Towards Unobtrusive Mental Well-Being Monitoring for Independent-Living Elderly

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ABSTRACT

It is essential to proactively detect mental health problems such as loneliness and depression in the independently-living elderly for timely intervention by caregivers. In this paper, we introduce an unobtrusive sensor-enabled monitoring system that has been deployed to 50 government housing flats with the independent-living elderly for two years. Then, we also present our initial findings from the 6-month sensor data between August 2015 and April 2016 as well as the survey data to measure the subjective well-being indicator. Our study showed the promising results that "room-level movements within a house" and "going out" behavior captured by our simple sensor system has a potential to detect the cases of severe loneliness and depression with the precision of 10/16 and recall of 10/12.

Keywords

Monitoring System; Depression; Loneliness; Elderly

1. INTRODUCTION

The global population is aging rapidly. The number of seniors over the age of 60 is expected to be 2 billion by 2050 [12]. Global statistics also showed that over 20% of adults aged 60 and over suffer from a mental or neurological disorder [12] such as dementia and depression. The elderly have a much higher risk of depression and other mental well-being issues than the young due to medical illnesses, changes in physical status, loss of income on retirement, and loss of a life partner and friends. The risk is even higher for the independent-living elderly who tend to have poorer social communication and access to the healthcare services. These risks are prone to result in isolation, loneliness, depression and psychological distress of the elderly.

Diagnosing mental well-being problems such as anxious distress or depression requires a comprehensive understanding of patient's daily moods, behavior, and lifestyle by running a series of standard questionnaires and physical examinations. The diagnosis becomes even more challenging since each mental illness can manifest in various ways to different individuals. Moreover, mental health concerns are sometimes under-identified by healthcare professionals and the elderly themselves since the stigma surrounding mental illness makes people reluctant to seek help.

To address the challenges, we are working toward a cheap sensor-driven monitoring system that enables early detection of the mental illness of an elderly. It captures and analyzes the coarse-grained "in-home mobility" patterns and "going-out" behaviors of the elderly and reports potential problems to the family members or caregivers for preemptive care or timely intervention. For example, the elderly may spend too much time at home alone for a few days (compared to other days), the system suggests the caregivers visit the elderly to prevent social isolation and possible depression.

The primary focus of our work includes: (i) deploying a sensor-based system to capture and analyze the in-home mobility patterns of older participants, and then to detect abnormalities; (ii) examining the relations between the mobility patterns inferred from sensor data and the mental well-being of the elderly (subjectively measured by surveys). Our system is designed with the following key considerations: (i) it should require minimum involvement of the elderly (ii) it should be low-cost (as it is targeted to be deployed in government housing at a large scale), (iii) it should not capture sensitive private information from home. In this end, we leverage only the unobtrusive and passive infra-red and door contact sensors and investigated their potential to estimate the mental well-being status of participants.

Our contributions can be summarized as follows:

- We introduce our sensor system and its deployment to 50 homes. We demonstrate the feasibility of deploying a cheap, unobtrusive and passive sensor system to monitor "in-home" mobility patterns to estimate mental well-being and present our experiences.
- As a motivational study, we conduct a survey to assess various aspects of the mental well-being from the 50 elderly participants. Our survey data confirm that elderly that are living alone are at high risk of mental well-being problem such as loneliness and depression due to the lack of social interaction.
- We presented our initial findings from the analysis of our 6-month sensor data and survey data. Our results were promising in that such simple in-home mobility and going out behavior could be a good indicator of mental wellbeing problems such as severe depression and loneliness (precision 10/16, recall 10/12).
- We discuss several insights into the general behavior trends and the relations between the outing pattern

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derived from the sensor data and the mental well-being assessment of the independent-living elderly subjects.

2. BACKGROUND AND RELATED WORK

2.1 Monitor daily living activities

The use of sensor-based system to monitor the daily living activity pattern in general or in-home mobility of older people has been widely studied in the literature. Various types of sensors have been used to monitor the activities to infer and analyze the pattern daily living behavior. Specifically, Suryadevara et al. [9] reported a wireless-sensor-network-based home monitoring system for elderly behavior based on usage of household appliances connected through various types of sensor units. Several authors have also extended the works on in-home monitoring systems to detect the inactivity at both home and room levels. For example, Planinc and Kampel et al. [6] introduced a vision-based sensor system to detect abnormal behavior in the elderly's home by analyzing the deviation from normal behavior based on histogram comparison. A similar approach was applied in [7], in which the authors used sequence mining methods in the flow of binary motion sensor events to define frequent pattern and detect unusual activities. While most of those existing works using sensor-based system focus on monitoring the physical activities, we consider it as an intermediate step to assess the mental wellbeing of the elderly.

