Anomaly Detection in Daily In-home Activities Using the Multiple-Wireless Sensors for the Elderly

Feixiang Wu[1, a], Feiyu Hu[1, b, *] and Xiaodong Xiang[2, c]

[1]School of Science, Zhejiang University of science and technology, Hangzhou 310012, China

[2]School of Automation and Electrical, Zhejiang University of science and technology, Hangzhou 310012, China

[a]222009252030@zust.edu.cn, [b]120081@zust.edu.cn, [c]xxd@zust.edu.cn

Abstract

In order to recognize the daily in-home activities of the elderly, we applied unsupervised machine learning methods to analyze their behaviors through using home installed wireless sensors. Data used for 90-day behaviour analysis were collected by toilet water flow sensors, kitchen water sensors and magnetism sensors from 12 older persons living in Hangzhou, China. Using one class support vector machine (OCSVM), Isolation Forest (IF) and local outlier detection (LOF) we found the elderly have frequent abnormal activities at midnight and spend most of time at home. Through the analysis of correlation coefficients, we did not observe a significant difference between the abnormal behaviour detected from single type sensor and multi-sensors. The results suggest it is feasible to develop unsupervised models to detect the abnormal activities of the elderly in daily life using the real datasets without labels and explore the support needs of the elderly in the real world.

Keywords

Wireless sensors; elderly home-based care; Unsupervised models; Abnormal behaviour detection; Machine learning.

1. INTRODUCTION

The average life expectancy is increasing with the improvement of medical conditions and people's living standards. However, population aging significantly leads to the decrease of labor force and an increase of public expenditure. According to the National Bureau of Statistics of China, by the end of 2021, the population of the elderly aged 60 and above has reached 264 million, the proportion of older people in the total people has increased to 18.7%[1]. In recent years, with the improvement of family economic status, the elderly are more inclined to stay at their own homes. Compared to living in elderly care institutions, living at home is more convenient, comfortable and low-cost. The number of elderly people living alone has reached 118 million, accounting for 39% of the total elderly population. However, there are several disadvantages for the elderly living alone, for example, the lack of the company of relatives and lack of timely assistance in case of danger[2]. In addition, the current social care service providers cannot provide enough and high-quality home-based care services to support the elderly living alone. Especially, due to the outbreak of COVID-19 in the recent two years, the elderly living alone could not receive sufficient support from relatives or nursing staff, which greatly increased the risk of illness and psychological vulnerability[3,4].

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The new generation of information technology, such as Internet of Things (IoT) and big data etc., have shown promising potential to play an important role in home-based care service to ensure the construction and development of care services for the elderly in communities[5-8]. For example, instead of home visiting support from community workers, intelligent sensors (smart temperature sensors, water flow sensors, pressure sensors and smart smoke sensors etc.) can be installed at home, real-time monitoring through using these sensors can help community workers and service providers to identify activities and living conditions of the elderly at home, remotely[9]. At present, studies on the behavior of the elderly home living mainly relied on intelligent sensors.

Wireless binary sensors have the advantages of easy installation, low maintenance cost and long service life. Usually, wireless binary sensors are installed at home, such as wireless WiFi[10], water flow sensor[11], motion sensor[12], smoke sensor[13], SOS sensor and door magnetic sensor[12] etc.. The non-wearable sensors will be triggered if a person conducts activities at home, and then relevant digital signals will be transmitted via the sensors to the gateway and saved in the server. Data collected from wireless binary sensors provide the opportunity to analyze the elderly's daily behaviors and detect abnormal behaviors. In the activities of daily living (ADL), abnormal data points indicate the behavior of the elderly may be abnormal, and the abnormal behavior of the elderly is often the precursor of several diseases (such as depression, Parkinson's disease, Alzheimer's disease etc.)[14,15]. Therefore, there is increasing concern about abnormal behaviors detection for the elderly from the sensor data.

However, most data collected from sensors cannot be directly recognized as normal or abnormal. Manually labeling the sensors’ data is a very complex work which requires a lot of labor cost and time cost. Most studies applied unsupervised learning to recognize the abnormality of behaviors without using pre-made labels. Literally, the so-called abnormality is that the sample data obviously deviates from other sample points, and these sample data are also called outliers. Previous studies found the outliers are significantly associated with abnormal behaviours. Fiorrini et al. analyzed 100-day unlabeled data recorded by three infrared sensors installed in 17 elderly families and distinguished the elderly with abnormal behavior using unsupervised algorithm[16]. Koutli et al[17]. combined the classification and regression methods to provide medical staff with the location and relevant information of abnormal events based on the 90-day wireless sensor data collected from 10 elderly families. In addition, Uddin et al. reviewed previous studies using door magnetic sensor, temperature sensor, water flow sensor and smoke sensor to monitor the elderly's movement at home, and found these sensors have the characteristics of strong practicality and low cost in identifying the abnormal activities[18]. Furthermore, the daily behavior data of the elderly collected in the real environment is very rare and non-public, many studies used public datasets which are simulated in the laboratory as the daily activities of the elderly[19-21].

