Predicting Occurrence Time of Daily Living Activities Through Time Series Analysis of Smart Home Data

Wataru Sasaki[1], Masashi Fujiwara[1], Manato Fujimoto[1], Hirohiko Suwa[1], Yutaka Arakawa[1,2], Keiichi Yasumoto[1],
[1] Nara Institute of Science and Technology, Ikoma, Nara 630-0192, JAPAN
E-mail: http://ubi-lab.naist.jp/
[2] JST PRESTO

***Abstract*—Recently, various smart home services such as smart air-conditioning, monitoring of elderly/kids and energy-efficient appliance operations are emerging, thanks to technologies of indoor positioning of users and recognition of Activity of Daily Living (ADL). Meanwhile, to realize more convenient home services, it will become more important to be able to predict occurrence time of each ADL. ADL prediction is a challenging problem since it is difficult to train a prediction model by general machine learning algorithms which use only the data at a moment for classification. In this paper, taking into account temporal dependency of data (consumed power of appliances and position of users) collected during daily life, we propose a method for constructing models to predict ADL with LSTM (Long Short-Term Memory). In the proposed method, we construct LSTM-based models by setting occurrence time of each activity to an objective variable. First, we tried to construct a multi-class classification model which outputs one of several predefined time ranges (time elapsed from present) as the occurrence time of the activity. Through preliminary experiment, we found that this model results in low accuracy in predicting the occurrence time. Then, as the second approach, we constructed a before-or-after classification model which judges if the activity occurs within a specified time or not. We applied this model to our smart home data and confirmed that it achieves better prediction accuracy for all activities.**

***Index Terms*—smarthome, daily living activities, activity prediction, lstm**

I. Introduction

Recently, with the advance of the indoor positioning technology which identifies the resident's position in a home, many services utilizing the position information have been developed. In particular, various smart home services, such as automatic on/off of the lighting, automatic air-conditioning including airflow direction adjustment, etc., have been realized in the latest home appliances. Also, many studies on the recognition of Activity of Daily Living (ADL) have been conducted aiming to realize various services such as elderly monitoring and energy-efficient appliance operations.

Meanwhile, to realize more convenient home services, we believe that it will become more important to be able to predict occurrence time of each ADL. In general, it is desirable for residents to configure environment and/or operate some appliances when or before an activity occurs. It will definitely make our daily life more comfortable if home appliances are automatically controlled to satisfy such resident's desires before an activity occurs. Examples include services such as coffee preparation service according to wake-up time and automatic hot-water filling service before bathing. To realize such smart home services, a method for predicting occurrence time of each activity is mandatory.

There have been some existing studies on ADL prediction. Wu et al. [1] proposed the activity prediction method using the Bayesian network. This method is able to predict 16 types of ADLs by making Bayesian networks based on three types of information: activities, time and date. However, this method focuses only on the type of the next occurring ADL, and does not consider the prediction of the occurrence time of each ADL.

Assuming that time series analysis of sensor data is essential for ADL occurrence time prediction, in this paper, we explore different approaches to time series analysis of sensor data toward ADL prediction. Since the ADL prediction is considered an extension of ADL recognition, we first applied time series analysis to the ADL data collected in a smart home (time series data of ECHONET Lite[1] based appliances' statuses and motion sensors) [2] for ADL recognition. As a result, we found that a classifier trained through time series analysis using LSTM (Long Short-Term Memory) improves the recognition accuracy of some activities [3].

In this paper, we propose a method for constructing models to predict ADLs with LSTM. The proposed method can construct models to predict the next occurrence time for each activity type. Specifically, the method constructs models with time series features computed from the sensor data collected in our smart home as an explanatory variable and the time when an activity occurs as an objective variable. A model is constructed for each type of activity and the models of all activities work together to predict occurrence time of all the activities. We use LSTM to construct models, hence the proposed method enables learning from time series sensor data of motion sensor, power meters attached to appliances and so on for ADL prediction, thanks to the characteristic of

[1]ECHONET Lite is a communication protocol for the control and the sensor network of IoT devices and appliances in a smart home and has been standardized as ISO/IEC-4-3.

978-1-5386-9151-9/19/$31.00 ©2019 IEEE

LSTM that reminisces the past sensor data for learning (e.g., an activity happens after a particular sensor responds).

