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# Managing Sensor Systems for Early Detection of Mild Cognitive Impairment in Community Elderly: Lessons Learned and Future Work

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**Abstract**—The aging population is a pertinent issue faced by governments globally. One of the most common and costly health issues associated with the aging population is cognitive decline, leading up to dementia. In this paper, we describe a non-intrusive, continuous and scalable system for early detection of Mild Cognitive Impairment (MCI) in the elderly, which enables early medical interventions to be provided. We focus on the system design and feature extraction of the sensor system, to validate our hypothesis of the use of sensor systems for early detection of MCI. Lessons learned from deploying the sensor system is presented, together with the solutions that are implemented to improve system reliability.

**Keywords**—*sensor systems; mild cognitive impairment; early detection of MCI; continuous system monitoring; system reliability.*

## I. INTRODUCTION

The elderly population is increasing rapidly, both in Singapore and worldwide [2,8]. Apart from physical deterioration, one of the most common health issues faced by elderly is the onset of cognitive decline, leading to eventual dementia [5]. In Singapore alone, it is estimated that 187,000 of the population will suffer from dementia by the year 2050 [1,5]. This can have severe impact on the national healthcare infrastructure, support and budget. At an annual cost of SGD1.4 billion [1], dementia contributes to one of the largest cost in Singapore’s healthcare system.

Although the process of dementia is irreversible, elderly who have been diagnosed with Mild Cognitive Impairment (MCI) and subsequently receive timely medical interventions, can decelerate the pace of cognitive decline and prolong the period during which they enjoy decent quality of life. Currently, methods to diagnose MCI include questionnaires such as the Mini-Mental Status Examination (MMSE), which is subjective and labor-intensive. In addition, such questionnaires are often impractical for continuous assessment; this can lead to delayed detection and treatment of MCI, resulting in the eventual development of dementia in the elderly. It is therefore important to have a scalable and efficient mechanism for the early detection of MCI in the elderly. This can bring about benefits to the various stakeholders - such as the elderly, caregivers and the healthcare providers.

Our ongoing research project studies the feasibility of using in-home sensor systems to objectively, continuously and unobtrusively collect data on elderly’s behavior for early detection of MCI. Our primary hypothesis is that certain activity patterns (such as time, duration and frequency of different activities) derived from continuous in-home sensor data acquired over a brief period of two months will differ between two groups of community-dwelling elderly who are living alone: (i) those with MCI (Petersen’s criteria); and (ii) those who are cognitively healthy. Our secondary hypothesis is that sensor-based activity patterns will correlate with validated psychometric measures of cognition, mood, sleep and social connectedness of these two groups of community dwelling older adults living alone. We aim to validate the above hypotheses with up to 70 community-dwelling elderly over an 18-month period.

In this paper, we focus primarily on the technical aspects of the in-home sensor monitoring system. We share initial lessons and experiences gleaned from deploying the system in the first 8 months of the project, in 17 residential homes of elderly who are living alone in the community.

The rest of this paper is organized as follows: Section II discusses related work. In Section III, we describe our in-home sensor system for activity feature extraction. Section IV details the issues faced during the initial system setup, along with the lessons learned, and the corresponding solutions to mitigate these issues. We analyze the deployment durations required for each home in Section V. Finally, we conclude the paper with future work in Section VI.

## II. RELATED WORK

Existing research to distinguish elderly with MCI from those without, typically fall into two categories: (i) conventional (non-technology-based) approaches; and (ii) technology-based approaches. Conventional methods, such as the MMSE, include a series of questionnaires and getting the patient to follow simple verbal and written commands, and require the time, effort as well as judgement of a trained examiner for the correct assessment of the patient [11]. While early detection of MCI with such approaches is practically infeasible, the use of technology for continuous and frequent assessment can potentially enable the early detection of MCI.

Sacco et. al., proposes an in-home video monitoring system for the assessment of instrumental Activities of Daily Living (iADL) scores, to infer the existence of MCI in the elderly [6]. However, such systems are intrusive and may not be practical in the context of Singapore, whereby privacy is viewed as a major concern. Furthermore, there is a rising trend in the compromise of in-home camera systems, resulting in the online postings of recorded video contents for public viewing [3].

