mSleepWatcher: Why didn't I sleep well?

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ABSTRACT

It has been medically proven that one's sleep quality directly affects his or her personal health, social behavior, and work effectiveness. Understanding sleep quality, hence, is an important topic and has been attracting a vast amount of research efforts. In addition, with the advent and ever-increasing number of mobile and wearable devices, many attempts have been made towards monitoring one's sleep using these ubiquitous devices. However, there were none on exploring the complex relationship between sleep quality and sleeping environment. In this paper, we propose *mSleepWatcher* as an on-going attempt answer the question of *"Why didn't I sleep well?"*. By mining the environmental sensing information collected by built-in sensors of off-the-shelf mobile and wearable devices in combination with the sleep quality sensing information, a set of causality analysis techniques is adopted and applied to exploit the existence of temporal dependencies between the environment during sleep and sleep quality. Resulted from *mSleepWatcher* system, latent relationships between the environment and sleep quality can be inferred which are then used to provide recommendation to users to suggest users adjusting their sleep environment for a better sleep. The proposed system is the first attempt to bring a fresh picture of sleep study associated with different scenarios of environmental variations. Derived from our preliminary work, both strength and limitations for developing the complete system in mobile devices are discussed in detail.

Keywords: causality analysis, environmental factor, sleep quality, MVAR model

1. INTRODUCTION

Sleeping is a vital activity that people have to spend nearly a third of their lifetime to do. Many studies have reported that a good sleep can freshen a human body involving energy restoration, muscle growth, tissue repair, protein synthesis, heart break, and growth hormone release. In equivalent, other researches have shown how an unhealthy sleep can impact on a structure and organization of a human brain. Poor sleep quality usually leads to daytime sleepiness, fatigue, and a wide range of weak abilities to learn and carry out a variety of tasks. As a consequence, how people sleep the night before results in how they work and do everything else during the day after.

The more modern the society, the faster a number of poor-quality sleeps increases. In order to understand how well people sleep as well as possible factors altering its wellness, more and more research on sleep health [6, 10] has been explored. Generally, information about the sleep quality can be categorized into four common groups, which are science, bedroom, lifestyle, and age. Among these categories, unconsciousness of changes in the bedroom while sleeping makes people curious about what environmental occurrence matches up with what affects their sleep quality.

Recently, with the rapid increase of sensors integrated in wearable and mobile devices, a lot of non-clinical systems serving needs of monitoring human sleep have been developed. Leveraging physical activities such as body movement during sleep via accelerometer, commercial devices such as Jawbone [4], Fitbit [1], and Misfit [5] have been produced. Similarly, Zeo and iBrain [3] are head-band devices that also help detect the performance of sleep by monitoring brain waves. However, none of these devices considered effects of changes of the environment on sleep. On the other hand, although a diversification of devices such as Lullaby [30], Sense [7], etc. and phone applications such as BeWell [31], Sleep As Android [8], Good Night [2], SleepHunter [25], etc. has aroused studies of the environment in the bedroom, none of these systems until now automatically elucidated hidden environmental causes of poor sleep quality. Only noncausal analyses were simply determined. Hence, manually looking at the sensed information provided by such systems is extremely difficult to identify dynamic sleep-environment interactions.

In this paper, we would like to propose *mSleepWatcher*, a novel framework of a system working on sensors built in mobile devices for automated sleep analysis. This system will pave a new way of developing an intelligent application that can clearly tell users effects of the environment on their sleep that a doctor cannot tell sufficiently. In detail, *mSleepWatcher* first senses environmental data including the amount of illumination, room temperature, air humidity, air pressure, and noises in the surrounding. All changes of these environmental factors are then computed and constructed in the form of time series individually. A well-established method named Granger causality analysis [15] of multivariate time series is next utilized to yield a deep insight into investigating the correlation between environmental variations and sleep quality. Consequently, not only significantly explicit and implicit environmental causes of poor sleep quality over nights are determined but also how to set up the best environment for sleep improvement in a specific actual home is advised.

To address the problem, we face both technical and non-technical challenges of implementing such idea into the practical system. The first challenge is how to distinguish discriminative sound events from acoustic signals recorded. An algorithm of sound classification should be sufficiently effective to separate both ambient sounds and sleep-related sounds such as body movements, snoring, coughing, and breathing sounds. The second challenge is that different smartphones produce recordings in different ranges of value from the same kind of sensors in the same environment. As a result, a new form should be considered to normalize the data and let the system run well on diverge off-the-shelf smartphones. The final challenge is how to deal with the sensitivity of each sensor while recording the surrounding. For instance, the data sensed by a light sensor can be influenced by shadows of stuffs around the device. Overlooking these bottlenecks lists main contributions of our work as follows:

- We present a comprehensive system framework to distinctly reveal uncommon interconnections between sleep and environmental variations.
- Beyond mere statistical correlations, we put forward the concept of "Granger causality" to deal with the need for mining causal sleep-environment relationships.
- We conduct a preliminary implementation of *mSleepWatcher* with a good design on Android platform.

