Recognizing ADLs of One Person Household based on Non-intrusive Environmental Sensing

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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 user and house, we exploit an IoT-based environment-sensing device, called *Autonomous Sensor Box* (SensorBox) which can autonomously measure 7 kinds of environment attributes. We apply machine-learning techniques to the collected data, and predicts 7 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 88%, by carefully developing the features of environment attributes.**

***Index Terms*—Non-intrusive environment sensing, Activities of Daily Living, ADLs recognition,Feature Engineering, Machine Learning.**

I. 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% households will become OPH in 2030. [1] In seven states of USA, the percentage of OPH exceeds 30.3% in 2015 [2]. In China, there are more than 60 million of people currently living alone. The number of OPH will increase to 162 million in 2050 [3]. According to [4] [5], people in OPH easily lost control healthy life rhythm, since on 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 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 labeled 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

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conducted an experiment for ten days. Experimental results show that the average accuracy of all the seven ADLs was around 87% with Decision Forest supervised learning. The accuracy of some specific ADLs achieved over 90%. From this result, we confirmed that the proposed system achieves non-intrusive and practical ADL recognition in OPH, using SensorBox.

II. Preliminary

A. Activities of Daily Living (ADL)

ADL is a professional word originally used at hospital. It is the minimum action required for daily life such as sleeping, meal, toilet and bathing, etc. It be used as an indicator of the aging and degree of disability. The discovery and recognition of ADL is an essential function of the system that provides necessary assistant to the residents of OPH. Based on the results of this process, the intelligent system can decide which action to take in order to support the residents' well-being and understand residents' life rhythm based on the regular record of ADLs.

B. ADLs Recognition

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.

C. SensorBox

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. It was designed to minimize the cost-intensive infrastructure and configuration labour. Once connected to power and network, SensorBox autonomously measures environment attribute around the box and uploads detected data to cloud server.

D. 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 (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.

III. Outline of Proposed System

In order to achieve the research goal, we propose a new ADL recognition system for OPH. To minimize the intrusions

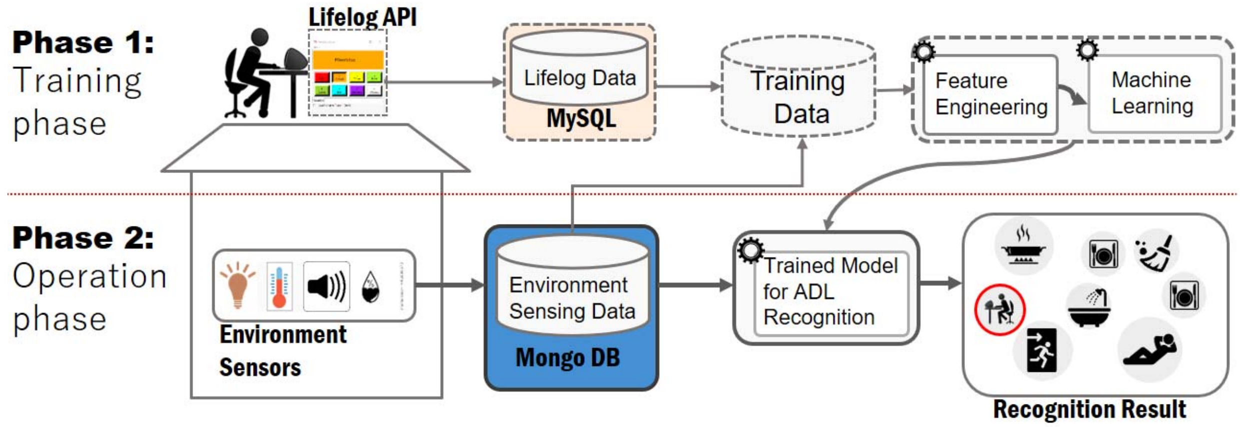

Fig. 1: Proposed System Architecture

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, 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.

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.

