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Brian CHEN
Singapore Management University, brian.chen.2017@mitb.smu.edu.sg

Hwee-Pink TAN
Singapore Management University, hptan@smu.edu.sg

Irus RAWTAER
SingHealth Duke NUS Academic Medical Centre

Hwee Xian TAN
Singapore Management University, hxtan@smu.edu.sg

Objective Sleep Quality as a Predictor of Mild Cognitive Impairment in Seniors Living Alone

Brian CHEN*, Hwee-Pink TAN*†, Iris RAWTAER‡, and Hwee-Xian TAN*
*School of Information Systems, Singapore Management University (SMU), Singapore
†SMU-TCS iCity Lab, Singapore
‡Department of Psychiatry, Sengkang General Hospital, Singhealth Duke NUS Academic Medical Centre, Singapore
{brian.chen.2017@mitb.smu.edu.sg, hptan@smu.edu.sg, iris.rawtaer@singhealth.com.sg, hxtan@smu.edu.sg}

***Abstract*—Singapore has the fastest ageing population in the Asia Pacific region, with an estimated 82,000 seniors living with dementia. These figures are projected to increase to more than 130,000 by 2030. The challenge is to identify more community dwelling seniors with Mild Cognitive Impairment (MCI), a prodromal state, as it provides an opportunity for evidence-based early intervention to delay the onset of dementia.**

In this paper, we explore the use of Internet of Things (IoT) systems in detecting MCI symptoms in seniors who are living alone, and accurately grouping them into MCI positive and negative subjects. We present feature extraction methods and findings from real data captured via selected sensors installed in the homes of 49 seniors for up to two months. Performance evaluation shows that the sleep state variability, as measured through bed sensors, yields a recall of over 70% in predicting MCI in these community dwelling seniors.

Index Terms - Internet of Things (IoT), senior monitoring, mild cognitive impairment, early detection, eldercare, dementia

I. Introduction

Dementia affects millions of people worldwide, mostly older adults or seniors, and is viewed as a 'late and irreversible stage' in the continuum of cognitive disabilities. In Singapore, seniors aged 65 years old and above will constitute 20% of the population by 2025, where the prevalence rate of dementia is about 6.2%. However, there is evidence to show that pathological changes begin many years prior to the onset of dementia, in the form of Mild Cognitive Impairment (MCI). The challenge therefore is to identify subtle changes in cognition [1], as intervention is most likely to be effective [2]. In a Singapore-based study on 473 MCI seniors aged 55 years and above [3], 44% reverted to normal cognition. In particular, MCI individuals who were significantly younger and more educated, as well as those with greater participation in leisure-time activities and higher Mini-Mental State Examination (MMSE) scores, were more likely to revert to normal cognition.

The ability to detect MCI through objective monitoring of seniors' activities can overcome the limitations of conventional assessment questionnaires and ad-hoc health screenings, which are labor intensive and unable to track longitudinal changes in daily living patterns of the seniors. Studies on objective monitoring for early detection of MCI [4] can be categorized as: (i) scenario-based assessment; or (ii) real-life monitoring. In the latter, seniors continue with their daily routines with privacy-preserving sensors - such as passive infrared (PIR) motion sensors, contact sensors and other environmental sensors - installed in their homes for weeks to years, without any ground truth recording. In scenario-based assessment studies, seniors are invited to research lab apartments that are designed to simulate real-life situations. Seniors are then asked to perform a series of Activities of Daily Living (ADLs) and instrumented ADLs (iADLs), in fixed or flexible order and over a short duration (typically between hours to days). Their performances are observed by an experimenter and recorded through multimodal sensors - including video [5] and audio recording devices. Although scenario-based assessments tend to result in fine-grained objective data and can be validated through ground truth observations by the experimenter, they are limited by high set-up and running costs, as well as short observation periods that may not capture the seniors' daily routines as compared to real-life monitoring.