In the rest of this paper, we start with a clinical background of sleep-environment relationships as well as related works done in the field of sleep assessment using various methods. After that, Section 3 provides a lucid architecture of the system. Its detailed framework are described in Section 4. At the end of this paper, a thorough design and initial implementation of the *mSleepWatcher* application, future works, and our conclusions are provided respectively.

2. BACKGROUND

2.1 Sleep-Environment Relationships

Many researches have demonstrated that environmental factors (e.g. light intensity, room temperature, air humidity, air pressure, and ambient sounds) can be an essential reason for interrupted and poor sleep quality, which actually impacts on human's daytime functionality. There have been studies that recommend people to get a good sleep in a room with a specific environment, which is nice cold and dark and has pure air quality. Specifically, related to temperature, a warm environment can negatively influence the sleep quality [32]. A significant increase in the total sleep time and more alert in the morning were noticed at a room temperature of 16°C compared with 24°C. Moreover, patients with sleep apnea generally have longer and better efficiency in sleep while being in a cold temperature [24]. On the other hand, Haskell et al. in [27] found that a very cold environment could be more disruptive to sleep than the warm. Generally, the room temperature has a larger influence on sleep quality than on sleep architecture. In the heat, the total sleep time decreases while the number and duration of awakenings and the number of changes of sleep stages increase [32]. Also, the results indicated that the sleep quality could be so poor if high humidity has combined with heat. They found that REM stage decreased, wakefulness increased and sleep efficiency index (SEI) significantly decreased at high humidity [35]. Humidity could also harm the nasal of the patients [24]. In addition, some studies have demonstrated that central apnea becomes significantly more common at increasing altitude where the atmospheric pressure decreases [36, 39]. High altitude adversely affects sleep quality in otherwise healthy adults, both subjectively and objectively with increased sleep fragmentation, decreased slow-wave sleep, and increased arousals associated with periodic breathing. It can also be a cause of sleep breathing disorders (SBD) [33, 36]. Since the higher the altitude, the lower the air pressure, a tracking of fluctuation of air pressure can help determine how much the sleep is affected through symptoms of SBD. Moreover, scientific researches have demonstrated that sharp and frequent acoustic noise can lead to significant sleep disturbance and may lead to insomnia, which impacts the physical and mental health [18]. Environmental acoustic noise significantly increase the arousal level that leads to increase wake stage and decrease slow wave sleep (SWS) and REM sleep. Sleeping in acoustic noise is significantly more disturbed, lighter, and can affect the body condition after waking up [28]. Also, researches have shown inefficient sleep in lighting room. A long exposure period of light, regardless the intensity of the light, may affect the sleep quality [29, 22]. The reason is that light triggers all types of chemical events occurring in the human body, which causes changes in both our physiology and behaviorFor instance, when the illumination is reduced at night, our body temperature falls. In opposition, the body temperature rises as the morning begins [6]. The issue here is that some of these environmental factors are noticeable, while others are difficult to be observed. Also, since people are unconscious when sleeping, they are not aware of the environmental changes that can effect their sleep quality.

2.2 Sleep Quality Assessment Methods

There are medical and non-medical approaches to measure the sleep quality. The Pittsburgh Sleep Quality Index (PSQI) is a popular approach that uses individual self-report questionnaires to evaluate sleep quality of the previous nights [19]. PSQI distinguishes between good and poor sleepers, as well as provides a concise assessment of sleep disturbances. It considers many aspects of sleep quality that include wake patterns, sleep duration and frequency and the perceived influence of poor sleep on day-time functioning. It assess specific issues contributing to poor sleep, such as pain, urinary frequency, breathing, snoring, dreams, etc. However, this method depends on the subjective observations to assess the overall sleep quality and can not infer sleep stages.
In sleep laboratory the only validated and standardized method to evaluate the sleep quality and the sleep disordered is Polysomnography (PSG). It provides a rich source of physiological data [23]. During the process, the patient is required to wear a number of complex devices to be monitored with multiple recording modalities including electrocardiogram (ECG), electromyogram, eye movement, respiratory effort, etc. Similar objective sleep measurement method is called Actigraphy [14]. It is easier to use and less uncomfortable than PSG. Actigraphy monitors the human body movement via accelerometers.

