一般社団法人　電子情報通信学会
THE INSTITUTE OF ELECTRONICS,
INFORMATION AND COMMUNICATION ENGINEERS

信学技報
IEICE Technical Report
SC2017-8 (2017-06)

屋内環境センシングデータを用いた独居者の生活行動の検知

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Analyzing Indoor Environment Sensing Data for Recognizing ADL of One Person Household

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Abstract　Pervasive sensing technologies are promising for increasing one-person households (OPH), where the sensors monitor and assist the resident to maintain healthy life rhythm. Towards the practical use, the recognition of activities of daily living (ADL) is an important step. Many studies of the ADL recognition have been conducted so far, for real-life and human-centric applications such as eldercare and healthcare. However, most existing methods have limitations in deployment cost, privacy exposure, and inconvenience for residents. To cope with the limitations, this paper presents a new indoor ADL recognition system especially for OPH. To minimize the deployment cost as well as the intrusions to the user and the house, we exploit an IoT-based environment-sensing device, called *Autonomous Sensor Box* (SensorBox). Just placed in the house, SensorBox autonomously measures seven kinds of environment attributes, and uploads them to a cloud server. We apply machine-learning techniques to the collected data, and predicts seven kinds of ADLs. We conduct an experiment within an actual apartment of a single user. The result shows that the proposed system achieves the average accuracy of ADL recognition with more than 90%, by carefully developing the features of environment attributes.

Key words　Environment sensing, Activities of Daily Living, ADLs recognition, Big data, Machine Learning

1. Introduction

The growing number of unmarried people and late marriages in developed countries leads to a social issue of *one-person households* (OPH). In Japan, the number of OPH increasing rapidly. It is estimated that 37.4% of all households will become OPH in 2030 [1]. Not only in Japan, it is a worldwide phenomenon. In China, there are more than 60 million of Chinese people currently living alone. The number of OPH will increase to 162 million in 2050 [2]. In seven states in USA, the percentage of OPH exceeds 30.3% in 2015 [3]. According to [4] [5], people in OPH easily lose healthy life rhythm, since no one else can take care of the living in OPH. Since the loss of healthy life rhythm often leads to health deterioration, it is essential to maintain the life rhythm especially in the context of OPH. In general, a life rhythm is characterised by *activities of daily living* (ADL, for short). Typical ADLs in OPH include cooking, working, eating, taking bath, sleeping, etc. If the cycle of ADLs becomes very different from the one in a healthy life rhythm, the resident is losing his/her life rhythm. To maintain the life rhythm, one has to keep a regular record of ADLs. However, keeping manual recording requires strong mind and patience.

To automate the ADL recording in OPH, pervasive sensing technologies combined with machine learning are quite promising, because they can *recognize* ADLs from automatically measured data. There have been many studies for ADL recognition. Some approaches (e.g., [6] [7]) try to directly capture the living using camera, or microphone. However, such systems are too intrusive of the user in the sense that the daily living is exposed as it is. There are many studies using wearable sensors, and/or indoor positioning systems to recognize ADLs (e.g., [8] [9]). However, the wearable sensor is intrusive to a human body, as the user always has to wear the sensor device at home. Indeed, the home is a place where the user is free from tedious things. The indoor positioning is intrusive to a house, in the sense that sensors and beacons must be installed into the house and objects. This usually causes expensive cost for deployment and maintenance.

To overcome the limitations, we propose a new system that recognizes ADLs of OPH based on non-intrusive environmental sensing with machine learning. In the proposed system, we exploit an IoT-based environment-sensing device, called *autonomous sensor box* (we simply call SensorBox, hereinafter). SensorBox has been developed in our previous work [10], and is designed to minimize the effort of deployment and operation. Once a power cable is connected, SensorBox autonomously measures seven types of environment attributes (temperature, humidity, light, sound, vibration, gas pressure, and motion) around the box, and then periodically uploads the data to a cloud server. Thus, all the operations for deployment and maintenance are performed without human intervention, or expensive infrastructure.