Between Sep 2016 to May 2018, we conducted a study in partnership with a clinical investigator from a healthcare organization, whereby in-home sensors are setup for real-life monitoring to distinguish between seniors with healthy cognition (HC) from those with mild cognitive impairment (MCI) [6–8]. We recruited a total of 59 seniors aged 65 and above who are living alone, across 6 blocks of 7-9 seniors each; 49 of these seniors eventually completed the study. Each block, comprising both HC and MCI seniors, are monitored with in-home sensors for 2 months.

Unlike prior work on cross-sectional designs [9–12], our study comprises a richer set of sensors that includes fixed passive sensors and wearable devices to monitor activities related to mobility, leisure and self-care [13]. The novel contributions in this paper are two-fold:

1) blind analysis of objective data with the Pittsburgh Sleep Quality Index (PSQI) to uncover sensor-derived features to differentiate between HC and MCI seniors; and
2) subsequent validation by the clinical investigator.

In Section II, we describe related work on the use of sensor data for real-life monitoring of mobility and self-care activities for early detection of MCI. We describe the various data sources as well as our approach to data preparation and analysis in Section III. We discuss interesting and important findings of our study in Section IV before we conclude and present our future work in Section V.

Fig. 1: Typical sensor deployment for MCI detection.

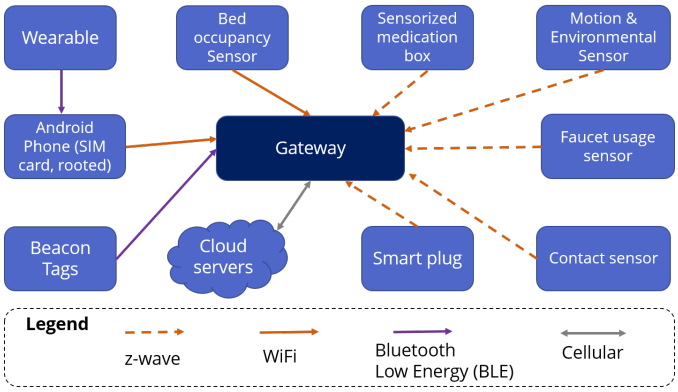


Fig. 2: System architecture.

II. Related Work

In this section, we describe related work on the use of sensor data for real-life monitoring of mobility and self-care activities for early detection of MCI: (i) outside of; and (ii) in Singapore.

Outside of Singapore: In [9], 10 HC and 4 MCI seniors between 67 to 90 years old and living alone in Japan, were monitored over 78 days with PIR motion sensors deployed in each zone of the apartment (corresponding to a subset of our setup as depicted in Figure 1). MCI seniors were found to have significantly less outings and shorter sleeping times as compared to HC seniors. In [10], 18 seniors aged between 73 and 92 years old were monitored over a 2-year period with PIR motion sensors, contact sensors, as well as light and temperature sensors. At baseline, 7 were HC, while the remaining 11 were at risk or had cognitive difficulties. The study found significant correlations between the level of mobility at home and clinically-provided cognitive scores. In [11], 59 HC and 26 MCI seniors, aged 70 years and above and living alone, were monitored with a similar setup as [9], and included contact sensors at the main door. Using combined room activity distribution over a 20-week window, the system was able to detect MCI seniors with an F0.5 score of 85.6%. Finally, in [12], 35 HC and 3 MCI seniors, aged 75 to 99 years old, received 7-day pillboxes that continuously tracked inferred medication for at least one prescription medication over a 13-month period. Seniors with poorer cognitive scores were found to have higher and increasing variance in their medication intake timing.

Singapore: In [6], we present practical insights gained in terms of the design, testing and deployment of the in-home sensor systems in the first 2 blocks that resulted in significant improvements in system uptime and reduction in maintenance visits in subsequent blocks. Early results based on blind analysis [7] on the first 2 blocks comprising 12 MCI and 5 HC seniors indicate that the use of IoT for early detection of MCI is promising. Using only three features (forgetfulness incidents of personal items, forgetfulness incidents of medication intake, and medication intake timings), we identified 2 seniors who were likely to have MCI, and 4 seniors who were likely to be CH. This corroborates with corresponding non-blind analysis [8], whereby MCI seniors were more likely to forget personal effects (keychain, wallet) and skip doses of medication, as compared to HC seniors. In particular, MCI seniors were more likely to forget their wallets than their keys, as compared to HC seniors. In addition, qualitative feedback from participants were positive and there was enthusiasm for the system to be fine-tuned to support more seniors living alone.

