International Journal of Software Innovation
Volume 6 • Issue 4 • October-December 2018

Using Non-Intrusive Environmental Sensing for ADLS Recognition in One-Person Household

Long Niu, Graduate School of System Informatics, Kobe University, Kobe, Japan

Sachio Saiki, Graduate School of System Informatics, Kobe University, Kobe, Japan

Masahide Nakamura, Graduate School of System Informatics, Kobe University, Kobe, Japan & RIKEN AIP, Tokyo, Japan

ABSTRACT

This article describes how pervasive sensing technologies are promising for increasing one-person household (OPH), where a system monitors and assists a resident to maintain healthy life rhythm. Automatic recognition of activities of daily living (ADLS) has been a hot research topic in pervasive computing. However, most existing methods have limitations in development cost, privacy exposure, and inconvenience for residents. To cope with the limitations, this article presents a new ADL recognition system especially for OPH. To minimize the development cost as well as intrusions to user and house, the system exploits an IoT-based environment sensing device, called autonomous sensor box (sensorbox) which can autonomously measure 7 kinds of environment attributes. The system then applies machine-learning techniques to predict 7 kinds of ADLS. Finally, this article conducts an experiment within an actual apartment of a single user. The result shows that the proposed system achieves the average accuracy of ADLS recognition with about 88%, by carefully developing the features of environment attributes.

KEYWORDS

Activities of Daily Living, ADLS Recognition, Feature Engineering, Machine Learning, Non-Intrusive Environment Sensing, One-Person Household

INTRODUCTION

The growing number of unmarried people and late marriages in developed countries leads to a social issue of one-person household (OPH). In Japan, the number of OPH increasing rapidly. It is estimated that 37.4% households will become OPH in 2030 (Ministry of Health, Labour and Welfare, 2010). In seven states of USA, the percentage of OPH exceeds 30.3% in 2015 (Statista, 2017). In China, there are more than 60 million people currently living alone (Yeung & Cheung, 2015). According to Asaoka, Fukuda & Yamazaki (2004) and Fujino et al. (2006), people in OPH easily lose control 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 characterized by activities of daily living (ADLs, for short). Typical ADLs in OPH include eating, taking bath, sleeping, etc. If the cycle of ADLs

DOI: 10.4018/IJSI.2018100102

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., Fiore, Bodor, Drenner, Somasundaram & Papanikolopoulos, 2008; Ouchi & Doi, 2013) 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 system to recognize ADLs (e.g., Kusano, Muro, Hayashi, Harada & Shimakawa, 2011; Pei et al., 2013). However, the wearable sensor is intrusive to 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 (Sakakibara, Saiki, Nakamura & Matsumoto, 2016), 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 ADLs (cooking, working, cleaning, taking bath, sleeping, eating, absence), 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 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.

PRELIMINARY

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, taking bath, etc. it is 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.

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 analyzed. 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, Reignier & Crowley (2007) 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 (Hensel, Demiris & Courtney, 2006), 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 analyzed.

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. (2011) 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.

Tapia, Intille & Larson (2004) 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. They installed state-change sensors on daily items to collect the interaction data.

Philipose et al. (2004) 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. (2013) combined a positioning system and motion sensor of a smartphone to recognize human movements in natural environments. However, when turning on the motion-sensor, 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.

SensorBox

SensorBox is an IoT device with multiple environment sensors, developed by our research group (Sakakibara et al., 2016). 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 labor. Once connected to power and network, SensorBox autonomously measures environment attribute around the box and uploads detected data to cloud server.

Challenges and Research Goal

The ADL recognition has been widely studied for few years. By keeping track of ADLs, a smart pervasive system can provide reminders for residents, as well as react to hazardous situations (Wren & Tapia, 2006). 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 system 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 different 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.

OUTLINE OF PROPOSED SYSTEM

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) (Sakakibara et al., 2016). 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. 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.