In this study, we investigated the daily behavior of the elderly based on the real data collection from toilet water flow sensor, kitchen water flow sensor and door magnetic sensor. Our aim is to derive a model that could identify the feasibility of the elderly abnormal behavior detection through multiple different sensors without labelled data.

2. MATERIALS AND METHODS

2.1. Dataset

The Ambient Assisted Living (AAL) System for Home-based Care Program started from 2018 at Zhejiang University of Science and Technology, aiming at making aging in place possible and independent. The system consists of smart sensors, software application, wireless network and computer servers. The smart sensors mainly include toilet seats sensors, kitchen water sensors and magnetism sensors. An elder and the elder’s family can select the sensors’ amount and

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types installed at home based on the personal choice preference and affordability. From July 2018 to September 2021, 695 elderly families living in Qingbomen community, Gudun community and Lingyin Street Community etc. in Hangzhou, China, have installed the AAL system.

The de-identified older persons were selected for analysis based on the following criteria:

(1) Include the older person whose home had three types of sensors installed from July 2018 to September 2021. During this period, 155 homes installed toilet seat sensors, 258 homes installed the kitchen water sensors and 205 families installed magnetism sensors. 643 older persons were excluded because their homes did not have all three types of sensors installed. Therefore, only 52 homes have installed all three types of sensors.

(2) Include the older person who had been used the three types of sensors for at least 3 months. 17 older persons were excluded due to at least one sensor installed at their homes had been working for less than 3 months. Moreover, 20 persons were excluded as they were not living during the study period for personal reasons (in hospital, travelling, staying with friends/children etc.). Thus, data collected from 15 homes are available for 3 months analysis.

(3) Excluded the older person whose living address is unknown in the system. In this study, 3 older persons were excluded, and then 12 older persons living at Sandun Street, Gudang Street and Lingyin Street were remained for analysis.

Different environmental sensors send signals to the gateway in different cycles, the cycle of kitchen water is 3 minutes, and both of toilet sensors and door sensors are 15 minutes. Table 1 shows an example of the type of data which was acquired by toilet seat sensors, kitchen water sensors, magnetism sensors. Under normal conditions, the sensor sends a signal to the gateway regularly. For example, the state record 0 of the toilet sensor (T01) at 0:00:23 refers no event occurred and the status changed to 1 at 0:02:47 indicates the sensor was triggered.

Table 1. An example of the type of data which was acquired by one family (Status 0/1 represent the sensor was triggered/untriggered)

Elderly_id	Activity	Sensor_Id	Sensor_Type	Day	Time	Status
Elderly_1	Toilet	T01	Water flow	2021/5/28	0:00:23 0:02:47 ……	0 1 ……
	Kitchen water	K01	Water flow	2021/5/28	5:26:39 5:27:38 ……	0 1 ……
	Magnetism	M01	Wireless infrared	2021/5/28	7:02:34 7:03:15 ……	0 1 ……

2.2. Outcome

We detected abnormal behaviour of elderly people in different time period during daily life in terms of abnormal points (outlies) in data sets collected from multiple types of sensors, in this study 0.2 was set as the proportion of outliers. The number 0.2 is commonly used to define the proportion of abnormal data points for unsupervised learning[22-24]. As people's bahaviour changes with the time of the day, we divided 24h into four time periods (morning (06:00-12:00), afternoon (12:00-18:00), evening (18:00-24:00) and midnight (00:00-06:00)) to perform anomaly detection in four different time periods.