In this paper, we extend the blind analysis and establish statistically significant relationships of extracted sensor-derived features against psychometric evaluation measures based on data collected from 49 seniors. We explore these features for grouping of MCI versus HC seniors, and present the performance of our classification model through ground truth validation by the clinical investigator.

III. Data Sources

At the beginning of each block, a sensor system is deployed in the home of each participant. Each study participant must be: (i) 65 years of age and above; (ii) able to provide written informed consent in English or Mandarin; (iii) cognitively healthy or suffering from MCI; and (iv) able to function independently within the community. The sensor system measures various activities of daily living that are hypothesized to differ between MCI and HC seniors. To derive meaningful measures of these activities while minimizing withdrawals from the study, the in-home sensor system should achieve a minimum of one-month's sensor data with minimum active participation from the seniors, as well as maintenance visits.

In the following, we describe the various data sources, as well as our approach to data preparation and analysis.

A. Description of supporting data

Among various questionnaires administered at baseline, only the gender, Pittsburgh Sleep Quality Index (PSQI) as well as Geriatric Depression Scale (GDS) are provided to the technical research team for blind analysis. The PSQI consists of 19 individual items that measure different aspects of sleep, offering seven component scores and one composite score. Each item is weighted on a 0-3 interval scale. The global PSQI score is calculated by totalling the seven component scores, where a score of 5 or greater is indicative of poor sleep quality [14]. With the GDS, users respond in a Yes/No format to 15 questions. Scores above 5 are suggestive of depression [15].

TABLE I: Sensor modalities and their contribution to the measurement of in-home functions and ADLs.

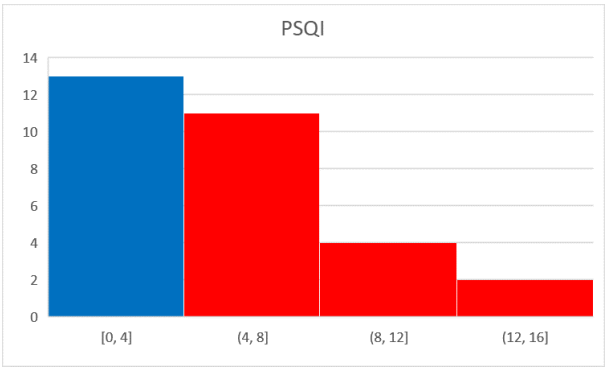
Device	Monitoring of	Update rate	ADLs measured
Wearable	Heart rate Skin temperature Pedometer	Every few mins	Physical activity level
BLE Beacon	Keys Wallet/ Handbag	Every 4 mins	Forgetfulness Going out patterns
Motion	Living room Kitchen Toilet	When triggered	Zonal activity level
Contact	Main door	When triggered	Going-out activity level
Medication Box	Inferred medication intake	When triggered	Self-care activity and forgetfulness
Faucet Usage	Water use at kitchen sink	When triggered	Forgetfulness
Smart plug	TV usage	Every 10 mins	Forgetfulness
Bed occupancy	sleep state	Every 5 mins	Sleep quality

B. *Description of sensor data*

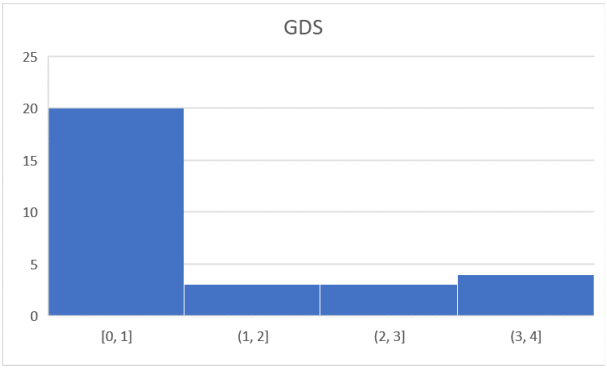
The in-home sensor system comprises two key components: (i) IoT device frontend deployed for in-home sensing and monitoring; and (ii) backend server that houses the data management, data analytics and system monitoring engines. The IoT device frontend, as illustrated in Figure 1, comprises: (i) infrastructured sensors such as PIR motion sensors in each zone of the apartment, contact sensor at the main door, bed sensor, sensorized medication box, water sensor in the kitchen faucet and smart plug; (ii) non-infrastructured sensors including a commercially available wearable, as well as BLE-enabled proximity beacons that are attached to personal items (such as house keys and wallets/purses); and (iii) gateway devices, including an Android Phone and a Raspberry Pi to aggregate and transmit data from the sensors to the backend server. The system architecture is depicted in Figure 2. Each sensor modality contributes to the various measures of in-home functions and activities of daily living according to the mapping shown in Table I.

