

Sleepify: A system towards personalized and optimal sleeping environments

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Abstract— Sleeping quality is one of the indicator to associate human health in physical, mental, social and emotional functioning. From teeth grinding to night terrors, insomnia is serious enough to interfere human normal daily life [1]. As the rapid adoption in smartphones, mobile healthcare is a commonly used to acquire, transport, store, process and secure raw and processed data to deliver better healthcare system. This project aims to investigate the relationship between room temperature and human sleeping quality by developing a mobile healthcare system to improve sleeping quality. It is a system that provides optimal room temperature in real time for each user by using machine learning and acquiring physiological measurement of the user.

I. INTRODUCTION

It is estimated that people spend about one third of their life asleep. Good sleep is important for both the physical and psychological health of a person. For example, sleep aids in the healing and repair of the blood vessels and heart. Studies have shown that sleep deficiency has been linked to an increased risk of stroke, high blood pressure, heart disease and diabetes [2]. Sleep deficiency has also been linked to mental health problems such as depression, bipolar disorder and anxiety disorder. The mechanism of regulating sleep is complex, there are many factors which affect sleep quality, such as the psychology of a person. In addition, the thermal environment is a key determinant to achieving good quality sleep [3]. Furthermore, disturbed sleep affects not only physical and psychological health status, but also mortality rates in the elderly [4]. Previous studies conducted on human subjects have shown that sleep is strongly linked to thermoregulation - a process that maintains the body's core internal temperature at a constant level [3]. This mechanism is also controlled by sleep regulation and circadian rhythm. These findings indicate that maintaining a comfortable thermal sleep environment is important for a healthy life. Several other works have also investigated on the effects of room temperature on sleeping pattern in human [3][5].

These findings are our motivation for creating a product that improves sleep quality by first monitoring vital physiological data of the user, before using machine learning on the data to return a target room temperature.

BACKGROUND

A. Sleep

In order to understand how the physical environment affects sleep quality, we must first define what sleep is. Sleep is typically differentiated into five phases; stages 1, 2, 3, 4 and rapid eye movement (REM) [6]. These stages cycle repeatedly during sleep, starting from stage 1 to REM. Electroencephalogram (EEG) measurements are often used to determine these stages as different stages of sleep presents peaks at different region of the signals. This is shown in figure 1.

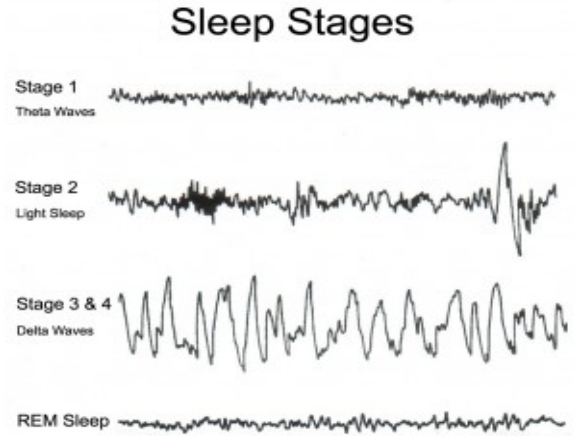


Figure 1 shows different waveforms of EEG signals at different stages of sleep

Stage 1 is commonly known light sleep. During this stage the eyes move very slowly and muscle activity slows. Sometime, we may even experience hypnic myoclonia –a sudden and involuntary muscle contraction. Stage 2 is marked as the onset of sleep where the person becomes disengaged from their surroundings, eye movements stops, heart rate and breathing rate returns to normal, and core body temperature drops.

Stage 3 and 4 is the slow wave sleep (SWS) also called deep sleep stage. In this stage, there are no eye movements or muscle activity. This is the stage where the body repairs and heals itself, muscles are relaxed, blood supply to muscles increases, blood pressure drops and breathing becomes slower.

REM stage is the final stage of a sleep cycle and it is significantly different from previous stages in that the brain is active. REM EEG waves are very similar to stage 1.