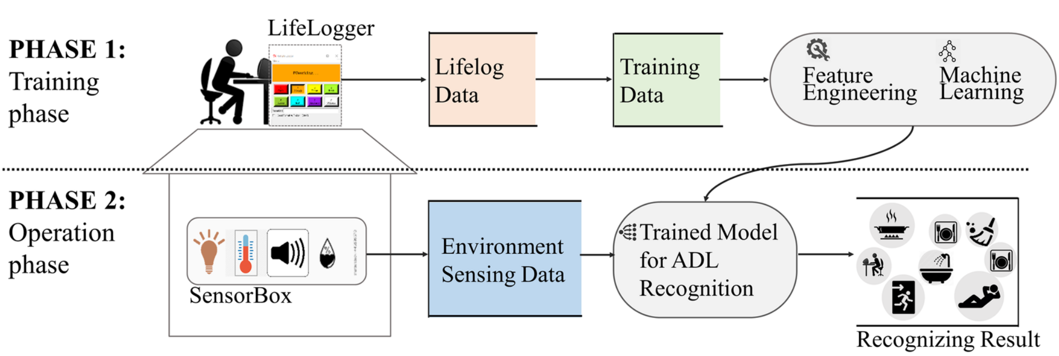
Finally, the system joins the two time-series data with the timestamp to form the training data. We apply machine learning to the training data to construct a prediction model of ADL recognition.

DATA COLLECTION

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.

Figure 1. Architecture of proposed system

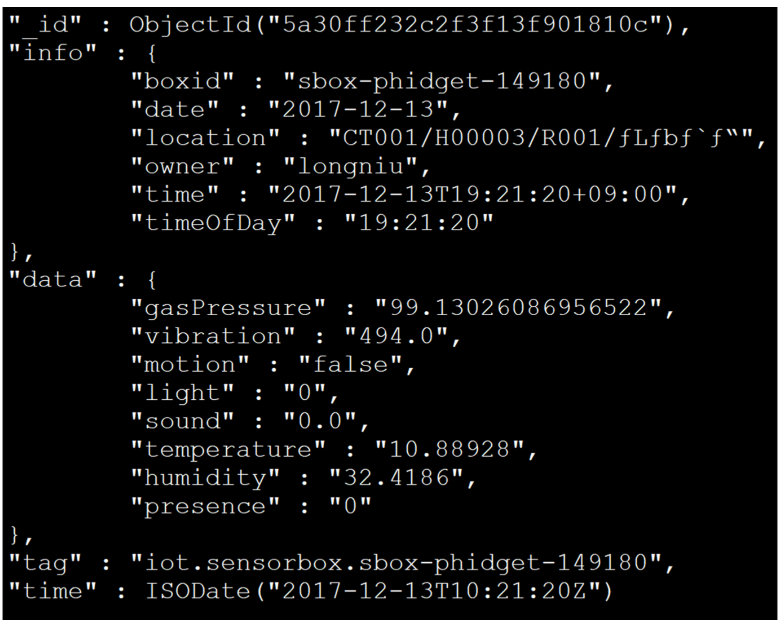


SensorBox measures seven environment attribute, which are temperature, humidity, lighting intensity, atmosphere pressure, sound volume, human motion and vibration, in every 10 seconds. Figure 2 shows the screenshot of the raw sensors data that be modified to JSON format text. And Figure 3 shows the screenshot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

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 the relevant studies (Fujino et al., 2006; Fiore et al., 2008), we have chosen eight types of typical ADLs (sleep, eat, cook, working at

Figure 2. Raw sensors data



```
"_id" : ObjectId("5a30ff232c2f3f13f901810c"),
"info" : {
        "boxid" : "sbox-phidget-149180",
        "date" : "2017-12-13",
        "location" : "CT001/H00003/R001/ƒLƒbƒ`ƒ“",
        "owner" : "longniu",
        "time" : "2017-12-13T19:21:20+09:00",
        "timeOfDay" : "19:21:20"
},
"data" : {
        "gasPressure" : "99.13026086956522",
        "vibration" : "494.0",
        "motion" : "false",
        "light" : "0",
        "sound" : "0.0",
        "temperature" : "10.88928",
        "humidity" : "32.4186",
        "presence" : "0"
},
"tag" : "iot.sensorbox.sbox-phidget-149180",
"time" : ISODate("2017-12-13T10:21:20Z")
```


Figure 3. Sensor data visualization

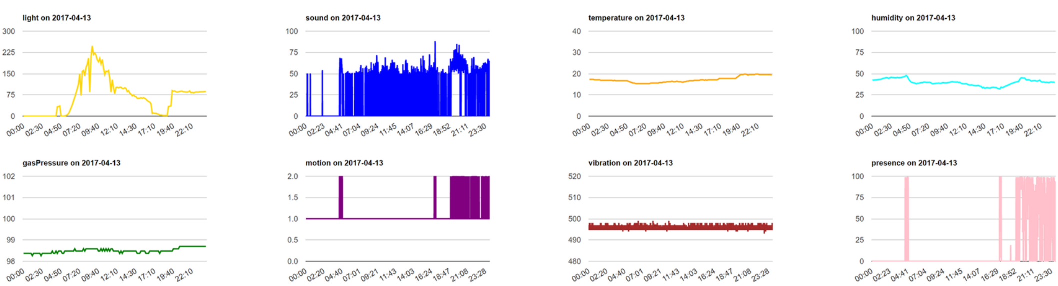


Figure 4. Lifelogger tool

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.