As SensorBox is measuring the environment in OPH, the proposed system also requires the *initial training*, where the resident manually records ADLs using a designated lifelog tool. The initial training is supposed to be performed in several days, to associate labels of ADLs with the sensor data. In the proposed system, we define seven basic ADL (cooking, working, cleaning, taking bath, sleeping, eating, going out), which are the most typical ADLs for maintaining the life rhythm. For the labelled dataset, we apply supervised learning algorithms to construct a model of ADL recognition for the house. For this, we perform careful *feature engineering* to determine essential predictors that well explain ADLs in OPH. Furthermore, we try several different classification algorithms to compare the performance.

To evaluate the proposed system, we have deployed one SensorBox in an actual apartment of a single person, and conducted an experiment for ten days. Experimental results show that the average accuracy of all the seven ADLs was around 90% with Decision Forest supervised learning. The accuracy of some specific ADLs achieved over 97%. From this result, we confirmed that the proposed system achieves non-intrusive and practical ADL recognition in OPH, using just a single SensorBox.

2. Related Work

The ADL recognition is not a brand-new research topic. Since the need of ADL recognition is great, researchers have been studying and developing a number of methodologies to tackle this problem. The approaches to the ADL recognition can be divided roughly into two categories, depending on the type of contextual information analysed. The first category uses multimedia data taken by video cameras or microphone recordings, to capture the daily living directly. The second category uses time-series data measured by various sensors, including accelerometer, gyroscope, RFID, and power-meters sensors.

Multimedia data: Brdiczka et al. [11] proposed a smart home that takes videos of residents, and processes the video to recognize activities. Although general people have been resisted to the at-home video monitoring [12], the acceptance of this technology in the home is increasing. On the other hand, processing the video is computationally expensive. It relies upon the first tracking of the resident before the correct video data can be captured and analysed.

Sensor data: Since taking video and audio exposes too much information of daily living, it is considered to be intrusive to the life. Therefore, it is more appreciated to use passive information. Hence, most of the current research in ADLs recognition use sensor data. Researchers have found that combining different types of sensor is effective for classifying different types of activities.

Kusano et al. [8] proposed a system that derives life rhythm from tracking elderly movement by using RFID positioning technology. They install many RFID readers on the floor of a house, and ask participants to wear slippers with RFID tags. The readers capture indoor location of resident. The system reasons the life rhythm of the user from the time-series location data. However, it is difficult to determine the exact activity using the movement history. As a result, the accuracy of ADLs recognition is low.

Munguia-Tapia et al. [13] focused on interactions of a resident with an object of interest such as a door, a window, a refrigerator, a key, and a medicine container. Munguia-Tapia et al. installed state-change sensors on daily items to collect the interaction data. Philipose et al. [14] attached an RFID tag on every item, and asked a participant to wear gloves with an RFID tag reader. When the participant is close to the item, the interaction is recorded.

Pei et al. [9] combined a positioning system and motion sensors of a smartphone to recognize human movements in natural environments. However, when turning on the motion-sensors, Wi-Fi and GPS simultaneously, the battery drain is very high. Another problem is that a user may not want to carry smartphone all time at home, which is the limitation of collecting data.

3. Challenges and Research Goal

The ADL recognition has been widely studied for a few years. By keeping track of ADLs, a smart pervasive system can provide reminders for residents, as well as react to hazardous situations [15]. Most of these studies apply to elderly people, cancer patients, and ordinary families. However, there are not so many studies for One-Person-Household

