Integrating Environmental Sensing and BLE-based location for Improving Daily Activity Recognition in OPH

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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 proposed an ADLs recognition system based on non-intrusive environment sensing for people in One-person Household (OPH). However, the proposed recognition system did not perform well, the micro-averaged and macro-averaged precision of most of the recognition models was only around 60%. In order to improve the quality of the system, in this article, we propose a new ADLs recognition system by integrating environment sensing and Bluetooth Low Energy (BLE) beacon technology and evaluate the new version of the ADLs recognition model by comparing the experimental data collected from a real resident in OPH.

CCS CONCEPTS

• **Applied computing → Health care information systems**; • **Human-centered computing →** *Activity centered design*; • **Computing methodologies →** Supervised learning by classification;

KEYWORDS

Activities Recognition, non-intrusive environment sensing, Beacon, data integration, ADLs, Machine Learning, Smart Home

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1 INTRODUCTION

Recently, the development of wireless, inexpensive sensor and AI has promoted the development of health care related systems that are expected to solve some social issues, such as aging population, the cost of health care, quality of life for residents in One-person households (OPH), and the important fact that people are more willing to remain independent in their own homes [5]. People need to be able to complete Activities of Daily Living (ADLs) such as eating, cooking and sleeping, to lead a functionally independent life. Thus, automating the recognition of these ADLs is an important step toward monitoring the functional health of a smart home resident [8].

Nowadays, in many countries, the growing number of unmarried people and late marriages cause the high rates of OPH that lead to some social issues. In Japan, the number of OPH is increasing rapidly. It is estimated that 37.4% of households will become OPH in 2030 [10]. In about seven states in the USA, the percentage of OPH exceeded 30% in 2015[21]. In China, there are more than 60 million people currently living alone [23]. According to [20] [4], people in OPH easly lose control of life rhythm, 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 a manual record requires a strong mind and patience. Automating ADL recording in OPH is therefore quite promising.

Many studies of ADL recognition have been conducted for real-life and human-centric applications such as eldercare and healthcare. Some approaches (e.g., [3] [16]) try to directly capture daily living using camera, or microphone. However, such systems are too intrusive on the user, in the sense that all aspects of daily living are exposed. There are many studies using state-change sensors, and/or indoor positioning systems to recognize ADLs (e.g., [12] [17]). However, these systems are also intrusive in the home, as the user has to install the sensors into around the house and into objects. The deployment and maintenance is usually expensive. Thus, our research goal is to minimize the cost of ADLs recognition development and reduce the level of intrusions for residents and their place of residence.

In our previous work, we developed a system that recognizes ADLs of OPH based on non-intrusive environmental sensing with machine learning. The non-intrusive environmental sensing data covers environment attributes (sound volume, light, temperature, humidity, presence), which is collected by an IoT-based device called *autonoumous sensor box* (SensorBox) [19]. The system has been tried out in a real OPH [15]. However, when tested by more than a hundred activity recognition models, the Micro&Macro-averaged precision of the system was low, about 60% [13]. By analyzing the experimental results, we fond that the environmental sensing data does not contain enough feature value for every recognized ADL. The feature value is data that is effective to identify ADLs. One reason for this result is that the impacts of some ADLs on the indoor environment attributes are similar.

In order to improve the precision accuracy, it is necessary to collect more information created by residents to strengthen the

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feature value of each ADL. In order to do this we proposed a new ADL recognition system based on the integration of non-intrusive environment sensing and BLE-based location information.

To evaluate the new system, we deployed it in an actual setting, and the apartment with single resident (OPH) and conducted the experiment for more then a month. Experimental results show that the new system improved the Micro&Macro-averaged precision about 7% and significantly improved some ADLs accuracy precision over 10%. From the results, we confirmed that integrating non-environment sensors and BLE-based location improved the precision of ADLs recognition.

In this paper, we describe the structure of the proposed system and the process of environment sensing data and BLE-based location data. Then we give a detailed evaluation of the new system in comparision with the previous experimental data.

2 PRELIMINARIES

2.1 ADLs Recognition

ADL is an acronym for *Activites of Daily Living* originally used at hospitals, it means the minimum action required for daily living such as sleeping, eating, cleaning, etc. In this paper, our target ADLs are based on relevant studies [4] [3]. We have chosen seven types of typical ADLs (sleeping, eating, cooking, working at PC, cleaning, bathing and absence). The recognition of ADLs is an essential function of the system that provides necessary assistance to the residents of OPH. Based on the results of this process, an intelligent system could decide which action to take in order to support the residents well-being and understand their life rhythm based on a regular record of ADLs.

