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A SITUATION-AWARE ABNORMALITY DETECTION SYSTEM FOR ELDERLY CARE USING SVDD

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Abstract. *Elderly care is a very serious social problem in many countries, especially in advanced countries, such as Japan, Korea, USA, and Singapore. To take care of elderly people, first we should clearly understand their situations and support them based on each situation. Abnormal activity detection is a particularly important task, especially in specific situations, e.g., sleeping or going to the bathroom. Based on some abnormal activities, some kinds of diseases may be predicted. However, detecting abnormal activities in a real-time situation is a critical research problem. To solve this problem, we propose a situation-aware abnormality detection system based on support vector data description (SVDD) for elderly people. First, a sensing system is proposed to detect the details of a person's situation. Then, we discuss various features that are analyzed and designed for each situation. Then, a method to detect abnormal activities in a situation based on SVDD is presented. To show the performance of the method, an evaluation is performed.*
Keywords: Internet of Things, Elderly care, Situation-aware, Abnormal activity detection, SVDD

1. **Introduction.** Effectively taking care of elderly people is becoming one of the serious social problems in many countries, especially in advanced countries such as Japan, USA, Korea, and Singapore. Currently, in Japan, which has the highest proportion of elderly citizens worldwide, 21% of the population is over the age of 65 [1]. Care for elderly people living alone is a particularly important research topic, since these people are isolated from society and may lack family support. According to the Tokyo medical examiner's office, 2,211 people over 65 died alone in their residence in 2008 [2].

Using current technologies and research to solve the above social problem is becoming a widespread research topic, especially in the field of the Internet of Things (IoT), whose basic idea is that a variety of smart objects augmented with various abilities, including sensing, wireless communication, and processing, are able to interact with each other and cooperate with their neighbors to reach common goals. Based on the cooperation of multiple smart objects, the details of the situations of elderly people can be detected and the corresponding information can be quickly sent to other smart objects in remote places, e.g., the home of remote family members or a care center. Abnormal activity detection is particularly important, since elderly people may face harm in such situations. For example, some diseases often cause abnormal activities. Diseases, e.g., hyperplasia of the prostate, chronic nephritis, bladder inflammation, diabetes, can be predicted if an elderly person goes to the restroom too many times at night.

To detect the abnormal activities of elderly people, various studies have been performed [7-10]. However, recording the details of abnormal activities in various specific situations has not yet been made possible by the existing research. For example, behaviors such as the frequency at which people go to the bathroom and sleeping patterns cannot be monitored. Understanding and detecting the details of abnormal activities can greatly help caregivers take care of elderly people. To solve the above problem, in this paper, we propose a situation-aware abnormality detection system based on support vector data description (SVDD) for elderly people.

Situation-awareness is a very important research topic in the research paradigm of ubiquitous computing, Situation-awareness detects the situations around the user and provides corresponding services or automatically changes the environment to adapt to the user. In this paper, not only general situations but also abnormal activities can be recognized to support the users.

To detect abnormal activities in various situations, first a sensing system is proposed to detect the situations of the user. Then, various features are analyzed and designed to detect abnormal activities in these situations. Next, a method to recognize abnormal activities based on the designed features and SVDD is presented. Finally, we perform an evaluation to show the performance of the method and the accuracy of the system. Through the evaluation we see that the method can effectively recognize abnormal activities with high precision, when the abnormal activities are not so similar to normal activities.

The main contribution of the paper can be summarized as follows:

(1) We have proposed a new method to automatically detect situations and abnormality in the corresponding situations. We have developed various sensing devices to detect situations and designed a reasoning mechanism to recognize situations.

(2) We have given a detail analysis of features to detect abnormality and proposed a method to detect abnormality based on SVDD.

(3) We have studied a special case, i.e., sleeping, in details, by collecting real data from the system and given a detail evaluation of the system and the designed features.

The rest of this paper is organized as follows. Related work is discussed in Section 2 and the basic concept is shown in Section 3. The system design is shown in Section 4 and the evaluation results are presented in Section 5. In Section 6 we conclude the paper and show future directions.

2. **Related Work.**

Activity recognition has been the focus of various research projects based on variety of classification methods [3-6], including hidden Markov models (HMMs) [5], support vector machines (SVMs) [6], and Naive Bayesian classifiers. In [5], an HMM-based human activity recognition method is implemented by using a single accelerometer based on a proposed HMM structure that allows both backward and skip transitions. In [6], classification of human activities is performed with an SVM based on an autoregressive model. The result for four activities (running, still, jumping, and walking) is shown to be better than the result of a traditional time and frequency domain. However, most of these works focused on the normal activities of humans, which cannot be directly used in detecting abnormal activities due to the different features and training datasets.

Meanwhile, various researches have been proposed on abnormal activity detection. And basically, there are two approaches. The first one is a kind of threshold-based approach. For example, in [7], a similarity-based method was proposed to detect abnormal human behavior when the similarity is larger than a threshold. Another threshold-based method was proposed in [8] to detect human abnormal movement in a wireless sensor network. However, the threshold is really hard to design. And for flexible adapting to the time passaging and habit changing, threshold may be timely changed, which is too hard for the system.

Some abnormal activity detection methods have been proposed based on an outlier detection method in machine learning, e.g., in SVMs and SVDDs. In [9], an abnormal human activity detection method was proposed based on a one-class SVM. First, they adopt a set of HMMs to model the normal traces and after transforming n training traces into a set of features, they train a one-class SVM to detect abnormal activity. The method was further enhanced in [10] by employing the hiearchical Directlet process (HDP-HMM) and a Fisher kernel. However, the methods are lacking detailed analyses of the features of the abnormal activities of elderly people. Therefore, they cannot be directly used in elderly care without a detailed design of the features for the abnormal activities of elderly people. In [11], a method to detect abnormal living patterns for the elderly people was proposed based on SVDD. The SVDD method, inspired by SVM, was proposed by Tax and Duin [12,13]. In [11], they first analyze the features for daily behavior pattern classification in detail, based on the kinds of disease that can be predicted. Then, the abnormal activity is recognized based on a trained SVDD using a training dataset. However, in the above systems, it is really hard to detect the detailed situation around users, e.g., user is sleeping or eating, and the abnormality happened in the detected situations. In the paper, we mainly focus on the above research problem. We detect situations (e.g., environment and gesture) of users by developing various sensing devices, designing features based on sensing data, and finally recognize abnormality.