3. SYSTEM ARCHITECTURE

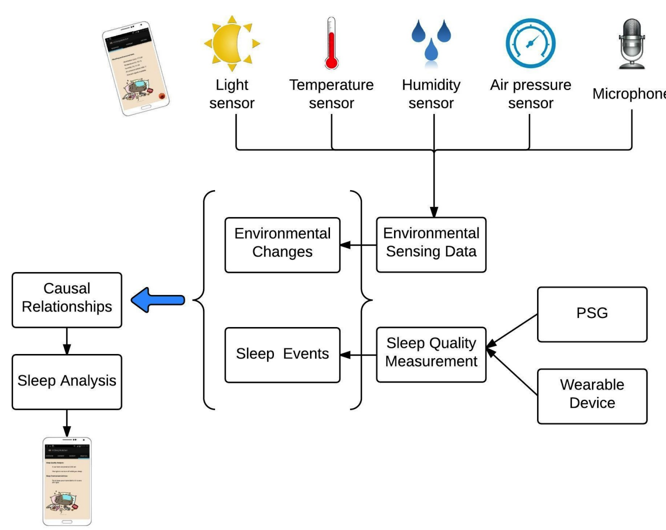

Figure 1: An overview of the proposed sleep analysis system

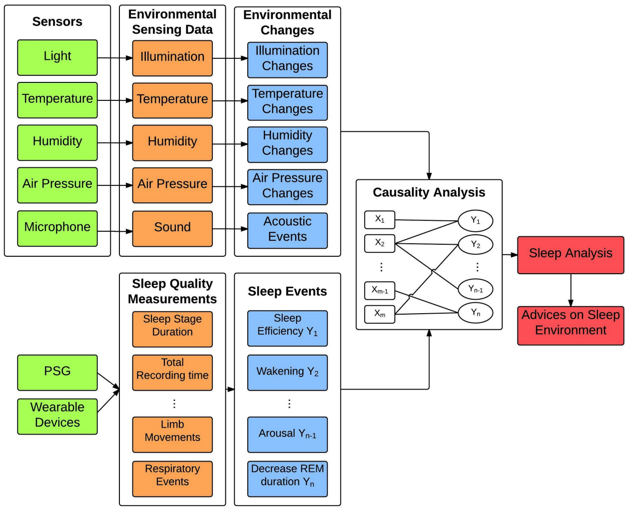

Figure 2: A three-layer architecture of the proposed system

In this section, an overview of the environment-based sleep analysis system is first introduced. Next a specific design of the system architecture is explained.

3.1 System Overview

Generally, our sleep analysis system runs several types of sensors built in off-the-shelf mobile devices to collect environmental data unobtrusively and non-invasively.

As shown in Figure 1, the system comprises five compulsory sensing components that are a light sensor, a temperature sensor, a humidity sensor, a pressure sensor, and a microphone. By fusing these sensors, necessary environmental data including light intensity, room temperature, air humidity, atmospheric pressure, and acoustic signals are recorded. Detection of temporal changes of the non-acoustic signals and recognition of ambient noises from the sound recording are then proceeded concurrently. After attaining all these variations, they are marked as critical *environmental changes*. On the other hand, common measurements of sleep quality done by polysomnography (PSG), which is then clinically evaluated by sleep doctors in sleep lab, or a combination of heartbeat, respiration, and body movements, which are monitored and analyzed by a variety of commercial wearable devices, includes

- *Total recording time*: is the time from when the light is turned off and to when it is turn on (usually in sleep lab).
- *Total wake time*: is the total amount of time in which the sleeper awake during the recording.
- *Total sleep stage duration*: is the total time of a particular sleep stage (i.e. Stages N1, N2, N3, and REM) divided by total sleep time.
- *Periodic limb movements*: is a sleep disorder in which limbs are moved involuntarily and causes partial arousals or awakenings during sleep.
- *Respiratory events*: include apneas (obstructive, central, and mixed), hypopneas, and respiratory effort related arousals (RERAs) during the sleep.

From a bunch of such outcomes, *sleep events* that result in different sleep quality (e.g. an occurrence of arousal or an awakening, a decrease of duration at REM stage, etc.) are subsequently inferred chronologically, which are later imported to the system. Finally, linking the environmental changes with the sleep events, actual *causal relationships* between them are mined to generate a comprehensive sleep analysis. These causalities are visually displayed on the user's device after that with a confidence factor. Meanwhile, appropriate fine-grained comments can be provided to assist the user in improving the environment for a better sleep at the next nights. Furthermore, continuously running the system every night will help increase the confidence level of the analysis of the system for existing causes as well as study potential relations if any.

