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Online detection of behavioral change using unobtrusive eldercare monitoring system

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Online Detection of Behavioral Change Using Unobtrusive Eldercare Monitoring System*

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ABSTRACT

The rapid ageing population is posing challenges to many countries all over the world, particularly in the provision of care to the growing number of elderly who are living alone. Allowing the elderly to *age-in-place*, *i.e.*, live safely and independently in the comfort of their own homes is a model that can potentially address the resource constraint in health and community care faced by many nations. To make this model a reality and provide appropriate and timely care to the elderly, unobtrusive eldercare monitoring systems (EMS) are being deployed in real homes to continuously monitor the activity of the elderly. In this paper, we study the feasibility of detecting behavioral changes using rudimentary binary sensors similar to the ones used by many commercial EMS, as a trigger for early intervention by caregivers. We propose Online Behavioral Change Detection (OBCD), a scheme to automatically detect behavioral changes using online streaming data from binary sensors. OBCD extends existing changepoint detection methods to reduce false positives due to extraneous factors such as faulty sensors, down gateways or backhaul connectivity observed in real deployment environments. The Mann-Whitney test is complemented with a comparison of quartile coefficient of dispersion and a threshold test of the means before and after the change, to filter out changes due to the above-mentioned factors. Our case studies show that OBCD can significantly reduce false positives by 80% or more without increasing the detection delay, *i.e.*, the time between event occurrence and its detection.

CCS Concepts

•**Information systems** → *Data analytics;*

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Keywords

Behavioral change, elderly monitoring systems

1. INTRODUCTION

The rapid rise in elderly population [2] is posing challenges to many countries all over the world in terms of shortage in healthcare and eldercare facilities, manpower, and other related resources. A new paradigm that may address or alleviate the increasing resource shortfall is *ageing-in-place*, whereby the elderly remains independent and stays at the comfort and safety of his own home [1]. But ageing-in-place not only tackles the logistical challenges of ageing, it can also boast the wellbeing and quality of life of the elderly, as staying in their homes and communities keep them in contact with their friends and loved ones, and empowers them to have full control of their lives.

In the context of Singapore, it is estimated that one in every five or roughly 900,000 will be aged 65 and above by the year 2030 [12]. More worrisome is the upward trend of elderly who are staying alone. If the current trajectory continues, there will be 83,000 elderly who are staying alone by themselves in 2030. Ensuring the safety of these category of elderly is a difficult challenge, as there is severe shortage of caregivers and volunteers to monitor their wellbeing on a day-to-day basis. Fortunately, the maturing of sensing and communication technologies is enabling the deployment of eldercare monitoring systems that can continuously monitor the day-to-day activities of the elderly in a real-time manner.

A new challenge that immediately emerges from such a widespread deployment of sensors is the accumulation of large amounts of sensor data that need to be processed and analyzed to identify elderly who may need close attention and help. Manual inspection of such voluminous data is not practical, hence there is a need to develop algorithms to automatically detect behavioral changes through sensor readings. In this paper, we investigate a widely used unobtrusive eldercare monitoring system (EMS) that consists of motion sensors and door contact sensors, with the aim of determining whether it is possible for such a rudimentary system to detect behavioral changes of the elderly resident.

We propose Online Behavioral Change Detection (OBCD), a scheme to automatically detect behavioral changes using online streaming data from binary sensors. OBCD builds on top of existing changepoint detection methods to reduce false positives due to extraneous factors such as faulty sensors, down gateways or backhaul connectivity. At its base, we use the Mann-Whitney test to detect behavioral change, as we expect such a change to result in change in the mean of the elderly's activity intensity. Furthermore, Mann-Whitney can filter out changes due to sporadic or intermittent sensor faults. The Mann-Whitney test can detect changes in the mean, but we anticipate that behavioral change will also entail a change in the dispersion. OBCD therefore compares the quartile coefficient of dispersion before and after the purported change. If the change in the coefficient exceeds a predefined threshold, OBCD then proceeds to identify whether the change is due to gateway or communication failure using a simple threshold test on the means before and after the change. If the change is not due to the latter causes, it is then tagged as behavioral change. To determine the performance of our approach, we have conducted case studies involving 4 elderly participants. Our results show that OBCD can indeed significantly reduce false positives by more than 80% without any increase in the detection delay.

The rest of the paper is organized as follows. Section 2 presents a brief survey of related work. Section 3 provides a detailed description of the unobtrusive eldercare monitoring system that is deployed in 500 homes. Section 4 introduces the proposed scheme that improves on the non-parametric Mann-Whitney changepoint detection to significantly reduce false alarm rate. Section 5 presents case studies to validate the proposed scheme. Finally, section 6 concludes the paper and highlights some important future research work.