2.2 Related Works

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 ADL recognition can be divided roughly into two categories depending on the type of contextual information analyzed. The first category uses electronic media data frome video cameras or microphone recordings, to capture daily living directly. The second category uses sensor data based on various sensors, including accelerometers, gyroscopes, Radio Frequency Identifier (RFID), and power-meter sensors.

Multimedia data: Brdiczka et al. [2] proposed a smart home system that takes videos of residents, and processes the video to recognize activities. Although in general, people have been resistant to in-home video monitoring [6], acceptance of this technology is increasing. On the other hand, processing the video is computationally expensive.

Sensing data: Since video and audio recording expose too much information of daily life, it is considered to be intrusive. Therefore, it is more acceptable to use passive information. Hence, most current research in ADL recognition uses sensor data. Researchers have found that combining different types of sensor is effective for classifying different types of activities.

- **Kusano et al.** [9] proposed a system that derives life rhythm by tracking elderly movement 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 locations of residents. 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.** [12] focused on interactions of residents with objects of interest such as doors, windows, a refrigerator, keys, and medicine containers. They installed state-change sensors on daily items to collect the interaction data.
- **Philipose et al.** [18] attached RFID tag on many daily items and asked participants to wear gloves with an RFID tag reader. When participants are close to the items, the interaction is recorded.
- **Pei et al.** [17] 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 substantially increase the drain on the battery.

2.3 Challenges and Goal of Research

Despite the fact that *Activity recognition (AR)* has been widely studied for many years, there are few studies on OPH. The unique characteristic of OPH is that the resident is living alone and is often busy to do everything by their own. They do not want to change their own way of living or pay for expensive systems just to monitoring ADLs. As mentioned above, there are many existing systems that use video monitor, object-embedded sensors, and wearable devices. However, we consider it is difficult for people in OPH to accept these technologies, because they are too intrusive and expensive. Although researchers and companies can manage large-scale equipment, it is still too expensive to deploy in OPH.

Therefore, our research goal is to minimize the limitations of the conventional approaches and achieve high-quality AR system suitable for use in OPH.

2.4 Previous Study

To achieve the research goal, in our previous work [14] [15], we proposed an AR system based on non-intrusive environment sensing technology. We established over one hundred AR models based on careful feature engineering to determine essential predictors that well explain ADLs in OPH. Furthermore, we tested three classification algorithms to compare their performances.

In the system we used two IoT-based environment-sensing devices called autonomous sensor box (we simply call SensorBox, hereinafter). The SensorBox was developed by our lab [19], and was designed to minimize the effort of deployment and operation. Once connected to power, it 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 and expensive infrastructure.

While SensorBox is measuring the environment in OPH, the AR system requires initial training where the resident manually records ADLs using a designated lifelog tool. The initial training is supposed to be performed over several days, to associate labels of ADLs with the sensor data. In the proposed system, we defined seven basic ADLs (cooking, working, cleaning, bathing, sleeping, eating and going out).

We deployed the system in the actual apartment of a single person, and conducted our experiment for over a month. Experimental results show that the average accuracy of all seven ADLs was around 90% and the accuracy of some ADLs recognition achieved more than 92%, in cooking, sleeping and absence. However, the other four ADLs could not be correctly measured, so the precision of those ADLs was lower than 50%, which cause the Micro-average precision and the Macro-average precision to be only around 60%. The micro-averaging represents the weighted average based on the frequency of samples from each ADL. The macro-averaging represents the unweighted mean of precision, recall and accuracy metrics [22]. Both micro and macro-averaged precision are important since micro-averaged precision tends to weigh the most frequent ADLs heavily while macro-averaging considers all ADLs to be equally significant [1].

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%

Figure 1: Confusion Matrix of Predicted Result

2.5 Previous System Problems

By analyzing the results of multiple trained models, we found that environment attributes are not sufficient to distinguish some basic ADLs. For instance, Figure 1 displays the result of one trained AR model based on two SensorBoxes. The 2nd row of the matrix shows that the AR model cannot differentiate "PC-working" and "Absence". When the resident is working in front of his desktop PC, the system predicts nobody is in the room with 59.3% probability and predicts user is sleeping with 17.9% probability. The 3rd, 4th and 6th rows of the matrix show that the system also fails to recognize cleaning, bathing and eating. 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 these results is that the environmental states caused by the ADLs are similar. However, those ADLs can be easily identified by the user's position and motion information. For example, for PC working and going out, the two ADLs current locations are obviously different. Therefore, it is necessary to add new information to the previous system to strengthen the feature values of every ADLs.