IV. Data Collection

A. Environment Sensing

To be able to detect ADL by analyzing non-intrusive environment attributes, the target attributes must be sensitive to the changing of resident's ADL. Considering that the range of sensible is only around the SensorBox, the box should be put on where resident's ADL is frequently conducted. However, the layout of each house and living stay of each single are different things from OPH to OPH. Hence the most suitable position of SensorBox is also different from OPH to OPH.

SensorBox measures seven environment attribute, which are temperature, humidity, lighting intensity, atmosphere pressure, sound volume, human motion and vibration, in every 10 seconds. Figure 3 shows the screenshot of the raw sensros data that be modified to JSON formal text. And figure 2 shows the screenshot of an application, which visualizes collected raw sensors data on cloud service. The first graph of Figure 2 shows the changing of brightness with time. And we can easily find that those changing is man-made.

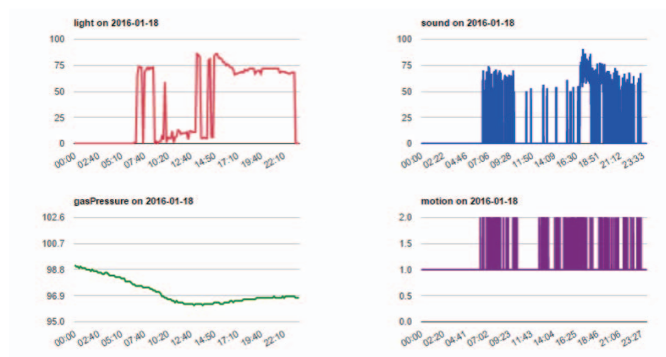

Fig. 2: Screenshot of SensorBoxLogService

"sbox-phidget-406364":{"info":{"boxid":"sbox-phidget-406364",
"date":"2016-02-10","location":"CT002/H00001/R003/shoebox",
"owner":"yasuda.kiyoshi","time":"2016-02-10T21:06:42 09:00",
"timeOfDay":"21:06:42"}, "data":{"motion":"false","light":"0","humidity":
"49.38199999999999","sound":"0.0","gasPressure":"99.7824347826087",
"temperature":"10.222620000000006","vibration":"500.0","presence":"0"}}

Fig. 3: Raw Sensors Data

B. Activity Labeling

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, 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] [6], 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.

Fig. 4: Screenshot of Lifelogger Tool

C. Integrate Environment Sensing and Activity Labeling Data

For supervised learning, the system needs to training data which have the correspondence between the ADLs and data in advance. In order to establish training data, we integrate the two time-series data collected by SensorBox and LifeLogger by joining based on timestamp. Since data labelled as 'other' was beyond the scope of the ADL recognition, those noise data must be filtered. Table I shows the training data.

V. Establish Machine Learning Recognition Model

A. Analysis Activity-sensitive Environment Sensing Sensors

For accurate ADL recognition, it is essential to identify what environmental values in the sensing data well predict the ADL. 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). For example, from the four graphs of Figure 2 shows the changing of four environment attributes in one day, we can see only the graph of gasPressure is a smooth curve. According to this figure we make judgments that the gasPressure is almost not affected by the resident's ADL.

B. Feature Engineering

Feature value is data that is effective to identify the ADLs. In our study, we get the feature value from training data, as the following process.

First, 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 3 variations of 1, 2 and 3 minutes. In order to facilitate the discussion in Section VI, we use symbols ('A', 'B', 'C') to present different datasets with different size of time window. The detail is **A:** 1minute, **B:** 2 minutes and **C:** 3 minutes.

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 MAX, MIN, AVG, STDEV, and so on. Based on the nature of each environment attribute, we carefully choose an appropriate function. We need to apply different aggregation function to each environment attribute. By analyzing all the test, we will find the optimal combination of aggregation function from test. However, if we want to test all situations, we need to conduct hundreds rounds of test, which will take a lot of time. To effectively tests all cases of function combination, we used a tool called PICT [16]. PICT generates a compact set of parameter value choice that represent the test cases you should use to get comprehensive combinatorial coverage of your parameters. Table II shows the 9 cases of combination generated by PICT.