Table 1 gives a more detailed comparison based on the following four aspects, which are very important to evaluate a system for detecting abnormal activities: Feature Design and Evaluation for Abnormal Detection (FEDAD), Situation Detection (SD), Ability of Abnormal Detection Method (AADM), and Richness of Sensor Data (RSD).

The first item, Feature Design and Evaluation for Abnormal Detection, is a very important factor for detecting abnormal activities. Some methods are proposed to detect abnormal activity. However, they are lack for a detailed analysis and evaluation that which features are suitable for the abnormality detection, e.g., in [9,10]. Without detailed consideration and design of features for abnormal activities, the accuracy of an abnormal detection system is difficult to guarantee. Meanwhile, to detect abnormal activity more accurately, we consider each kind of situation in more detail and examine what can be achieved in Situation Detection. For example, we detect an elderly people have an abnormal activity, meanwhile we can know the situation of the users, e.g., the user is taking medicine. Then the service can be provided more thoughtfully.

Table 1. Comparison of related research

No.	FEDAD	SD	AADM	RSD
[7]	×	△	○	△
[8]	×	○	△	△
[9,10]	×	△	○	×
[11]	○	△	○	△
[21]	△	△	○	△
[22]	△	○	△	△
[23]	×	○	△	△
[24]	△	△	○	△
[25]	○	○	×	△
Our System	◎	○	○	○

Meanwhile, we compare the abnormal detection systems based on the aspects of Ability of Abnormal Detection (AAD) and Richness of Sensor Data (RSD). Ability of Abnormal Detection shows the ability of a detection method, e.g., whether it is adaptive for time passaging or whether a classifier can be easily and effectively created. Richness of Sensor Data shows whether the system is designed with various sensor data to detect user situation and activity more accurate. Much more rich sensing data, abnormality detection also can be achieved more correctly. In a comparison with related research, our system has especially contributed to the detailed analysis of features, collecting data from rich sensors, detecting situations around the user, and detecting abnormal activity.

3. **Basic Idea and System Image.** The basic idea is shown as Figure 1. First, the situation of elderly people is detected in a smart home. To get precise location information of the elderly people, we have developed a u-tiles sensor network [14,15], as shown in Figure 1. Through the u-tiles system, the location and the relation between the elderly people and surrounding objects can be grasped. The basic idea of the u-tiles system is that, first we classify a whole floor in a room into many pieces, and on the back of each piece of tile we attach a radio-frequency identification (RFID) antenna and pressure sensors. A management and concentrator unit (MCU), which has a program to select one RFID antenna from all tiles to read its information, controls all the tiles. For example, we suppose an object or a person is on tile 5, and then a signal from the pressure sensors of tile 5 will be sent to the MCU. Based on that, it can know that someone or some object is on tile 5. Then it can further read information from the RFID antenna attached on the back of tile 5 to obtain more detailed information, e.g., name, age. After that, we define various meaningful zones in the smart home. The situation of the elderly people will be detected based on zones and other detailed information, e.g., status of the home appliances, actions of the user.

To detect actions of the user, we developed a mini device called Magic Ring, which can be worn on a finger of a user to recognize finger gestures or daily life activities, e.g., tooth brushing. Meanwhile, to further know the situation of users, we also want to know the status of home appliances, e.g., a light is on or off in a room. For that, we have employed a smart plug [18] in our system, which can get such information and also can be used to control home appliances, e.g., turning on/off a TV.

We are able to collect various data from the sensors: location and relation information from the u-tiles sensor network, actions/gestures information from the Magic Ring, and

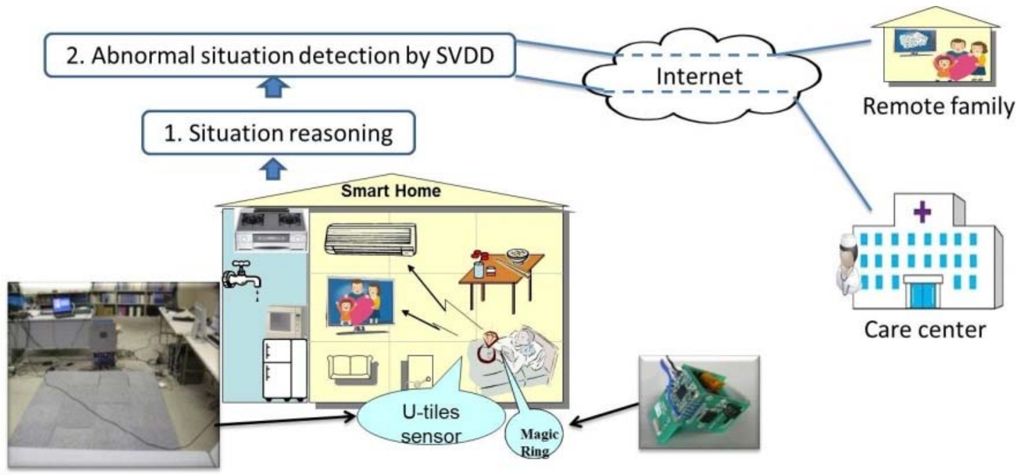


Figure 1. Basic idea of the system

home appliance information from the smart plug. Then, we can further describe that information as a situation, which is introduced in detail in Section 4. Then, for each situation, we define the detailed features and detect abnormal activities in the detected situations based on SVDD. Finally, the system sends the corresponding information to caregivers, e.g., remote family members and staff in a care center.

4. **Situation and Abnormal Activity Detection.** In this section, we mainly present how to detect the situations around the elderly people and the abnormal activities in the situations.

4.1. **Hardware for detection.** The system mainly consists of a sensing part and a display part, as shown in Figure 2. The sensing part further includes the u-tiles sensor network to detect the position/trace of the elderly people, a Magic Ring to detect the behavior of users, and a smart plug [16] to control home appliances. The basic idea of the u-tiles sensor network is to detect the precise location and position relation between the elderly people and surrounding objects by embedding various sensors, including pressure sensors and RFID antennas under the floor. Figure 3 shows the structure of u-tiles sensor network, where a single u-tile is almost 40×40 cm. Pressure sensors and RFID antennas, which are connected with a reader through a PIC-based switch, are under each u-tile. The IDs of users and objects can be read by each u-tile, and the position relation between users and objects can be grasped. The detail of u-tiles hardware environment can be found in [14,15]. Besides the u-tiles sensor network, our implemented smart plug developed by NTT Company is in our system to detect and control the status of home appliances, such as turning on or off of a lamp, as shown in Figure 2.