3 PROPOSED METHOD

3.1 Key Ideas of Proposed Method

In order to solve these problems, it is essential to collect location information of residents performing ADLs.

First, we classify the activities according to the location where the activity occurrs, such as ADLs of kitchen, ADLs of living room. And we also add a spatial attribute for the SensorBox, in other words, we also classify the environment sensing data based on the location of sensors. We then set the system to recognize the ADLs of people by only mining the environment sensing data of the zone where the ADL is occurring, instead of mining the information of all rooms.

Second, regarding measuring and collecting the indoor position of people, the precision of measured position information is much higher than the motion sensor data, which was only able to perceive the presence of human activity. So we need to install an indoor positioning system. In order to adhere to the original research goal mentioned in section 2.3, a complex and expensive *Indoor Positioning System (IPS)* was excluded from the design and hence we consider using BLE Beacon which enables smart phones and other devices to sense location by measuring the Received Signal Strength Indicator (RSSI) [7] transmitted from another beacon.

Last, we integrate the environment sensing data and Beacon RSSI data with a timestamp and build an ADLs recognition model based on the integrated information.

3.2 Architecture of System

Figure 2 shows the architecture of the proposed system. Based on the figure, in this subsection, we will give a brief explanation on the function of each component and the data processing.

First, we set up the system in a target OPH. We deploy SensorBoxes where ADLs can be well observed and place Beacon stations to measure the indoor position of people. We also install a *LifeLogger* software on resident's PC and a beacon measuring app in their smart phone. To apply supervised machine-learning algorithms, the system requires training data at the initial phase of operation. So the system contains 2 phases: training and operation.

In the training phase, we ask the user to manually record *lifelog data* by using LifeLogger. The lifelog data is used to attach correct labels of ADLs to the environment sensing data and beacon RSSI data. Then, the system converts raw *lifelog data* into time-series data by an application that is drawn as a black square marked by 'C'. For beacon and sensor data, the system converts them by applications that are shown as a black square marked by 'AF' and

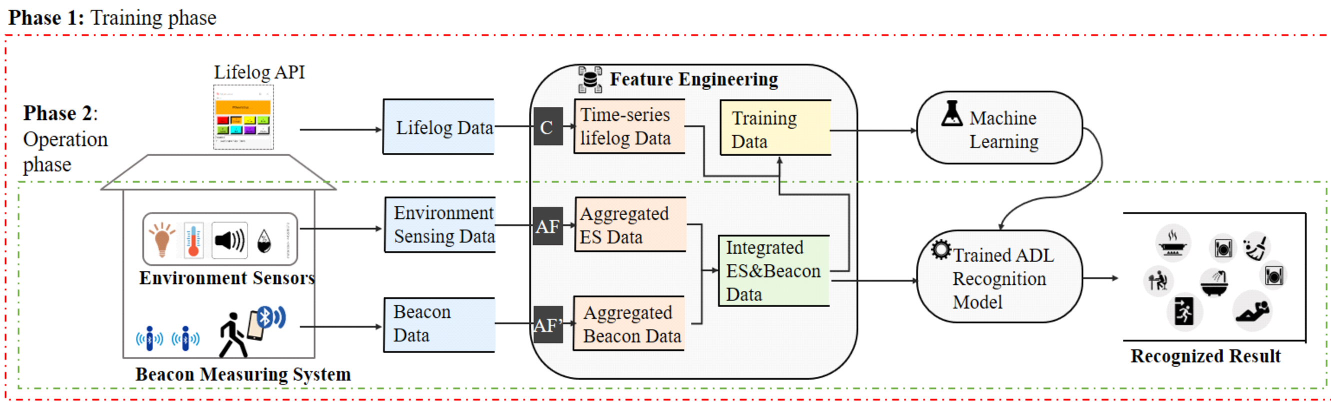

Figure 2: Architecture of proposed system

'AF'', and then integrates the converted sensor and beacon data by the timestamp and location. Next, the system create training data by joining the time-series ADLs log and integrated data based on the timestamp. Finally, we apply a multi-classification algorithm to the training data to construct AR model.

