Recognizing ADLs Based on Non-intrusive Environmental Sensing and BLE Beacons

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***Abstract*—Recently, many studies about Activities of Daily Living (ADLs) recognition have been conducted, which can be applied to many real-life, human-centric problems such as eldercare and healthcare. In our previous work, we have proposed an ADLs recognition system based on non-intrusive environment sensing. However, the overall accuracy of the system is only about 70%. In order to improve the quality of the system, based on the analysis of appeared problem, in this article a new ADLs recognition system by using environment sensing and Bluetooth Low Energy (BLE) beacon technologies be proposed. By learning the Beacon RSSI log, get user position and movement information, which will let the system better recognize ADLs.**

***Index Terms*—Non-intrusive environment sensing, Beacon, ADLs recognition, Machine Learning.**

I. Introduction

In developed countries, more and more people are living in one-person households (OPH). The high rates of OPH in those countries leads to some social issues. According to [1] [2], people in OPH loses control of life rhythm easily, and the loss of life rhythm often leads to health deterioration. 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 are quite promising. Many studies of the ADL recognition have been conducted so far, for real-life and human-centric applications such as eldercare and healthcare. Some approaches (e.g., [3] [4]) 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 state-change sensors, and/or indoor positioning systems to recognize ADLs (e.g., [5] [6]). However, those systems are also intrusive to a home property, as the user has to install those sensors into the house and objects. This usually causes expensive cost for deployment and maintenance.

To overcome the limitations, in our previous work, we have proposed a system that recognizes ADLs of OPH based on non-intrusive environmental sensing with machine learning [7]. In the system, we exploit IoT-based environment-sensing device, called *autonomous sensor box* (we simply call SensorBox, hereinafter) [8]. However, tested by more than a hundred trained models, the overall accuracy of ADLs recognition is about 70%. The experimental results show that the environment sensing data does not contain enough feature value of ADLs. Feature value is data that is effective to identify the ADLs.

According to the detailed result data, we considered the problem is that the impacts of some ADLs on the indoor environment attributes are similar. Based on the conclusion, in order to improve the accuracy of recognition, it is necessary to collect information created by residents to strengthen the feature value of each ADL.

In this paper, we propose a new ADL recognizing system based on non-intrusive environment sensing and BLE beacon technology. The structure of proposed system and the construction of ADLs recognition model will be described.

II. Preliminary

A. ADLs Recognition

ADLs are the activities residents normally do, such as sleeping, feeding themselves, bathing, work, cleaning. The discovery and recognition of ADL is an essential function of the system that provides necessary assistance 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.

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 et al. [9] 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 [10], the acceptance of this technology in the home is increasing. On the other hand, processing the video is computationally expensive.

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 researches in ADL recognition use sensor data. Researchers have found that combining different types of sensor is effective for classifying different types of activities.

Kusano et al. [11] 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. [5] 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. [12] attached a 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. [6] combined a positioning system and motion sensors of a smartphone to recognize human movements in natural environments. However, simultaneously turning on the motion-sensors Wi-Fi and GPS increase drain the battery.

B. Challenges and Research Goal

Despite the ADL recognition (AR) has been widely studied for a few years, 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 above, there are many existing systems that use monitor camera, object-embedded sensors, and wearable devices. However, we consider it difficult for people in OPH to accept these technologies, because they are too exaggerated and high cost of deployment. 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. Previous Study

In our previous work, an ADL recognition system based on non-intrusive environment sensing technology has been proposed. To minimize the intrusions and the cost, only environmental sensing data are used for analyzing in AR model. As the recognition model is based on supervised machine learning algorithms, the system contains a training phase and an operation phase.

In the training phase, it is essential to attach correct labels of ADLs to training data by using LifeLogger, an application, which is installed on user's computer. And one or multiple SensorBoxs be deployed at where ADLs are well observed as environmental measures. Then system begins to collect environment attributes and upload the measured data to the cloud server, whereas LifeLogger inserts the lifelog into MySQL in the cloud data. Next, the two time-series data are joined with the timestamp to form the training data. Then, extracted feature values from training data are part of feature engineering. Finally, based on the feature value of every ADL, different models we built based on some popular multi-classification algorithms, such as Logistic Regression, Decision Forest, Neural Network.

In the operation phase, based on the trained AR model, ADLs of residents are recognized and recorded automatically with analyzing the stream sensors data.