Kaye et. al., tracks usage behaviors of home computers, to differentiate between participants with MCI and those without [4]. However, such an approach may not be feasible in the context of Singapore, as: (i) existing literature shows that elderly aged 65 and above are more likely to develop MCI [9]; but (ii) only 27% of elderly aged 60 and above in Singapore make use of computers [10].

Our study differs from existing work in that we aim to distinguish between elderly with MCI from those without, through the use of passive and non-intrusive sensors to monitor in-home activity patterns of the elderly, over a period of two months. This study has the potential of providing a non-intrusive, scalable and cost-effective system for the continuous assessment and early detection of MCI.

### III. IN-HOME SENSOR MONITORING SYSTEM FOR ACTIVITY FEATURE EXTRACTION

#### A. Initial System Design (v1)

To validate our hypotheses, we aim to install sensor systems into the residential homes of 70 community-dwelling elderly. Figure 1 depicts the initial design of the sensor system.

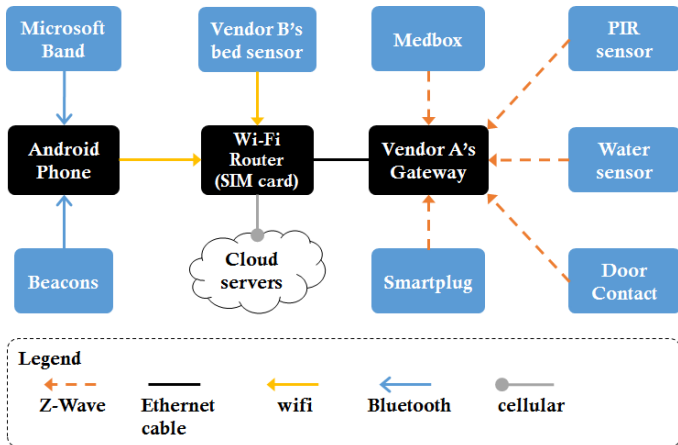


Figure 1: Design of in-home sensor system (Block 1/v1).

The system comprises the following sub-systems: (i) *in-home infrastructured sensors*, including Passive Infra-Red (PIR) motion sensors in the living room, kitchen and bathroom, medication box sensor, smart plug sensor, water sensor and door contact sensor; (ii) *wearables* including proximity beacons and the Microsoft Band; and (iii) *gateways* or

*aggregators*. In our initial system, a third-party vendor (Vendor A) gateway is used to manage the Z-Wave based sensors, such as door contact, motion, water, medication box and smart plug. As the Vendor A gateway cannot be integrated with non Z-Wave devices, a low-cost Android commodity phone is used as an intermediary gateway for data from the proximity beacons and wearable (Microsoft Band). Data that is collected by the respective gateways are pushed to the cloud servers using cellular connectivity via a mobile router, including data from the bed sensor provided by another vendor B.

Due to budget constraints, the deployment is staggered into 7 blocks of up to 10 elderly per block. The system objective is thus to achieve reliable data collection over a two-month period, for the accurate extraction of activity features that allows for the classification of elderly participations into two groups – those with MCI and those without.

#### B. Activity Feature Extraction

The primary activity feature of interest is *forgetfulness*, while the secondary activity features of interest include in-home activity levels, appliance usage patterns, sleep quality, physical health (anxiety level as inferred from heart rate) and physical activity (number of steps taken daily and going out patterns).

The in-home activity levels as well as going out patterns are inferred from the PIR sensors and door contact sensor, which detects the opening and closing of the main door of the residential home. The smart plug is used to measure usage levels of key appliances, such as the television. The sleep quality, as measured by duration and disturbances in sleep, can be derived from the bed sensor and PIR sensors. Each participant is also provided with a Microsoft Band to measure the physical health and physical activity at home.

A combination of sensor data is used to measure forgetfulness. Firstly, each participant is provided with a sensorized box to store medication; data is generated whenever the box is opened. This data point, along with the participant's declared medication routine, enables us to determine the level of medication non-adherence, which then serves as a proxy for forgetfulness. Secondly, we can determine if the participant has forgotten to turn off the water tap – this information is derived from a water sensor that is installed in the kitchen sink, in combination with the PIR sensor in the kitchen. Lastly, proximity beacons are placed onto the participant's personal effects such as keychain and wallet, allowing us to estimate the distance between the item and the gateway. Coupled with the Microsoft Band and PIR motion sensors, we can thus determine if the participant has forgotten to bring these essential items along with them, when he/she leaves the home.