3.2 System Design

For mapping the system overview, a three-layer architecture is designed explicitly in Figure 2.

Particularly, in this architecture, the first layer consists of five essential modules: illumination change detection, temperature change detection, humidity change detection, air pressure change detection, and acoustic event recognition. Each module coincides with its primitive time series sensed by the correspondent sensor listed in Section 3.1 and is associated with a relative signal processing algorithm that helps filter outliers and extract events (or ambient noises) in the acoustic signal or significant variations in the non-acoustic signals. As a result, these modules provide a set of changes described in the form of time series. Together with information gathered by either the PSG or the wearable device, in the second layer, a network of Granger causality (G-causality) between these time series of environmental changes and sleep events is studied. Relied on environment-sleep relationships determined in the network, the third layer gives a thorough analysis of sleep to the user visually as well as delivers appropriate tips for getting an improvement of poor sleep quality caused by specific effects of sleep environment.

4. THE mSleepWatcher SYSTEM

Following the architecture mentioned in Section 3.2, an extensive algorithm for the complete system is pointed out in Algorithm 1. Overall, the most key insight in this algorithm is to build an efficient technique served for the second layer, in which the *mSleepWatcher* system can discover both trivial and non-trivial relationships between the environmental factors and the sleep quality chronologically.

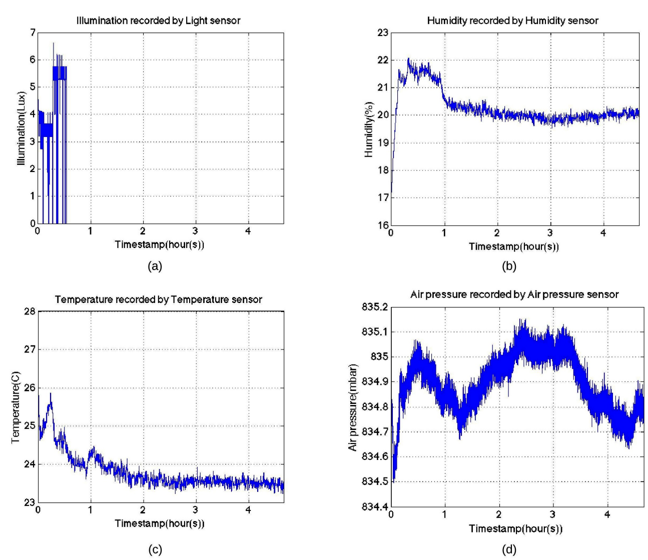

Figure 3: An illustration of environmental signals recorded by built-in sensors

4.1 Environmental Variation Detection

Leveraging sensors built in smartphones to track sensitive information about the surrounding we concern, a demonstration of how these sensed signals look like throughout one night is given in Figure 3. Because each environmental factor has its own attributes (e.g. acoustic and non-acoustic signals), modules in the first layer of the system should apply different algorithms to detect variations or events occurring along the signal. However, when a sleep event happens depends on not only the change of magnitude but also the duration and the frequency of the occurrence of the environmental variations. For instance, if a loud car horn suddenly or continuously occurs, it can cause a sleeper to awake immediately. Otherwise, the change of temperature may exist for an hour before a sleeper can feel it and then her sleep is disrupted. Derived from characteristics of how long and how often variations in the environment appear influences the sleep, a list of different environmental changes can be picked up. Furthermore, unlike existing papers in which the authors set fixed ranges of value for the environmental variations [30], our system focuses on the change of their amplitude as main signs causing sleep events. Its advantage results from that each of persons has a distinct flexible limitation on the environmental changes for sleep. Thus, an algorithm of detecting only the changing amplitude can adapt well with the environment since its detection is based on the proportional value of the environmental factors in the current surrounding. Consequently, an adaptation to diverse users brings our sleep analysis system on better experiments.