IV. Data Analysis and Findings

Among the 52 participants with complete PSQI, GDS and gender data, 3 participants withdrew from the study without completing the required 2-months of monitoring. As the system was upgraded from Block 3 onwards, the data analysis in the rest of this paper will be based on data from 32 participants (S21 to S59) from Blocks 3-6. Based on the histogram of PSQI and GDS scores in Figure 3, we observe that while the participants experience both good (PSQI < 5) and poor (PSQI ≥ 5) sleep quality, there is no indication of risk of depression in any participant (GDS < 5). As such, we proceed to analyse each set of sensor modalities as follows:



(a) PSQI.



(b) GDS.

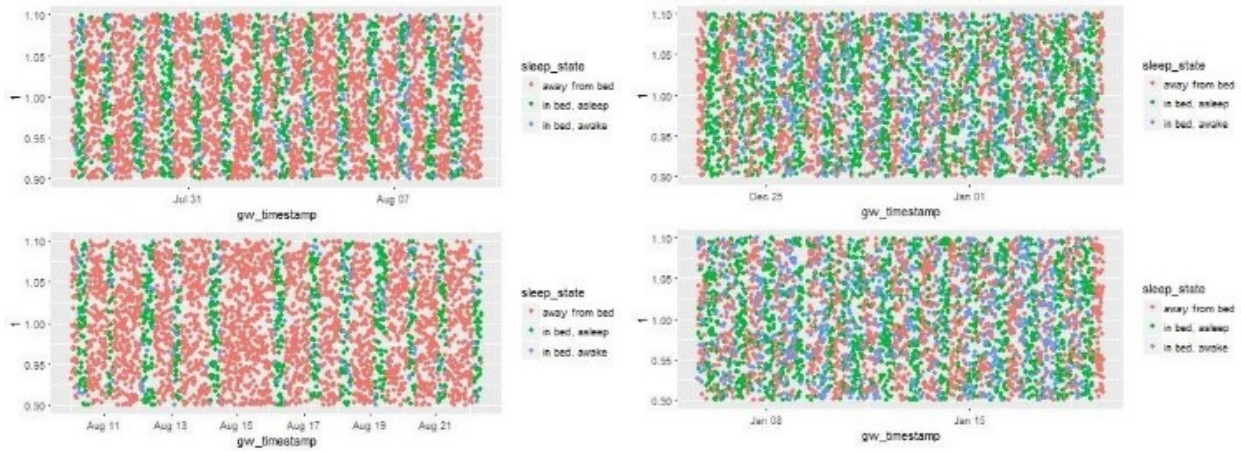
Fig. 3: Histogram of PSQI and GDS scores of 32 participants.

1) Clean data and visually explore different sets of sensor modalities of interest that may lead to areas of further investigation.
2) Perform deep exploration by generating data visualizations of different activity patterns for participants.
3) Define and quantify measures, as well as perform statistical analysis of both sensor data and PSQI scores to identify correlations to inform grouping of participants.

Each grouping of participants is validated with the ground truth that is known only to the clinical investigator. We note that in our performance evaluation, recall is more important than precision, as the cost of a missed detection (i.e., a senior with MCI is not recommended for screening) is much higher than the cost of wrong detection (i.e., a HC senior is recommended for screening, which turns out to be unnecessary).

