Identifying Elderly with Poor Sleep Quality using Unobtrusive In-home Sensors for Early Intervention

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ABSTRACT

Along with the upward trend in population ageing is the increasing proportion of the elderly population living alone in the community. This group is especially vulnerable as the onset of various physical, social and mental health issues may be more likely and may go undetected. However, smart homes enabled with elderly monitoring and care systems (EMCS) can now be used to alert caregivers of anomalies in the daily living patterns of the elderly. In this study, we focus on the sleep quality as the key living pattern, as it has been shown that poor sleep quality can lead to health issues. To ensure data collection while preserving their living patterns, we have deployed the EMCS comprising passive and unobtrusive sensors in more than 90 homes of elderly living alone in Singapore. We have built a binary classification model based on Random Forests using the sensor data collected and the subjective PSQI scores obtained from surveys as the ground truth. From the latter, the elderly's sleep qualities for each survey were divided into 2 groups, representing *good* and *poor* sleep qualities. Our model, based on data from 39 participants, achieved 84% classification accuracy, and holds promise for improved accuracy with additional data points.

CCS CONCEPTS

• **Applied computing** → **Health care information systems**; • **Hardware** → *Sensor applications and deployments*;

KEYWORDS

Health and social care, Sleep Quality, Smart Home, IoT

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1 INTRODUCTION

In recent years, we have witnessed a rapid upward trend in population ageing [22], where the elderly may have multiple chronic conditions and diverse healthcare needs. Hence, ageing-in-place, which enables home and community-based care for elderly, has gained increased attention as an effective alternative to the costly and labor-intensive institutionalized elderly care system [25]. Among the elderly, there is an increasing proportion who live alone [21], exposing them to additional risks in terms of their physical and mental well-being. Thus, community caregivers and volunteers often face challenges in providing care for the elderly living alone. In this regard, ambient assisted living technologies are becoming increasingly popular as feasible solutions to assist caregivers in remote monitoring and care provision.

Smart homes, enabled with various sensors installed at different locations of the house, could enhance the quality of life for the elderly living alone by providing unobtrusive and continuous monitoring and integrated services needed for provision of care [7]. However, to ensure that the elderly are ageing safely and healthily, the smart home solutions for ageing-in-place must enable not only reactive care [26], but also preventive care through early detection of potential health risks. The latter can be achieved by identifying anomalies in daily living patterns and alerting the caregivers for remote monitoring. For example, changes in elderly's performance in day to day activities such as eating, grooming, toileting, sleeping, watching TV or going-out could indicate a decline in their physical health [19]. As a result, the passive and accurate detection of elderly's activities of daily living has become an important aspect of smart home solutions.

The sleep quality of the elderly has been linked to various health issues ranging from existence of underlying physical health conditions, mental health disorders to environmental changes. Over the past years, various technologies have been introduced to monitor sleep patterns [15, 17] and sleep quality [11] of individuals. Well known solutions include mobile devices, wearables and devices that can be embedded into one's sleeping environment [14]. However, such technologies require active participation by the individual to ensure the effectiveness of the solution (e.g., the user has to remember to charge the device or wear it). In this study, we propose a preliminary framework to predict the sleep quality of the elderly so as to detect elderly with poor sleep quality for community intervention using data collected from a smart home solution comprising unobtrusive and non-participative passive infrared (PIR) motion sensors.

2 RELATED WORKS

A wide variety of sleep monitoring devices have emerged over the past decade for personal and clinical sleep quality assessment. Actigraphy, the measurement of one's motor activity based on rest and active cycles using actometer [1], has been widely studied as an inexpensive solution to assess sleep and wakefulness overnight [18]. Actigraphy posits that the state of being awake or asleep can be inferred from the amount of movement of the body during the sleep [1] and has been widely used in commercial sleep quality assessment products. For example, some smart watches [3] and fitness trackers [6] are designed based on actigraphy technology. Several scoring algorithms have been proposed based on the measures such as total sleeping period, total sleep time or mid-sleep awakenings etc., to derive sleep quality from actigraphy results [12]. These algorithms are extensively used by researchers and practitioners to identify patients with sleep disorders such as insomnia or sleep apnea [18]. A wearable neck-cuff system based on oximetry sensor, microphone and accelerometer was introduced by [17]. However, the device is obtrusive in nature as it has to be worn to ensure the effectiveness of the solution. Apart from wearables, accelerometers that can be attached to bed mattress, pressure-sensitive bedsheets or sleep mats were also proposed as feasible solutions for sleep quality monitoring [13, 16]. Despite many benefits, these systems need professional installation and maintenance [11].