2. RELATED WORK

The use of sensors to learn activities of daily living and to detect behavioral changes have been widely investigated in the literature. Barger et al. [3] have shown that motion sensors can be used to detect behavioral patterns reliably, i.e., with low classification uncertainty. The study by Barger et al. is one of the many works that have looked at learning daily living patterns. A natural extension would be the application of such learned patterns to detect changes or deviations from the "normal" patterns. Timely detection of such changes are important because they indicate changes in health conditions. We survey some of the latest results on this specific area in the following paragraphs.

In [5], the authors designed a rules-based engine to analyze the activity of their elderly participant and to infer health issues and possible emergency conditions. Using their inference engine, they detected several urinary tract infections or UTI (using sensor data on frequency of bathroom visits) and increasing pain in memory care patients due to restlessness in bed.

A similar study by Rantz et al. [7] to detect potential illness or functional decline used "sensor hits" which is essentially the dwell time in a particular room or usage time of an appliance or furniture such as chairs and beds. They developed a system that generated alerts when the number of hits of a particular sensor exceeded a certain pre-defined threshold (the thresholds were derived with the help of expert gerontological nurses and family physician). Their system enabled the early detection of UTI in two of their elderly participants.

In another study, Wang et al. [11] proposed the use of activity density map to represent PIR sensor readings. Changes in behavior can then be determined by comparing activity density maps across different time intervals. Dissimilar density maps indicate behavioral changes, which may indicate health problems. Their results show that monthly density map comparison can detect behavioral changes.

Another detection strategy was proposed by Sprint et al. [9]. First, sensor data are labeled to correspond to activities such as "sleep", "eat", etc. Features are then extracted and used as inputs to change detection algorithms such as RuLSIF, virtual classifier, and sw-PCAR. If the change is significant, change analysis is performed to explain the source of change.

3. UNOBTRUSIVE ELDERCARE MONITORING SYSTEM

In this section, we describe in detail the unobtrusive eldercare monitoring system (EMS) that have been deployed in the homes of elderly who are staying alone, for the purpose of monitoring their safety. At the end of the section, we describe the sensor data collected from the EMS, focusing on the data that we will use to detect behavioral changes.

3.1 EMS Setup

Lions Befrienders, a voluntary welfare organization formed in 1995 by the Lions Clubs of Singapore, aims "to provide friendship and care for seniors to age in place with community participation, enabling them to enjoy meaningful and enriching lives". As part of their effort to employ new technologies in enhancing the provision of eldercare, they have engaged a commercial company to deploy unobtrusive sensors in the homes of 500 of their elderly beneficiaries who are living alone.

A home installation consists of five passive infrared (PIR) motion sensors and a reed switch. 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 unobtrusive, these sensors do not require any action from the elderly and they do not need to change their daily activities to accommodate them. Note that in addition to these unobtrusive sensors, every elderly is also given a panic button that she can carry around the house. She can press this panic button to call for help in case of emergency situations. The home installation is similar to the smart-enabled home used in [10].

The beneficiaries of *Lions Befrienders* are elderly who are living alone, or alone most of the time, and are staying in studio-type rental apartments. Figure 1 shows a typical layout of such an apartment, including the placement of the sensors. The five PIR sensors are oriented to cover 5 areas, namely: (*i*) living area; (*ii*) bed area; (*iii*) kitchen area; (*iv*) toilet area; and (*v*) door area. Because there are no walls to separate these areas, there is substantial coverage overlap among the sensors, except for the toilet.

Every device (sensor and panic button) is equipped with short-range radio operating in the license-free band. The collection of sensor readings from all the sensors and the panic button is performed by a gateway device that is also equipped with the same short range radio. These collected sensor data are eventually transmitted to a backend server, using a 3G connection, for processing and storage.

3.2 Sensor Data

The sensors are configured to sense and log their respective states once every ten minutes. Both PIR sensor and reed switch are binary sensors, which means that their state can be represented by two values, as shown in Table 1.

The gateway aggregates the sensor logs and transmits them to the backend server once every ten minutes. From

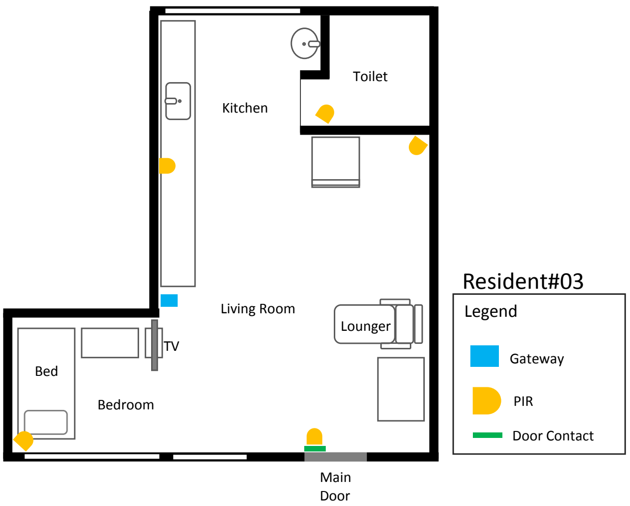


Figure 1: A typical home layout and sensor positions.