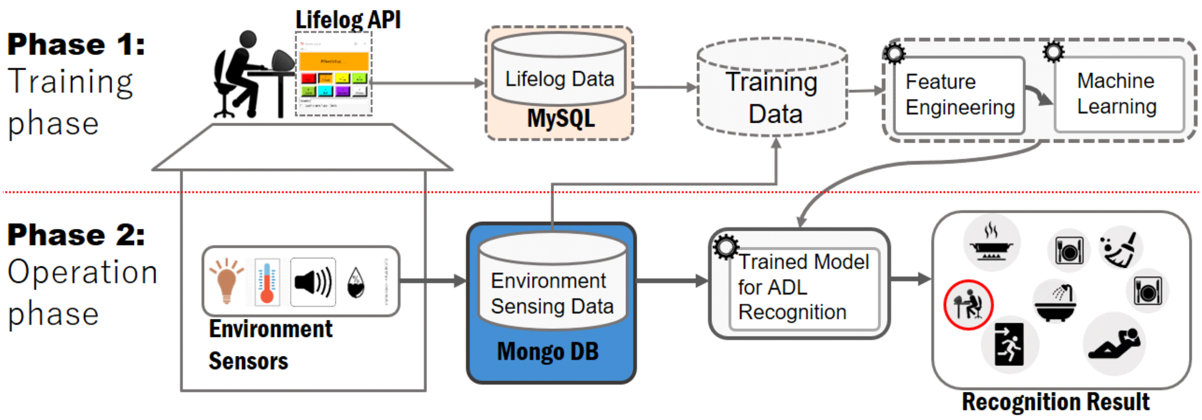

図 1　Proposed System Architecture

(OPH). The unique characteristics of OPH are: the resident is living alone, and is often busy to do everything by oneself. He/she does not want to change the own way of living, or pay for expensive systems just for monitoring ADLs.

As mentioned in Section 2, there are many existing systems that use wearable sensors, object-embedded sensors, or indoor positioning systems. However, we consider it difficult for people in OPH to accept these technologies, because they are too exaggerated and intrusive for their life. We can easily imagine that most residents will forget or give up wearing the sensor, since the home is the place where the resident make oneself comfortable. Although labs or companies can manage the large-scale equipment, it is still too expensive to deploy in OPH.

Our research goal is to minimize such limitations of the conventional approaches, and to achieve high-quality ADL recognition of OPH.

4. System Architecture

In order to achieve the research goal, we propose a new ADL recognition system for OPH. To minimize the intrusions and the cost, the proposed system just relies on the environmental sensing by the autonomous sensor box (SensorBox) [10]. Figure 1 shows the architecture of the proposed system. Using the Figure 1, we explain the proposed system from left to right.

First, we set up the system within a target OPH. We deploy a single (or multiple if necessary) SensorBox in a position where ADLs are well observed as environment measures. We also install a software, called LifeLogger, on user's PC or smartphone. To apply supervised machine-learning algorithms, the proposed system requires training data at the initial phase of operation. For this, LifeLogger is used to attach correct labels of ADLs (as lifelog) to the environment sensing data.

Then, the system begins to collect time-series data. SensorBox uploads the measured data to MongoDB in a cloud server, whereas LifeLogger inserts the lifelog into MySQL in the cloud data.

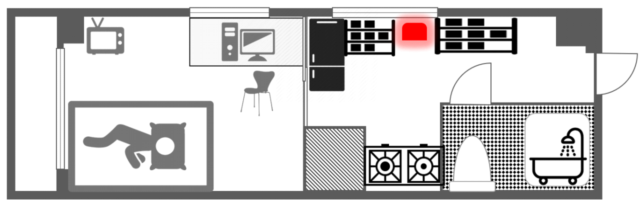

図 2　Apartment of Testbed, position of SensorBox

Finally, the system joins the two time-series data with the timestamp to form the training data. We apply machine learning to the training data to construct a prediction model of ADL recognition.

We explain details of the processes in the following subsections.

4.1 Deploying SensorBox in OPH

In this paper, we deployed the proposed system in an actual apartment of a single resident. As shown in Figure 2, the apartment is an ordinary apartment in Japan, consisting of a bed/living room, a bathroom and a kitchen. We have placed one single SensorBox in the kitchen room, so that SensorBox can observe ADLs of the resident well. The position of SensorBox is shown in a red rectangle in Figure 2.

SensorBox is an IoT device with multiple environment sensors, developed by our research group [10]. It can measure seven environmental attributes around the box, which are temperature, humidity, lighting intensity, atmosphere pressure, sound volume, human motion and vibration.