2.2 Assess mental wellbeing using technology

Conventional method to assess the mental well-being includes standard questionnaire and physical screening. In addition to that, a variety of new approaches from using social network data to mobile and wearable sensing enable passive monitoring of different factors related to mental health status such as social interaction, physiological responses, mobility, and location. For instance, Burke et al. has shown that active engagement on Facebook has been associated with less loneliness and greater feelings of social connectedness [1]. Besides, LiKamWa et al. [4] and Wang et al. [11] have demonstrated the potential of using mobile phone usage and sensor data to infer user's moods and mental health respectively. However, those are hardly applicable to measure the mental wellbeing of the elderly people considering their lack of access to mobile devices and social network.

Another approach to assess the mental wellbeing is using physiological measurements such as Electrocardiogram (ECG), Galvanic Skin Response (GSR) which may help to better understand the depression, stress or anxiety conditions and provide physicians with more reliable data for interventions [8]. In spite of that, prior studies on mental stress detection using those sensors were limited in a laboratory environment where participants generally rested in a stationary position. The physiological responses to the stress or depression states can be masked by variations of motion artifacts caused by daily physical activities, which makes this approach impractical in real deployment.

There are also risks, of course, to bringing technology into the clinical encounter. Privacy is a significant concern both to individuals as well as health systems. It is critical that patients understand who has access to their data, how frequently it is monitored, and whether a clinician will intervene when negative mood patterns, thoughts, or behaviors are detected. Another important issue should be considered is the lack of access to advanced technologies among low-income, elderly, or rural populations could increase disparities in accessing the healthcare service. Therefore, in this work, we explore the possibility of deploying a cheap, unobtrusive and passive sensor system that is capable of assessing the mental well-being status of the elderly people.

3. SYSTEM OVERVIEW

3.1 System Overview

Figure 1 shows an overview of the end-to-end system infrastructure of our project including the two key stakeholders which are the elderly citizens and healthcare service providers. The main technology components of the system are: (i) sensor-enabled home of the elderly resident to sense the in-home physical activities; (ii) gateway to transmit the sensor readings from home to back-end; (iii) back-end servers for storage, analytics, and dissemination; and (iv) user interfaces in the form of web and mobile apps. The sensor-enabled home monitors the elderly resident and in cases of abnormal behavior detected, the back-end sends alerts to the assigned caregivers.

3.2 Deployment Setup

Elderly people are generally amenable to in-home monitoring systems that are unobtrusive (i.e., the systems do not employ vision-based or audio-based technologies) and require minimal action from participants [3]. Based on this and our survey result on the sensor system design in prior works [5, 10], we have chosen two types of non-intrusive sensors, namely, passive infra-red (PIR) sensor and reed switch. The PIR sensor is used to detect motion within a region of coverage while the reed switch is used to detect main door opening and closing. In addition to being non-intrusive, these sensors do not require any action or changes in daily activities of the elderly to accommodate them.

A typical home installation is shown in Figure 2. Note that the target participants of our project are senior citizens living alone in Housing Development Board (HDB) rental flats. A typical rental flat consists of one bedroom, one kitchen, one bathroom, and one living room. Every region or location in the home is covered by one PIR sensor, while the reed switch is attached to the main door of the unit. Thus, an installation requires only 5 sensors (4 PIR sensors and 1 reed switch.) In addition to the sensors, every home is also equipped with a gateway which is responsible for relaying all sensor data to the back-end for storage and processing.

4. DATA COLLECTION

4.1 Study methodology

The data used in this study were collected from residents of the Sensor-Enabled Homes & Personalized Home Care for Senior Singaporeans Living in HDB Environment project (SHINESeniors) [10]. This IRB-approved study currently involves 50 senior citizens living independently in Singapore who have been monitored for two years (since March 2015). A core set of technologies is continually maintained in all homes, including passive infra-red (PIR) motion sensors in each room and contact sensor on the main door of each home. Along with the sensor-enabled home system to collect sensor data, we conduct a survey with the 50 senior