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2.3. Anomaly detection models and evaluation

In this study, three unsupervised models, local outlier detection (LOF), one class support vector machine (OCSVM) and isolated forests (IF) were applied to explore the hidden behaviour patterns and detect anomalies using the unlabeled data. LOF is an unsupervised algorithm for abnormal detection through measuring the similarity between data objects[25]. The key parameters of LOF include the *n_neighbors* and *contamination*, *n_neighbors* is the number of selected adjacent points, which is associate with the classification performance of the model. And *contamination* represents the outliers of the data sample. OCSVM is a variation of the support vector machine (SVM) and can be used for anomaly or outlier detection in an unsupervised setting[26]. In OCSVM, *n_outliers* is the proportion of outliers, γ reflects the distribution of data after mapping to the new feature space. Gaussian radial basis function (RBF) kernel was used in this paper as the data collected from sensors does not meet the linear condition. IF is a model for unsupervised anomaly detection[27]. In IF, *n_estimators* and *contamination* are two key parameters. The parameter of *n_estimators* represents the number of trees in this algorithm, the ability of the algorithm to identify outliers will be reduced with the increase of trees. The *contamination* is the proportion of outliers in the dataset.

Furthermore, Silhouette Coefficient (SC) and Calinski-Harabaz Index (CHI) were used for model evaluation and comparison. SC is a measure for clustering performance evaluation, ranges from -1 to +1. The higher value of SC, the better defined clusters in a model[28,29,17,30]. CHI also known as the variance ratio criterion measures the similarity of a sample to its own cluster compared to other clusters, and a high CHI value indicates better clustering[31-34]. All analysis and evaluation were undertaken in Python[35] version 3.8, Numpy version 1.19, Sklearn version 0.24 and Pandas version 1.2.

2.4. Analysis

All values collected from toilet water flow sensors, kitchen water flow sensors and door magnetic sensors were standardized applying Z-score standardization. Usually, hyperparameters are determined by grid search in practice. We applied grid search on *n_neighbors* (10, 20, 30) for LOF, γ (0.1, 0.01, 0.001) for OCSVM and *n_estimators* (100, 120) for IF. The best hyperparameters for each model were selected through the comparison of SC and CHI values. The SC was used as the primary criteria for hyperparameters selection because SC can more accurately reflect the performance of dividing the data into two categories[36,28,37]. Table 2 shows the hyperparameter selection for three methods. We define the combination of three different sensors' data as Three_sensor for the convenience of research. This study adopts the voting mechanism about ensemble learning[38], in which each algorithm with the best performance is used as the base classifier, the output results of the classification will be counted, and the result with the largest proportion will be taken as the final result of this voting (that is, the principle that the minority is subordinate to the majority, and the category with the largest number of votes will be judged as this category). Three_sensor's three-dimensional data (including toilet seat, kitchen water, magnetism) was input into three base classifiers, and we respectively counted the number of final abnormal points in each time periods.

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Table 2. Model comparison OCSVM, LOF, and IF (The parameter of n_outliers and contamination stands for the rate of abnormal behavior) in elderly_1

	Toilet		Kitchen		Magnetism		Three_sensor	
	SC	CHI	SC	CHI	SC	CHI	SC	CHI
OCSVM($n\_outliers$, RBF, γ=0.01)	0.64	48.82	0.7925	369.3424	0.6858	81.7915	0.5873	87.3409
OCSVM($n\_outliers$, RBF, γ=0.001)	0.75	78.98	0.6947	342.661	0.7404	102.888	0.7473	114.088
OCSVM($n\_outliers$, RBF, γ=0.0001)	0.85	136.44	0.5434	32.8094	0.8336	210.75	0.7972	221.86
LOF ($n\_neighbors$=10, $contamination$)	0.6437	78.1139	0.7826	170.6462	0.4871	66.8784	0.6645	86.1245
LOF($n\_neighbors$=20, $contamination$)	0.8249	126.8838	0.6829	103.9058	0.7337	100	0.7558	92.198
LOF($n\_neighbors$=30, $contamination$)	0.5908	13.3605	0.4313	80.8171	0.6982	89.6481	0.7305	90.4354
IF ($n\_estimators$=100, $contamination$)	0.7976	97.899	0.7595	254.5182	0.6781	66.0358	0.7113	93.8851
IF ($n\_estimators$=120, $contamination$)	0.7976	97.899	0.7581	239.0893	0.6844	65.036	0.7128	94.702

In addition, we analyzed and compared the results of Three_sensors and each single type of sensor on detecting the abnormal behavior of the elderly, the correlation coefficient between sensors was calculated based on the number of abnormal events detected by each sensor in four time periods. A significance test was performed to test the correlation coefficient.