A. *Bed Sensor (24 hourly)*

Among the 32 participants, 30 have bed sensors installed, of which 23 have sufficient data (1 month or more) for further analysis. Each bed sensor comprises a sleep mat and a WiFi-enabled interrogator. The sleep mat is installed under the senior's bed mattress, and actively sends the sleep state to the backend servers via the WiFi-enabled interrogator at every 5-minute intervals. Figure 4 compares the pairwise distinct sleep patterns between: (i) S21 and S45; and (ii) S56 and S35. Our exploratory analysis thus indicates that there are differences in sleep latency, duration and variability between participants with good (PSQI < 5) and poor (PSQI ≥ 5) sleep quality.



(a) S21 (PSQI = 2) has regular sleep patterns with consistent changes and duration of each state.

(b) S45 (PSQI = 5) has irregular sleep patterns with less consistent changes and duration of each state.

(c) S56 (PSQI = 3) has less time spent in bed, and less in-bed time during the day.

(d) S35 (PSQI = 13) has longer in-bed duration and higher frequency of in-bed time during the day.

Fig. 4: Pairwise comparison of sleep patterns: S21 vs S45 and S56 vs S35 over 4-week duration. The sleep states are colored as follows: (i) 'Away from bed' - red; (ii) 'In bed, awake' - blue; and (iii) 'In bed, asleep' - green.

TABLE II: Measures derived from the bed sensor.

Sensor-derived measure	Definition
Sleep latency	N_2
Sleep latency ratio	$\frac{N_2}{N_2+N_3}$
Sleep duration	$\frac{N_3}{N_1+N_2+N_3}$
Sleep state variability	$\sum_t s_t - s_{t-1}$

We then define various sensor-derived measures of sleep quality as shown in Table II, whereby N_j denotes the total number of recorded instances of sleep state j for each participant, and $s_t = \{1, 2, 3\}$ is the sleep state at time t according to the following mapping:

1 'Away from bed'
2 'In bed, awake'
3 'In bed, asleep'

The scatter plot between sleep state variability and PSQI in Figure 5 reveals that seniors who frequently switch between different sleep states tend to have higher PSQI scores (i.e., poorer sleep quality). Following this, we perform a logistic regression with PSQI as the predictor response variable, and each sensor-derived measure as the independent variable. A

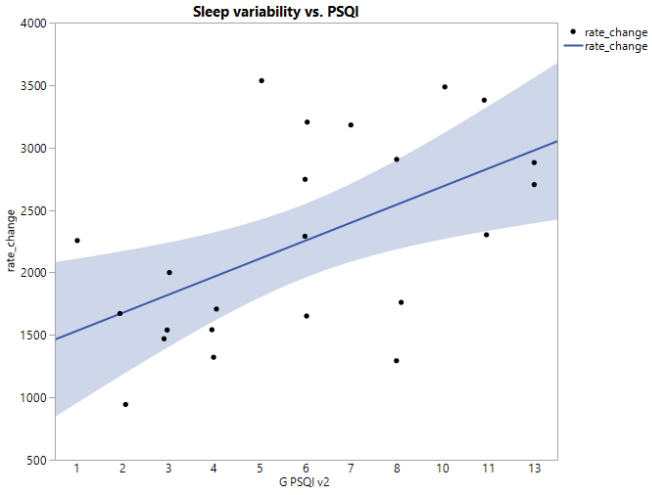


Fig. 5: Scatter plot between sleep state variability and PSQI.

Fig. 6: Grouping of participants based on sleep variability.

TABLE III: Confusion matrices for participant grouping based on sleep state variability.

Sleep State Variability (n = 23)	Predicted: Yes	Predicted: No
Actual: Yes (MCI)	10	4
Actual: No (HC)	1	8

TABLE IV: Confusion matrices for participant grouping based on PSQI.

PSQI (n = 23)	Predicted: Yes	Predicted: No
Actual: Yes (MCI)	12	2
Actual: No (HC)	2	7

statistical significant result of 0.006 was obtained in the overall model test for only sleep state variability.