4.2. **Zone based situation reasoning.** With the hardware introduced above, in this subsection we present the detection of the situation of elderly people. A zone is a meaningful area related to some specific locations, furniture, and home appliances. In a zone, specific activities may happen with high possibility. For example, when an elderly person is in the sofa zone and the TV is on, he may be watching TV. By further considering other factors, e.g., environment factors, actions, the detailed situation around the elderly person can be understood. In this paper, we mainly consider the following four factors to represent a situation: zone, status of related home appliances, actions of the elderly person, and the environment. We developed a wearable device called the Magic Ring,

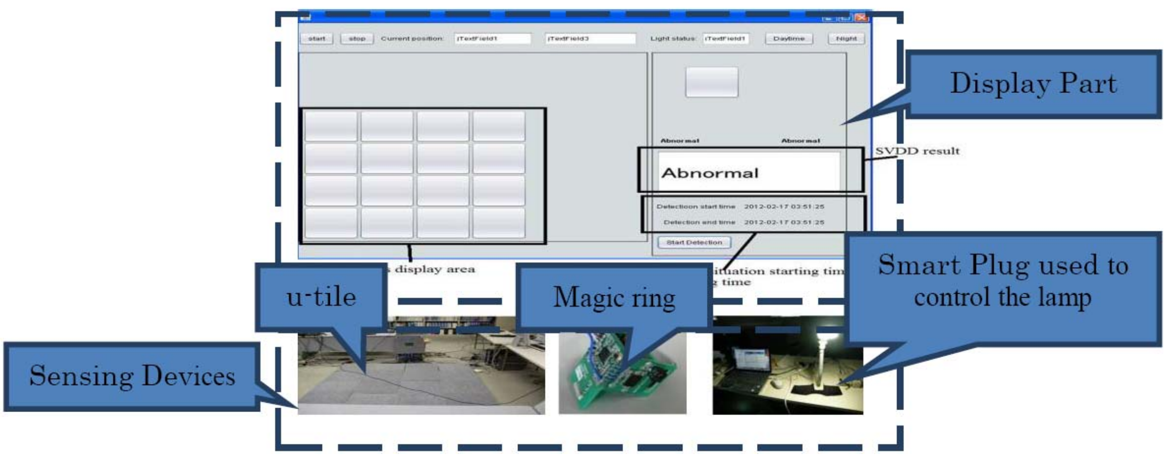


FIGURE 2. U-tiles hardware environment

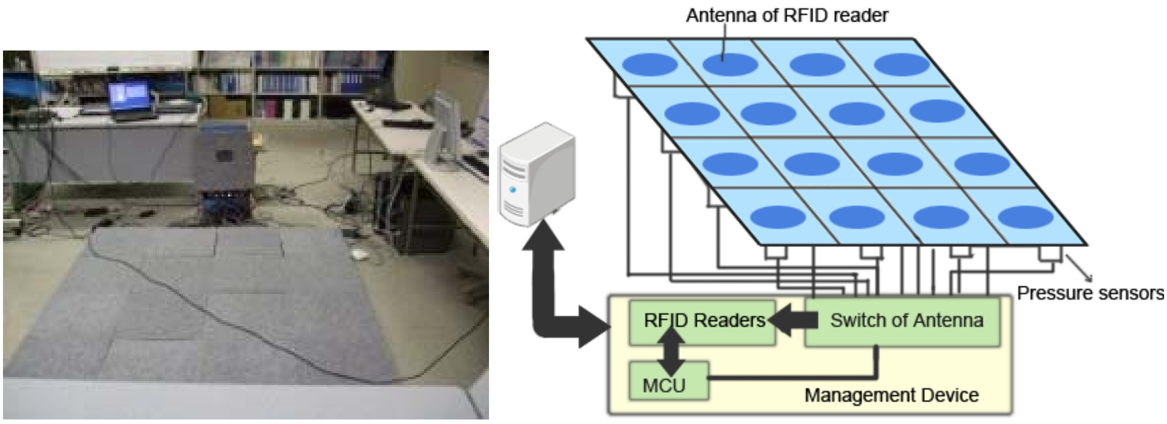


FIGURE 3. The structure of the u-tiles sensor network

TABLE 2. Situation detection

Situation	Detection rules			
	z	D	A	E
Going to the restroom	Bathroom zone	Light of the bathroom is on	N/A	N/A
Sleeping	Bed zone	Light of the bedroom is off	Almost no action	No light
Eating	Dining table zone	N/A	Eating	N/A
Taking a walk	Out of the yards	N/A	Walking	N/A

by which some basic gestures/actions can be detected [17]. Then, a situation s can be represented by the following four tuple,

$$s = < z, D, A, E >,$$

where
z is used to represent the current zone of the elderly person;
D is a set including the status of related devices;
A is a set including current actions of the elderly person;
E is a set including environment factors.

Table 2 shows detection rules based on the zone-based situation definition. For example, if the system detects that the elderly person is in the bathroom zone and the light of the bathroom is on, the situation of the elderly person can be recognized as "going to the restroom".

4.3. **Abnormal activity recognition based on SVDD.** After detecting the situations of the user, we should recognize whether an abnormal activity occurs in these situations. In this paper, we use SVDD to recognize abnormal activities.

SVDD was proposed in [12,13] and inspired by the SVM, which is a method of machine learning. SVDD constructs a boundary around the target data by enclosing the target data within a minimum hypersphere. The boundary of a dataset can be used to detect target data or outliers. The details can be found in [12,13].

Unlike other abnormal activity detection research, we create several hyperspheres based on the different situations with various features, as shown in Figure 4. For each kind of situation, a hypersphere is created to recognize abnormal activities.