The mapping between sensor data and activity feature extraction is illustrated in Figure 2.

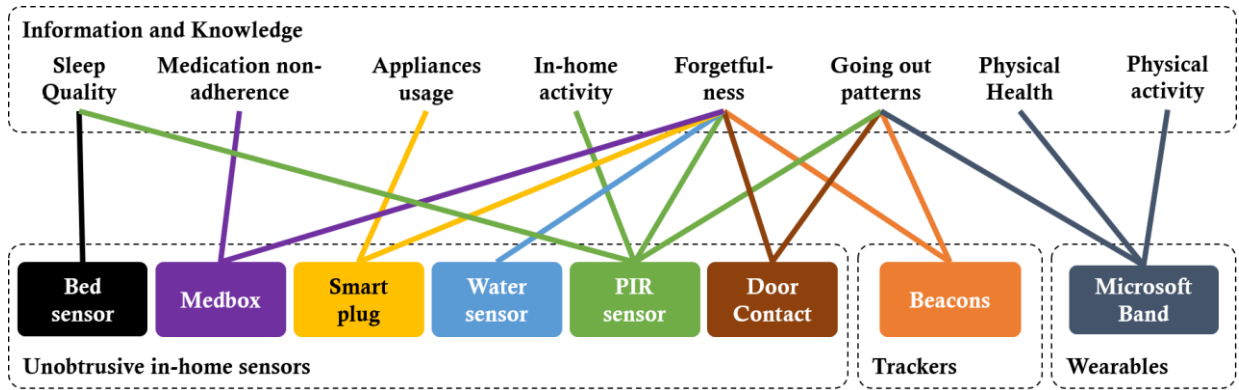


Figure 2: Mapping of sensors with activity features of interest.

### C. System Monitoring and Management

Reliable data collection is particularly important in our system, as each deployment and data collection phase is conducted over a short time span of two months. To ensure that system faults are identified and rectified as quickly as possible, we implement real-time monitoring tools for the system heartbeat, as well as all individual sensor components. Through historical data and visualization of the system health, we can thus identify system issues as soon as they occur.

## IV. CHALLENGES, LESSONS LEARNED AND SOLUTIONS

In this section, we describe the key challenges and lessons learned during the deployment of Block 1 between Oct 2016 and Jan 2017 for 8 elderly homes, based on the system (v1) depicted in Figure 1. Over this period, a total of 24 system maintenance visits were made by 5 members of our research team, where issues were detected and identified. Subsequently, we ran tests in the laboratory environment for 1 month (Feb 2017) to fix as many issues as possible, resulting in a significantly more reliable system (v2), as depicted in Figure 4, for deployment of Block 2 between Mar to Jun 2017 for 9 elderly homes. We highlight the key issues and their corresponding solutions for v1 (Section IV.A-C) as well as v2 (Section IV.D-E) in the following.

### A. Issues with Android Commodity Phone as a Gateway

Commercial wearables in the market (e.g., Microsoft Band) are typically only able to transmit data via a mobile application, and cannot be integrated with smart home hubs/gateways. A low-cost Android commodity phone is thus used as an intermediary gateway to track body vitals – such as heart rate, breathing rate and pedometer – from the Microsoft Band. However, several processes scheduling and control operations can neither be controlled, nor managed in the Android operating system, resulting in numerous issues.

#### 1) Root Access and Super User Settings

It is common research practice to root Android-based devices, to attain enhanced (root) access to the operating system, and enable features such as remote reboot. With remote reboots, system rectifications and maintenance become more manageable. However, the Automation Tool (AT) used to trigger remote reboots may intermittently lose root privileges, thus disabling remote reboot. Subsequently, the

research team will need to physically visit the elderly for system maintenance whenever the need arises, which can be cumbersome for the elderly.

To ensure that the AT does not lose its root access, the SuperSU application is installed to manage root privileges for applications in the phone. Although root privileges can be granted to all applications by default, we do not enable this, and it can pose severe security threats.