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 1 shows the training data.

ESTABLISH MACHINE LEARNING RECOGNITION MODEL

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

Table 1. Training data

DateTime	vibration	light	motion	gaspressure	temerature	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

temperature, humidity, lighting intensity, sound volume and human 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 3 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 judgements that the gasPressure is almost not affected by the resident's ADL.

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 feature 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 4, we use symbols ('A', 'B', 'C') to present different datasets with different size of time-window. The detail is A: 1 minute, 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 function includes 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 (Jacek, 2009). 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 2 shows the 9 cases of combination generated by PICT.

Establish Recognition Model

For the developed features of the training data, we apply machine-learning algorithm, 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.

Table 2. Nine groups of aggregation function

Group	light	motion	temperature	humidity	sound
G1	MIN	MAX	AVE	AVE	AVE
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

EVALUATE OF EXPERIMENT

Experiment Setup

We deployed the proposed system in a real 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 resident well. The position of SensorBox is marked by a red pin in Figure 5. A total of 45,693 rows of labeled sensor data, which do not include data labeled with 'other', be collected during 10 days within the apartment.

Result

We have established 81 recognition models based on the 3 size of time-windows, 9 combinations of Aggregation Functions and 3 machine-learning algorithms, and tested those models by training and learning the collected data. In this subsection, we show the test result of all models, the Average Accuracy of each trained ADLs recognition model. Accuracy measures the goodness of a classification model as the proportion of true result to total cases. Average accuracy which is the average of each accuracy per class (sum of accuracy for each class predicted/number of class).

In order to facilitate the observation, we divide all the models into three tables by the size of time-window, Table 3, 4 and 5, and draw a bar graph for each table, Figure 6, 7 and 8.

For the tables, each column stands for the method of data processing in feature engineering and is identified by a name that contains 2 characters, a capital letter and a number. The capital letter means the size of time-windows, as mentioned in subsection Feature Engineering. The number means the combination of aggregation functions' group number in Table 2. In one example, in Table 3, A4 stands for the size of time-window is 1 minutes and utilized combination of Aggregation Functions is G4 on the data process of feature engineering. The row of table is identified by the name of machine-learning algorithm. Each cell shows the average accuracy of each model. In one example, the recognition model's average accuracy exceeded 88.10% in the situation where the size of time-window is 3 minutes, utilized combination of aggregation function is G4 and algorithm is the multiclass decision forest.

For the three bar graphs, the vertical axis is average accuracy and the lateral axis stands for the column of relevant table. The color of bar stands for the algorithms, the row of relevant table.

By comparing the average accuracy of models on different size of time-window, such as the blue bars of A1 B1 and C1, we can see that the size of time-window has slightly influence on the average accuracy of model. By comparing the result of models on different methods of feature engineering in one graph, we can see that the models have significantly different performance with the combination