In the operation phase, the system automatically classifies the stream data into ADLs based on the trained AR model established in the training phase.

```
[2017/05/29T09:56:55]:<user@DESKTOP-G3JFFRR>:Button 4: Starting Bath
[2017/05/29T09:58:55]:<user@DESKTOP-G3JFFRR>:Button 4: Ending Bath
[2017/05/29T09:58:55]:<user@DESKTOP-G3JFFRR>:Button 1: Starting Cook
[2017/05/29T10:32:10]:<user@DESKTOP-G3JFFRR>:Button 1: Ending Cook
[2017/05/29T10:32:10]:<user@DESKTOP-G3JFFRR>:Button 4: Starting Bath
[2017/05/29T10:42:49]:<user@DESKTOP-G3JFFRR>:Button 4: Ending Bath
[2017/05/29T10:42:49]:<user@DESKTOP-G3JFFRR>:Button 8: Starting Others
[2017/05/29T10:51:24]:<user@DESKTOP-G3JFFRR>:Button 8: Ending Others
[2017/05/29T10:51:24]:<user@DESKTOP-G3JFFRR>:Button 6: Starting Eat
[2017/05/29T11:23:10]:<user@DESKTOP-G3JFFRR>:Button 6: Ending Eat
[2017/05/29T11:23:10]:<user@DESKTOP-G3JFFRR>:Button 3: Starting Clean
[2017/05/29T11:30:33]:<user@DESKTOP-G3JFFRR>:Button 3: Ending Clean
```

Figure 3: Raw ADL Record data

3.3 Data collection

During the 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 which just logs the begin and end time of ADL. Figure 3 shows the raw data of lifelog and Figure 4 visualizes the actual activity log as a list of double direction arrow lines.

For the collection of sensor data, considering that these sensors' sensible range is only around the SensorBox, the box should be place near where the resident's ADL is frequently conducted. However, the layout of each house and living styles individual are different from OPH to OPH. Hence the most suitable position of SensorBoxes is also different from OPH to OPH. Considering that apartments normally consist of multi-zones that human activity, for instance, a living room for eating, studying and relaxing, a kitchen for cooking, we should distribute SensorBoxes in each main zone of the normal life as far as possible. Therefore, based on the location of the zone where the ADL occurred, the system selects appropriate Sensorbox to measure the activity of the resident. The SensorBox measures seven environment attributes, which are sound volume, lighting intensity, temperature, humidity, vibration, gas pressure and presence, every ten seconds. Table 1 shows one SensorBox's raw sensor data obtained from a MongoDB server by exported as csv file. Figure 4 shows a visualization of two sensors' data.

To collect beacon RSSI, a simple Beacon Measuring System is deployed in user's home. In the system, multiple beacon stations are deployed in the apartment, and a mobile device with a beacon measure app installed should be carried or handy, then the RSSI of each beacon station will be measured and uploaded to the cloud server ten times every second. We can calculate the position of the user based on the RSSI value. Figure 4 shows the visualization of Beacon data, and Table 2 shows the raw data of one beacon, the data is obtained from a MongoDB server by exported as csv files. The 'Minor' is the ID of a beacon station in the stations group of one building.

3.4 Feature Engineering

Feature Engineering is the process of using domain knowledge of the data to create feature values that make machine learning algorithms work. This is fundamental to the application of machine learning. The feature value is data that effectively identifies the ADLs. In this paper, we propose a methodology for the Beacon data and the integration of Beacon and sensor data. In this subsection, we will describe in detail the data processing of feature engineering.

For lifelog data, we developed a lightweight application for converting the semantic ADL log data into time-series log data by the second, thereby it is convenient to label sensor and beacon data with timestamp.

For environmental sensing data, we get the feature value by the following process. First, analyze activity-sensitive environment attributes. 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 dataset to enhance the features of the time-series data. Typical aggregation functions include MAX, MIN, AVG, STDEV, and so on. Detailed methodology of this has been presented in our previous work [15].