Table 1: Meaning of Sensor Values

State	PIR	Reed Switch
0	No motion was detected within the last 10 minutes	Door did not close or open within the last 10 minutes
1	Motion was detected within the last 10 minutes	Door closed or opened within the last 10 minutes

these raw sensor logs, we can then derive a *daily activity count per area*, which is just the total number of motions (or 1's) per day for every PIR sensor. We formally define this notion as follows.

DEFINITION 1. *The daily activity count of area r on day k, denoted by $A_r(k)$ is the total number of time intervals that motion was detected by the PIR sensor covering the area r, where $r \in \{\mathrm{PIR0}, \mathrm{PIR1}, \mathrm{PIR2}, \mathrm{PIR3}, \mathrm{PIR4}\}$*[1].

The above definition is general enough and can be used in conjunction with most of the commercially-available PIR sensor-based EMS. In this particular study, the EMS divides the 24-hour period into equal intervals of 10 minutes. Thus, a day can have at most $24 \times 60/10 = 144$ intervals which means that $0 \leq A_r(k) \leq 144$ for any r and k.

$A_r(k)$ essentially summarizes the daily "activity intensity" of an elderly in an area r, *i.e.*, it reflects the amount of activity that she has undertaken at that particular area of her house. Figure 2 shows the daily activity count of one of the elderly in 5 areas of her house, for an interval of 30 days. One noticeable aspect of these sensor data is the fact that $A_r(k)$ is both temporally and spatially variable. Note however that the daily activity count for each area r is somehow distinct and traces a "pattern" or "trend". From Figure 2, we can roughly infer that the elderly stays in the living area (PIR1) most of the time. The distinct pattern or trend established by $A_r(k)$, for every r, is the fact that we will exploit in this paper to detect behavioral changes.

[1]The indices indicate the 5 areas in the house, i.e., PIR0: door area, PIR1: living area, PIR2: bed area, PIR3: kitchen area, and PIR4: toilet area. Note that in the text, we use r to either refer to the area being covered or the PIR sensor itself.

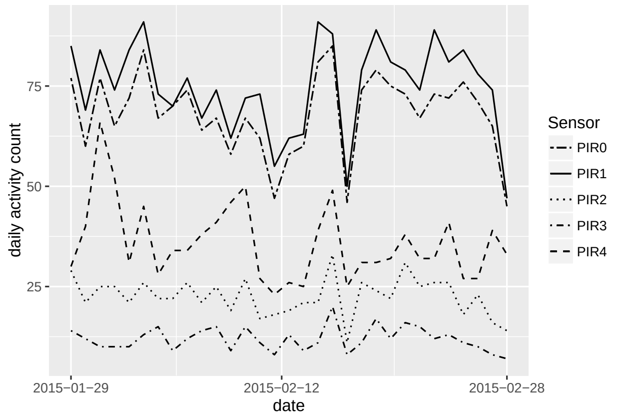


Figure 2: Daily activity count of an elderly for an interval of 30 days.

4. ONLINE DETECTION OF BEHAVIORAL CHANGES

We now present the key contribution of this work which is the online detection of behavioral changes using daily activity count per area. We call the proposed scheme Online Behavior Change Detection (OBCD) which consists of three distinct phases. To understand the rationale behind the phased approach, we first discuss the key challenges in *online* detection.

4.1 Challenges of Online Detection

Compared to offline detection, online detection is more challenging because in the latter, raw streaming data is used to quickly detect events of interest. Raw data presents numerous difficulties and in the context of this study, we have identified several factors that may contribute to false positives, *i.e.*, the algorithm detecting behavioral change when there is none.

Down Gateway.

Gateway is a critical component in the EMS because when it is down, data from all the sensors are lost. This means that $A_r(k)$ may not provide the true activity intensity of the elderly in all areas r. In the worst case when the gateway is down for the entire day k, $A_r(k) = 0$ for all areas r.

Down or Faulty Sensor.

A down or faulty sensor will not be able to detect movements, resulting in activity intensity that is lower than the true value in the area being covered by that sensor. That is, if the PIR sensor for area r is down or faulty on day k, $A_r(k)$ will not provide the true activity intensity of the elderly in area r. In the worst case, when a sensor is down for the entire day k, $A_r(k) = 0$ for all faulty/down sensors r.

Down or Faulty Communications.

As mentioned in Section 3.1, the sensor data from the home installations are transmitted to the backend via 3G connection. While 3G is relatively reliable, we have observed several communication outages. When the outage persists for a prolonged duration, the gateway will start losing data as its buffers will overflow. From the data perspective, this case is similar to the gateway down case and can therefore be handled in the same way.