Figure 5. Testbed apartment

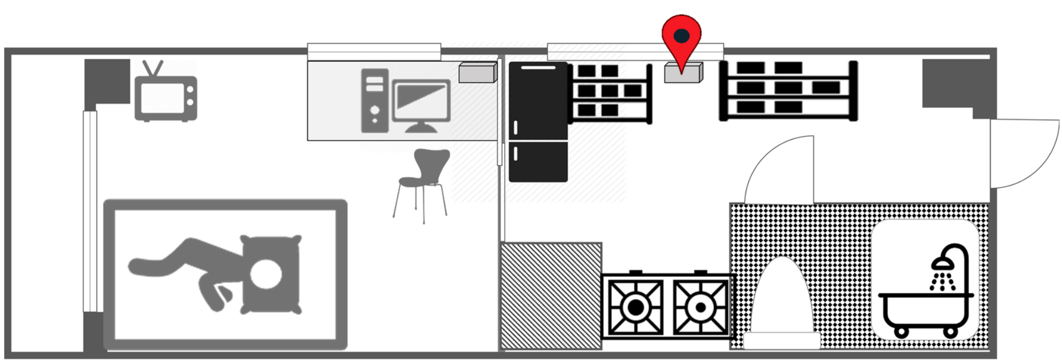


Table 3. All results of time-windows on 1 minute

Multiclass Algorithm	A1	A2	A3	A4	A5	A6	A7	A8	A9
Neural Network	84.36%	83.98%	84.27%	83.95%	83.96%	84.61%	84.28%	85.27%	84.23%
Decision Forest	85.83%	86.56%	86.24%	83.91%	84.43%	86.78%	87.54%	87.83%	86.41%
Logistic Regression	83.51%	85.23%	85.21%	83.16%	85.73%	83.18%	85.92%	82.05%	85.22%

Table 4. All results of time-windows on 2 minute

Multiclass Algorithm	B1	B2	B3	B4	B5	B6	B7	B8	B9
Neural Network	84.10%	84.92%	84.87%	85.14%	83.08%	85.66%	84.45%	85.14%	85.09%
Decision Forest	84.52%	87.68%	86.18%	87.56%	84.62%	84.59%	87.30%	83.72%	86.49%
Logistic Regression	83.57%	85.79%	85.14%	83.05%	85.57%	83.92%	85.94%	82.53%	85.71%

Table 5. All results of time-windows on 3 minute

Multiclass Algorithm	C1	C2	C3	C4	C5	C6	C7	C8	C9
Neural Network	84.62%	85.14%	85.07%	84.99%	82.11%	85.44%	84.25%	84.29%	84.70%
Decision Forest	85.92%	86.44%	85.10%	88.10%	85.25%	84.62%	87.10%	84.66%	86.21%
Logistic Regression	83.00%	86.77%	84.99%	82.59%	85.44%	84.29%	85.99%	82.59%	86.44%