In clinical settings, Polysomnography (PSG) technology is widely used to predict the patients' sleep quality. For example, in [24], the authors sampled electroencephalography (EEG) signals from subjects in a controlled experiment, and used machine learning methods to predict subjects' sleep quality. The authors in [20] also relied on EEG data and attempted to auto-label the sleep stages using a combination of CNN (Convolutional neural network) and RNN (Recurrent neural network). However, these studies need to be conducted in clinical settings.

Several studies have proposed indirect methods of predicting the sleep quality based on individual's contextual information such as sound, light, postures and positions and acoustic signals captured by the microphone during the night [2, 11]. For example, [11] proposed a sleep quality assessment solution using smartphones by detecting events such as body movement, cough or snores that are highly correlated with the sleep quality.

Past studies have shown the potential of sensor-based smart home monitoring technologies to identify living patterns and physical and mental health impairments of residents [8, 10, 23]. In this study, we propose an approach to identify elderly with poor sleep quality based on the movement patterns detected by motion sensors installed in different parts of the house (i.e., their natural environment). We believe that such approaches will be more amenable to acceptance by the elderly due to the cumbersomeness of the usage of technologies that need active participation from the user and/or a change in the user's daily routines.

3 DATA AND MEASURES

This study was conducted as part of the SHINESeniors project [9], a research project that aims to enable a new-generation model of elderly care using Internet of Things (IoT) technologies and predictive analytics. Specifically, the project has deployed sensor-enabled homes to facilitate preventive and reactive care for the elderly who are living alone in the community in Singapore. The elderly were chosen on a voluntary basis if they are above 60 years of age, live alone in government subsidized apartments and are affiliated to a neighbourhood caregiving organisation. All elderly agreed to have an elderly monitoring and care system (EMCS) installed in their houses and to participate in baseline as well as follow-up psychosocial surveys. The EMCS consists of a minimum of 4 passive infrared motion sensors, one door contact sensor and a customized gateway using a Raspberry Pi, a popular small single-board computer that is able to run a Linux operating system. Figure 1 illustrates a typical deployment of an EMCS in a house, in which 4 motion sensors were installed at the living room, bedroom, kitchen and toilet and a door contact sensor on the main door.

The EMCS installation started in November 2014, and underwent one major system upgrade during the project. The final version of EMCS has been deployed in more than 90 homes since June 2017. In this study, we will be using the sensor data gathered after June 2017.

3.1 Surveys and Labels

We conducted two guided surveys in September/October 2017 and April/May 2018 to collect information pertaining to the elderly's demographics, physical health, psychological status and sleep quality. The sleep quality of the subjects

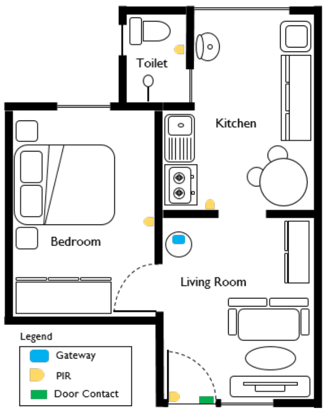

Figure 1: An illustration of the deployment of EMCS in a typically elderly's house.

were measured using the Pittsburgh Sleep Quality Index (PSQI) [5], a self-rated questionnaire that assesses subject's sleep quality over the month preceding the survey [4]. The PSQI score consists of 7 component scores, each of which addresses a specific aspect of sleep quality. Each component has a score ranging from 0 to 3 and the total score ranges from 0 to 21.

Past research has shown the validity of the PSQI to discriminate healthy adults and patients with sleep disorders [5]. A score of 5 has been often used to identify subjects with poor sleep [4]. Based on this, we separated the elderly into two groups: the elderly with good subjective sleep quality (*good_sleep*) and those with poor subjective sleep quality (*poor_sleep*). In this way, we model the sleep quality prediction as a binary classification problem. Sensor data up to 30 days before each survey was used for the model and the corresponding survey result was used to label the data.

Subjects were dropped from the study if they did not participate in the survey, did not sleep in the bedroom or had helpers or long-term visitors during the period we have collected data for this study. Consequently, 39 subjects were chosen for this study.