B. Sleep and thermoregulation

The sleep-wake rhythm is strongly correlated with the circadian rhythm of the core body temperature (T_{core}). Core body temperature decreases upon the onset of sleep due to the circadian rhythm; sleep further enhances this effect by keeping T_{core} low [7]. The fundamental driving force behind this decrease in T_{core} is due to the peripheral skin temperature. Vasodilatation near the peripheral skin allows rapid decreases in T_{core} and promotes onset of sleep [5], [7]–[9]. Studies have concluded that elevated room temperature does degrade sleeping quality [10] [11], as sleep and decreases in skin temperature are related to cardiac activity, it has been suggested that the use of heart rate variability (HRV), skin temperature and galvanic skin response (GSR) can infer to the different stages of sleep and indeed this is how wearables such as Fitbit, and Jawbones detect sleeping patterns.

II. HYPOTHESIS

This project aims to provide a better sleeping experience overall from having the room temperature automatically adjust to sleeping schedules and information from a myriad of sensors from a tracking device. This project also advises the user about the best times to go to bed from calendar integration, reducing the effects of jet-lag where possible. The user will benefit from our project according to the following hypotheses:

1. Better sleep quality can be achieved by sleeping in an ideal sleeping temperature, thereby preventing situations where the user cannot fall asleep because the environment is too cold or hot.
2. The feeling of grogginess can be reduced when waking up by setting the alarm to go off when the user is not in deep sleep.
3. The effects of jet-lag can be minimized by gradually adjusting to the destination time zone by modifying sleeping times, before and during the trip [12].

III. RELATED WORK

A. Existing products

There are many sleep trackers on the market that use a variety of ways to track sleep quality. Most sleep trackers monitor the user's different stage of sleeping, sleeping environment and provide sleep coaching advice. Majority of the trackers are found in the form of software application for iOS and Android. These applications use the accelerometer found in smartphones to track body movement throughout the sleep cycle. Using this data, "Sleep Cycle" wakes the user up during the lightest sleep phase, preventing the feeling of tiredness in the morning. In addition to the accelerometer, "Sleep as Android" [13] records audio through the microphone to detect snoring, speech, and ambient noise. This can be played back to the user the following morning, and can be a good indicator of sleep disturbances and stress [14]. Additionally, some applications also include the feature of playing soothing sound or music to make the user fall asleep peacefully.

Hardware sleep trackers such as "S+ By ResMed personal sleep solution" contain even more features, such as synchronizing the output music with the respiratory pattern of the user to provide a calming effect [15]. Another interesting feature by "Aura Smart Sleep system" includes a red light to induce the user into sleep [16]. "Sense" has a slow wake up light alarm to gradually wake the user up. Most of the aforementioned also have questionnaires for the user to record their daily behavior to help analyze their sleeping pattern.

However, some of the down sides of these applications include inaccuracy in telling whether the user is just lying in bed or actually sleeping. Some drain the battery of both the device or the phone quickly. Some of the applications lack a snooze alarm function.

Sleepify has taken into account the pros and cons of these existing sleep trackers in the market when prioritizing its aims. In addition to the generic functions such as sleep coaching advice and sleep environment monitoring, it has taken an active role to provide a novel edge to sleep tracking

- adjusting the sleeping environment. Sleepify analyses the best sleeping temperature and connects to smart heating devices to adjust the optimum sleeping temperature automatically. Manually changing the start time of the sleep record would also be enabled to prevent the problem of false sleep detection.

IV. SYSTEM DESIGN

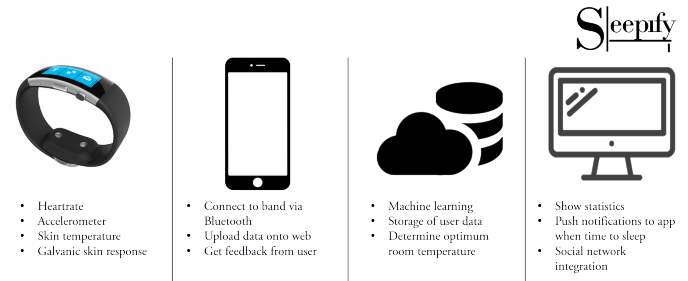


Figure 2: Proposed flow of system

A. Hardware

1) Sensors

The data-as-a-service platform for healthy lifestyle and preventive medicine has provided a comprehensive report on the state of art wearables. It was clear that the Microsoft Band 2 contains sensors such as GSR, PPG, Skin temperature that are ideal for our project, hence for our project data will be collected using this wearable. Nevertheless, other sensors that can be incorporated into the user environment should be considered, such as integrating pressure sensors into the mattress. This idea has been shown feasible with works such as [17]