3. RESULTS

A total of 12 older persons were included for analysis. Figure 1 shows the number of outliers from the three sensors data detected in four time periods during the three months study period. Less than 25 abnormal points were found for around 75% of the elderly within 90 days. The median number of abnormal points detected by each sensor was 20. It can be observed the least detected abnormal points from Three_sensor, toilet seat sensor and magnetism sensor were during 18:00-24:00. The kitchen water flow sensor detected the least outliers in 06:00-12:00. In particular, it can be found that most abnormal events were detected at midnight (0:00-06:00:00) compared to other three time periods.

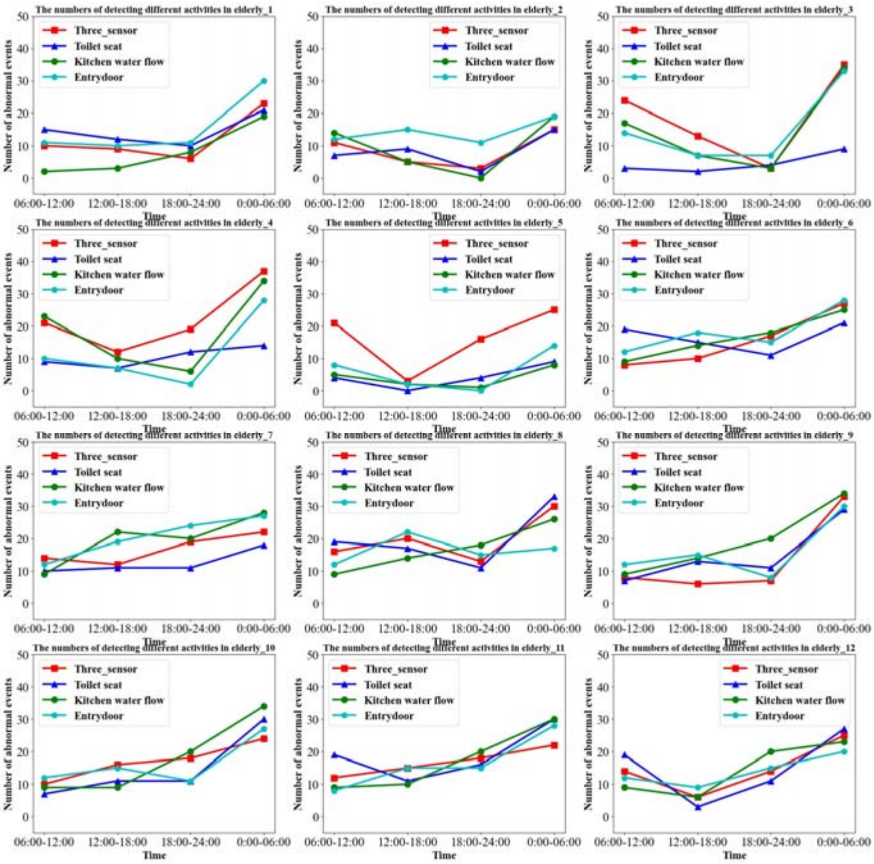

Figure 1. The detected anomalies of different activities in different time slots from 12 elderly

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Table 2 shows the correlation coefficients between the sensors in terms of the abnormal events detected by the three sensors for the older person_1. The significance test of correlation coefficient indicates the P values for toilet sensor and door magnetic sensor are significantly smaller than 0.05, but the P value for Kitchen water sensor and Three_sensor is greater than 0.05. The tables of correlation coefficients for other 11 person can be found in the appendix.

Figure 2, Figure 3 and Figure 4 show the comparison of detected abnormal values and recorded real values from a single type of sensor. The red dots above represent the abnormal values detected by each sensor, and the blue dots represent the original record values from each sensor. From these three figures, we can see that the record values of kitchen water and magnetism significantly are higher than toilet seat, the distribution of sample points approximately obeys a normal distribution, and the outliers detected by the sensor are mostly concentrated on the more extreme values accounting for about 75% of the total outliers. The similar distribution for the other 11 persons can be found in the appendix.