Figure 4 shows an image of the SVDD to detect an abnormality. First, suppose we have some training sets of normal activities in the situation as shown by the small circles

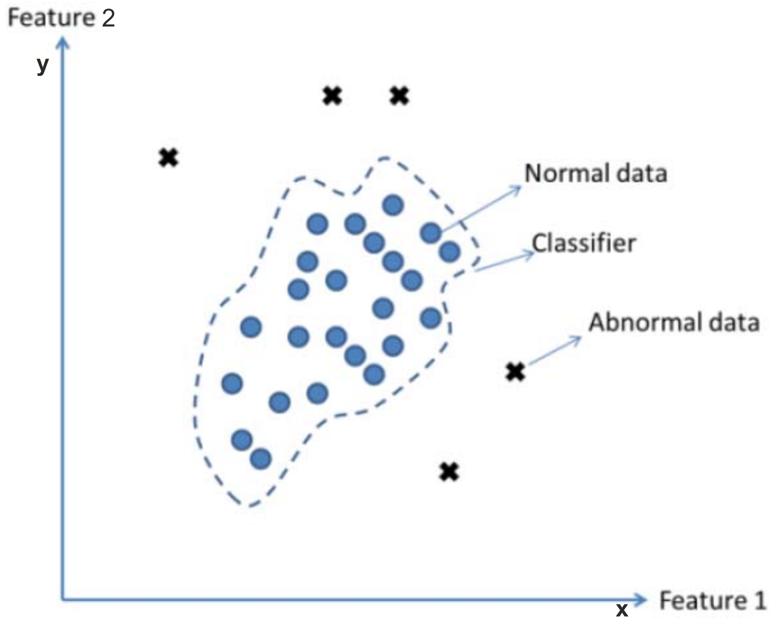


FIGURE 4. Hypersphere created by SVDD to detect abnormality

in Figure 4. Two features are represented as feature 1 on the x-axis and feature 2 on the y-axis. Based on [12,13], we can draw a hypersphere to include all of the normal activities in the training set with center a and radius R, presented as follows,

$$F(R, a) = R^2 + C \sum_i \xi_i \tag{1}$$

with the constraints that all normal activities are within the hypersphere:

$$\|x_i - a\|^2 = R^2 + \xi_i, \quad \xi_i \geq 0 \quad \forall i \tag{2}$$

We minimize the volume of the hypersphere in Equation (1), by minimizing R^2 and the constraints in Equation (2) by Lagrange multipliers. The details can be found in [12,13].

Suppose the minimized hypersphere can be computed as shown in Figure 4. Then, the outliers, shown as crosses in Figure 4, are recognized as abnormal activities. If there are N features for a situation, the hypersphere should be N dimensions.

4.4. **Feature design.** To detect the abnormal activities of elderly people, first we analyze the features to predict a disease. We classify the features into two types, basic features (BF) and special features (SF). The BF represents common features, which can be used to detect an abnormality in most situations. The SF is used to represent special features just for specific situations.

In this paper, we consider the situations and features shown in Table 3 for elderly people.

First, we focus on the insomnia problem. Insomnia is an unhealthy activity for elderly people and may be related to a neurasthenic disease. Long-term insomnia may cause nerve cell aging and metabolic disorders. Likewise, too much sleep is not good for the elderly people since it affects metabolism. Therefore, we want to detect whether elderly people have a sleeping abnormality. To achieve this goal, we select two BFs, which are the start time and end time/duration to detect whether elderly people sleep on time and whether they have suitable sleeping hours. Furthermore, we design six SFs, which are the number of times they go to the bathroom during the night, the time spent in the bathroom, getting up times, duration of getting up, naps in the daytime and duration

TABLE 3. Situation and feature design

Situation	Situation Features			
	Basic Features			Special Features
	Start time	Duration/end time	Times per day	
Sleeping	○	○	×	Times to Bathroom at night, Duration in Bathroom, Getting up times and duration, Naps in daytime and Duration of Naps
Midday sleep after a lunch	○	○	×	Times to Bathroom during sleeping, Duration in Bathroom, Times of Movement during sleeping (turning over in sleep), Total Static Time during sleeping, Maximum Duration of Static
Going to the restroom	×	○	○	Times per hour and at night

of naps to evaluate the sleeping quality. If elderly people get up too many times or the duration of getting up is too long, they have the possibility of experiencing insomnia. Also, if elderly people have too many naps or the duration of naps is too long, they have a high possibility of experiencing poor sleeping during the following night. Therefore, we use the above six SFs coupled with two BFs to detect abnormal activities in sleeping situations.

For another situation, we consider the sleeping/rest quality of a midday sleep/rest after lunch. A long poor midday sleep influences the health of elderly people especially. The special features designed for the situation are Times to Bathroom during sleeping, Duration at Bathroom, number of Times of Movement during sleeping (mainly represented by turning over during sleep), Total Static Time during sleeping and Maximum Duration of Static (maximum duration between two movements). In contrast with sleeping at night, midday sleeping/rest takes a shorter period of time, e.g., one hour. To detect an abnormality in a midday sleeping/rest, we design more detailed features. To describe the sleeping/rest quality in a short period, we first design a feature to represent the number of movements/turning over during sleeping. If elderly people move too many times, we assume that they did not have a good rest. Furthermore, we design the feature of Total Static Time during sleeping and Maximum Duration of Static to represent sleeping quality in more detail.

The third situation in Table 3 is for going to the bathroom, based on some problems that could be detected, e.g., renal function. For example, if elderly people go to the restroom too many times at night, they may have some disease, e.g., chronic nephritis, bladder inflammation, diabetes.

Besides the above situations, other situations such as eating and appropriate body exercise could be detected based on the system.

5. **Evaluation.** We evaluated the proposed method in the following two aspects, (1) feasibility and scalability of the method and (2) accuracy of the system to detect situations and abnormal activities. To evaluate the method in detail, we focus here on the detection

of abnormal activities in the situation of sleeping. The abnormal activities in other situations can be detected in a similar way.

5.1. **Evaluation environment.** To evaluate the system, first we built an evaluation environment of a smart home, as shown in Figure 5. The system has two home servers. Home server 1 computes the position information of the user from the u-tiles through UDP and wireless communication modules. To evaluate the proposed method, we created several zones in the u-tiles sensor network. These include the bed zone and bathroom zone shown in Figure 5. Home server 2 obtains the status of home appliances, e.g., on/off information, and control home appliances through the smart plugs introduced in Subsection 4.1. Home servers 1 and 2 send the corresponding information to a remote monitoring server, which can be set in a care center or home of a remote family member through the Internet.