3.2 Sensor data and Preprocessing

The motion sensors are event-based, generating either a *motion-on* or *motion-off* signal. A *motion-on* signal is fired when a movement is detected after no movement is detected for at least 4 minutes. A *motion-off* signal is fired when no movement is detected for 4 minutes after a *motion-on* signal has been fired. Therefore, our raw data can be visualized as bars of various lengths, each of which starts with a *motion-on* signal and ends with a *motion-off* signal. We refer to such bars as *active-durations.* A sample data collected from one elderly over a 24 hour period from four zones (*bedroom, living room, kitchen, toilet*) is shown in Figure 2.

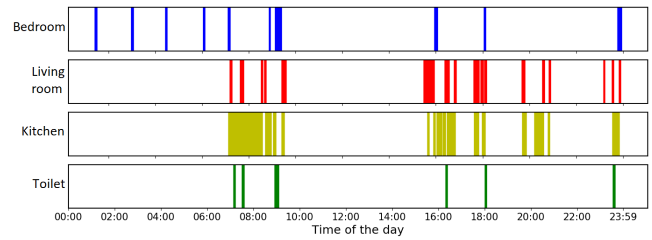

Figure 2: Visualization of in-home active-durations derived from EMCS from one elderly's house on a typical day.

As the raw data is unstructured (as shown in Figure 2), we first transformed the *event-based* sensor data to an *interval-based* representation by computing the sum of the active-durations for each 30 minutes interval, resulting in 48 intervals per zone (sensor) per day. For example, if an active-duration is recorded in the living room from 08:40 to 09:10, the first 20 minutes (08:40 to 09:00) is assigned to the 08:30 - 09:00 interval and the second 6 minutes is assigned to the 09:00 - 09:30 interval (since each *motion-off* occurs 4 minutes after the last detected motion).

Second, we obtained 30 days of the *interval-based* data before each survey date and separated them to 2 sets: *bedroom* and *outside_bedroom*, the latter of which is generated by aggregating (interval by interval) the *interval-based* data from all locations except the bedroom.

Once the *bedroom* and *outside_bedroom* sets were generated, we computed the means of active-durations over 30 days for each 30 minute interval for each set. Ultimately, both the average *bedroom* activity levels and the average *outside_bedroom* activity levels in a day can be represented by 48 values (we refer to these 48 values as '*activity levels*'). Two examples are illustrated in Figure 3 and Figure 4, in which the top and middle subgraphs display activity levels for *bedroom* and *outside_bedroom* respectively (the 3rd subgraph will be explained in Section 3.3).

This method of preprocessing was chosen to allow us to easily determine each subject's typical sleep pattern. During a typical sleeping period, the average activity level detected outside the bedroom over the 30 days should be very low compared to the rest of the times, thus generating a *bowl* shape (refer to Figure 3, *outside_bedroom*, 23:00 to 07:00). In addition, the extraction of features will be more tolerant to subjects' different living patterns, as the data outside the bedroom will be combined to one single graph.

3.3 Feature Extraction

Our feature extraction focuses on identifying features based on subjects' activity levels that may directly or indirectly

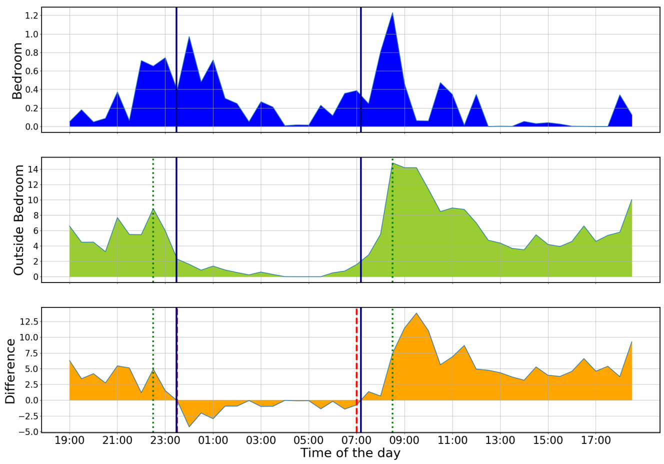

Figure 3: Aggregated activity levels of an elderly with *good_sleep* (PSQI score of 0). The y-axis represents the average active duration over 30 days for each 30 minute interval in minutes.

