

We tested the correlation between overall wrist temperatures and mean PVT task scores by calculating Pearson's Correlation Coefficient. As Figure 4 shows, no linear correlation was found between wrist temperature and PVT mean value ($r = 0.026$, $p = 0.263$). However, we found for certain participants, who are subject f2, subject f3, and subject m1, moderate linear correlations existed. And each subject's result was summarized in Table 1. Figure 2 shows three types of body temperatures' changes and corresponding PVT values for subject f2, subject f3, and subject m1. Compare with in-ear and forehead temperature, the wrist temperature fluctuated more frequently and to a larger extent.

participants	r	pvalue
f1	0.067	0.636
f2	0.402	0.009
f3	0.430	0.046
f4	0.094	0.662
f5	-0.290	0.135
m1	-0.316	0.057
m2	-0.009	0.971

Table 1. Correlation between wrist temperature and PVT mean of 7 participants

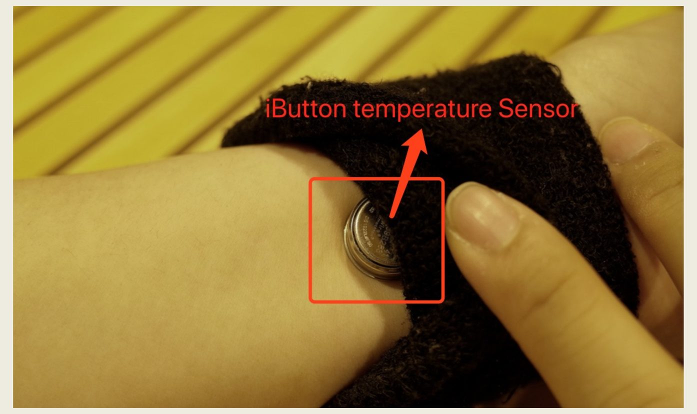

Figure 1. The iButton Ds1922L temperature sensor worn on the left wrist of participants during the experiment.

Figure 3. Control Measures of the forehead and in-ear temperature

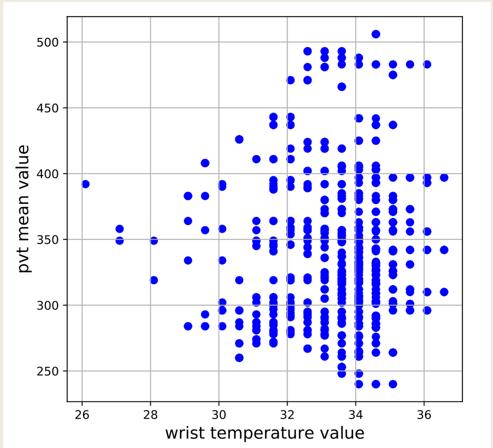

Figure 4. Correlation between wrist temperature and PVT

From the results above, though we failed to prove the correlations between wrist temperatures and PVT scores by using data mixed, we still found correlations exist within certain subjects. This may imply that the individual difference and corresponding calibrations can not be ignored when researchers try to estimate sleepiness in daily life. Furthermore, comparing with the change of in-ear temperature, forehead temperature, and wrist temperature (See in Figure 2), wrist temperature is more sensitive to alertness. Therefore, this may prove we can use wrist temperature sensors to detect even minor changes in alertness promptly.

CONCLUSIONS

Our results show some correlations between wrist temperatures and PVT scores within-subject. However, not all initial results were not all promising. Our findings still indicate that tracking wrist temperature to detect sleepiness might be possible in some participants. More data is required to conclude.

Data in this study were all collected from a real-life condition and we will make the data-set open to using for other researchers. This method of data collection is closer to a practical concept, but also inevitably led to some limitations. First of all, due to the long period of data collection, we only had 8 subjects joining this experiment so that it would be hard to train a real model for detection and prediction. Additionally, measuring temperature by participants themselves turned out to reduce data accuracy. In a follow up study we will prepare a training protocol on how to measure in-ear and forehead temperature for the participants.

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