Accordingly, the seniors are categorized into two groups based on the: (i) median value of sleep state variability; and (ii) PSQI threshold of 5. This is illustrated in Figure 6, where the horizontal line depicts the median value of sleep state variability. We observe that seniors with high PSQI scores have diverse sleep state variability values that span across the entire y-axis, while seniors with low PSQI scores have sleep state variability values that are below the median value.

Grouping based on PSQI scores (threshold of 5) yields an accuracy of 82% with recall and precision of 85.7%, while grouping based on sleep state variability (with the sample median as the threshold) yields an accuracy of 78% with recall of 71.4% and precision of 91%. This suggests that PSQI (among other assessment scores) seems to be a good predictor of MCI. With significant statistical correlation between sleep state variability and PSQI, the former is a promising sensor-derived measure for predicting MCI.

B. Bed Sensor (Bedtime only)

In Section IV-A, the various sensor-derived measures are computed based on sensor readings that are acquired throughout the day, and only aggregate PSQI scores are used in the analysis. We explore potential enhancements by filtering the sensor-derived measures based on individual participants' bed times (i.e., the period between going to bed and waking up) and exploring statistical correlations with PSQI component scores. As self-reported bed times may be inaccurate [16] and recognized bed times may not be locally contextualized, we extract each senior's bed times from the sensor data.

TABLE V: Mapping of sleep-related features with statistical correlation with PSQI component scores.

PSQI Component Scores	Relationship to variables
Q4 (hours of sleep)	sleep state variability, duration ratio & latency.
C3 (Q4 comp. score)	
Q5c (get up to use bathroom)	sleep state variability and duration
Q5g (feel too hot)	sleep latency
Q5h (have bad dreams)	sleep state variability
Q6 (sleep medication)	sleep state variability
Q8 (enthusiasm to do things)	sleep latency

TABLE VI: Confusion matrix for participant grouping based on bedtime-normalized sleep state variability.

Bedtime-normalized sleep state variability (n = 23)	Predicted: Yes	Predicted: No
Actual: Yes (MCI)	11	3
Actual: No (HC)	3	6

The same measures (c.f. Table II) are re-computed for each senior's bedtime. Statistical analysis between each measure and the aggregate PSQI score reveals that, as like before, a statistically significant relationship exists only between the sleep state variability and PSQI. We then repeat the statistical analysis between each sensor-derived measure and the component PSQI scores. The latter are found to be correlated with various sensor-derived measures as tabulated in Table V. As expected, existing correlations are usually associated with the sleep state variability measure.

Finally, the seniors are categorized into two groups based on the median value of bedtime-normalized sleep state variability. The resulting confusion matrix is shown in Table VI. This grouping yields an accuracy of 74% with recall and precision of 78.6%. We note an improvement in the recall from 71.4% to 78.6% as a result of removing the effects of day-time napping on the sleep state variability.

V. Conclusions and Future Work

In this paper, we present our findings based on blind analysis of objective sensor and subjective assessment data collected from a real-life monitoring study of 32 seniors living alone in Singapore, who are either cognitively healthy (HC) or have mild cognitive impairment (MCI). The objective data is drawn from a rich set of in-home fixed passive sensors and wearable devices that unobtrusively monitor activities related to mobility, leisure and self-care over a two-month period. These seniors experience both good and poor sleep quality (based on PSQI), but do not have any risk of depression (based on GDS). We perform data preparation and exploration, define

sensor-based measures and analyze potential correlations with PSQI to inform the MCI/HC grouping of participants. The accuracy of these groupings are then validated by the clinical investigator.

Among the sensor-based measures, sleep state variability is promising in detecting seniors with MCI, with a recall of over 70%. This result is consistent with the corresponding results obtained by using PSQI scores for grouping (with recall of 86%). In particular, statistical correlations between various sleep-related measures and PSQI component scores reveal that correlations exist primarily with sleep state variability. While promising, the correlation analysis is limited to the availability of assessment measures, as well as the duration of usable data. As such, we intend to extend the analysis to include other assessment measures (such as MOCA and MMSE), where well-defined thresholds exist for MCI seniors in Singapore. In addition, together with the clinical investigator, we will soon commence a follow-up study of 100 seniors (both HC and MCI) with continuous in-home monitoring for up to 2 years.

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