Table 1: Raw Environmental Sensing Data

Light	Sound	Motion	Temperature	Humidity	Vibration	gasPressure	Presence	Datetime
0	68.61	false	23.7	34.7	495.0	98.2	0	2017-05-28T00:31:46+09:00
0	69.60	false	23.7	34.7	495.0	98.2	0	2017-05-28T00:31:56+09:00
0	68.09	false	23.7	34.8	496.0	98.2	0	2017-05-28T00:32:05+09:00
0	68.61	false	23.7	34.7	495.0	98.3	0	2017-05-28T00:32:15+09:00
0	69.60	false	23.7	34.7	495.0	98.3	0	2017-05-28T00:32:24+09:00
0	69.60	false	23.7	34.7	495.0	98.3	0	2017-05-28T00:32:34+09:00
0	69.60	false	23.7	34.8	496.0	98.3	0	2017-05-28T00:32:43+09:00
0	68.61	false	23.7	34.7	496.0	98.3	0	2017-05-28T00:32:53+09:00

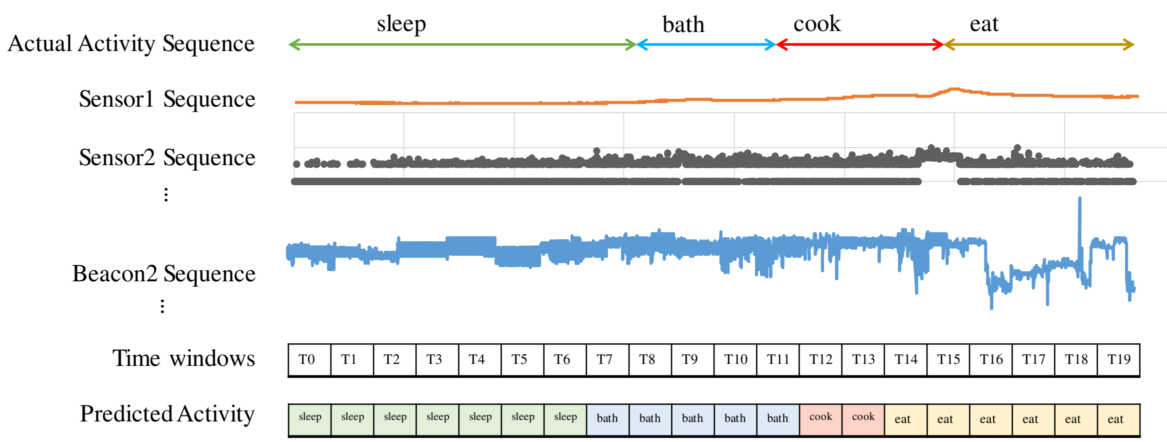

Figure 4: Visualization of Raw data

Table 2: Raw Beacon Data

Lastupdate	Minor	RSSI
2017/05/29 01:18:51	03	-70
2017/05/29 01:18:51	03	-70
2017/05/29 01:18:51	03	-70
2017/05/29 01:18:51	03	-72
2017/05/29 01:18:51	03	-72
2017/05/29 01:18:51	03	-73
2017/05/29 01:18:51	03	-68
2017/05/29 01:18:52	03	-68

For the beacon data, the processing is similar to that of the environment sensing data. The system extracts the feature value from aggregate data within the time-windows. Since the beacon signal is susceptible to changes in the environment, such as humidity, the number of humans present, and it is also easily reflected by surfaces (walls, ceiling, floors, etc.), many of the signals received by the mobile device are noise data. Hence, the first step is noise reduction, especially to filter signals reflected by surfaces. Signals that are farther away from transmission are weaker signals, we extract and save the max RSSI in one second. Then, we determin the same size time-window with sensor data and aggregate data by function such as MIN, AVE, and MAX.

And then, we integrate the aggregated sensor data and beacon data based on this consistent time-window. To achieve the first key idea, that only mining the environment attribute in the room or zone where ADL is occurring, we integrate the sensor data and beacon data based on the location information, which is calculated by the RSSI. When RSSI of one Beacon is larger than a defined value, then we judge the ADL is currently occurring in that room. And then we integrate this room's environmental sensing data with Beacon data.

Lastly, we create training data by joining the time-series ADL log data and integrated data based on the timestamp. Table 3 shows the real training data. In the table, the 'b2.ave' means the average RSSI value of beacon whose Minor is '02'.

3.5 Establish Recognition Model

We apply machine-learning algorithms to the developed features of the training data, in order to construct an AR model. We use a popular classification algorithm 'Multiclass Decision Forest' [11]. By using this algorithm, we constructed a prediction model that classifies the given environmental sensor data and beacon RSSI data into one of the seven ADLs.