Table 2. The correlation coefficient analysis

	Toilet seat	Kitchen water	Magnetism	Three_sensor	P-value(<0.05)
Toilet seat	1	0.7228	0.9049	0.9695	.030
Kitchen water	0.7228	1	0.9463	0.8414	.157
Magnetism	0.9049	0.9463	1	0.9698	.031
Three_sensor	0.9695	0.8414	0.9698	1	

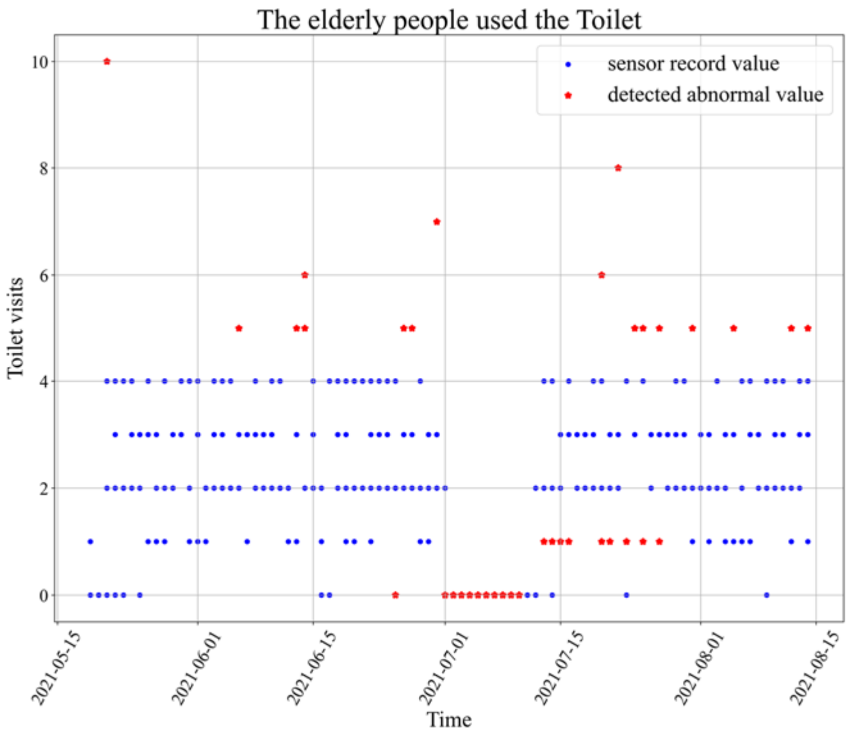

Figure 2. Distribution of abnormal behaviors detected by the toilet water flow sensor from Elderly_1

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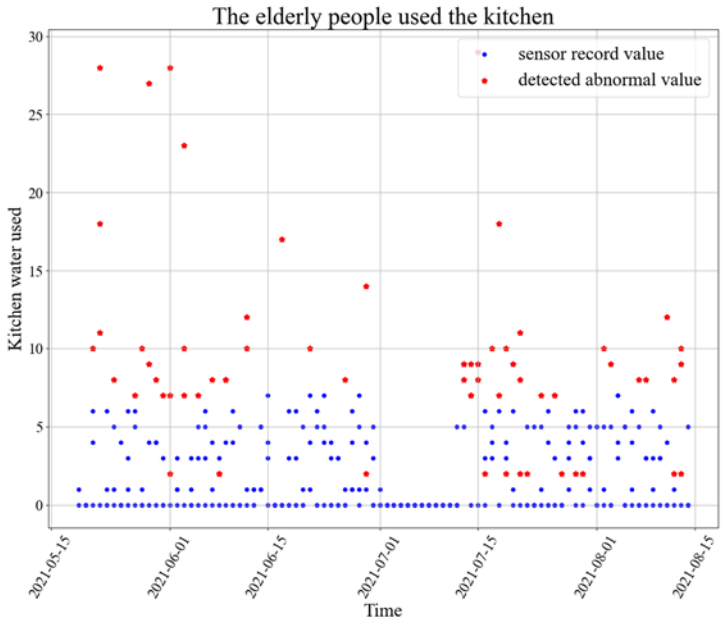

Figure 3. Distribution of abnormal behaviors detected by the kitchen water flow sensor from Elderly_1