We use the data collected in [3]. This data contains 20 days of ADL data collected from 5 participants where each participant stayed in the smart home for 3 nights each.

First, we tried to construct a multi-class classification model which outputs one of several predefined time ranges (time elapsed from present) as the occurrence time of the activity. Through preliminary experiment, we found that eating activity occurring within 10 minutes can be predicted with 45.5% of accuracy, but overall this model results in low accuracy in predicting the occurrence time of activities due to too many classes (time ranges).

Then, as a second approach, we constructed a before-or-after classification model which judges if the activity occurs within predefined time interval or not. As a result, we confirmed that it achieves better prediction accuracy for all activities.

II. Related Work

Wu et al. [1] proposed an ADL prediction method where they created a Bayesian network from the information of activity labels, time and date, and predicted 16 types of activities. Kim et al. [4] proposed a method for predicting ADLs using an approach to model the ADL prediction problem as a problem of natural language processing and could predict 23 types of ADLs using LSTM at 82.36% of accuracy. Iram et al. [5] proposed an ADL prediction method using CRF (Conditional Random Fields). Jakkula et al. [6] proposed a method for ADL prediction based on probability variation by the combination of responding time of various sensors. These existing studies for ADL prediction focus on what activity occurs next but does not predict when the activity occurs.

Our proposed method is different from these existing studies in the sense that it uses time series sensor data to predict the occurrence times of activities. Moriya et al. [2] proposed an ADL recognition method using ADL data of ECHONET Lite appliances' statuses and motion sensors and recognized 9 activities with 68% of accuracy. Ueda et al. [7] recognized 10 ADLs with 91% of accuracy from the data of resident's position and power consumption of appliances. However, since these existing studies use features at a moment (e.g., 10 seconds) for ADL recognition and do not take into account temporal dependency in data, it is difficult to apply the methods in these studies to ADL prediction.

We applied a deep learning based method to recognize ADLs [3] and confirmed that LSTM can achieve recognition accuracy comparable to the above machine-learning based methods. Hence, we believe that the LSTM-based method can be used for prediction of ADLs.

III. Proposed Method for ADL Prediction

We propose methods to construct LSTM models which learn occurrence time of ADLs from sensor data.

The goal of ADL prediction is to know what activity occurs next and when it occurs. To achieve this goal, we employ an approach that constructs a model to predict the occurrence time for each activity type. Specifically, we train an LSTM model using sensor data as explanatory variables and occurrence time as objective variable.

Fig. 1. Living Room of Smart Home

We consider two approaches in defining occurrence time. First approach is to represent the occurrence time by multiple time ranges. For instance, we can define occurrence time of an activity in three time ranges: within 10 minutes, between 10 and 30 minutes, and more than 30 minutes. If this kind of prediction becomes possible, we can realize a service such as automatic hot water filling of bathtub in advance by predicting occurrence of "taking a bath" activity. Second approach is to just judge if the activity occurs within a specified time or not. For example, we can set 10 minutes to a threshold and judge if the activity occurs within 10 minutes from now or not. If this prediction is realized, we can realize a service such as automatic air-conditioning in a bedroom by predicting occurrence of "going to bed" activity. We analyze the ADL data by the above two approaches.

The sensor data we used for training models include different sampling rates depending on sensors and the activity label of every second. Hence, we transformed the data to samples of statistical values with 10 second window. Objective variables are set as follows: First, the activity label for each 10 second interval is replaced with the label showing if it is the target activity or not. Then, the time until the target activity is found is calculated by searching forward. Finally, the new label is determined by examining to which class the calculated time belongs.

IV. Experimental Environment

In this section, we describe the experimental environment for collecting ADL dataset. Experimental environment is a smart home (a living room with a kitchen, a bedroom and bathroom, etc) in Nara Institute of Science and Technology. Fig. 1 shows the photo of the living room in the smart home. The ADL data is collected for 15 nights in this smart home. The installed sensors are ultrasonic positioning system [8], Bluetooth watt checker, clamp-on CT (Current Transformer) sensor, ECHONET Lite ready appliance, and motion sensor.