Table 3: Training Data

datetime	light	sound	temperature	humidity	presence	b2.ave	b2.min	b3.ave	b3.min	ADLid
2017/5/29 1:20:00	5.00	86.94	0.10	0.08	88.00	-58.35	-55	-66.94	-63	5
2017/5/29 1:20:30	6.00	88.22	0.00	0.00	67.00	-57.62	-57	-64.75	-62	5
2017/5/29 9:55:30	3.00	88.16	0.00	0.08	92.33	-56.35	-55	-67.60	-64	5
2017/5/29 9:57:00	163.00	17.65	0.00	0.08	78.33	-79.65	-686	-61.44	-52	4
2017/5/29 10:33:30	193.00	68.54	0.00	0.41	3.33	-78.37	-73	-63.00	-56	4

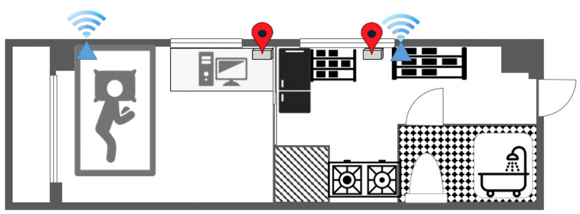

Figure 5: Testbed

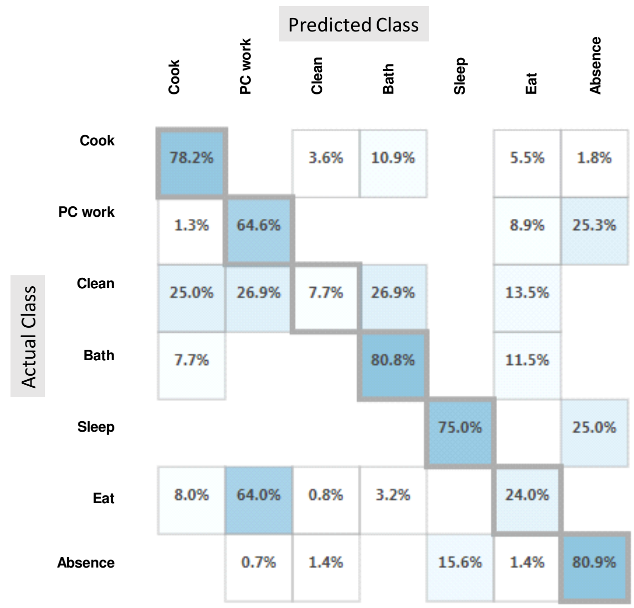

Figure 6: Confusion Matrix of Previous Method

4 EVALUATION OF EXPERIMENT

4.1 Experiment Setup

We deployed the proposed system in the 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 placed two SensorBoxes shown by the red pins in the figure five, one in the kitchen and one in the living room. For beacon stations shown by blue triangles, we placed two stations in the apartment, one at the head of the bed and one near the SensorBox in kitchen.

A total of 645,705 rows of raw sensor data was collected by the kitchen SensorBox. The living room SensorBox collected 483,862 rows of raw data. The living room beacon collected 368,047 rows of raw data. And the kitchen beacon collected 370,372 rows of raw data. For the feature engineering, we set the time window size at 30 seconds, and the aggregation function of environment sensing data at {Min(light), Ave(sound), Std(temperature), Std(humidity), Ave(presence)}. We applied *Multiclass Decision Forest* algorithm to build the AR model and learn the experimental data.

4.2 Results

In order to evaluate the performance of the proposed system, we performed three experiments using the same raw data and same aggregation functions for sensor data and beacon data in the feature engineering, and then used the same algorithm to recognize ADLs.

Figure 6 shows the detailed results of our previously designed system. Figure 7 shows the confusion matrix of the proposed method but only labeled the sensor data with a spatial attribute to build the training data. Figure 8 shows the recognized results of the proposed method along with labeled integrated data for training and testing.

Figure 9 shows the precision of each ADL recognition,and the Micro-average precision and Macro-average precision of each experimental system.

4.3 Evaluation

By comparing the Micor&Macro-average precision of the system, we can see that the new version, which uses integration data, performs significantly better on the 7 typical ADLs recognition.

From Figure 9 we found that the accuracy of cooking, sleeping and absence significantly increased by integrating BLE-based location information. The reason maybe that the three ADLs always occurrs in the same zone in normal life.

However, when ADLs overlap in the same zone, such as PC working and eating, the accuracy of the proposed system is no better than the previous system. When using only labeled sensor data, the precision of overlapping ADL recognition is lower than the previous system. Here the location information is unable to classify these ADLs. The results are counterproductive.