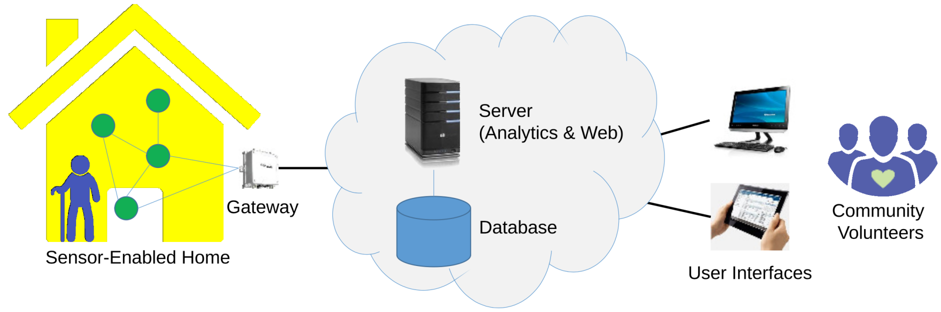


Figure 1: System overview

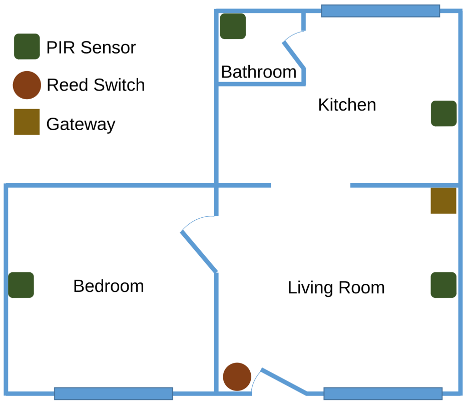
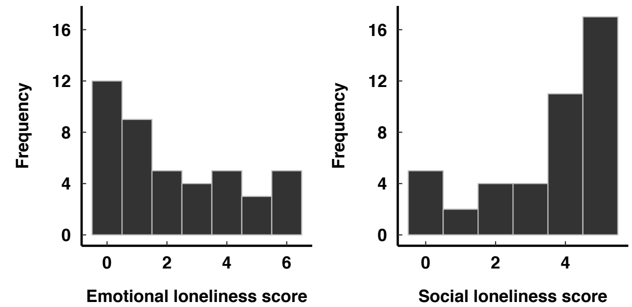


Figure 2: System overview



(a) Emotional Loneliness Score (b) Social Loneliness Score

Figure 3: Histograms

citizens in which we use standardized questionnaires to assess various aspects of the participants' mental well-being.

4.2 Sensor data

Data from motion sensors in each room of the home as well as contact sensors on the doors of the home are binary signal and simultaneously collected. The PIR motion sensors function by firing a signal every ten seconds: '1' to indicate some movement in the covered region is detected and '0' to indicate that there was no movement detected in the last 10 seconds. with a refractory period after firing of about 6 seconds. The contact sensor is reed switch, and fire a '0' signal when the two magnets are together (the door is closed) and a '1' signal when they are apart (the door is open). The sensors are also configured to log their respective battery states every ten seconds. The gateway aggregates the sensor logs and transmits them to the back-end once every two minutes.

4.3 Survey data

In April and May of 2016, the elderly participants were administered a mental well-being assessment survey which covers two components including social function (loneliness scale), mental health (depression scale). The following standard questionnaires are included in our study.

4.3.1 Social function

We use a well-validated survey for assessing loneliness, the 11-item version of Loneliness Scale developed by De Jong Gierveld [2]. The questionnaire is used to assess both Social Loneliness Scale and Emotional Loneliness Scale of participants. This survey asks questions such as 'I miss having people around' or 'My circle of friend and acquaintances are too limited' (Social Loneliness Scale) and 'I experience a general sense of happiness' (Emotional Loneliness Scale), where response options are 5-likert scales from 'No' to 'More or Less' to 'Yes'.

Table 1 shows that the majority (83.72%) of participants in this study are experiencing loneliness at some level (from mild to severe level).

Loneliness level	Score	Number of subjects
None	0 - 2	7
Mild	3 - 8	26
Moderate	9 - 10	8
Severe	11	2

Table 1: DeJong loneliness scale of 43 elderly subjects

Figure 3 shows two components of the DeJong general loneliness: emotional and social loneliness scores (higher score means lonelier). The emotional loneliness score measures how an individual subjectively feels lonely and empty while the social loneliness score assesses the social relationship or connection of the participant (i.e. if there are people that the participant can talk to or get help from). The histograms indicate that while more than two third of the population do not subjectively feel lonely (emotional loneliness score less than 4), the majority of them are having social loneliness problem (social loneliness score are higher than or equal to 4). This means that the loneliness problem at the participants is mostly due to the lack of social connection or interaction. This phenomenon is reasonable as the participants are all independent-living elderly, and it also suggests that monitoring the social activities, such as how often a subject goes outside and meet other people, is a relevant approach to assess loneliness of the elderly.