As shown in Figure 5, the monitoring software in the remote monitoring server is built on Net Beans IDE 7.0.1 with Java. A Matlab control interface connects the Java program with Matlab. Furthermore, to detect abnormal activities based on SVDD, we import dd_tools [18,19] into Matlab as a module to provide tools, classifiers and evaluation functions for one-class classification. Finally, the position, activity information, and abnormality information are shown on the monitoring interface.

5.2. **Evaluation of the method.** To detect these abnormal activities, first we train classifiers in SVDD based on historical living data. Two people participated in our evaluation. The detected data is the training data in the proposed method, as shown in Figure 6. We selected the following features: Time of Sleep (ToS), Time of Getup (ToG), Number of Times to Bathroom during sleeping (ToT), Duration at Bathroom (DiT), Number of Times of Movement in bed during sleeping (ToM), Total Static Time (TST) during sleeping, and Maximum Duration of Static (MDS).

Specifically, ToM is the number of times that the person turns over during sleeping. TST is the total time of the user remaining static during the sleep, and MDS is the maximum duration between two nearby movements.

For convenient computing, we use decimal numbers to represent the features of ToS and ToG time, e.g., 13:30 is represented as 1.5. Meanwhile, the measurement unit for DiT is minutes, and the measurement units of TST and MDS are hours. For ToT and ToM the measurement units are number of times. Figure 6 shows the training data from the two people. After each daily evaluation, they provided feedback about their sleep quality. We

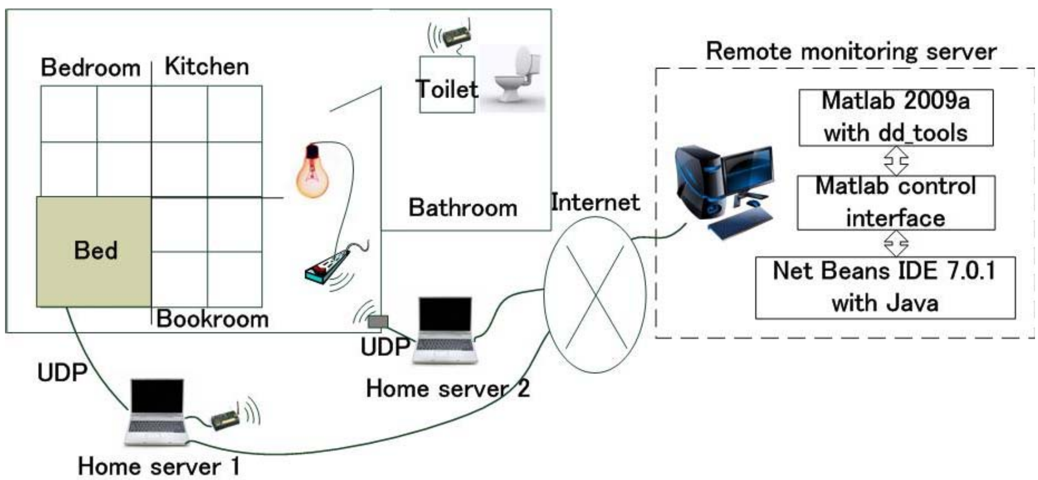
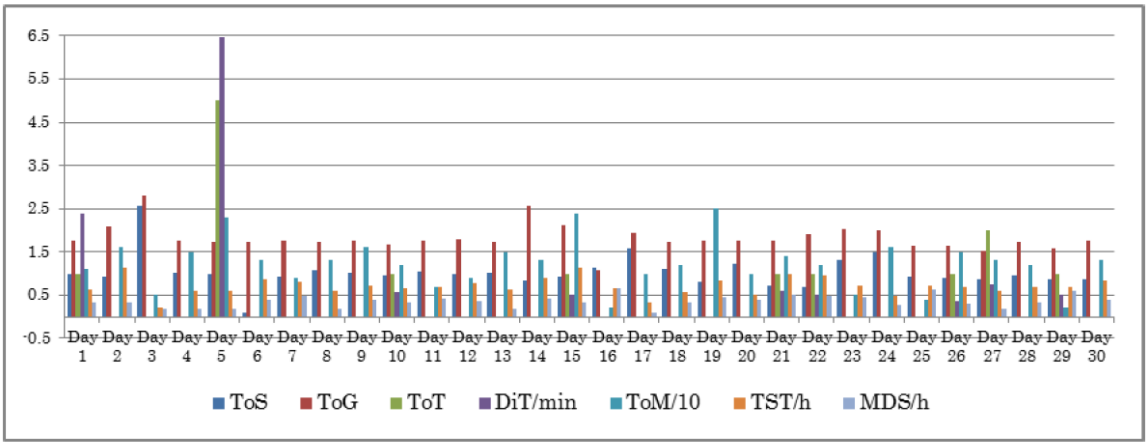
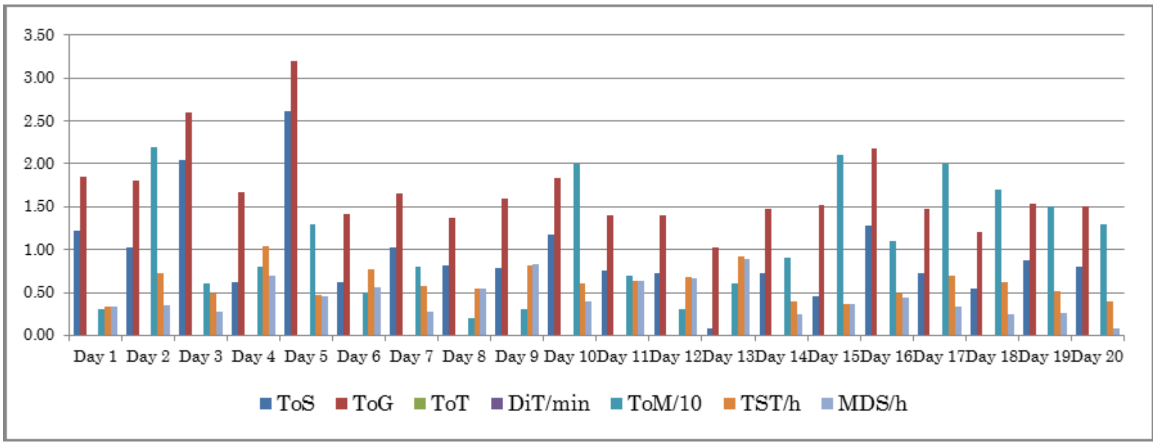


FIGURE 5. Evaluation environment



(a) Training dataset from the first person



(b) Training dataset from the second person

FIGURE 6. Training datasets for two participants

evaluated our method based on their feedback. We divided ToM by 10 to conveniently show all the features in one figure.