4.2 Collection Data

Once the power is connected, the SensorBox autonomously boots and connects to the network. Then, it starts to measure the environmental data, and uploads the data to a cloud server. Figure 3 shows the physical form of SensorBox. By default, SensorBox samples environmental data every ten seconds. Every time of measurement, SensorBox represents the measured data in a JSON formal text, and then uploads to the Mongo Database in the cloud server.

During initial several days, the resident needs to input correct labels of ADLs, so that the system can learn the ADLs from the environment sensing data. For this, we ask the resident to use LifeLogger. Figure 4 shows the user interface of LifeLogger. As shown in the Figure 4, LifeLogger has eight buttons, each of which corresponds to an ADL. When the resident starts an ADL, he/she just presses the corresponding button to record the current ADL. Based on relevant studies [5] Fiore2008, we have chosen eight types of typical ADLs (sleep, eat, cook, working at PC, clean, bath, absence and other), and registered them in LifeLogger. When the resident presses a button, the system records the label, and stores it in MySQL in a cloud server.

Finally, the two time-series data collected by SensorBox and LifeLogger are joined using the timestamp, which forms the training data. The data collection has been performed for consecutive ten days within the apartment. The data labelled as 'other' was beyond the scope of the ADL recognition. After filtering such data, we have obtained the total 45,693 rows of labelled sensor data.

4.3 Applying Machine Learning

In this study, we apply supervised learning to the labelled dataset to recognize indoor ADLs of OPH. This process consists of the following two steps.

Feature Engineering: For accurate ADL recognition, it is essential to identify what environmental values in the sensing data well predict the ADL. In this step, we develop such feature values from the training data. First, from the seven environmental attributes of SensorBox, we only choose temperature, humidity, light, sound volume, and motion, since the rest attributes (vibration and atmosphere pressure) seem irrelevant to the target ADLs (i.e., sleep, eat, cook, working at PC, clean, bath, absence and other).

Second, we determine the size of *time-window*. To enhance the features of the time-series data, we aggregate the raw data within the same time-window into one data. For this, the window size affects the accuracy. If the size is too large, the window is likely to contain different activities. If too small, the window will not contain sufficient data to reason and predict an ADL. Hence, we test four variations of 30 seconds, 1, 2 and 4 minutes.

図 3　Prototype of SensorBox

図 4　Screenshot of Lifelogger Tool

Finally, for each of the five environment attributes chosen, we determine an aggregation function. An aggregation function aggregates all the data within the same time-window. Typical aggregation functions include SUM, MAX, MIN, AVG, STDEV, and so on. Based on the nature of each environment attribute, we carefully choose an appropriate function.

Construction of Recognition Model: For the developed features of the training data, we apply machine-learning algorithms, in order to construct a predict model for ADL recognition. We use popular classification algorithms, including Logistic Regression, Decision Forest, and Neural Network. By using these algorithms, we have constructed prediction models that classifies given environment sensor data into one of the seven ADLs.

5. Experimental Results

In this section, we will show the accuracy of ADL recognizing with defining different size of time windows and applying different machine learning algorithms. All of results are based on data that be collected from an actual apartment of a single resident. And we will also show the detail accuracy of each ADL recognition on condition that time-window is 1 minute and algorithm is Decision Forest.

Table 1 shows the average accuracy of all ADL recognition by different size of fixed-time widow and different machine

表 1 Average accuracies of all ADLs of each dataset and algorithm

Alogrithm	30 sec	1 min	2 min	4 min
Logistic Regression	81.60%	86.42%	84.33%	86.04%
Decision Forest	84.66%	90.36%	90.00%	88.25%
Neural Network	84.33%	86.12%	86.72%	87.15%

learning algorithms. Accuracy measures the goodness of a classification model as the proportion of true results to total cases. Average accuracy is the average of each accuracy per class (sum of accuracy for each class predicted/number of class). We can see the average accuracy of all ADLs achieve more than 81.6%. In addition, on condition that size of time window be set on 1 minute and applying Decision forest algorithm to analysis, the average accuracy of all ADLs recognition achieves the highest accuracy 90.36%.