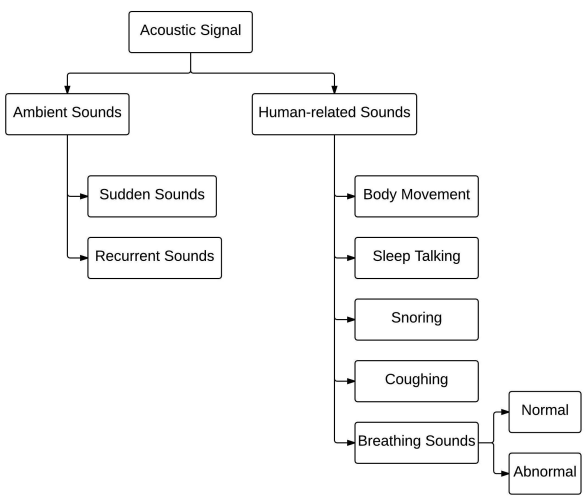

Figure 4: The hierarchical sound classification

In this layer, we faces two fundamental challenges of designating both sufficient and efficient inputs for the next step of analyzing causalities. Firstly, with non-acoustic signals, due to the sensitivity of sensors, an uncountable number of temporal variations is turned out. Thus we need to eliminate the trivial variations by comparing both the changing value and the duration of its occurrence to some thresholds relatively. For example, if the temperature slightly increases or decreases in a short duration, such change will be considered as a minor and be excluded because the human body may not perceive it. Secondly, acoustic signals sensed by the microphone is sensitive enough to record information about both human activities and the environment. As a result, not only ambient sounds but sleep-related sounds such as sounds caused by human body movement, sleep talking, snoring, coughing, and breathing sounds are recorded. Its hierarchical classification is shown in Figure 4.

In the scope of this research, we however only consider acoustic sensing related to the environment. So as to recognize ambient noises during the sleep, acoustic features are first selected in both time and frequency domains including short-time energy, the loudness, zero crossing rate (ZCR), power spectral density (PSD), and spectral entropy. They are then used to detect acoustic events in the recordings. Finally, the detected events that depict sudden and recurrent ambient sounds are chosen by a non-linear classifier.

4.2 Sleep-Environment Causality Mining

Our main goal in this study is to explicitly answer the question of *"Why didn't I sleep well?"* by mining latent causal connectivities between the environmental variations and the sleep events. Such expected causalities can be manifested as in Figure 5.

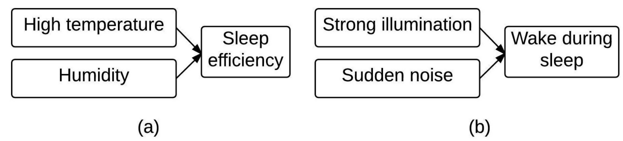

Figure 5: Examples of causal sleep-environment relationships

In the domain of analysis making, even though a combination of statistical modeling and data mining method is usually made, it is hardly good enough to find out merely the statistical relationships that exist obviously in the data or have been stated in research publications. Accordingly, the utilization of a well-established method, Granger Causality (G-causality) [15], which depends on "temporal precedence" is suggested in our study. Its principle as specified by Granger's concept of cross prediction [21] is stated that a time series X is said to "Granger cause" another time series Y if and only if incorporating the past values of X improves the future prediction of Y rather than only using past information from Y.
In this section, utilizing the idea of G-causality, we perform a multivariate autoregressive (MVAR) model to identify causal connectivity in our sleep study. Specifically, given a time series collection of both the variations of five environmental factors $X_1, ..., X_5$ (i.e. illumination, room temperature, humidity, air pressure, and ambient noises relatively) and the sleep events Y, the MVAR model for G-causality is constructed as below

$$Y_i(t) = \sum_{j=1}^{5} a_{i,j} X_j^{t,Lagged_j} + \varepsilon \tag{1}$$

where $X_j^{t,Lagged_j} = [X_j(t - Lagged_j), ..., X_j(t-1)](j = 1..5)$ is a *lagged time series* vector related to a change of the environmental factor j detected at time t with its appropriate *maximal time lag* ($Lagged_j$). $X_j(t-i)$ is thus a specific value of the environmental factor X_j at timestamp $t-i$. $a_{i,j} = [a_{i,j,1}, ..., a_{i,j,Lagged}]$ is a *regression coefficient* vector in which the element $a_{i,j,k}(k = 1..Lagged)$ represents the dependence of $Y_i(t)$ on the lagged time series $X_j^{t,Lagged_j}$. $Y_i(t)$ is a sleep event occurring at time t. ε is a *residual* vector, which is also called "*prediction errors*" or "*innovations*" for each time series. This parameter is usually assumed to be independently and identically distributed (iid) and uncorrelated noises. Closely, the regression coefficients represent the predictable structure of the data and the residuals do the unpredictable one in the network of causality. So as to detect G-causality, the model performed in Equation (1) should be solved, which is equivalent to estimate its parameters. Hence, to fit the above MVAR model, we face some crucial challenges that are next represented successively in detail.