TABLE I
APPLIANCES AND OUTLETS FOR MEASURING POWER CONSUMPTION

Object	Location	Watt	CT	EL
Air conditioner	Bedroom	○	○	○
Outlet on a desk	Bedroom	○		
Outlet of bedside	Bedroom	○		
Lighting	Bedroom			○
Outlet	Bedroom		○	
Refrigerator	Kitchen	○		○
IH heater	Kitchen		○	○
Microwave	Kitchen	○		
Pot	Kitchen	○		
Rice cooker	Kitchen	○		
Outlet	Kitchen		○	
TV	Living room	○		○
Air conditioner	Living room		○	○
Fan	Living room	○		
Lighting	Living room			○
Outlet	Living room		○	
Outlet near sofa	Living room	○		
Lighting	Bedroom, Kitchen Living room		○	
Outlet	Hallway, Kitchen		○	
Bathroom dryer	Bathroom		○	
Outlet	Wash basin room		○	
Lighting	Entrance, Hallway, Bathroom, Toilet, Wash basin room		○	
Electric water heater	Outdoor		○	

A. Sensors used

1) Ultrasonic Positioning System: Ultrasonic Positioning System [8] can measure a position of a person by receiving ultrasonic waves transmitted from a transmitter at multiple receivers which are installed on the ceiling of the smart home. Position information of the person can be obtained in three-dimensional coordinates (x, y, z). The subjects are equipped with a small transmitter on their shoulder to measure the positional information in the smart home. This location information can be measured twice a second.

2) Bluetooth watt checker: Bluetooth watt checker is a sensor capable of measuring the power consumption by installing it between power outlet and appliances. The value of power consumption is measured at a period of once per second. This value is measured in 10 appliances. "Watt" column in Table I shows a list of appliances whose power consumption is measured with this sensor.

3) CT Sensor: Clamp CT sensor is a sensor that can measure the power consumption of the power system where some built-in appliances, lighting devices, water heater, etc. are connected. This sensor is installed in each power system of distribution board. The value of the current flowing in each room can be measured once per second by the CT sensor. The number of power systems measured by CT sensors is 12. "CT" column in Table I shows a list of appliances and outlets whose power is measured as part of a total power of its belonging power system with this sensor.

4) ECHONET Lite: ECHONET Lite is a communication standard that supports some home appliances. In this study, the power on-off information of air conditioning, ceiling light,

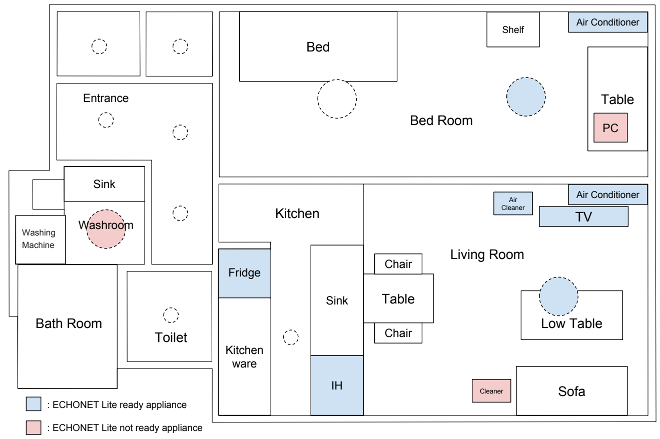

Fig. 2. Location of ECHONET Lite Ready Appliances

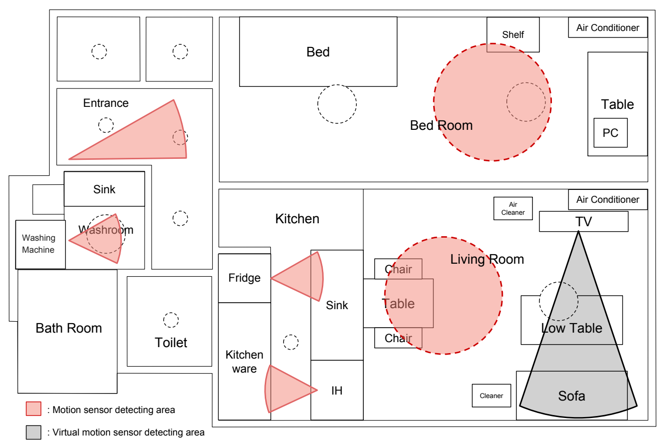

Fig. 3. Installed Positions of Motion Sensors

IH cooking heater, TV and the air purifier, and the door open-close information of the refrigerator are measured. Data is collected at the timing of power on-off and door open-close. In Fig. 2, the blue color shows the ECHONET Lite ready appliances, while the red color shows ECHONET Lite incompatible appliances. Suppose that more appliances will be ECHONET Lite ready in the future, we created the data of on-off information for ECHONET Lite incompatible appliances based on the value of power consumption. "EL" in Table I shows a list of ECHONET Lite ready appliances.