C. Establish 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. .

VI. Evaluate of Experiment

A. Experiment Setup

We deployed the proposed system in an actual apartment of a single resident. As shown in Figure 5, 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 5. Total 45,693 rows of labeled sensor data, which do not include data labeled with 'other', be collected during 10 days within the apartment.

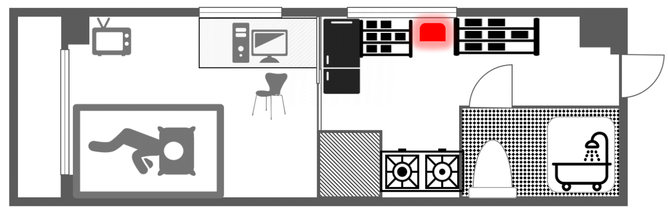

Fig. 5: Apartment of Testbed, position of SensorBox

TABLE I: Training Data

DateTime	vibration	light	motion	gaspressure	temperature	humidity	sound	activityID
2017/2/19 3:33:02	495	1	0	98.8	13.33	35.84	50.15	5
2017/2/19 3:33:12	494	1	0	98.8	13.33	36.04	0	5
2017/2/19 3:33:22	494	1	0	98.8	13.33	36.04	51.62	5
2017/2/19 3:33:32	494	1	0	98.8	13.33	36.04	0	5

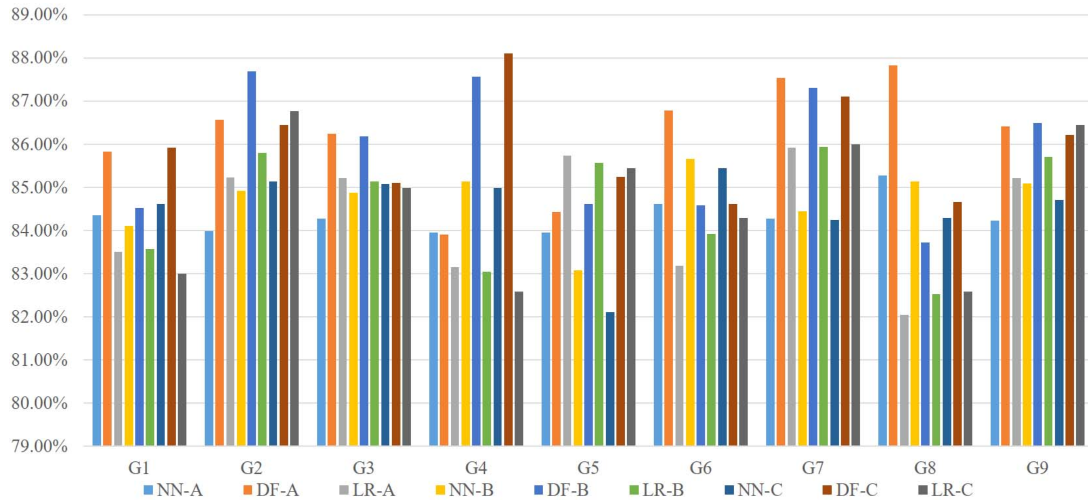

Fig. 6: Detailed Results of All AF Groups

TABLE II: 9 Groups of Aggregation Funcations

Groups	light	motion	temperature	humidity	Sound
G1	MIN	MAX	AVE	AVE	MAX
G2	MAX	MAX	STD	STD	STD
G3	AVE	AVE	STD	STD	MAX
G4	MAX	AVE	AVE	AVE	MAX
G5	MIN	AVE	AVE	STD	AVE
G6	AVE	AVE	AVE	AVE	STD
G7	MAX	MAX	STD	AVE	AVE
G8	AVE	MAX	AVE	AVE	AVE
G9	MIN	AVE	STD	STD	STD