#### 2) Memory Issues

The use of a commodity phone results in an intermediary gateway with relatively lower technical specifications (such as RAM and processing speed). As there are several pre-installed applications running on the phone, it is often operating at a low and critical memory state. This causes our custom applications to be automatically ‘killed’ by the operating system, to reduce phone memory usage.

By implementing the below-mentioned fixes, we have managed to reduce the memory usage of the phone, and thus mitigate the possibility that key applications are removed by the operating system.

- All application icons and widgets are removed from the home screen of the phone.
- All unnecessary pre-installed applications (bloatware), which are running in the background and consume excessive memory, are uninstalled from the phone.
- All phone notifications are disabled.
- Call Barring is enabled to block all incoming and outgoing phone calls.

#### 3) Default Application Optimization Settings

By default, application optimization is turned on in Android devices, which removes any application from running in the background if there is no user interaction for three days. As the elderly in our study do not need to interact with any of the phone applications [7], the default application optimization setting can cause our applications to terminate unexpectedly. We hence turn off the application optimization settings for key applications that are required for our system to function.

#### 4) Intermittent Acquisition of Band Data

During the laboratory test following the deployment of Block 1, it is observed that there is intermittent sensor data

from the Microsoft Band. This is resolved by keeping the screen of the phone (which goes to sleep by default) on, through the following measures:

- Modification of developer settings, to keep the phone awake when it is charging.
- Installation of the *Keep Screen On* application, to keep the screen on indefinitely.
- Addition of a rule into the AT, to wake the screen when it dims.

To quantify the impact of these changes, we conduct data collection for three consecutive days each, before and after the changes. Based on our analysis, the percentage of Microsoft Band that is collected has increased from 47% in v1 to 93% in v2, thus providing significant improvements in the reliability of data collection from the Microsoft Band.

### 5) Local Data Caching in the Phone

Intermittent data connectivity may occur due to poor WiFi connectivity between the phone and the mobile router, and/or poor cellular coverage in the home. When this happens, sensor data collected by the phone is cached locally, and pushed to the server when connection is re-established.

However, whenever there is a huge volume of data that is cached in the phone (arising from poor connectivity issues), the phone application may experience significant performance deterioration, as it is unable to transmit the cached data at a faster rate than it is receiving new data. This issue is resolved by redesigning the software process on the phone, through using efficient SQL processing methods.

## B. Other Technical Issues

Despite performing burn-in tests for the entire system in the laboratory environment, several hardware issues surface only after the devices are deployed in the elderly homes. These are primarily due to differences in environmental conditions – such as operating temperature, wear and tear, and strength of cellular connectivity in the real operating environment.

### 1) Unstable Wi-Fi Connectivity

Based on root cause analysis of the system monitoring data from Block 1, there is an issue with the WiFi chip on the phone, resulting in intermittent data to the server due to unstable Wi-Fi connectivity between the phone and the router.

To mitigate the intermittent WiFi connectivity issue, we move the SIM card from the router to the phone, and use a USB cable to tether Internet connection to the WiFi router.

### 2) Unstable Power Supply to Bed Sensor

Due to the loose cabling between the electrical outlet plug and the AC power adapter of the bed sensor, the latter is often subjected to unwarranted and intermittent powering off. This issue arises, as the bed sensor uses the vendor-provided two-pin plug, which is easily dislodged from the electrical outlet. By changing the power adapter to a three-pin plug, we observe a marked improvement in the amount of data collected from the bed sensor, and consequently a reduction in the frequency of maintenance for such miniscule issues.

## C. Maintenance Scheduling Issues

The lead time to carry out system maintenance is usually long, due to scheduling conflicts between the elderly and research team. To reduce the number of maintenance visits and system downtime duration, an automation tool (AT) known as *Tasker* is installed, which allows the phone to perform self-recovery when certain system faults take place. We describe two of the scenarios that are handled by the AT, viz., *Remote Maintenance* and *Automated System Settings*.