Figure 5 make Table 1 visible. Average accuracy of each algorithm be draw on different colour. Each line shows result that change of average accuracy by change the size of time window. We can see that average accuracy reached the highest value as time window be set on 1 minute except neural network. The result verifies the content mentioned at subsection 4.2 that the size of time window should not be too large or too small.

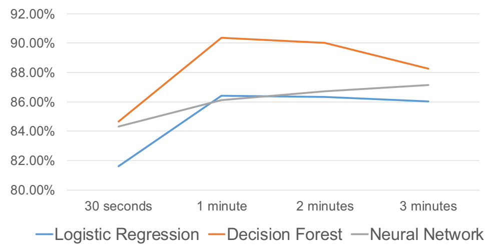

図 5 Polygonal Line Graph of Table 1.

Figure 6 shows the detail accuracy of each ADLs recognition on the condition that size of time window is 1 minute, algorithm is Logistic Regression and aggregation function are MIN(light), AVE(motion), STD(temperature), AVE(humidity), MAX(sound). We can clearly find accuracy of sleep recognition is relatively high and absence's accuracy is relatively low. As the proportion of the two ADLs of datasets are also particularly high, we should verify whether the average accuracy of all ADLs is affected by the two ADLs sleep and absence. We reanalysed the data, after filtered out the datasets labelled with the 2 types of ADLs. The results are shown in Figure 7. The results of reanalysed shows that the accuracy of other ADLs recognition and average of all ADLs recognition slightly cut down.

Through the results of experiment, we got the conclusion

Actual Activity \ Predicted Activity	Cook	PCwork	Clean	Bath	Sleep	Eat	Absence
Cook	67.2%	4.9%	26.2%			1.6%	
PCwork		68.3%	2.9%		28.8%		
Clean	11.0%	8.5%	74.4%		2.4%	3.7%	
Bath		58.3%	12.5%		20.8%		8.3%
Sleep		0.3%			99.2%		0.5%
Eat	1.0%	59.4%	6.3%		25.0%	8.3%	
Absence		9.2%	0.2%		87.5%		3.1%

Average Accuracy : 86.42%

図 6 Confusion Matrix of 1 minutes & Logistic Regression

Actual Activity \ Predicted Activity	Cook	PCwork	Clean	Bath	Eat
Cook	80.3%	2.8%	15.5%		1.4%
PCwork		97.2%	2.8%		
Clean	28.9%	19.8%	49.6%		1.7%
Bath		87.5%	12.5%		
Eat	6.0%	71.7%	4.2%		18.1%

Average Accuracy : 81.83%

図 7 Filtered sleep and absence

that by analysing indoor environment sensing data can predict the ADLs of One-person household with relatively accuracy of ADLs recognition.

6. Conclusion

In this paper, we have proposed a new system that automatically recognizes activities of daily living (ADL) in one-person household (OPH). Considering the characteristics of OPH, the proposed system exploits only environmental sensing by SensorBox. This minimizes the cost of deployment, as well as the intrusion to the resident and the house. To evaluate the proposed system, we deployed the system in an actual apartment of a single resident, and collected sensor data and lifelog (as correct labels) for ten days. Through supervised machine learning with careful feature engineering, we were able to construct practically feasible models of seven types of ADLs. The average accuracy of all ADLs achieved more than 90%. For sleeping recognition, the accuracy of recognition achieved more than 97%.

As for the future work, we evaluate the proposed system in multiple houses to see how the learning processes varies from one house to another. Moreover, we want to validate if the proposed eight types of ADLs are enough to capture the life rhythms in OPH. Finally, developing services that actually assist healthy life rhythm using the recognized ADLs is our long-term goal.

謝辞 This research was partially supported by the Japan Ministry of Education, Science, Sports, and Culture [Grant-in-Aid for Scientific Research (B) (No.16H02908, No.15H02701), Challenging Exploratory Research (15K12020)], and Tateishi Science and Technology Foundation (C) (No.2177004).

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