A. Measures of evaluation

To evaluate the feasibility of the method, we use the standard metrics of Precision (P), Recall (R) and F-measure (F) [20].

$$P = \frac{\text{Number of correct detected targets}}{\text{Number of all detected targets}} \tag{3}$$

$$R = \frac{\text{Number of correct detected targets}}{\text{Number of all example targets in the test dataset}} \tag{4}$$

$$F = \frac{2 \cdot P \cdot R}{P + R} \tag{5}$$

P is the number of correct targets in all detected targets. R is the number of correct targets in all example targets in the test dataset. Generally, we want to ensure that both P and R are as high as possible, as evaluated by F, which increases with the growth of both P and R.

Furthermore, dd_tools has two parameters to optimize the ability of the SVDD classifiers to detect outliers, FRACREJ (from 0 to 1) and SIGMA (an integer larger than 0). FRACREJ represents the fraction of the target set that is rejected as outliers when

TABLE 4. Means μ and deviations σ of normal data of two participants

		ToS	ToG	ToT	DiT	ToM	TST	MDS
First	μ	0.93	1.77	0.35	14.19	12	0.76	0.38
Person	σ	0.22	0.25	0.56	30.22	5.45	0.17	0.13
Second	μ	1.00	1.75	0.00	0.00	9.19	0.62	0.50
Person	σ	0.61	0.53	0.00	0.00	6.59	0.20	0.20

creating the hypersphere. A higher FRACREJ means more target data in the training set is treated as outliers. When FRACREJ is equal to 1, all of the training data is rejected as outliers; otherwise, when it is equal to 0, all of the training data are accepted as target data. SIGMA represents the widths of the Gaussian kernel.

B. Evaluation results

(1) Evaluation 1 (E1): Basic evaluation for feasibility based on cross validation

In evaluation 1 (E1), we evaluated (i) whether the method to create the hypersphere in SVDD effectively detected outliers, and (ii) the influence on the generated classifiers in SVDD by changing parameters FRACREJ and SIGMA.

To achieve this goal, we employed cross validation in the evaluation. We used the data of five days as testing data and the data of the other days as training data for each person. The evaluation was performed six times by dividing all data into six groups of testing data.

Furthermore, in the evaluation, we changed FRACREJ and SIGMA to evaluate the performance of the method. In the evaluation, FRACREJ was changed from 0 to 0.2 by 0.02, as shown in Figure 7(a), and SIGMA was set as a fixed value of 7. In Figure 7(b), SIGMA is changed from 3 to 15 and FRACREJ is set as a fixed value of 0.05. For each FRACREJ and SIGMA, we computed P, R and F six times for six groups of testing data. The averages for P, R and F are shown in Figure 7(a) and Figure 7(b) for increasing FRACREJ and SIGMA, respectively.

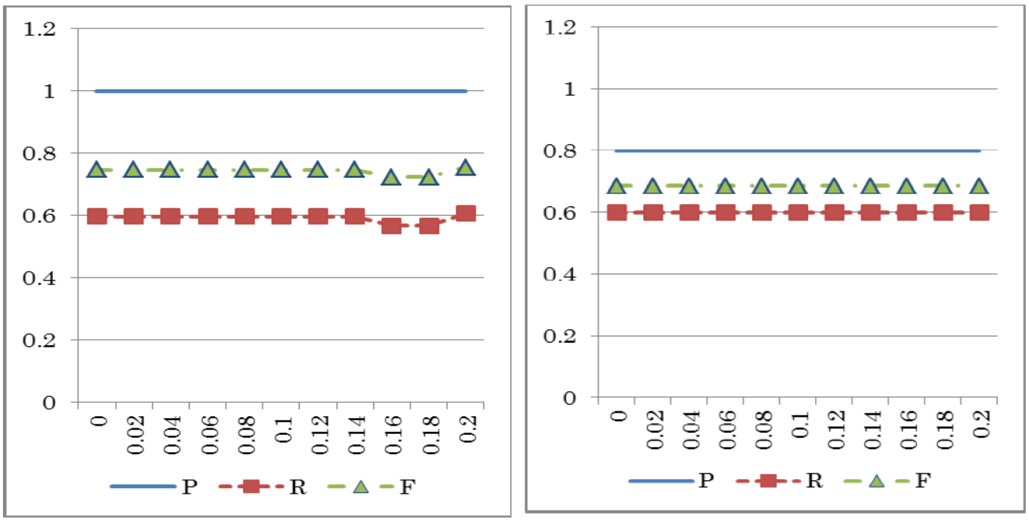
From the result in Figure 7(a) we can see that the precision is acceptable for both people and does not change much with the change of FRACREJ from 0 to 0.2. FRACREJ decides the percentage of the training dataset to be recognized as abnormal data. The larger FRACREJ is, the more accurate the method is. However, the ability of the method may decrease because some normal data cannot be recognized.

Through the evaluation result in Figure 7(b), we can see that the precision becomes a high value by changing SIGMA for both participants. In addition, R rises very clearly with increasing SIGMA. SIGMA adjusts the shape of the classifier to let the classifier better fit the data. R is a higher value with larger SIGMA.

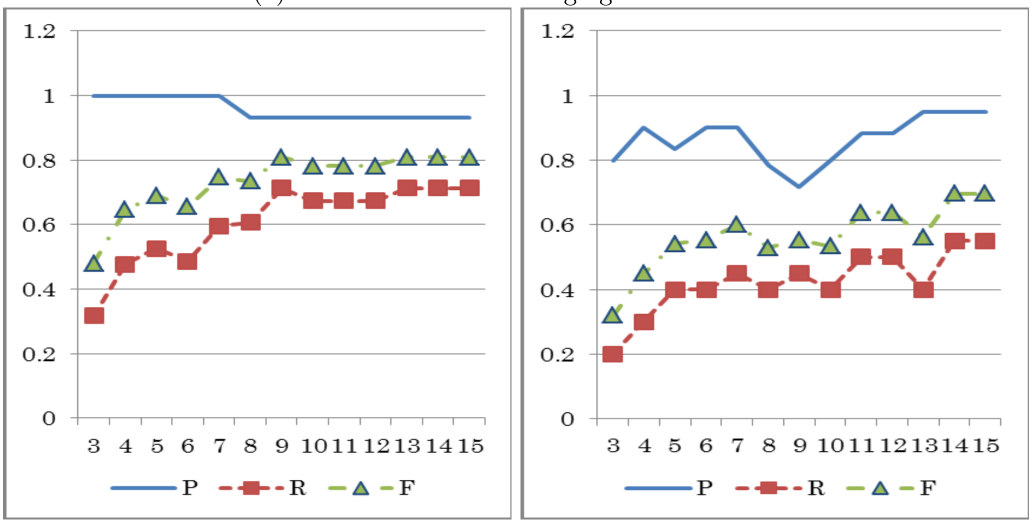
(2) Evaluation 2 (E2): Evaluation of ability of the method to detect abnormal activity at different abnormal levels (simulation approach)