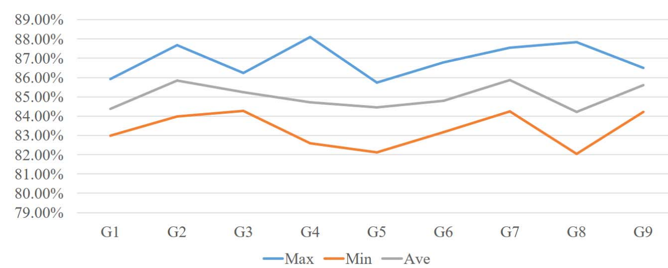

Fig. 7: MAX, MIN and AVE of Each Group AF

B. Result

Figure 6 shows the detailed average accuracy of each dataset. 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).

In order to observe the performance of each case of aggregation function, we calculated all the results of each case of aggregation function. Figure 7 shows the result of calculate by MAX, AVE and MIN of all datasets' average accuracy on 9 cases of combination.

Figure 8 shows the average accuracy of all cases with different size of time window. And Figure 9 shows the changing of accuracy of all cases with 3 classification algorithms.

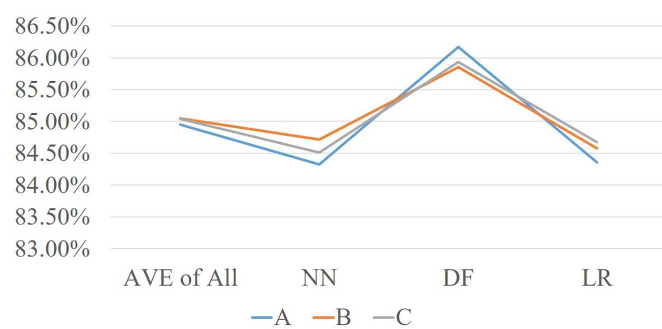

Fig. 8: Accuracy Change with Size of Times Windows

C. Discussion

From Figure 7, we can find that cases of G2 and G7 have better performance on AVE, MAX and MIN. In contrast, G1, G8 have worse performance on the three count calculates. And G7 is the best performance dataset group on AVE, but the G8 is the worst.

However, some dataset of G8 has much better performance on accuracy of some ADLs than some dataset of G7. Table III shows 2 datasets' detailed accuracy of 3 ADLs, which are clean, sleep and absence: first dataset is generated by using

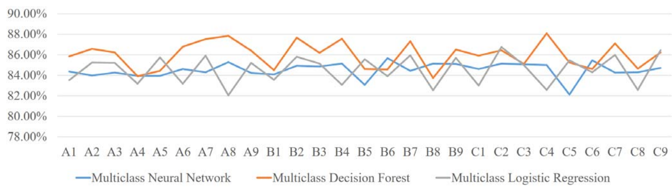

Fig. 9: Accuracy Changes on Each Algorythms

aggregation function is G7, the next is generated by using G8. And both of them is generated on the condition that size of time window is 1 minute and applied algorithms is Decision Forest. The first case have a higher prediction accuracy for sleeping, but for cleaning and absence was significantly worse than the second dataset. So we can see that each ADLs' feature value is different. We need to apply different aggregation function for different ADL recognition.

TABLE III: Compare to 2 Dataset's Accuracy of Special ADL

Dataset	Accuracy-3	Accuracy-5	Accuracy-7
G7-DF-A	39.4%	95.5%	21.2%
G8-DF-A	62.6%	72.7%	62.4%

From Figure 8 we can see the average accuracy of all datasets with different size of time windows are very close. However, 3 dataset group by different algorithms have 3 different optimal size of time window. The cause of this phenomenon may be due to the change in the size of time window is not big enough.

From Figure 9, we can easily find that the 3 algorithms' performance are not very stable with different time window's size and aggregation function. And we can see that Decision Forest's overall performance on AVE, MAX and MIN of all cases of dataset is better than others.

VII. Conclution

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 10 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 88%. For sleeping recognition, the accuracy of recognition achieved more than 90%.

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.

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