B. Software

1) Machine Learning

The main function of the machine learning module is to provide predictions on the optimal room temperature setting during the period when the mobile application is providing real-time data over the entire sleeping period. The module is composed of two elements: model training, and the prediction block. The model training block persists the incoming data and apply training algorithms to adapt the underlying model when certain amount of data is collected to achieve online learning. Meanwhile, the prediction block handles the incoming data as prediction input and responds to the mobile application by providing returning the prediction result. Specifically, the response will be either binary information on the heater setting or current sleeping quality.

Our primal solution is to build a sleep quality classifier and use its result, along with the current body temperature, to adjust the heater setting. The classification is defined as a binary model based on features extracted from heart rate, skin impedance, accelerometer, and skin temperature readings collected from wearable sensors around wrist.

The development plan for this classifier can be split into three stages: feature generation, model selection, and model deployment. The primary aim for feature generation is to

discover the optimal set of parameters to accomplish the classification between ‘good’ and ‘bad’ sleeping quality. Since sleeping quality is highly subjective to everyone, we decided to obtain data for ourselves by using a Microsoft Band 2 with a simple mobile application to collect data and label the sleeping quality. Next, parameters that can represent the raw data in terms of sleeping quality will be investigated. Since all the data collected are time series format, the time interval used to calculate these suggested parameters can be varied. The MATLAB machine learning tool box can also be leveraged to perform preliminary analysis on these features. Upon a new set of features, multiple models will be trained and the optimal set will be one with highest average accuracy across models. Furthermore, it is also necessary to obtain the statistical properties on each feature, for example, their distribution function and interclass correlations. Most importantly, we need to investigate on correlation between sleeping quality and the body temperature. There has been some work done on this by Okamoto-Mizuno and Mizuno [18].

The model selection stage focuses on determining the optimal model for this application. The choice of each model is based on the required accuracy and performance to handle real time prediction. In this application, prediction speed is essential as it necessary to provide a response when the mobile application sends a request. Furthermore, the model should be selected based on the feature properties and the preliminary benchmarking result from MATLAB

After a specific model is chosen, advance techniques can be applied to improve the model computational and behavioral performance. For example, principal component analysis can reduce the feature dimension and allow the model to perform prediction based on smaller feature dimensions and hence use fewer computational iterations [19]. Furthermore, feature rescaling may allow models to fairly learn the importance of each feature and hence prevent overfitting.

Finally, the model deployment stage will implement the designed machine learning model into the whole system. Our initial design platform is to use the Python library Scikit-learn [20], and the Python frameworks Django, and Celery to link machine learning with backend end server maintenance. Scikit-learn will provide the machine learning model and training framework for our design while Django, and Celery can act as the mobile application interface and the model online training respectively.

2) Web Interface

The web interface serves as a hub where users can access the data provided by their mobile application reported during the night’s sleep. Here, the user can register a new account, login, check their profile, adjust their preferences (temperature and alarm settings), and check recent statistics (plotted using Python libraries such as Matplotlib). There is also a small section planned for a small wiki and FAQ’s. Figure 3 shows a mock up design.

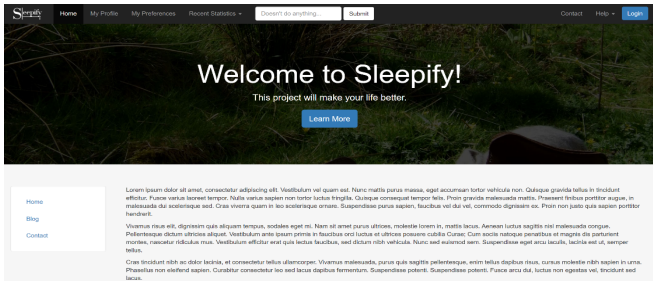


Figure 3: Prototype website homepage

The underlying technology will be provided by the Python framework Django; the website will be styled using Bootstrap. Both these frameworks allow for rapid development and are deeply supported with extensive documentation. Initially a PHP and MySQL stack was considered as the group had prior experience, but the process of setting up all the proper database queries while exercising caution about the many security issues mean development would be lengthened. Given the timeframe of the project, the decision was made to abandon the PHP and MySQL stack and instead focus on learning Django from scratch. A few days was all it took to come up with a prototype machine learning backend and a functioning homepage. The IDE used is PyCharm on Windows 10.