In E1, we presented the basic evaluation for the feasibility of the method. In E2, we evaluate the ability of the method to detect abnormal activities at different abnormal levels.

To achieve this goal, we randomly generated more testing data based on the statistics of the real living data in Figure 6 by using a Gaussian distribution. This kind of method has also been used to simulate living pattern data in related research [11]. Table 4 presents the means μ and deviations σ of normal living data for each feature of the two people. Then, we generated the data of 120 days of normal living as the target data (normal activity) for the testing dataset in E2 based on Table 5, which is described later.



(a) Result in E1 with changing of FRACREJ



(b) Result in E1 with changing of SIGMA

FIGURE 7. Evaluation result of E1 ((a): FRACREJ is changed, (b): SIGMA is changed)

To evaluate the ability of the method for detecting different kinds of abnormal activities, we designed the parameter called *Abnormal Degree (AD)*, which represents how much an abnormal activity deviates from the normal living pattern, as shown in Formula (6).

$$\text{Abnormal Degree} = \frac{|\text{Value}_{\text{abnormal}} - \text{Value}_{\text{normal}}|}{\text{Value}_{\text{normal}}} \tag{6}$$

$\text{Value}_{\text{normal}}$ represents the value of the normal living data and $\text{Value}_{\text{abnormal}}$ represents that for the abnormal living data. We used the data in Figure 6 to represent $\text{Value}_{\text{normal}}$ for each feature.

To evaluate the ability of the method to detect abnormal activities at different levels, we generated some testing data that includes various levels of abnormal activities. We generated the testing data by considering different abnormal levels, which are 0-0.5, 0.5-1, 1-1.5, 1.5-2, 2-3, 3-4 and 4-5, as shown in Table 5, based on the Gaussian distribution.

Using the definition of abnormal degrees, we enlarged the testing data with different abnormal degrees, e.g., 0-0.5, 0.5-1, etc. For each row in Table 5, we show the values of

Table 5. Abnormal activities with different abnormal degree for the first person

AD \ Features	ToS		ToG		ToT		DiT		ToM		TST		MDS	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
0-0.5	1.16	0.23	2.21	0.44	0.43	0.09	0.28	0.06	15	3	0.95	0.19	0.48	0.1
0.5-1	1.6		3.05		0.6		0.4		20.7		1.31		0.66	
1-1.5	2.09		3.98		0.79		0.52		27		1.71		0.86	
1.5-2	2.53		4.83		0.95		0.63		32.7		2.07		1.04	
2-3	3.26	0.46	6.19	0.88	1.23	0.18	0.81	0.12	42	6	2.66	0.38	1.33	0.2
3-4	4.19		7.97		1.58		1.04		54		3.42		1.71	
4-5	5.12		9.74		1.92		1.27		66		4.18		2.09	

the features representing an abnormal degree. For each feature in the columns, we show μ and σ, calculated in the following formulas, to generate data.

Specifically, for each feature, e.g., ToS, μ and σ represent the means and deviations in the Gaussian distribution to create the corresponding testing data set. In Table 5, μ is computed by Formula (7), based on the average of two bound values for each row, and σ is computed by Formula (8), which shows the deviation of data for each period of abnormal level for each row.

$$\mu = \frac{|\mathrm{VoF}(\mathrm{AD} = \text{Lower bound}) + \mathrm{VoF}(\mathrm{AD} = \text{Upper bound})|}{2} \tag{7}$$

$$\begin{aligned} \sigma &= |\mathrm{VoF}(\mathrm{AD} = \text{Upper bound}) - \mu| \\ \text{or} \quad \sigma &= |\mathrm{VoF}(\mathrm{AD} = \text{Lower bound}) - \mu| \end{aligned} \tag{8}$$

VoF(AD = Lower bound) and VoF(AD = Upper bound) represent the values of the features when the abnormal degree is set in a lower bound and an upper bound for each row in Table 5.

For the first person, based on the data in Table 5, we generated a testing dataset of 30 days for each period of an abnormal degree. Also, we generated a normal living dataset of 120 days based on Table 4, which shows the average values of the normal living data. For the second person, we generated 150 days of living data with 120 days of normal data and 30 days of abnormal data in a similar way for each period of the abnormal degree.

We performed an evaluation to show the scalability of our method with the generated abnormal data. We set FRACREJ as 0.05 and SIGMA as 7 in the SVDD. For each dataset, we computed P, R and F five times, and the average values for the different kinds of abnormal activities are shown in Figure 8. The left part shows the evaluation result for the first person and the right part is for the second person.

From Figure 8 we can see that, for both people, the precisions increased with the growth of AD. When AD is 0-0.5, the precision is almost 0.8, which means in all detected normal activities, almost 80% are normal activities and almost 20% are abnormal activities. The precision is not so high because the abnormal activities for 0-0.5 are too close to normal activities. For example, for a month, normally the average time of getting up during sleeping is almost 12, as shown in Figure 6. When AD is 0-0.5, the getting up times may be 15, which is very close to 12. We think that this can also be seen as a normal living pattern. Therefore, even though the precision is not so high when AD is 0-0.5, the precision is acceptable, since the abnormal activity is too close to the normal activity. Additionally, through the evaluation we found R is not so high due to using a small amount of data as training data and more data as testing data; that is, one month of real data was used as training data, and 150 days of generated data was used as testing data. R can be increased by increasing the amount of training data.