4.2 Overview

OBCD is designed to detect changes in the daily activity count $A_r(k)$. In particular, OBCD aims to detect changes that can be attributed to behavioral change on the resident being monitored. In this respect, OBCD uses a phased approach to tackle the above-mentioned challenges and thereby improve its detection accuracy. In the first phase, OBCD employs a changepoint detection scheme (in this paper, we use the Mann-Whitney test for reasons elaborated in the following subsection) for detecting changes in $A_r(k)$. If no change is detected, OBCD will not proceed to the next phase and will wait for the next data. In the second phase, OBCD compares the *quartile coefficient of dispersion* before and after the supposed changepoint. If the coefficients differ significantly (*i.e.*, exceeds a threshold), OBCD continues to the third phase; otherwise, it will wait for the next data. In the third phase, OBCD determines whether the change is due to communication failure (*i.e.*, the home gateway is down). If the change is due to communication issues, OBCD will not proceed further; otherwise it generates an alert to flag potential behavioral change.

4.3 Changepoint Detection

Suppose that we now have data until day K, that is, we are given the daily activity count $A_r(k)$, for $k = 1, 2, 3, \ldots, K$. Suppose further that the sequence prior to K_0 is different from the one onwards, i.e., K_0 is a previous changepoint. If there is a point ν such that the sequences $\mathcal{A}_r = \{A_r(k), K_0 < k \le \nu\}$ and $\mathcal{A}'_r = \{A_r(k), \nu < k \le K\}$ exhibit differences in location, scale or other arbitrary distributional parameters, then ν is called a changepoint.

Many tests are available in the literature for changepoint detection [6] and in this study, we use the Mann-Whitney test for four important reasons. First, the Mann-Whitney test is amenable for use in online detection settings. Second, we expect that behavioral change would result in change in the mean of the daily activity count. The Mann-Whitney test is one of the tests that can detect changes in the mean or location parameter. Third, Mann-Whitney is non-parametric and does not require the development of a suitable model for $A_r(k)$. The fourth and most important reason is related to the problem posed by faulty sensors. As mentioned, a faulty sensor r will cause $A_r(k)$ to show lower activity intensity than usual. Examination of the raw sensor data shows that sensor faults are sporadic (*i.e.*, they can happen at different times), and often short-lived (*i.e.*, they can last for a few hours). This implies that as long as the occurrences are independent and uncorrelated, faulty sensors will not significantly affect the mean of $A_r(k)$ over several days.

4.4 Comparing the Variability Before and After Change

When the elderly exhibits behavioral change, we expect not only the mean of the daily activity count to change, but also its spread or dispersion. The coefficient of variation σ/μ (where σ refers to the square root of the variance and μ refers to the mean) is the most common measure of relative dispersion used in the literature. However, for $A_r(k)$ which is non-negative and has positive support, the variance and the mean are not efficient and meaningful estimators of scale and location [4]. The more robust quartile coefficient of dispersion is preferred over the coefficient of variation in non-normal distributions.

To improve the accuracy of OBCD, we therefore compare the relative dispersion of the two sequences $\mathcal{A}_r = \{A_r(k), K_0 < k \le \nu\}$ and $\mathcal{A}'_r = \{A_r(k), \nu < k \le K\}$. Let $Q_m(X)$ denote the mth quartile of the sequence X. Then we can obtain the quartile coefficient of dispersion [4] for the sequences $\mathcal{A}_r$ and $\mathcal{A}'_r$ as follows:

$$q_r = \frac{Q_3(\mathcal{A}_r) - Q_1(\mathcal{A}_r)}{Q_3(\mathcal{A}_r) + Q_1(\mathcal{A}_r)} \tag{1}$$

and

$$q'_r = \frac{Q_3(\mathcal{A}'_r) - Q_1(\mathcal{A}'_r)}{Q_3(\mathcal{A}'_r) + Q_1(\mathcal{A}'_r)}. \tag{2}$$

We then compare q_r and q'_r, to determine the degree of difference between the two sequences. When there is behavioral change, we expect a noticeable difference which should reflect in a significant difference between q_r and q'_r as well. We therefore define the parameter ρ_r that can be used to test the difference between $\mathcal{A}_r$ and $\mathcal{A}'_r$:

$$\rho_r := \frac{\max(q_r, q'_r)}{\min(q_r, q'_r)}. \tag{3}$$

It is easy to see that $\rho_r \ge 1$ and that the higher the value of ρ_r, the more different the two sequences are.

Before discussing the next phase which is on the filtering out of changes due to gateway or communication faults, we want to highlight two major advantages of the comparison of the quartile coefficient of dispersion. First, it is simple and does not entail significant computational overhead. Second, *it does not cause the detection delay to increase*, *i.e.*, the detection delay is solely determined by the changepoint detection method used in the first phase. The comparison will just either "accept" or "reject" the outcome of the base changepoint detection method.