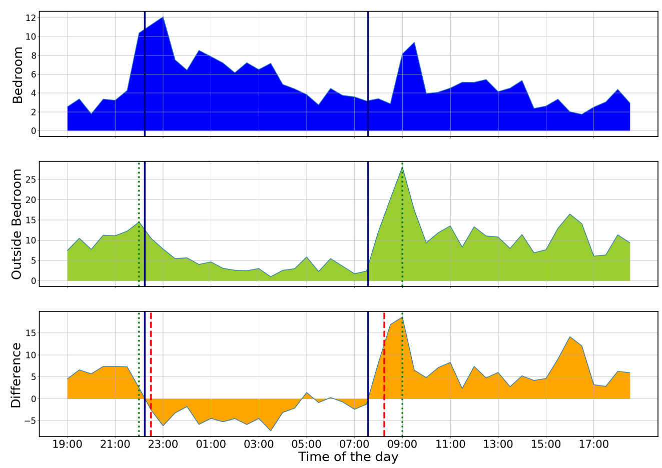

Figure 4: Aggregated activity level of an elderly with *poor_sleep* (PSQI score of 19).

reflect their sleep quality. Therefore, we first estimate a subject's general sleep period, and then attempt to extract useful features based on the activity levels during the sleep period.

To determine the sleep period of each subject, we estimate the going-to-bed time (denoted as '*bed-time*') and waking-up time (denoted as '*wake-time*') as follows:

1) The *outside_bedroom* graph should exhibit a *bowl* shape while the subject is asleep. The left and right peaks of this *bowl* shape can be considered as the upper bounds for the *bed-time* and *wake-time* respectively. To find the left peak, our algorithm first picks 7 'lowest' points between 00:00 and 05:00, assuming that in a typical scenario the subject is likely to be sleeping within this time period. Each point then obtains the left peak in its own perspective by finding a point on its left with the largest gradient and with a minimum 'distance' of one hour. The left peak that gains the most votes is then picked to represent the upper bound of the *bed-time*. The upper bound of the *wake-time* is determined in a similar manner. The green dash lines in Figure 3 and Figure 4 denote the estimated upper bounds of *bed-time* and *wake-time*.

2) To refine the estimates, we created a third graph, which equals to $[outside\_bedroom - bed\text{-}time * normalization\_factor]$ (illustrated in the third subgraph in Figure 3 and Figure 4), where the $normalization\_factor$ is heuristically set to $[max\_activity\_outside\_bedroom / max\_activity\_bedroom/2]$ based on each subject's own activity levels. This normalization process is to ensure subjects' relative activity levels (*outside_bedroom* vs *bedroom*) are of the same scale regardless of their life styles. The outermost points when the value equals 0 (refer to Figure 3 and Figure 4) within the upper bounds are taken as the refined estimates of the *bed-time* and *wake-time* (the solid blue lines in Figure 3 and Figure 4). This method was chosen because, when a subject goes to sleep, the activity level must drop outside the bedroom and increase inside the bedroom. Therefore the break-even points in subgraph 3 could provide a reasonable estimation of the subject's true *bed-time* and *wake-time*.

To collect the ground truth on sleep periods, we also asked the subjects to state their usual *bed-time* and *wake-time* over the past month. Examples of the answers are indicated in red dash lines in Figure 3 and Figure 4. The average absolute difference between the estimated times and the survey-based answers are 1.25 hours for *bed-time* and 1.01 hours for *wake-time* respectively.

Based on the estimated sleeping periods, we generated the following list of features from both the *bedroom* and the *outside_bedroom* graphs separately:

(1) The minimum activity level.
(2) The 10^{th}, 25^{th}, 50^{th}, 75^{th} and 100^{th} percentiles of the activity levels, and the differences between these percentiles and the minimum activity level.
(3) The standard deviation of the activity levels.
(4) Sum of the negative 2nd-order deviation of the activity levels, which will be 0 if it is a perfect *bowl* shape and a negative value if there are spikes.
(5) The estimated sleep duration.
(6) The estimated real sleep duration, which is the sum of the durations with activity levels below a threshold during the estimated sleeping period. We defined the threshold heuristically as $[(maximum - minimum) * 0.6 + minimum]$.
(7) The estimated sleep efficiency, which is the ratio of the estimated real sleep duration over the estimated sleep duration.

4 RESULTS

Our sample consists of 39 subjects after excluding subjects who claimed to not sleep in the bedroom or who had helpers or long-stay visitors. 19 of them participated in both surveys while the rest in one of the surveys. Among those who participated in both surveys, the minimum time that elapsed between the surveys is 140 days, allowing us to cautiously treat the results from both surveys from the same subject as 2 independent data points in this analysis. As a result, we have 58 data points, among which 28 are labeled as *good_sleep* and 30 *poor_sleep*.

Based on the list of features and the corresponding labels (i.e. *good_sleep* and *poor_sleep*) for each data point, we then train a machine-learning model to predict the sleep-quality class using the extracted features.