1) *Maximal time lag*
The estimation of any MVAR model requires specification of the time lag value $Lagged$. Providing a proper value can help achieve the best model fit while refraining from both underfitting and overfitting effects on a finite data sequence caused by the model in opposition to the number of regression coefficients. Despite that there are some standard criteria such as Akaike information criterion (AIC) [13] and Bayesian information criterion (BIC) [38] applied, the need of another solution for our defined model is challenging because of the below reasons:
   i) As explained in Section 4.1 why it is necessary to consider the duration of the environmental changes, each of the environmental factors should be picked up its own time lag differently in our model.
   ii) Although we can get these values from sleep doctors based on their expert knowledge, it is still different from person to person in reality.

2) *Statistical significance*
In order to accurately form the G-causality, the regression coefficient vector $a_{i,j}$ in Equation (1) have to be estimated first through a least-square method. Its zeroness is then tested by applying an statistical significance test on the null hypothesis of "*the vector* $a_{i,j}$ *is zero*". As a consequence, non-zero values in the coefficient vector, which is statistically significant, determine causalities between the environment and the sleep quality. Without loss of generality, for any statistically significant $a_{i,j}$ which does not equal to 0, the corresponding environmental change X_j is said to "Granger cause" the sleep event Y_i.
In other words, making an assessment of the statistical significance of causal relationships that the G-causality obtains is one of its most important issues. However, doing a statistic test needs to specify a threshold value to decide whether or not the null hypothesis is true. How to identify a suitable threshold is also challenging since we need enough the data to make the results returned by the G-causality more accurate and reliable.

Finally, from the statistic test, we also obtain a $p\text{-}value$ to see how confident the variation of all environmental factors at time t cause the appropriate sleep event. Hence, at the end of this layer, both the list of causal relationships between the environment and the sleep quality and their confidence factor are fetched. Moreover, when being continuously run every night, the proposed system in which a statistical approach is used will have an ability to increase its confidence level of analyzing existing causes as well as study potential relations if any by itself in the long term.

4.3 Suggestions for Better Sleep Environment

Having computed G-causality, the proposed system returns all possible causalities. Consequently, in the last layer of the system framework, both trivial and latent causal connectivities (as expected) are inferred from such causalities found among the data. For example, in case of the first sleep event Y_1 appearing at 2 a.m, non-zero $a_{1,2}$ and $a_{1,3}$ are given back by the system. In that way, the causal relations $X_2^{2,Lagged_2} \rightarrow Y_1$ and $X_3^{2,Lagged_3} \rightarrow Y_1$ are determined. Therefore, we can later conclude that the simultaneous occurrence of the two environmental factors X_2 and X_3 at 2 a.m caused an effect on the user's sleep described by the event Y_1. By responding to the user which changes of the environmental factors significantly cause the sleep events occurred at the night before, our system brings to the user a clear understanding of reasons for her poor and disrupted sleep quality. In more detail, the application tries to give a good overview of the main causes by displaying graphs of the processed data and recommend small tips for the user to modify her sleep environment if necessary. For example, after monitoring the user's sleep in a night, the system first produces notifications "There is sudden light appearing in your room at 2 a.m. Your room temperature is also decreased 5°C from 2:30 a.m to 4:00 a.m.". It next gives some detailed comments such as "Every time the light flushes, you tend to budge. Because of the change of temperature with its confidence level of 90%, you awaked for 1 minute at that time.". Finally "*intelligent*" advices are suggested personally such as "Try to keep you room dark or in a very dim light around 5 Lux at which your sleep is usually in depth.".

Algorithm 1: Environment based Sleep Analysis Algorithm

Input: Sleep events (SE), Environmental sensed data (ED), and thresholds TH_A, TH_D
Output: Sleep-Environment causalities (GC) with correspondent confidence factors (CF)

for *Each non-acoustic time series in* ED **do**
  Detect all temporal variations TV;
  for *Each* TV_i *at* t **do**
    Extract the changing amplitude δ_A, duration δ_D, and frequency δ_F of its occurrence: $TV_i(t) \leftarrow (\delta_{A_i}, \delta_{D_i}, \delta_{F_i})$
    if $(\delta_{A_i} < TH_A) \wedge (\delta_{D_i} < TH_D)$ **then**
      Eliminate $TV_i(t)$;
for *Acoustic signal in* ED **do**
  Detect all acoustic events AE;
  for *Each* AE_i *at* t **do**
    Extract acoustic features: $AE_i(t) \leftarrow (STE, LD, ZCR, PSD, PE)$
  Apply a non-linear classifier to recognize only ambient noises from AE;
Define $X_1..., X_5$ as time series collection describing changes of 5 environmental factors;
Define $Y_1, ..., Y_n$ as n sleep events in time series Y;
for *Each sleep event of* Y **do**
  Generate a MVAR model