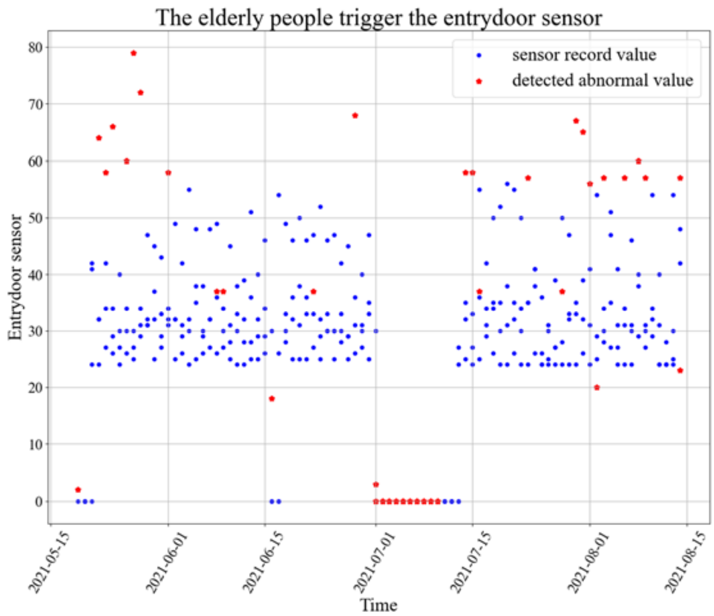

Figure 4. Distribution of abnormal behaviors detected by the magnetism sensor from Elderly_1

4. DISCUSSION

This study focused on the abnormal behavior identification for the elderly living at home based on the real data collection from wireless environment sensors. In this paper we found, in a day, the elderly had frequent activities at midnight, over 80% older persons used toilet more than 4 times, 66% of them used the kitchen water over 10 times and at least 74% of them triggered the magnetism sensor over 15 times. This abnormal behaviour may be explained by sleep disorder at midnight, which is consistent with previous studies. Qu et al. studied more than 2000 elderly over 63 years in China and founded that 50.11% of them had sleep disorder[39]. Similarly, Zhao et al. reported the sleep disorder occurrence in elderly rate was 49.7% in China[40]. Lee et al. reported that the elderly have an increased frequency of going to

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the toilet at night and repeat the mode from getting up to the toilet and then returning to bed, which may cause the reduce of sleep quality and the increase of fall risk[41]. Moreover, it was found that the elderly may carry out some abnormal activities at unusual time slots, such as eating at midnight and going to bed at 3 a.m[42]. Our finding suggests it is necessary to further investigate the demand of life support at night compared to daytime.

We observed that only 3 out of 12 older persons left home for 3-5 days during the three months study period as the sensors in the older person's home were not triggered. This may be explained by several reasons such as left for travelling or went to hospitalization. From another aspect, we can see most elderly spent more time at home and they were lack of communication with people outside of their home, which may lead to a sense of loneliness in their hearts. Goethals et al. pointed out staying at home too long will have a great negative impact on the elderly's physical and mental health[43] and Rondón et al. found the necessary social contact can improve the quality of life for the elderly[44]. Therefore, regular home visiting from the community workers and relatives of the elderly will be highly beneficial for the elderly. It is also essential for the elderly to go out during the daytime and keep contact with the outside world if they are able to go out-of-doors.

The results of correlation analysis and P-value test between a single sensor and Three_sensor show the abnormal events detected by multiple sensors and single sensor are basically consistent. As the structure of each elderly's home is different and there were few obvious abnormal behaviours detected during the daytime, the elderly can choose to install a single type of sensor to detect abnormal behaviors at midnight if they have the limitations of the device installation and maintenance cost.

There are several limitations in this study. First, the sensors may be triggered by other people. For example, movement activities from friends, relatives or community workers may lead to overestimation of behaviour frequency. Furthermore, the sample size of the elderly was limited to 12 persons and the study period was 3 months long, whereas larger samples and longer study period can provide more accurate estimates of abnormal behaviours and long-term behaviour patterns. However, previous studies with even smaller data sample have shown good results in monitoring the abnormal behavior of the elderly. For example, Soussa et al[45]analyzed the daily activity data of only two elderly volunteers collected from wireless infrared sensors, and found unsupervised models can be applied to monitor the elderly activities; this kind of sensor network model with small amount of data and low cost is especially suitable for underdeveloped countries and communities. Similarly, the association between the frequent spatial transformation and patients' agitation was found by applying the data collected from two disabled elderly patients with Alzheimer's disease using a mattress sensor and a motion sensor[46]. In this paper we did not explore the relationship between abnormal behaviors and health status of the elderly as their demographic factors and medical records are not available.

5. CONCLUSION

This study used unsupervised learning detection algorithms LOF, OCSVM and IF to detect the abnormal behavior of the elderly based on the data collected from wireless binary sensors. The results show the elderly have frequent activities at midnight which may be caused by sleep disorder, and there is no significant difference between using a single type of sensor and multiple types of sensors to detect the abnormal behavior of the elderly. In China, there are very few data sets recording the real daily activities of the elderly, our work suggests that it is feasible to develop unsupervised models to detect the abnormal activities of the elderly using the real datasets without labels and explore the support needs of the elderly in the real world.

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