4.5 Changes Due to Gateway or Communication Failures

Unlike changes due to behavior or sensor faults which can be subtle and difficult to detect, changes due to gateway or communication failures can be easily spotted. This is because when the gateway or communication fails, data from all the sensors are affected, resulting in apparent significant dip in activity across all the areas in the house. The opposite event of gateway or communication restoration will also register a noticeable change, that is, an apparent significant rise in activity across all areas in the house.

To detect events that can be attributed to these two causes, a simple test can therefore be conducted. Supposing again that ν is a changepoint and we want to determine whether the change is due to these two causes or not. Let μ_r and μ'_r denote the means before and after ν, that is,

$$\mu_r = \mathsf{E}(\mathcal{A}_r)$$

and

$$\mu'_r = \mathsf{E}(\mathcal{A}'_r)$$

where $\mathsf{E}(X)$ denotes the expectation of the sequence X. If either μ_r or μ'_r is less than a certain threshold, then we can say that the change is due to gateway or communication failure.

5. CASE STUDIES

To determine whether the proposed scheme can accurately detect behavioral changes, we conduct four case studies from among the 500 elderly who are being monitored by the eldercare monitoring system described previously in Section 3.1. The sensor data spans over 15 months of continuous observations, from January 1, 2015 to April 4, 2016. We compare the performance of off-the-shelf changepoint detection scheme (using the Mann-Whitney statistic in this paper) against our proposed scheme.

We use the *cpm* package in R [8] to perform the changepoint detection using Mann-Whitney. The average run length is set to 100, while the startup value is set to 30. We implement OBCD, which essentially extends the Mann-Whitney test to include the coefficient of dispersion test and the test to determine whether the mean before and after the change is lower than a certain threshold. For the former test, we use the threshold $\rho_r \geq 6$, for all r, as it provides a good tradeoff between false and missed detection. For the latter test, we set the threshold to 2 for PIR3 and PIR4 while 10 for the rest, as based on observations, the activity count in the respective areas falls below these thresholds most of the time when the gateway of backhaul link is down.

5.1 Case Study #1

Our first case study involves Resident #35, a 74-year old female elderly. From our interview with her, the participant said that she did not encounter any prolonged health issues during the observation period, and that she did not modify or vary her daily living patterns. This means that the sensor data should not show changes that could be attributed to behavioral changes.

To see if this is indeed the case, we ran changepoint detection algorithms on the daily activity count of the resident. Figure 3 shows her daily activity count as monitored by the 5 PIR sensors. Using the Mann-Whitney statistic alone (see Figure 3(a)), a total of of 42 changepoints are detected across all the 5 areas (the detected changepoints are indicated by the dashed vertical lines). However when we employ OBCD (see Figure 3(b)), only 5 changepoints are detected. This result demonstrates the ability of OBCD to significantly reduce spurious changepoints by more than 88%.

A closer examination of the data shows that around November 2015, there is an observable change in the door, bed and kitchen areas. (Note that OBCD actually detects the changes in kitchen and toilet data.) We have found out that the vendor conducted maintenance works around this time which included sensor orientation adjustments. The observable change in sensor data could therefore be attributed to these adjustments and not due to any behavioral change.

5.2 Case Study #2

Our second case study involves Resident #20, a 75-year old male elderly. Like our first case study, the elderly did not report any prolonged health issues during the observation period. However, this case study differs from the former as the sensor data is marred by changes due to either gateway failures or backhaul link failures. This is indicated by the sudden dip in the daily activity count across all the sensors.

Figure 4 shows the elderly's daily activity count as monitored by 5 PIR sensors, and the changepoints detected using (a) Mann-Whitney and (b) OBCD. From Figure 4(a), we can see that Mann-Whitney detects 82 changes. This is significantly higher compared to the 16 changes detected by OBCD. The performance of OBCD, which reduces spurious detection by 80%, highlights the significant contribution of the two additional tests added to augment the basic Mann-Whitney test.

5.3 Case Study #3

Our third case study is Resident #16, an 86-year old male elderly. We have gathered from our interview with the participant that his health deteriorated and that as a result this, he stayed on bed for most parts of the day. His change in daily living started around early November 2015. Later on, he also relied on food deliveries and stopped preparing his own meals.

Figure 5 shows his daily activity count as monitored by 5 PIR sensors, and the changepoints detected using (a) Mann-Whitney and (b) OBCD. From Figure 5(a), we can see that Mann-Whitney detects 79 changes. This is significantly higher compared to the 8 changes detected by OBCD.

Of the 8 changes detected by OBCD, 2 of them can be attributed to the behavior change of the resident. These are the changes detect in the bed and kitchen areas around November to December. While the activity in bed area increased, the activity in kitchen areas decreased. Once again, OBCD dramatically reduced the false positives by more than 92%.