3) Mobile Application

The mobile application will serve as the bridge between the cloud processing and the sensors, as well as the central hub on which users can add feedback about their sleep sessions. It will be coded in Swift 3 using Xcode on OSX.

Connecting to the band over Bluetooth, the app will collect all the raw data from the band as it records overnight, and send it to the web server. As the Microsoft Band 2’s sensors have different sampling frequencies [21], some pre-processing has to be done on the application to avoid sending huge amounts of data to the web server. To put this into perspective, the accelerometer record its values at 30Hz generates a 30MB log file in just 6 hours of sleep. Not only is the data sparse (lots of repeating values), uploading a 30MB log file to the server means the solution is not desirable in its scalability for many users.

A working prototype that connects, collects, and aggregates data from the Microsoft Band 2 has already been created (Figure 4).

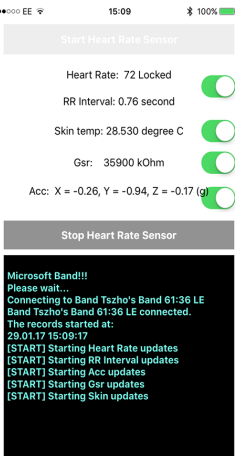


Figure 4: Prototype sensor data collection app

Apart from sensor data logging, the app is also responsible for getting feedback from the user. During the morning, the app will notify the user to rate his sleep last night by the means of a short survey. Some preliminary questions include how the user felt he slept, how hot/cold the user felt the room was, and how many times the user woke up (either naturally, so to use the bathroom, or unnaturally, because of external noise). Together with the data from the sensors, the survey will be sent to the cloud for further processing and statistics.

The mobile application is also responsible for receiving the data from the cloud after processing. As the machine learning algorithms come up with a suitable temperature value for the room, the app will connect to the home's smart heating solutions to change the thermostat to the desired temperature. The current plan is to support Google's Nest thermostats using their Nest API [22] as it comes with ample documentation and support.

Other features currently planned include the replication of the smart alarm clock feature present in many sleep apps, which wakes the user up during the lightest period of sleep. Additionally, calendar integration with the web interface is also planned, to allow for the cloud to send push notifications to the phone, reminding the user to sleep earlier/later depending on the time zone of the next few day's events. An intuitive GUI has also been drafted up (Figure 5).



Figure 5: GUI Mock-up

V. EVALUATION CRITERIA

To evaluate the true performance of the whole system, both short term and long term evaluation should be considered. Performance metrics such as specificity, sensitivity and accuracy, along with the confusion matrix should all be calculated to evaluate the performance of the classifier. However short term performance may not be as important as long-term performance, this is because as user use our system, the trained model will be specifically tailor to the user, hence we expect a better performance in the longer term.

Due to a lack of gold reference such as EEG measurement, relying on user feedback and Pittsburgh Sleep Quality Index (PSQI) to label data for training exposes weakness in data collection methods and may therefore affect the initial

performance of the system. As perceived sleep quality, does not often reflect true sleep quality.

For longitudinal test, a double-blind test can be conducted for a month or longer, that way we can be certain that placebo effect and biases from the developers are removed.

VI. CONCLUSION

In conclusion, this report highlighted the motivation behind in building a system that is capable to alter the users thermal sleep environment to achieve better sleep quality. We have identified that the thermal environment is a key factor in affecting sleep quality, this justifies our rational in controlling this factor in order to provide better sleep quality to users. We have discussed related works, however to the authors' knowledge there is no work that has developed a complete system to alter sleeping environments. Finally, we have also presented some of our preliminary works.

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