Figure 6. Visualization of Table 3

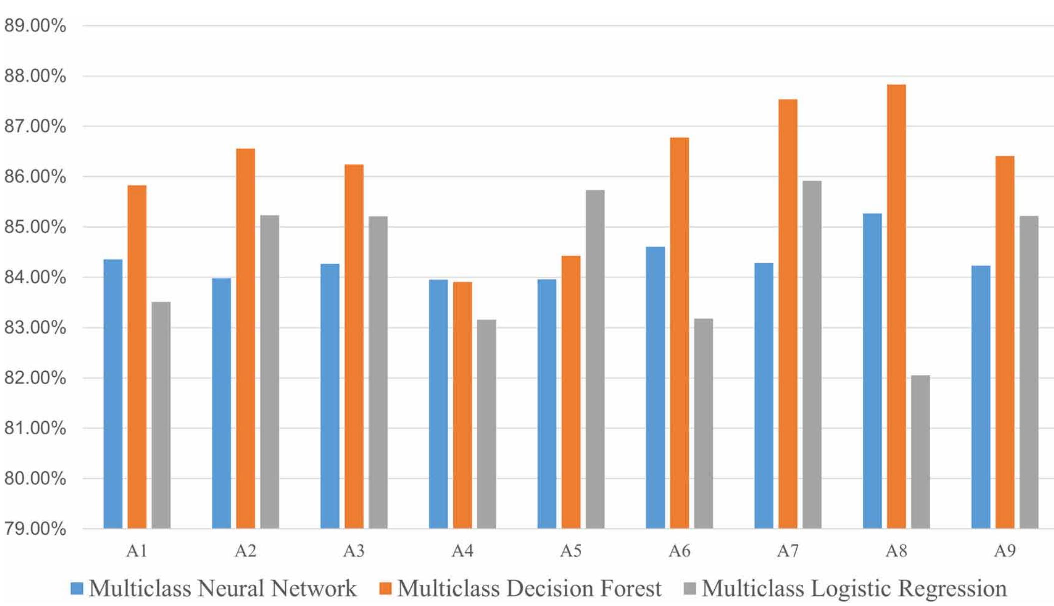


Figure 7. Visualization of Table 4

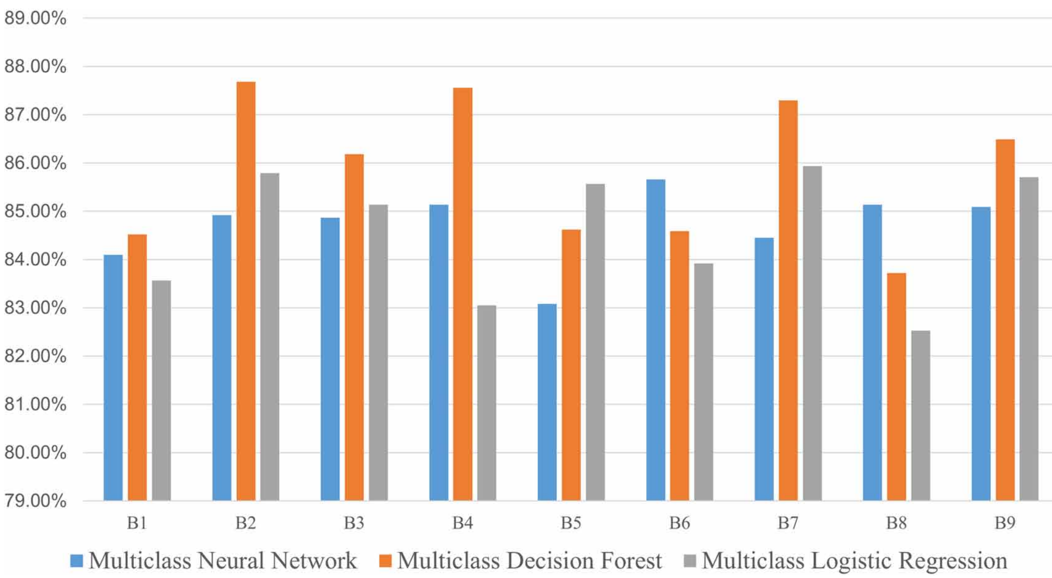
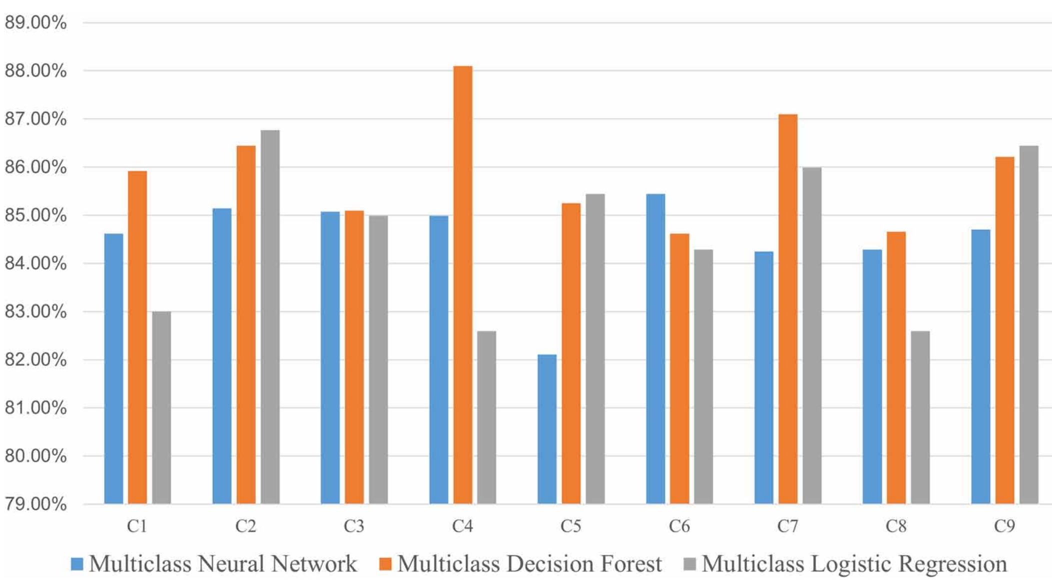


Figure 8. Visualization of Table 5



of aggregation functions. By observing the three graph of table, Figure 6, 7, 8, we can see the models utilized multiclass decision forest, represented by orange bars, have better performance than other models.

Evaluation

In the subsection, we evaluate the relationship between the 3 factors and accuracy of recognition ADLs based on the part of representative data which is selected from huge volumes of experimental data.