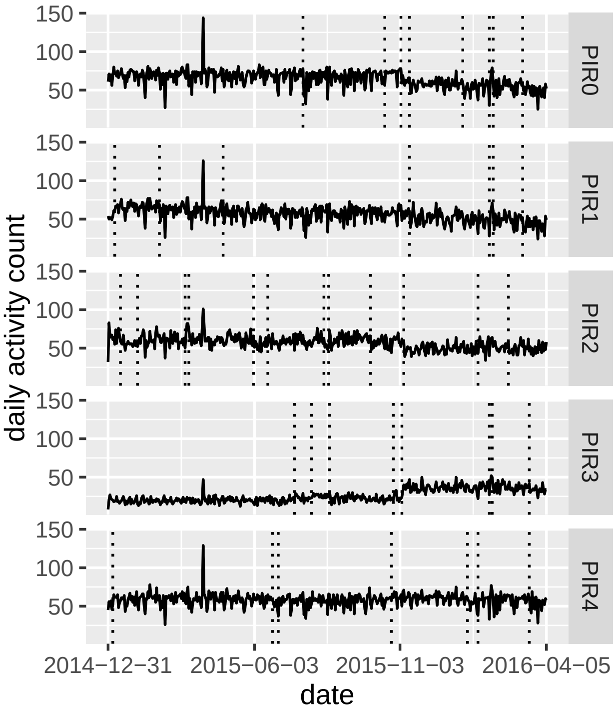
5.4 Case Study #4

Our fourth and last case study concerns Resident #3, a 79-year old male elderly. Examination of the sensor data from his home shows two noticeable changes. The first one is the decreasing toilet activity around November 2015 to around early January 2016. The second one is the sudden decrease in daily activity count in the bed area around January 2016. According to him, he did change his sleeping location (from bed to reclining chair in living area) around January 2016 because his standing fan broken down. While this explains the latter, the former is not accounted for and can be attributed to communication issues between the sensor node and gateway node.

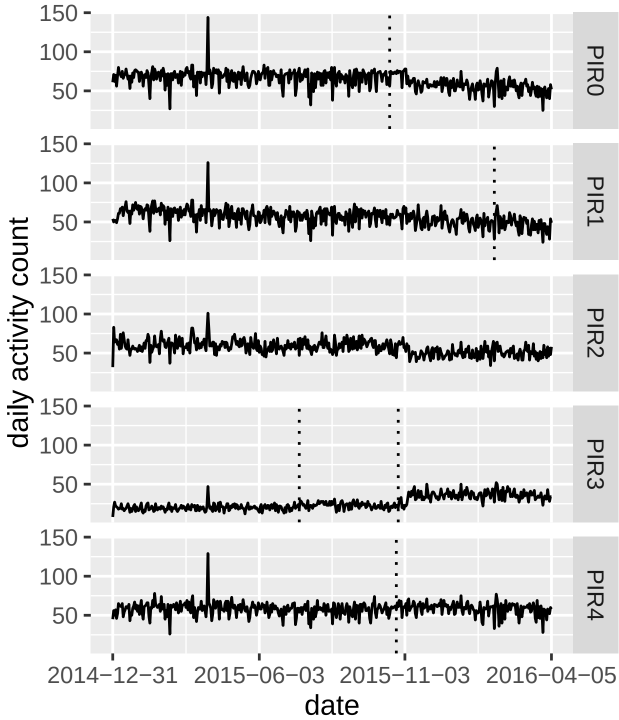
The change in behavior is indeed detected by both Mann-Whitney and OBCD. As shown in Figure 6, both schemes detect the sudden decrease in bed area activity around January 2016. However, OBCD outperforms Mann-Whitney, as it generates significantly lower false detections. In fact, while Mann-Whitney detects 70 changes, OBCD only detects 13 changes or more than 81% lower than the former.

6. CONCLUSION AND FUTURE WORK

Ageing-in-place is a paradigm that empowers the elderly to age safely and independently in the comfort of their own homes. Technology can play an important role in enabling this paradigm, specifically on the provision of safety and care. One particular solution that is gaining acceptability is the unobtrusive in-home eldercare monitoring system, a rudimentary system consisting of binary sensors such as motion and door contact sensors to monitor the activity intensity of the elderly in a real-time manner. In this paper, we