4.3.2 Mental health

While there are many standardized questionnaires to measure depression, the Geriatric Depression Scale (GDS) [13]

Depression level	Score	Number of subjects
None	0 - 4	29
Mild	5 - 8	11
Moderate	9 - 11	0
Severe	12 - 15	4

Table 2: Geriatric depression scale of 44 elderly subjects

has been tested and used extensively with the older population. The validity and reliability of the tool have been supported through both clinical practice and research. We use the GDS 15-item version in which participants are asked to answer 'Yes' or 'No' in response to questions regarding how they felt over the past one week.

The result of GDS survey (Table 2) shows that 34.09% of the participants are having depression problem at mild, moderate and severe level. Although the sample size is small, it indicates that the older independent-living citizens are at higher risk of depression.

4.4 Dataset summary

We collected and synchronized data from 50 participants. However, there were three cases that sensor system failure happened frequently in the period of 6 months prior to the survey (sensor data are partly not available), and four cases of uncompleted mental well-being assessment. As our goal is to examine the association between the patterns of daily physical activities extracted from the sensor data and the metal well-being status of participants from the survey date, we focus on the sensor data collected 6 months prior to the survey. After excluding those samples with missing sensor data and uncompleted mental well-being assessment, the final subset of data contains 43 samples. Among the 43 elderly participants (19 males, Mean age = 77.59, SD = 7.65), 41 of them are independent-living while the other 2 elderly have relatives visit and stay with them during the data collection period.

5. DETECTING DAILY ACTIVITY PATTERN

5.1 Flat status and room status detection

The sensor data from each home is first divided into segments based on the transitions of the door contact sensor signals. For each segment, the elderly resident is either in or out of home for the whole segment. The door contact sensor state changes from '0' to '1' and from '1' to '0' when the resident opens and closes the door respectively. We define two types of transition of door contact signals corresponding to the events when the residents enter or exit their homes:

- 'Enter' transition: the flat is empty before the transition and occupied after it. Consider transition (ts2,te2) in Figure 4 for illustration, there is no movement detected by PIR sensors before ts2 and there are detected movements right after te2 (the PIR sensor in the living room must be triggered if the resident enter the flat).
- 'Exit' transition: the flat is occupied before the transition and empty after it (transitions (ts1,te1) and (ts3,te3) in Figure 4).

We discard those transitions that cannot be classified as either 'Enter' or 'Exit' transition. One example of invalid transition is that the resident opens the door and go out to collect mails or throw garbage while the door is still open, then goes inside and closes the door. In that case, there are PIR signals right before and after the transition. The flat status indicates whether the elderly resident is inside the flat or outside (the flat is occupied or empty). We can determine the flat status of a segment as follows:

- 'Empty': the segment starts with an 'Exit' transition and ends with an 'Enter' transition.
- 'Occupied': the segment starts with an 'Enter' transition and ends with an 'Exit' transition.

We ignore the segments with duration less than five minutes.

After classifying the flat status of each segment, we extract various descriptive features including: Duration and frequency that subjects staying in their home and being out of home over the period of one month, three months and six months prior to the survey date; Days and Epochs: we divide 24-hour period into morning (00:00am - 07:59am), afternoon (08:00am - 03:59pm), and evening epoch (04:00pm - 11:59pm) and compute duration and frequency of being out-of-home in each epoch; Weekdays and weekends: descriptive features (e.g. mean, standard deviation) of outings duration and frequency over weekdays and weekends separately.

In order to detect which room the participant is currently in (room status), we split each data segment with 'occupied' flat status into 5-minute frames. During each frame, we assume that participant is in the room with highest number of PIR signals triggered (more motion detected), we assign that room as the room status of the frame such as 'living room' or 'kitchen'. Consecutive frames with a same room status are considered as a single room occupation session. Similar to the flat status features, we compute the room status features such as total duration and frequency of room occupation sessions in the morning, afternoon and evening.