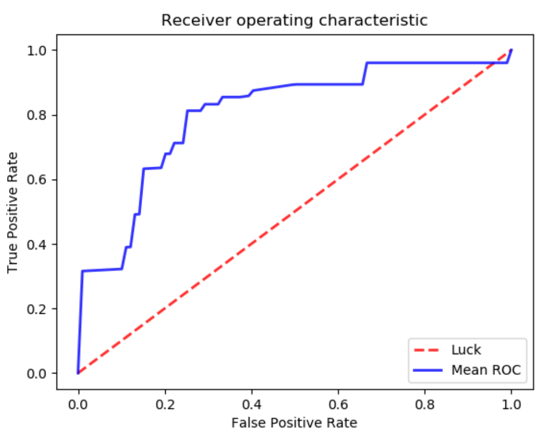

Figure 5: ROC curve for the prediction of *poor_sleep*. Each point on the ROC curve is the mean of 10 runs.

We chose Random Forests for our machine learning model and used the cross validation score based on 10 iterations of random train-test splits as the prediction accuracy score. In each split, 80% of the data points were used as the training set and the rest as the test set.

As we have a long list of features while our dataset is relatively small, we used the forward greedy selection algorithm to pick a good combination of features. We first obtained the single feature that led to the highest prediction accuracy and gradually appended the next feature to the selected list of features that achieved a new highest prediction accuracy. To avoid over-fitting, the maximum number of features to be selected was set to 5. The combination of features obtained are:

(1) The sum of the negative 2nd-order deviation using the *outside_bedroom* graph.

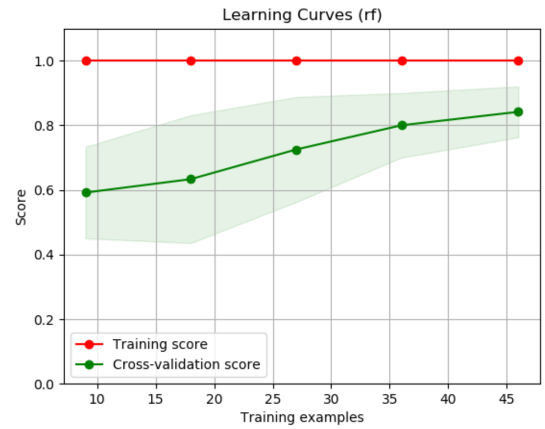

Figure 6: Learning curve for the prediction model.

(2) The maximum activity level (i.e. the 100^{th} percentile) using the *outside_bedroom* graph.
(3) The standard deviation of the activity levels using the *outside_bedroom* graph.
(4) The difference between the 10^{th} percentile and the minimum activity level using the *outside_bedroom* graph.
(5) Estimated sleep efficiency using the *bedroom* graph.

These features resulted in a prediction accuracy of 84% based on the cross validation score. One interesting observation about the features selected is that the subjects' behaviour outside the bedroom during the supposedly sleeping period are important indicators of their sleep quality. In addition, we defined *poor_sleep* as the positive case and plotted the ROC curve in Figure 5 to determine how well our model predicts the elderly with poor sleep quality. Accordingly, our model can achieve 80% true positive rate with 25% false positive rate. In addition, from the learning curve shown in Figure 6, the prediction result can be further improved if there are more data points.

5 CONCLUSION

Poor sleep quality can lead to various physical, social and mental health issues, which can affect the ability of elderly living alone to age-in-place in the community. Smart homes enabled with elderly monitoring and care systems (EMCS) comprising passive and unobtrusive sensors can be used to alert caregivers of anomalies in the daily living patterns of these elderly that could be linked to various health issues. In this paper, we presented our model of predicting elderly with poor sleep quality based on real data collected from a large scale smart home deployment in Singapore. The ground truth was collected through surveys and the PSQI score was used to classify elderly in to poor and good sleep quality classes. We are able to achieve promising results, with 84% classification accuracy among a study sample of 39 elderly. One particular note is that the elderly's activity levels outside the bedroom during the sleeping period are important indicators of their sleep quality.

Extensions of this study is highly feasible and worthwhile for the following reasons: (i) with passive and unobtrusive sensing, the elderly is not required to change their daily routines (for example, to wear and/or charge a wearable) and would therefore be more amenable to continue participation in the study; (ii) the learning curve demonstrates that prediction results can be improved with more data points, which can be achieved with more study participants, or extending the study longitudinally; and (iii) beyond preventive care, the same EMCS can also be used for reactive care, providing additional value to both the elderly and their caregiver.

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