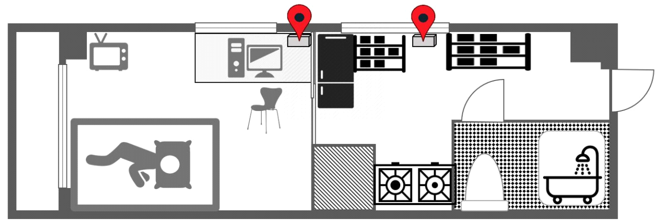

Fig. 1: Testbed Apartment

Predicted Class

Actual Class	Cook	PC work	Clean	Bath	Sleep	Eat	Absence
Cook	84.9%	1.1%	9.7%			3.2%	1.1%
PC work	0.7%	18.2%	1.3%		17.9%	2.6%	59.3%
Clean	39.8%	18.6%	29.2%		0.9%	7.1%	4.4%
Bath	8.0%	48.0%	8.0%	4.0%	16.0%	12.0%	4.0%
Sleep					88.4%		11.6%
Eat	6.3%	26.0%	6.3%		3.9%	41.7%	15.7%
Absence	1.0%	6.3%					92.7%

Fig. 2: Confusion Matrix of Predicted Result

A. Result of Experiment

We deployed the proposed system in a real apartment of a single resident. As shown in Figure 1, the apartment is an ordinary apartment in Japan, consisting of a bed/living room, a bathroom, and a kitchen. two SensorBoxes were deployed, one in the kitchen and one in the living room. The positions of the SensorBoxes are marked by red pins in Figure 1. A total of 269,833 rows of labeled sensor data were collected during 10 days within this apartment.

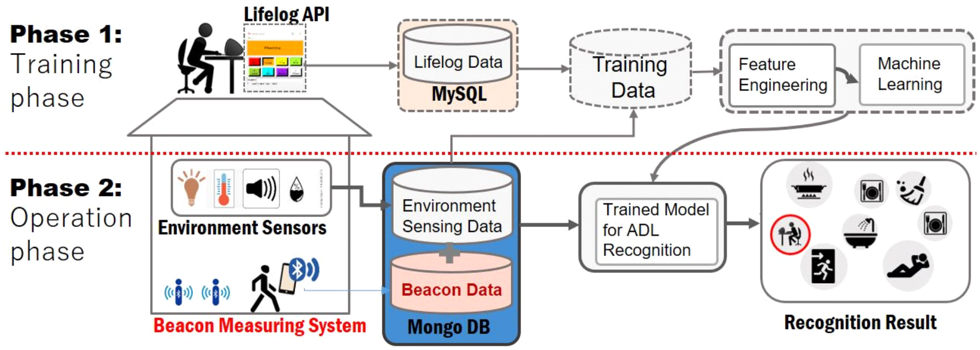

Fig. 3: New Propose System Architecture

However, the prediction accuracy of the obtained AR models is far lower than expected. The overall accuracy of all ADL recognition is only about 70%, which is significantly lower than other related studies. Figure 2 displays the result of one trained AR model. It details the accuracy recognition of each ADL. The overall accuracy of this AR model is 69.7%. Despite the recognition accuracy of sleep cook and going out were exceed over 84%, the recognizing accuracy of others ADLs were very low.

IV. Problem of Previous System

By analyzing the results of multiple trained models, the fact that environment attributes are not sufficient to distinguish some basic ADLs. For example, the 2nd row of the matrix shows that the AR model cannot differentiate "PC-working" and "Absence". When the resident is at work in front of his desktop PC, the system predicts nobody is in the room with 59.3% probability and it predicts user is sleeping with 17.9%. The 3rd, 4th, 6th rows of the matrix show that the system also fails to recognize clean, bath and eat. Moreover, by observing the 5th row of data, we can see that the system also mistakenly recognizes that no one in the room when the user is sleeping.

Obviously, the reason for this result is that the environment states caused by those ADLs are similar. However, those ADLs can be easily identified by the user's position and motion information. For example, for PC working and go out, the 2 ADLs states of user's position are obviously different. Therefore, it is necessary to add new information on the previous system to strengthen the feature values of every ADLs.

V. Proposed Method

In order to solve the problem of previous work, the new system will also collect information that reflects the user's position and movement status. To adhere to the original research goal mentioned in section II-B, complex and expensive indoor positioning system was excluded from the design. To approach the goal, we consider using Bluetooth Low Energy (BLE) Beacon which enables smartphones and other devices

Fig. 4: Screenshot of Lifelogger Tool

to sense close proximity by measuring the RSSI transmitted from another beacon.

Figure 3 shows the architecture of proposed system. The architecture of proposed system is similar to the previous work. The system will be explained in detail as follow.

A. Data Collection

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 press the corresponding button to record the current ADL. Based on relevant studies [2] [3], 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 on a cloud server.

TABLE I: Training Data

DateTime	vibration	light	motion	gaspressure	temperature	humidity	sound	B1-RSSI	B2-RSSI	activityID
2017/2/19 3:33:02	495	1	0	98.8	13.33	35.84	50.15	-44	-64	5
2017/2/19 3:33:12	494	1	0	98.8	13.33	36.04	0	-47	-66	5
2017/2/19 3:33:22	494	1	0	98.8	13.33	36.04	51.62	-46	-64	5
2017/2/19 3:33:32	494	1	0	98.8	13.33	36.04	0	-46	-62	5

For the collection of sensor data, 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.