### 1) Automated Remote Maintenance

To improve system reliability and data quality, it is important to be able to quickly detect and resolve system issues/faults as soon as they arise. We accomplish this through two tools that work in tandem: (i) a real-time system monitoring tool (comprising data visualization and analytics) is used to monitor incoming sensor data, and trigger alerts whenever data from any particular sensor is not received for more than a pre-specified time threshold of five minutes, thus reducing the mean time from system failure to detection to two minutes; and (ii) a tool that triggers remote rebooting of the phone for convenient system recovery, through a SMS service. Together, these two tools have resulted in significant reductions in number of maintenance visits required, as well as reductions in system downtime, leading to reliable data collection.

### 2) Automated System Settings

Due to the complexity of the system, there are several settings that must be configured on the intermediary gateway phone. To reduce the likelihood of human-attributed misconfigurations or errors during system deployment, automated system settings are put in place through the AT tool. This allows the gateway phone to be a plug-and-play system, thereby enhancing the ease during system deployment.

## D. Enhanced System Design (v2)

Based on our initial experiences and learnings from the system deployment in Block 1 (using v1), various improvements have been made to enhance system reliability, resulting in the system design v2 as illustrated in Figure 3.

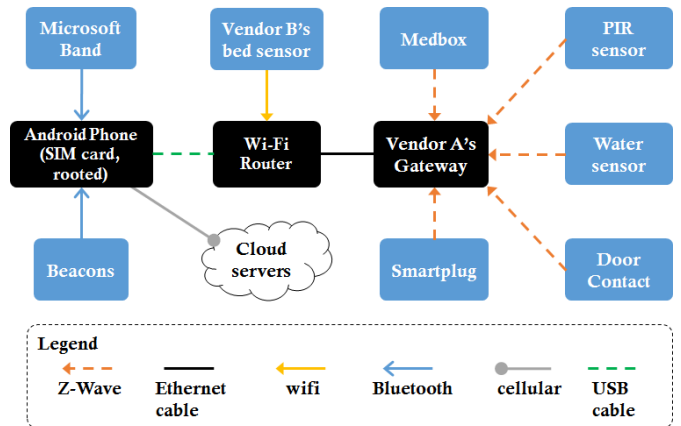


Figure 3: Design of in-home sensor system (Block 2/v2)



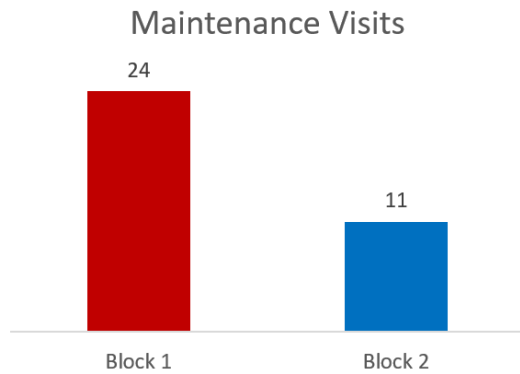


Figure 4: Comparison of system maintenance visits.

The enhanced system (v2) is deployed in Block 2 between Mar and May 2017, in 9 elderly homes. We compare the system performance between v1 and v2 in terms of the number of maintenance visits as well as the system uptime, in Figures 4 and 5 respectively. The results clearly show significantly fewer maintenance visits, and higher system uptime for v2. The larger variance in the system uptime for v2 is due to: (i) a much longer lead time (up to 3 weeks in some cases) in the maintenance process; and (ii) lack of a real-time monitoring system for the entire system.

Although we have developed a real-time monitoring system for this project, it excludes vendor-managed gateways and sensors. As the API for system data for the latter are not made available for real-time data processing and analysis, delays are incurred between the time that vendor systems experience downtimes, and the time that such downtimes are detected.

## V. ANALYSIS OF DEPLOYMENT DURATION PER HOME

One of the key issues that must be tackled in our research project is the question of whether there is sufficient data of good quality, to support our hypotheses that sensor data over two months of monitoring will exhibit differences between the two groups of community-dwelling elderly, viz., those with MCI and those who are cognitively healthy.

As with any system deployment, it is inevitable that system failures and downtimes will take place, and thus affect the data quality. To ensure that there is sufficient good quality for subsequent application-level (clinical) analysis, we study the historical and real-time system performance of individual deployments, to: (i) determine if there is sufficient data collected; and (ii) compute the ideal (extended) deployment end date whereby sensor data collection can conclude. This is subject to the following criterion:

[C.1.] Extension of deployment duration should be permissible by all the project stakeholders – including the elderly and the research team.