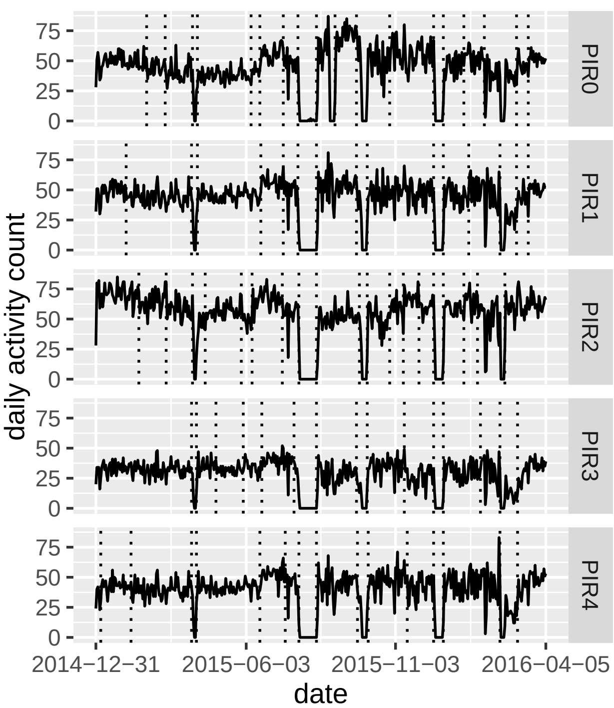


(a) Mann-Whitney

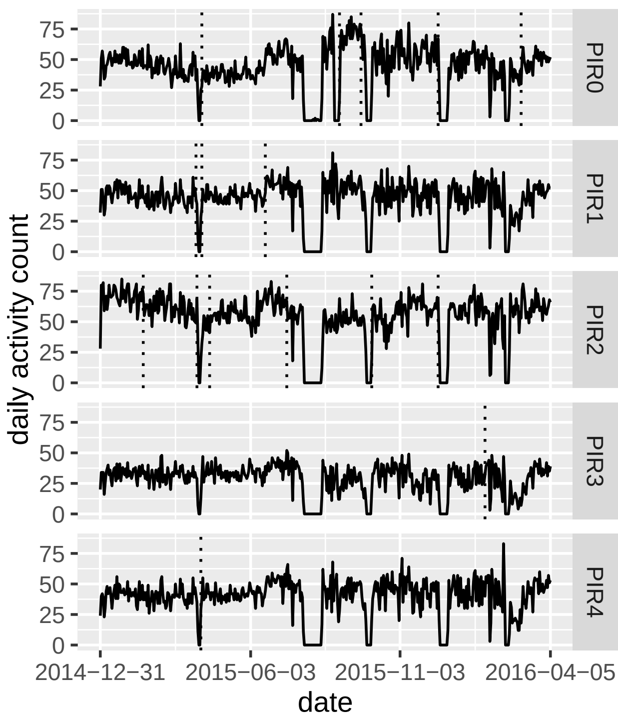


(b) OBCD

Figure 3: Daily activity count of Case Study #1 (Resident #35) and changepoints detected.