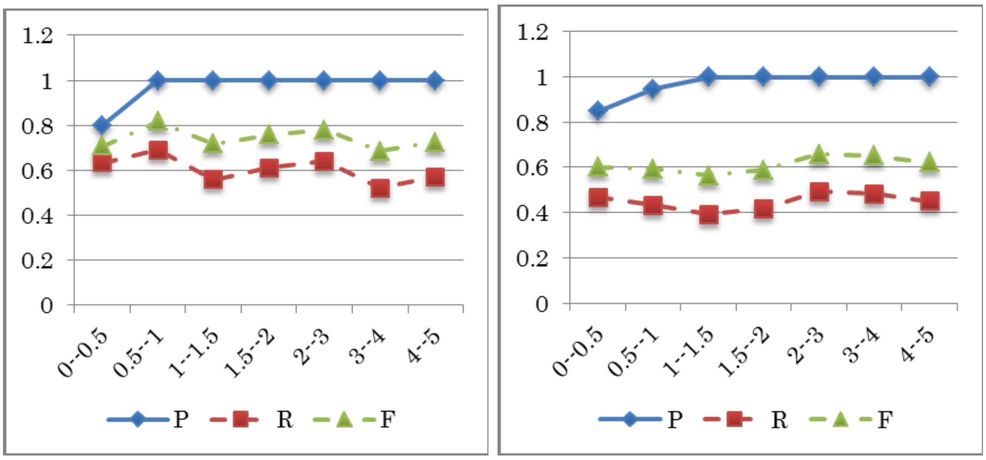


FIGURE 8. Evaluation result in E2 (left: first person, right: second person)

TABLE 6. Five cases for evaluating features of abnormal detection

	ToS	ToG	ToT	DiT	ToM	TST	MDS
V0	∘	∘	∘	∘	∘	∘	∘
V1	×	×	∘	∘	∘	∘	∘
V2	∘	∘	×	×	∘	∘	∘
V3	∘	∘	∘	∘	×	∘	∘
V4	∘	∘	∘	∘	∘	×	×

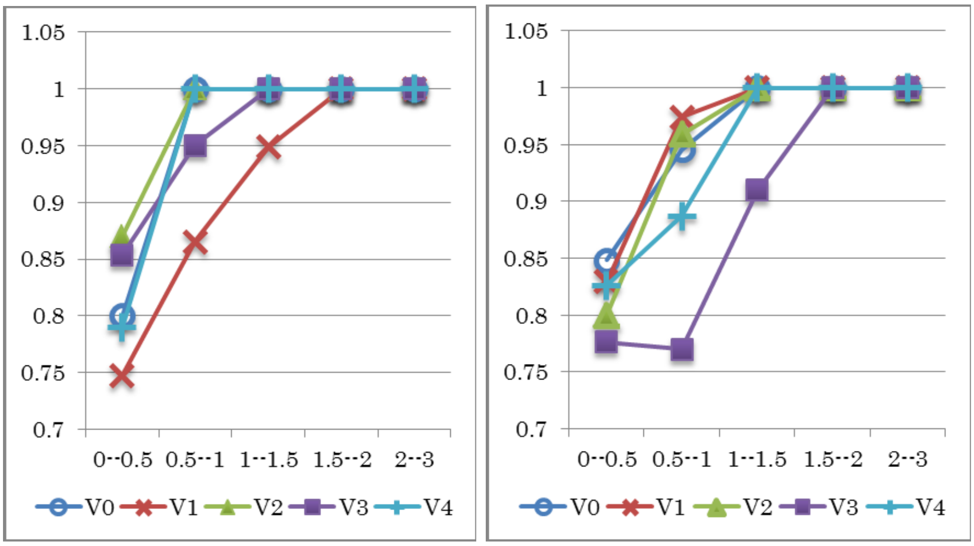


FIGURE 9. Evaluation result of features for abnormal detection (left: first person, right: second person)

Finally, we also evaluated the features for abnormal detection. We considered the following five cases shown in Table 6, where ∘ represents the corresponding features used to detect abnormal activity, and × represents the features not used for abnormal detection.

The evaluation result is shown in Figure 9, where the left part is for the first person and the right part is for the second person. The x-axis is the different abnormal levels, and the y-axis is precision. From the figure we can see that, for the first person in V1, the system cannot realize very high precision. According to this result for person 1, features ToS and ToG play a very important role in abnormal detection. Meanwhile, for person 2, the system shows low precision in V3 when removing the features of ToM. Furthermore, in V4, when removing the TST and MDS features, the system also does not show good precision. However, in our method, when considering all the features together, both systems are very stable for abnormal detection with high precision.

6. **Conclusions and Discussion on Possible Applications.** Elderly care is a particularly important problem in our society and a very widespread research topic. In this paper, we proposed a situation-aware system using SVDD to detect the abnormal activities of elderly people. From the evaluation, we can see that the method works well to detect abnormal activities. For situations having an abnormal degree larger than 0.5, the system shows good precision. The research results are expected to be applied in the future situation awareness applications. The detailed design and implementation of the whole system including sensing parts and recognitions parts is expected to help system engineering develop abnormality-detectable situation awareness system. The detailed analysis of features in the experiment based on real data is expected to support other researchers in the same field.

The proposed method can be possibly applied in the following applications with some extension. The applications have the following features.

(1) The situation around users should be detected and services should be provided timely. The situation can include location and relation information between the user and surrounding objects, gesture information of users, environment information and so on.

(2) Abnormality in situations should be further detected to provide more thoughtful services.

For example, we can provide a situation awareness services to an elderly person who needs medicine support for daily life. The service can be that when the elderly people is standing in front of the medicine box in a specific time, services will be provided to the elderly people to assist him take medicine. We can let user use the system for a period to collect training dataset. Then when the elderly people has some abnormal behaviors, e.g., taking medicine too many times in a day. The abnormality can be quickly detected based on the system, and then more thoughtful situation awareness service will be provided, e.g., a warning service to stop him and a message sent to the care center.

For another example, the system can be used to detect the situation when a user gets outside exercise, and provide services when finding abnormality during exercising, such as taking too long/short time. More specifically, whether and when the elderly people go to outside for exercising can be detected by the proposed u-tiles system. The activities, e.g., running or walking, can be detected by the developed Magic Ring. The abnormality in exercising can be detected by the proposed SVDD based method, by expanding the designed features. In the future, we will further implement and evaluate our system in some other scenarios, e.g., the above examples.

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