First, the effect of time-window on accuracy. Table 6 shows three recognition models' accuracy of some ADLs (cooking, sleeping, and eating). The three recognition models are utilized same

Table 6. Compare the accuracy of three models on different time-windows

Time windows	Cooking	Sleeping	Eating
1 minute (A)	86.00%	89.90%	54.10%
2 minutes (B)	89.70%	89.90%	55.70%
3 minutes (C)	87.80%	89.70f%	55.90%

aggregation function and algorithm expect the size of time-window. From the results, we can see that the accuracy of three ADLs is slightly affected by the size of time-window, and the 2 minutes is likely an appropriate value because accuracy of recognition ADLs is higher when the size of time-window is 2 minutes, expect recognition eating. Although the change of accuracy is also slightly cause of the change of size of time-windows is very small, the result confirms the view of the above-mentioned that the size of time-window should not too large and too small.

Second, the effect of aggregation function on accuracy. Table 7 shows three recognition models' accuracy of recognition some ADLs (cleaning, sleeping, and going out). The three recognition models utilized the same size of time-window and algorithm except the combination of aggregation function for the five environment attributes. From the result, we can see aggregation function has a great influence on the accuracy of each ADLs recognition. As for the G4, the accuracy of going out recognition is only 17.6%, which is 45% less than G8, but the accuracy of predict sleeping is almost equal to G8. For the three models, the accuracy of sleeping recognition achieves the highest value with using the combination of G7. But the model of G7 performs badly on recognition cleaning and going out. For G8, the accuracy of predict sleeping is less than G7, but the performance of predict cleaning and going out is much better than G7. Hence, from the compares we can see that system need to apply different combinations of function to each ADLs, in other words, the feature value of ADLs is different with each other.

Last, the effect of algorithms on accuracy. Table 8 shows three recognition models' accuracy of recognition some ADLs (cooking, sleeping, and eating). Those models utilized the same size of time-window and combination of aggregation functions except algorithms. From the results, we can see that Decision Forest performs better than Logistic Regression on the recognition three ADLs. For the Neural Network, it has the best performance on predict sleeping and eating, but it has worst performance on predict cooking. For the reason of abnormal result, we think that this amount of data

Table 7. Compare the accuracy of three models on different aggregate functions

Aggregate Function	Cleaning	Sleeping	Absence
G4	47.10%	73.00%	17.60%
G7	39.40%	95.50%	21.10%
G8	62.60%	72.70%	62.40%

Table 8. Compare the accuracy of three models on different algorithms

Multiclass Algorithm	Cooking	Sleeping	Eating
Logistic Regression (LR)	59.60%	44.30%	41.30%
Decision Forest (DF)	67.50%	72.70%	62.60%
Neural Network (NN)	20.20%	85.30%	93.50%

is not suitable for neural network. Because the amount of cooking and eating's data is only 3.8% and 5.2% of the total data, less than 400 elements. For these three models, the model of Decision Forest performs more robust than others with the limited number of training data.

CONCLUSION

In this paper, we have proposed a new system that automatically recognizes ADL in 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 propose 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 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%. And the influence of size of time-windows, aggregation function and machine-learning algorithms on the accuracy of recognition ADLs.

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.

ACKNOWLEDGMENT

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).

REFERENCES

Asaoka, S., Fukuda, K., & Yamazaki, K. (2004). Effects of sleep–wake pattern and residential status on psychological distress in university students. *Sleep and Biological Rhythms*, *2*(3), 192–198. doi:10.1111/j.1479-8425.2004.00138.x

Brdiczka, O., Reignier, P., & Crowley, J. L. (2007). Detecting Individual Activities from Video in a Smart Home. In *KES 2007 and XVII Italian Workshop on Neural Networks Conference on Knowledge-based Intelligent Information and Engineering Systems: Part I* (pp. 363-370). Springer-Verlag. doi:10.1007/978-3-540-74819-9_45

Fiore, L., Bodor, R., Drenner, A., Somasundaram, G., & Papanikolopoulos, N. (2008). Multi-Camera Human Activity Monitoring. *Journal of Intelligent & Robotic Systems*, *52*(1), 5–43. doi:10.1007/s10846-007-9201-6

Fujino, Y., Iso, H., Tamakoshi, A., Inaba, Y., Koizumi, A., Kubo, T., & Yoshimura, T. (2006). A prospective cohort study of shift work and risk of ischemic heart disease in Japanese male workers. *American Journal of Epidemiology*, *164*(2), 128–135. doi:10.1093/aje/kwj185 PMID:16707650

Hensel, B. K., Demiris, G., & Courtney, K. L. (2006). Defining Obtrusiveness in Home Telehealth Technologies: A Conceptual Framework. *Journal of the American Medical Informatics Association*, *13*(4), 428–431. doi:10.1197/jamia.M2026 PMID:16622166

Jacek Czerwonka. (2009). PICT 3.3 User's Guide. Retrieved February 04, 2009, from http://amibugshare.com/pict/help.html

Kusano, K., Muro, H., Hayashi, T., Harada, F., & Shimakawa, H. (2011). Derivation of Life Rhythm from Tracing Elderly Movement. In *The 10th Forum on Information Technology* (Vol. 10, pp. 891-892). IEICE.