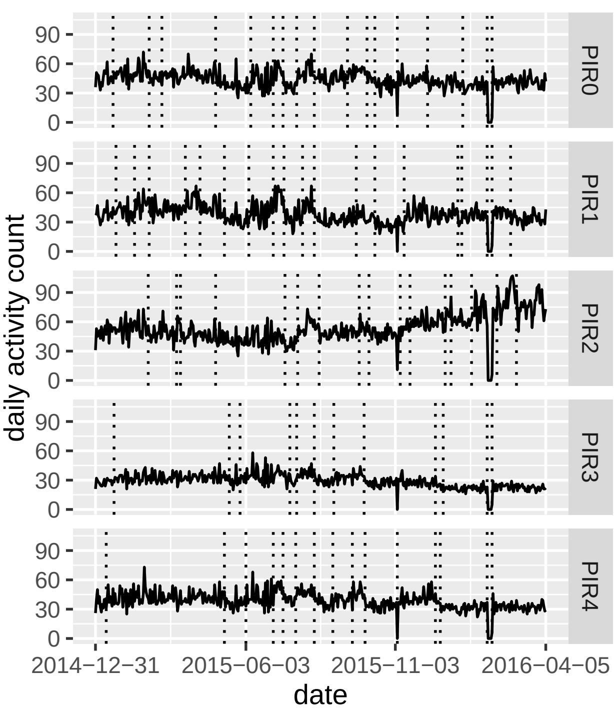


(a) Mann-Whitney

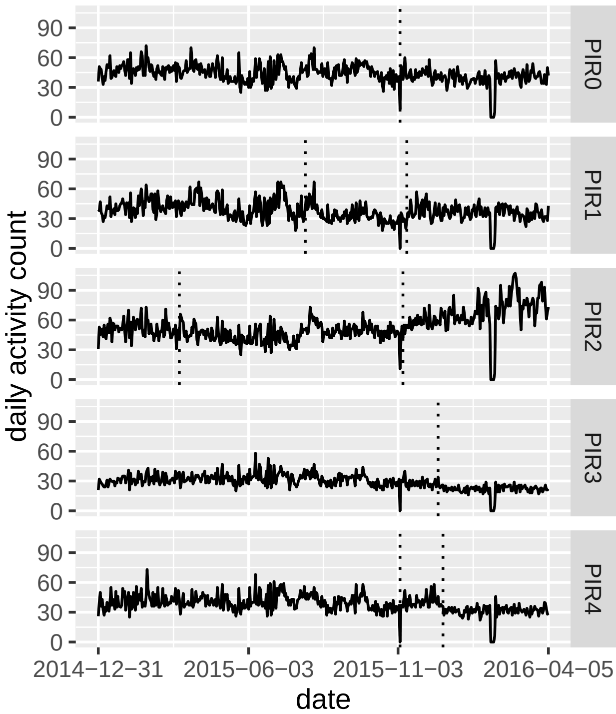


(b) OBCD

Figure 4: Daily activity count of Case Study #2 (Resident #20) and changepoints detected.

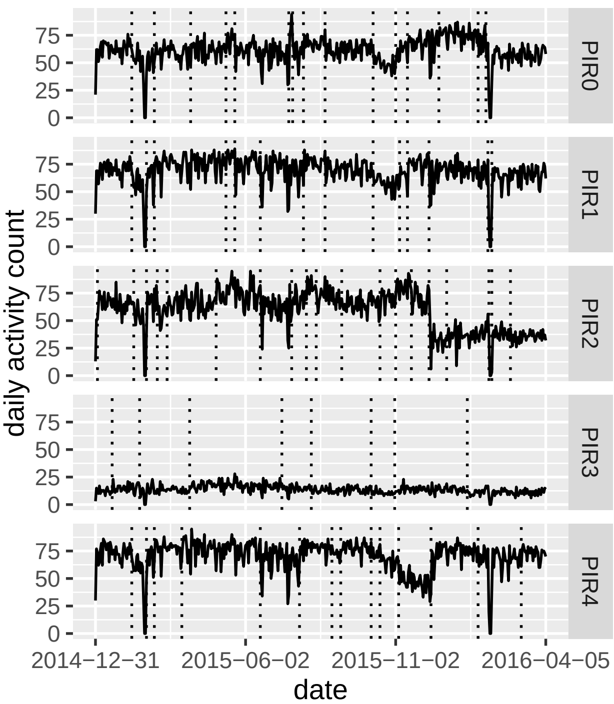


(a) Mann-Whitney

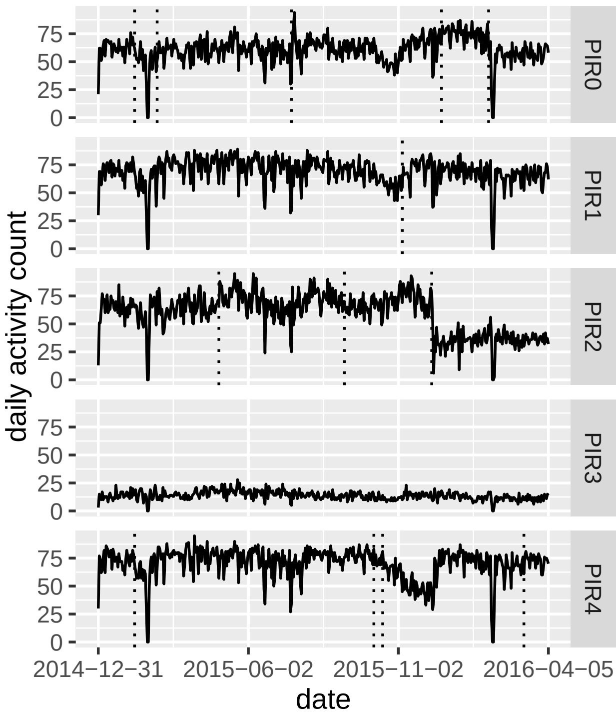


(b) OBCD

Figure 5: Daily activity count of Case Study #3 (Resident #16) and changepoints detected.



(a) Mann-Whitney



(b) OBCD

Figure 6: Daily activity count of Case Study #4 (Resident #3) and changepoints detected.

investigate whether it is possible for such a rudimentary system to detect behavioral changes of the elderly resident, so as to trigger care and intervention in a timely manner.

We propose Online Behavioral Change Detection (OBCD), a scheme to automatically detect behavioral changes using online streaming data from binary sensors. OBCD extends existing changepoint detection methods to reduce false positives due to extraneous factors such as faulty sensors, down gateways or backhaul connectivity. The Mann-Whitney test is complemented with a comparison of quartile coefficient of dispersion and mean comparison test to filter out changes due to the above-mentioned factors. Our case studies show that OBCD can significantly reduce false positives by 80% or more, without increasing the detection delay.

Moving forward, we would like to study the performance of OBCD using other changepoint detection methods. We also would like to investigate whether finer-grained data sets (*i.e.*, the interval between sensor readings is less than 10 minutes) could provide better detection performance.

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