$$Y_i(t) = \sum_{j=1}^{5} a_{i,j} X_j^{t,Lagged_j} + \varepsilon$$

  by
  1. Determine maximal time lags $Lagged_j$ ($j = 1..5$) for each environmental factors;
  2. Estimate the regression coefficient vector $a_{i,j}$ using a least-square method;
  3. Apply a statistic significance test to find out statistically significant non-zero $\vec{a_{i,j}}$
  for *Each statistically significant non-zero* $\vec{a_{i,j}}$ **do**
    $X_j^{t,Lagged}$ "Granger causes" $Y_i(t)$;
    $GC \cup \{X_j^{t,Lagged}\}$;
    $CF \cup \{p\text{-}value_{X_j^{t,Lagged}}\}$

5. PRELIMINARY IMPLEMENTATION

So as to study the environment for analyzing the quality of the user's sleep, we deploy an application named *mSleepWatcher* on the Android platform. In this section, its graphical user interface

(GUI) design and initial implementation for collecting necessary data in the surrounding are represented. Moreover, some technical issues of working on mobile devices are discussed as well.

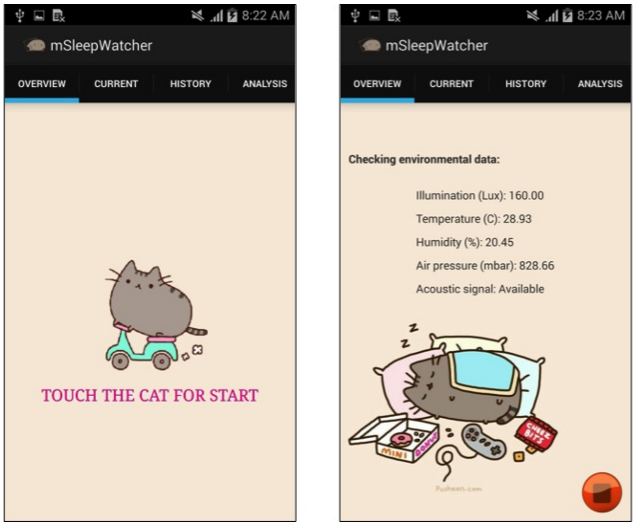

Figure 6: mSleepWatcher Application

Fundamentally, *mSleepWatcher* is a software running all processes on the smartphones only. Figure 6 illustrates a GUI drafted for making the application be friendly and attracting to the users. There are four main tabs designed to divide the GUI for its usability. The tab Overview yields a user-software interaction to let the application start recording the environmental data and response the availability of all sensors after checking. The sensed data are visualized both in real time and in a general view using graphs plotted in the tab Current and History, respectively. Lastly, the tab Analysis displays feedbacks about the sleep based on the causality analysis and provides specific recommendations to alter the environmental factors for better sleep quality. In depth, the *mSleepWatcher* application includes four basic components as follows

i) *Sensing component*, which utilizes only on-phone sensors and records various environmental information that might be relevant to sleep quality,

ii) *Processing component*, which deals with the data preprocessing, the temporal environmental variation detection, and the exploration of causal relationships between the environment and the sleep quality, and

iii) *User feedback component*, which returns fine-grained analysis as well as provides suggestions for sleep environment modification if needed.

Most present-day high-end smartphones (e.g. Samsung Galaxy S4) are well-equipped with many sophisticated sensors. However, one technical issue related to data collection is the sensitivity of sensors. Specifically, the built-in light sensor usually provides less reliable values as the phone is kept in the user's pocket or bag s or is placed face down on a surface. To minimize effects on sensors caused by the user, other built-in sensors (e.g. proximity sensor) can be leveraged to avoid such situations. For data processing with smartphones, battery life is another critical issue. To reduce the impact of power usage, we consider two following strategies. First, the application should adaptively set the rate of sampling various types of data. Second, the application will automatically stop its recording task when the phone battery is drained below a threshold. Lastly, how to minimize the data storage for the system to use in the long term is also a dominant issue because of the still limitation of its volume in the mobile devices. As a consequence, a structured form should be invented to convert the data to the most light-weight format, especially for sound recordings.