For the collection of beacon RSSI, a simple Beacon Measuring System is deployed in user's home. In the system, one or multiple of beacon stations should be deployed in the user's living zone, and wearable device which uses BLE beacon standard should be carried or put in closed position with the user. By using an application developed by our research group, the RSSI of each beacon station will be measured and uploaded to the cloud server.

Training data be established by integrating the 3 time-series data collected by SensorBox, Beacon measure system and LifeLogger based on timestamp. Since data labeled as 'other' was beyond the scope of the ADLs recognition, the data must be noise. Table I shows the training data.

B. Feature Engineering

In our study, we get the feature value from training data, as the following process.

First, analyzing activity-sensitive environment sensing sensors. For accurate ADLs recognition, it is essential to identify what environmental values in the sensing data well predict the ADLs. Then, determining the size of time-window and aggregating raw data within the time-window into one data, to enhance the features of the time-series data. Typical *aggregation functions* include MAX, MIN, AVG, STDEV, and so on.

C. Establish Recognition Model

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

VI. Conclusion

Based on the result of previous work, in this paper, we proposed a new system to improve the accuracy of ADLs recognition by adding Beacon Measuring System to the original system. To minimize the cost of deployment, the Beacon Measure System be designed as simple, which collect and upload raw data RSSI of beacon station. By analyzing the stream RSSI data, the system can get the feature value that cannot be provided by environment sensing data.

However, since the study is still in the primary stage, we should evaluate the system by experiment results in our future work.

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 Technology Foundation (C) (No.2177004) and CNRS-PICS Safe-Smartness (No.6999).

References

[1] S.Asoka, K. Fukuda, and K. Yamazaki, "Effects of sleep-wake pattern and residential status on psychological distress in university students," in *Sleep and Biological Rhythms*, vol. 2, 2004, pp. 192–198.

[2] Y. Fujino, "A prospective cohort study of shift work and risk of ischemic heart disease in japanese male workers," *Journal of University of Occupational and Environmenatal Health*, vol. 30, no. 1, p. 104, mar 2008.

[3] L. Fiore, D. Fehr, R. Bodor, A. Drenner, G. Somasundaram, and N. Papanikolopoulos, "Multi-camera human activity monitoring," *Journal of Intelligent and Robotic Systems*, vol. 52, no. 1, pp. 5–43, 2008.

[4] K. Ouchi and M. Doi, "Smartphone-based monitoring system for activities of daily living for elderly people and their relatives etc." in *Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication*, ser. UbiComp'13 Adjunct. New York, NY, USA: ACM, 2013, pp. 103–106.

[5] E. Munguia-Tapia, S. Intille, and K. Larson, "Activity recognition in the home using simple and ubiquitous sensors," in *Proceedings of PERVASIVE*, 2004, pp. 50–57.

[6] L. Pei, R. Guinness, R. Chen, J. Liu, H. Kuusniemi, Y. Chen, L. Chen, and J. Kaistinen, "Human behavior cognition using smartphone sensors," in *Sensors*, vol. 13, 2013, pp. 1402–1424.

[7] L. Niu, S. Saiki, and M. Nakamura, "Recognizing adls of one person household based on non-intrusive environmental sensing," in *18th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD 2017)*, N. H. Teruhisa Hochin, Hiroaki Hirata, Ed., no. CFP1779A-USB. IEEE Computer Society and International Association for Computer and Information Science (ACIS), June 2017, pp. 477–482, kanazawa, Japan.

[8] S. Sakakibara, S. Saiki, M. Nakamura, and S. Matsumoto, "Indoor environment sensing service in smart city using autonomous sensor box," in *15th IEEE/ACIS International Conference on Computer and Information Science*, June 2016, pp. 885–890, okayama, Japan.

[9] O. Brdiczka, P. Reignier, and J. L. Crowley, *Detecting Individual Activities from Video in a Smart Home*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2007, pp. 363–370.

[10] B. Hensel, G. Demiris, and K. Courtney, "Defining obtrusiveness in home telehealth technologies: A conceptual framework," in *Journal of the American Medical Informatics Association*, vol. 13, 2006, pp. 428–431.

[11] K. Kusano, H. Muro, T. Hayashi, F. Harada, and H. Shimakawa, "Derivation of life rhythm from tracing elderly movement," in *The 10th Forum on Information Technology (FIT2011)*, vol. 10, sep 2011, pp. 891–892.

[12] M. Philipose, K. P. Fishkin, M. Perkowitz, D. J. Patterson, D. Fox, H. Kautz, and D. Hahnel, "Inferring activities from interactions with objects," *IEEE Pervasive Computing*, vol. 3, no. 4, pp. 50–57, Oct. 2004.