[C.2.] The sensor system must be sufficiently stable, so that any extension of deployment duration will remain finite.

[C.3.] The project timeline should not extend indefinitely, and should complete within a pre-specified deadline.

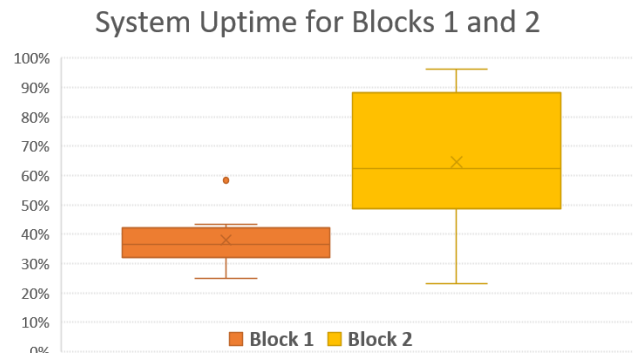


Figure 5: Distribution of system uptime for Block 1 (v1) and Block 2 (v2).

[C.4.] The time to detect individual component failures and subsequent maintenance must be improved.

We collect various performance metrics on the current system to determine the extension duration (buffer) required for deployment for each set of system to achieve the baseline requirement of acquiring 60 days of data of sufficient quality. Table 1 shows the deployment extension requirements for the deployment in Block 2.

TABLE I. ANALYSIS OF PREDICTED AND ACTUAL DEPLOYMENT TIMELINE

Set	Deployment Date	Estimated Deployment End Date (60 days)	Buffer (days)	Actual System Collection date	Total deployed days
1	27/2/2017	4/5/2017	1.1	6/5/2017	69
2	27/2/2017	16/5/2017	2.3	19/5/2017	82
3	27/2/2017	22/5/2017	5.8	28/5/2017	91
4	28/2/2017	7/5/2017	1.4	9/5/2017	71
5	28/2/2017	1/5/2017	0.8	2/5/2017	64
6	24/3/2017	7/6/2017	9.0	17/6/2017	85
7	24/3/2017	31/5/2017	3.8	4/6/2017	73
8	24/3/2017	14/6/2017	10.4	25/6/2017	94
9	4/4/2017	16/6/2017	10.8	27/6/2017	85

Due to project constraints, the system cannot be deployed in any home for more than 75 days. Subsequently, we monitor individual system health performance, and retrieve the deployed system whenever it has collected at least 60 days of data of sufficient quality.

## VI. CONCLUSION AND FUTURE WORK

Several practical insights are gained during the first 8 months of the project, through experience from the deployments, as well as from the rigorous testing of our system. The lessons learned have helped to significantly improve the system uptime in our subsequent deployment in Block 2: (i) tools and processes are required to allow the

system to recover remotely and in an automated fashion, to reduce maintenance efforts and improve data quality; (ii) significant improvements in uptime can be achieved with more robust system monitoring and better management of non-technical factors; and (iii) system performance is a key criteria that has to be monitored and measured in real-time, in order for improvements to take place.

As part of future work, we intend to improve the system in the following aspects.

#### A. System Architecture

Ongoing tests of the new system design in Block 2 reveal that persistent USB connections between the phone and the mobile router can lead to elevated risks of battery safety concerns. In addition, the presence of several gateway aggregators in the system leads to system inefficiencies; it may potentially be more viable and acceptable to the elderly, to have only a single gateway or aggregator in each home.

#### B. System Monitoring

It can be difficult to monitor the overall system performance, due to the use of sensors and devices from multiple vendors. We intend to integrate all system monitoring components into a unified, robust and real-time monitoring system. This allows for real-time detection of component failures, automated system recovery, user-friendly alert features, as well as metrics reporting.

#### C. Continuous Improvement framework

There is a need for continuous improvement throughout the project to further reduce system downtime and improve data quality. We intend to apply methodologies and tools from Lean Six Sigma [12], which is a continuous improvement framework, to further improve the system uptime from both the technical and non-technical aspects.

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