Score	Feature	Correlation
Loneliness	duration_kitchen_afternoon	0.41
Loneliness	frequency_outside_daily	-0.37
Depression	frequency_outside_daily	-0.43
Depression	duration_outside_weekend	-0.41

Table 3: Top features significantly correlated with loneliness and depression scores

5.2 Probability of being out-of-home

Besides the total duration and frequency of being out of home, it is also important to examine how the elderly participants spend their time during the day. We first divide the daily 24-hour period into 5-minute frames. For each frame, we compute the probability that the subject is out of home by counting the number of days over three months that the flat is empty at that particular frame. Figure 6 shows the average probability of outings of 43 elderly participants over 3 months. The main peak of this visualization is around lunch time, around 40% of the elderly subjects on average are out of the flat at 11:30am any given day. Their outing activities are less active after lunch time, and more than 70% of them on average stay in home after 12:30pm everyday.

6. RESULTS

The current analysis included only those subjects with (i) valid sensor data, (ii) fully answered the mental well-being assessment survey, (iii) and who live alone for the whole six months prior to the survey date (41 subjects).

6.1 Loneliness and daily activities

We examine the correlations between the loneliness score from the survey data and the all features extracted from

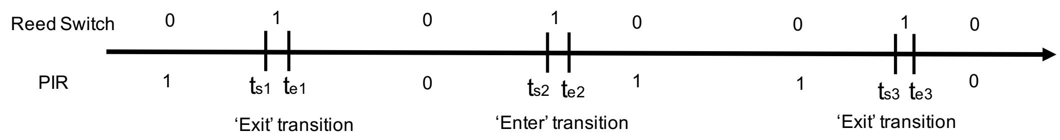


Figure 4: Segmentation of sensor data

sensor data mentioned in Section 5. Most of the flat status and room status features are just loosely correlated with the loneliness level, with the correlation coefficients are less than 0.3. The outing feature with highest correlation is the frequency of being outside daily (r=-0.37, p=0.003). Although being outside does not necessarily means that the participants meet and talk to other people, it could still be used as a good indicator of social interaction considering the context that all the participants are living alone. The duration that participant spending in the kitchen from 08:00am to 03:59pm is also significantly correlated with the loneliness level (r=0.41, p=0.007). It is worth noting that the participants in this study are living in a same community which has a common dining hall where it encourages older residents living in a same block to have lunch together as part of a social program for the elderly. Therefore, being outside around this time (instead of having lunch at home alone) could be an important factor to assessing social function of the elderly in this particular setting.

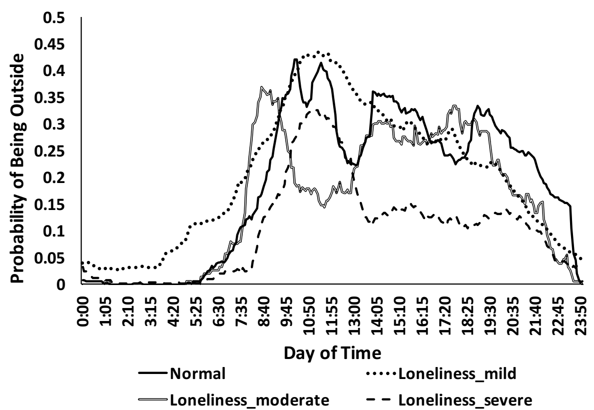


Figure 5: Average probability of being outside for four groups with different loneliness levels

The overall probability of the severely lonely group are much lower than the others. The group with 'moderate' level of loneliness has the outing pattern that appear to be different from the others. The main peaks of outing pattern visualization of this group are from 7:00 to 10:00 and from 17:00 to 20:00, which means that this group does not join the common lunch time with other in the community.

6.2 Depression and daily activities

Results from the correlation analysis of the Depression level and the flat status and room status features show very few significant correlations. As shown in Table 3, there are two outing features that are significantly correlated with the Depression score including: the average frequency that subject goes out daily (r=-0.43, p=0.003), the average duration of being outside during weekend (r=-0.41, p=0.006). The correlations are humble as there are obviously many other important factors that could affect the depression level such as physical health and sleep quality. We also observe that the outing patterns of those individuals with depression at severe level are diverge from the average.