6. FUTURE WORKS

In this section, we consider future works that must be done for our environment-based sleep analysis system to be run correctly, efficiently, and smoothly. (1) The algorithm proposed in Section 4 for the whole system will be able to be solved its own challenges. They are the unsolved challenges of the MVAR model for G-causality method mentioned in Section 4.2, the limitation of the built-in sensors while collecting the environmental signals, and the correctness of processing the data for good environmental variation acquisition. (2) The progress of formulating the G-causality analysis approach used to mining non-trivial causal relationships will be done level by level. In our case, we will conduct to start the approach in the simplest way by only considering pairs of time series between each environmental factor and sleep events. The environmental factors are further joined together to make the approach more complex but enhance its performance as well. Additionally, an idea of featuring the environmental variations by other properties beyond existing ones (i.e. the amplitude, the duration, and the frequency of occurrence of the changes) can be thought to bring more information of the causalities to the user. Later, our G-causality approach can cope with other potential issues of whether or not latent factors or nonlinearity of the inputs exist. (3) To do experiments for our system, a sufficient dataset in which all possible scenarios of different sleep environments and different evaluation methods for sleep quality will be built considered. (4) Finally, we will address minor technical issues (some of which have been mentioned in Section 5 already) that usually happen in mobile applications such as feasible sampling rates corresponding to each type of sensed data, battery drainage, storage limitation, etc.

7. RELATED WORK

A number of research projects and commercial products and applications have been existed to track different aspects of sleep process, including sleep quality and the duration of the sleep. Tracking can be done automatically via sensors or manually. Many of these automated systems require sensors to monitor the user or the sleep environment. Zeo [11], iBrain [3], Fitbit [1], Jawbone [4], a non-invasive wearable neck-cuff system [37], PATHOS [34], and SENSATION [16] require on-body or wearable sensors to monitor different human physical activities, which can be unsuitable and uncomfortable for long-term sleep. These systems mostly connect to mobile phone via Bluetooth to storage and retrieval the data. Lullaby system [30] uses external sensors that could be connected to a computer or a mobile device.Rather than using wearable sensors that could be uncomfortable or external sensors that could be hard to mange, our system use only phone's embedded sensors and it use all of the available sensors to give accurate understanding of the sleep environment.

iSleep system [26] uses only the built-in microphone to monitor sleep process based on acoustic events. Chen et al. [20] proposed an approach that leverages many built-in sensors (light sensor, accelerometer, and microphone) to infer various smartphone usage patterns to predict the sleep duration and wake the user at the light sleep stage in a completely unobtrusive way. This system infers the sleep using smartphones based on a novel best effort sleep (BES) model. Similar systems rely on user data entry such as Sleep as Android [8] and Sleep Cycle [9]. SleepMiner system [17] relies on mobile built-in sensors, such as GPS, accelerometers, light sensor, microphone, and camera, to extract human contexts such as daily activities and living environment. Based on these collected features, the system predicts the sleep quality.Abdullah et al. [12] have presented the results of an empirical study that uses smartphone daily usage pattern, to predict daily changes that indicate the quantity of the sleep, and the prefer time of the sleep.In contrast, our system doesn't consider the duration of the sleep, yet it considers all the surrounding sleep environmental factors that have a significant impact on the sleep quality rather than rely on just one or two factors. That includes the air quality (room temperature, atmospheric pressure, and humidity), illumination level, and acoustic noise.

Gu et al. [25] proposed a mobile service that leverages the built-in sensors (light sensor, accelerometer, microphone) on smartphones to integrates the physical activities with sleep environment to detect the sleep stages. Based on the duration of each sleep stage, the system predicts the sleep quality and further provides report about it and smart call service for users. On the other hand, our system doesn't predict the sleep quality, yet we infer the reasons of the poor sleep quality that is measured in the hospital.

8. CONCLUSIONS

In this paper, we propose a novel framework for analyzing the user's sleep quality through only the environmental data during sleep by mining causal interconnections between them. We first define the problem shown in the system architecture. Then its appropriate algorithm is designed in detail. In this system, all environmental factors in the surrounding are collected without the user's consciousness. These factors are then characterized by the amplitude, the duration, and the frequency of occurrence of their change. Later, we apply the Granger causality analysis using the MVAR model to explore all possible causal relationships in the data. The results returned from this approach is to help the user understand reasons of having poor sleep quality visually in the day after. The system is implemented on Android platform as the *mSleepWatcher* application. Taking advantages of the built-in sensors in the off-the-shelf smartphones, our proposed system is unobtrusive, non-invasive, and easy to use and does require only 1-touch execution for human-application interaction. In the future, we will complete implementing the proposed algorithm into the *mSleepWatcher* and make it be deployed successfully in various scenarios. We believe that our *mSleepWatcher* system has a strong ability of assisting people to realize the hidden environmental causes affecting their sleep quality.

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