Ministry of Health. Labour and Welfare. (2010) Supports for Independence in Order to Stabilize Living and Society. *Annual Health, Labour and Welfare Report 2008-2009*. Retrieved 2010, from http://www.mhlw.go.jp/english/wp/wp-hw3/

Ouchi, K., & Doi, M. (2013). Smartphone-based Monitoring System for Activities of Daily Living for Elderly People and Their Relatives etc. In *Pervasive and ubiquitous computing adjunct publication* (pp. 103–106). ACM. doi:10.1145/2494091.2494120

Pei, L., Guinness, R., Chen, R., Liu, J., Kuusniemi, H., Chen, Y., & Kaistinen, J. et al. (2013). Human Behavior Cognition Using Smartphone Sensors. *Journal of Sensors*, *13*(2), 1402–1424. doi:10.3390/s130201402 PMID:23348030

Philipose, M., Fishkin, K. P., Perkowitz, M., Patterson, D. J., Fox, D., Kautz, H., & Hahnel, D. (2004). Inferring activities from interactions with objects. *International Journal of IEEE Pervasive Computing*, *3*(4), 50–57. doi:10.1109/MPRV.2004.7

Sakakibara, S., Saiki, S., Nakamura, M., & Matsumoto, S. (2016). Indoor Environment Sensing Service in Smart City using Autonomous Sensor Box. In *15th IEEE/ACIS International Conference on Computer and Information Science* (pp. 885-890). IEEE. doi:10.1109/ICIS.2016.7550871

Statista. (2017). Percentage of single-person households in the U.S. 2015, by state. Retrieved 2017, from https://www.statista.com/statistics/242284/percentage-of-single-person-households-in-the-us-by-state/

Tapia, E. M., Intille, S. S., & Larson, K. (2004). Activity Recognition in the Home Using Simple and Ubiquitous Sensors. In A. Ferscha & F. Mattern (Eds.), *Pervasive Computing* (pp. 158–175). Springer Berlin Heidelberg. doi:10.1007/978-3-540-24646-6_10

Wren, C. R., & Tapia, E. M. (2006). Toward Scalable Activity Recognition for Sensor Networks. In M. Hazas, J. Krumm, & T. Strang (Ed.), *Location- and Context-Awareness: Second International Workshop* (pp. 168-185). Springer Berlin Heidelberg. doi:10.1007/11752967_12

Yeung, W. J., & Cheung, A. (2015). Living Alone: One-person households in Asia, a special collection in Demographic Research. *Demographic Research,* 32, 1099-1112. Retrieved June 03, 2015 from http://www.demographic-research.org/special/15/

Long Niu received a B.E. Degree in Information engineering from Zhengzhou University, China, in 2012, a M.E. Degree in Computational Science from Kobe University, Japan, in 2016. Now he has a Ph.D. candidate in the Graduate School of System Informatics at Kobe University. His research interests include Activity Recognition by Using Non-intrusive Environment Sensing Data and Integration Framework for Indoor Location.

Sachio Saiki is an assistant professor in the Graduate School of System Informatics at Kobe University. His research interests include software engineering education and signal processing.

Masahide Nakamura received B.E., M.E., and Ph.D. degrees in Information and Computer Sciences from Osaka University, Japan, in 1994, 1996, 1999, respectively. From 1999 to 2000, he has been a post-doctoral fellow in SITE at University of Ottawa, Canada. He joined Cybermedia Center at Osaka University from 2000 to 2002. From 2002 to 2007, he worked for the Graduate School of Information Science at Nara Institute of Science and Technology, Japan. He is currently an associate professor in the Graduate School of System Informatics at Kobe University. In 2015, he worked for Universite Grenoble Alpes as a visiting professor. In 2018, he joined RIKEN Center for Advanced Intelligence Project (AIP)

as a visiting researcher. His research interests include the service/cloud computing, smart home, smart city, and gerontechnology. He is a member of the IEEE, IEICE and IPSJ.