When ADLs occurr space across multi-zones, neither the previous nor the proposed systems can accurately classify them. For instance, the precision of cleaning recognition is likely little better than random return.

5 CONCLUSION

From the result of our previous work, in this paper, we proposed a new system to improve the accuracy of ADLs recognition by adding

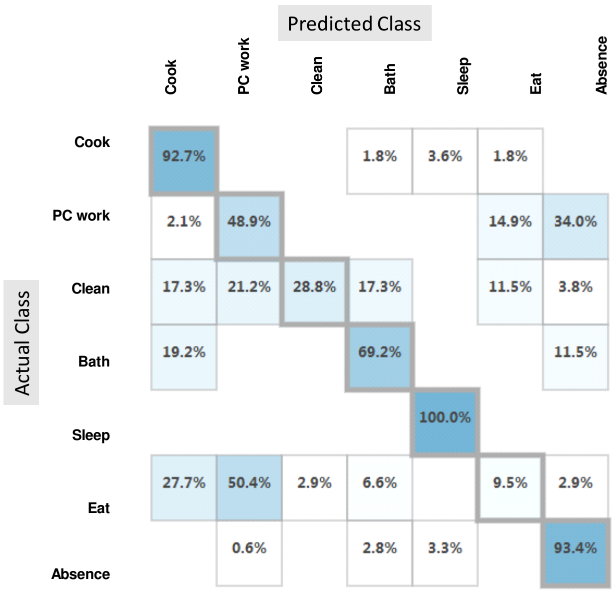

Figure 7: Confusion Matrix of proposed system, only use Sensor data

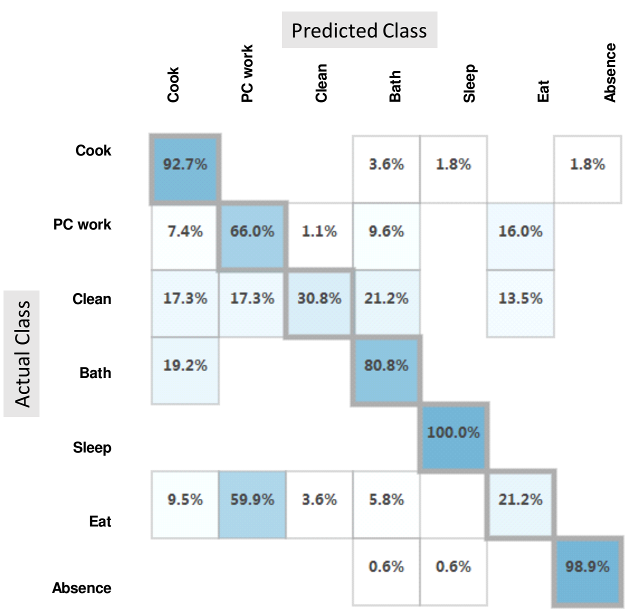

Figure 8: Confusion Matrix of proposed system, use integrate data

a Beacon Measuring System to the original system and integrating BLE-based location data with sensor data in the processing of feature engineering. To evaluate the proposed system, we performed three experiments to compare the precision of ADL recognition and average all ADLs.

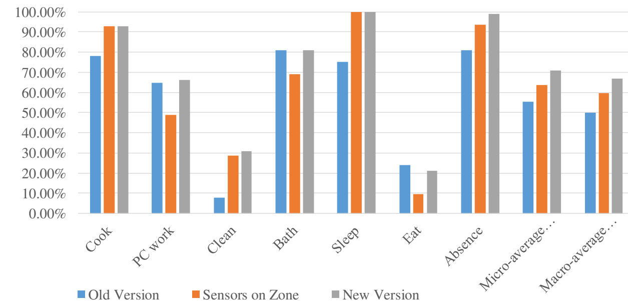

Figure 9: Compare the three AR system result

From the results, we can see that the Micro&Macro-average precisions and accuracy of some ADLs recognition have significantly improved. However, for ADLs where overlap occurrs with other ADLs or the activity space crosses multi-zones, the proposed system's accuracy recognition was not improved.

In the future, we will evaluate the proposed system in a number of houses to see how the learning process varies from one OPH to another. Moreover, we will validate whether the proposed seven types of ADLs are enough to capture the life rhythms in OPH. Finally, developing a servic to assist in the management of a healthy life rhythm based on the AR system is our long-term goal.

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