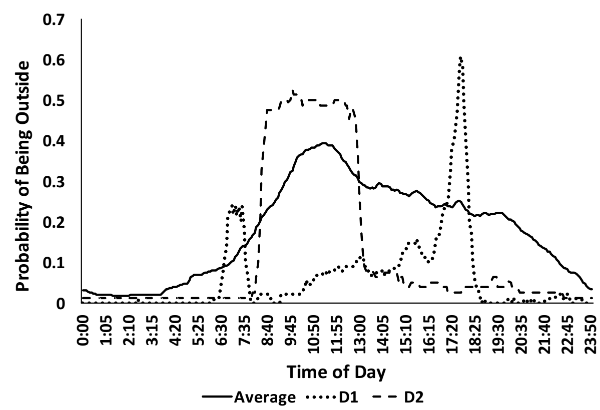


Figure 6: Average probability of being outside for two individuals with severe depression level, D1 and D2

While trends across population are important for giving an abstract of how the elderly spend their time, individual or group trends are also informative. Figure 6 illustrates the variability of outing probability (Section 5.2) throughout the day of two individuals with severe depression which appear to be very different compared to the average. The straight upward line in D1's pattern indicates that the participant has a very strict schedule, he (she) rarely went out before 8:00 and barely went out of home after 13:00 (only 2-3 times over 3 months) even at weekends. In case of D2, the participant usually went out in the afternoon from 16:30 to 18:30 and sometimes (p=0.2) went out in the early morning from 6:30 to 8:00. There were no outside activities at other time during the day, which means that the participant never joined the common lunch time with other.

6.3 Anomaly detection

Due to the limited number of data samples, instead of using machine learning classification algorithm, we scan through the list of flat status and room status features (Section 5) to select the most useful single feature to detect the cases with severe loneliness or depression. For each feature, we search for the optimal threshold value within the feature's value range that can distinguish the most participants with serious mental wellbeing problems from the rest. Figure 7 demonstrates the split with highest purity gain by the feature 'ratio of spent time inside and outside the flat'. The simple feature extracted from the flat status can determine the potential elderly candidates that having severe and moderate depression or loneliness issues with the precision 10/16 and recall of 10/12. Obviously, it is possible for some subjects to stay at their home most of the time and not experience any forms of severe loneliness or depression, it is still helpful for health professionals to be informed about all those ca-

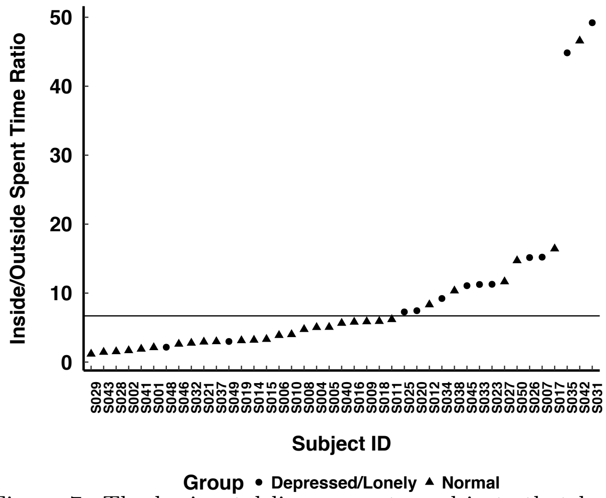


Figure 7: The horizontal line separates subjects that have the ratio of time spent inside/outside higher than 7 (spent less than 3 hours per day being outside of their flats) from the rest. Group Depressed/Lonely includes the elderly subjects that have either depression or loneliness problem at moderate or severe level (survey results in Table 1 and 2).

ses with very little social interaction for further well-being assessment.

7. DISCUSSION

At the current stage, our logic to detect the flat status relies on the trigger signals of door contact sensor and an assumption that at any certain time, there is at most one person in the flat. Although all participants in this study are independent-living, this assumption is not always true. For example, the elderly may have friends or relatives visit them, the visitors may even stay over for a few days. Our flat status detection does not address those situations. To address this problem, we plan to examine the PIR signal pattern to determine whether the flat is occupied by more than one person. Another limitation is that the survey was only conducted once during the six month period under consideration. However, we plan to extend the study duration to include periods where further surveys have been conducted.

Moreover, we are extending this work by deploying the system at 50 more flats of independent-living elderly and upgrading the sensor setup to enable further investigation into other aspect of daily living activities and how they are related to the mental and physical wellbeing of the elderly.

8. CONCLUSION

In this study, we present a real deployment of an unobtrusive and passive sensor-based monitoring system at 50 flats of the senior residents. We demonstrate that our sensor setup is simple yet efficient to monitor outing behavior of the independent-living elderly in order to study their daily living pattern and detect those cases with abnormal patterns likely to be linked to problems in mental wellbeing. Based on the ratio of spent time inside and outside the flat, we can determine potential candidates with severe loneliness and depression problems. Moreover, we also discuss the general behavior trends and the relations between the daily outing pattern derived from the sensor data and various mental well-being assessment (e.g. loneliness and depression scales) for this group of independent-living elderly participants.

9. ACKNOWLEDGMENTS

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