5) Motion sensor: The motion sensor is a sensor that can detect a person who passes nearby the sensor by detecting the infrared signal. The sensor uses the communication standard called EnOcean to send the data. The motion sensor is installed at seven places in the smart home. Additionally, we set a virtual motion sensor to detect a person on the sofa in front of the television by converting data of the ultrasonic positioning system to the sensor's reaction. Fig. 3 shows the installed places of the motion sensors.

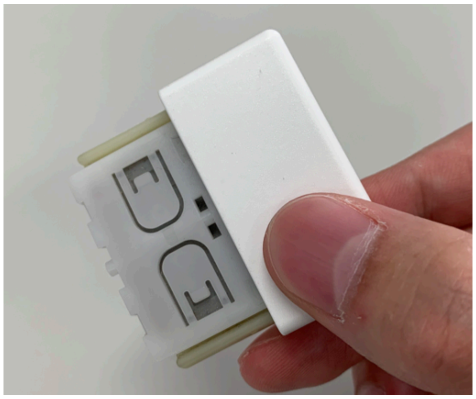

Fig. 4. Button for Recording Timestamp

TABLE II
TARGET ACTIVITIES

Bathing	Teeth Cleaning	Cleaning Room
Cleaning Bathroom	Cooking	Playing Game
Long Go Out	Laundry	Makeup
Eating	Working On PC	Reading Book
Short Go Out	Sleeping	Using Smarthome
Washing Dishes	Face Washing	Watching TV
Not Specified		

V. Data Collection

In this section, we describe the experiment for collecting ADL data.

A. Experiment Overview

Five participants (four males and one female in twenties) spent a daily life as usual in the smart home for three nights (four days) each. We obtained fifteen days of sensor data including positions, power consumption, appliance statuses, and reactions of motion sensors. Participants recorded videos of the rooms by themselves to get the ground-truth label of activities. The video camera was set at arbitrary point in the smart home by each participant. Additionally, participants recorded timestamps by pushing a mechanical button of EnOcean[2] which sends a packet when pushed, as shown in Fig. 4, when starting/finishing each activity.

B. Target Activities

After the experiment, the participants set ground-truth labels by referring videos and timestamps recorded by the button. Table II shows the 19 target activities including "Not Specified" which is activity not belonging to any of other 18 types. The difference between "Long Go Out" and "Short Go Out" is determined based on the go-out duration (over thirty minutes or less). In the smart home, restroom cannot be used. Therefore going to restroom is classified to "Short Go Out" because they have to go to the restroom outside the smart home.

[2]PTM 210:
https://www.enocean.com/en/enocean-modules/details/ptm-210/

C. Instruction to Participants

We instructed the participants as follows. Here, the participants were asked to follow the instructions but do activities anytime they want.

- always keep the button for recording timestamp with the participant
- Do each of activities shown in Table II except for "Makeup" more than once in each day
- Do activities other than "sleeping" for more than three hours in a total in each day.
- Stay in the smart home for more than 10 hours in each day.
- Push the button for recording timestamp at the beginning and end of each activity.

VI. Data Analysis

In this section, we describe analysis methods and results.

We use complete ADL data of 8 days for analysis. We employ two types of analysis methods which use LSTM (Long Short-Term Memory) to construct models. We used Keras [9] to construct LSTM models. Each constructed model has an input layer, a dropout layer, an LSTM layer, a dense layer, and an output layer. All the collected data is divided into 10 seconds segments and for each segment, features are calculated. Input data is reshaped as three-dimensional data (number of data, number of features, and data window).

We set parameters as follows: 100 for look back window length, 10 for number of epochs, and 512 for input batch size. These parameters are empirically decided. Output data is two-dimensional (number of data and number of classes). The one with the highest probability among the probabilities of the classified classes is regarded as the predicted label. As each layer's parameter, we empirically set dropout layer's dropout rate to 0.2, LSTM layer's units to 512, and dense layer's activation function to softmax.

Performance of constructed models is evaluated with Leave-One-Day-Out cross validation where one day is used as test data and the other days as training data.

From each 10 second data segment, we extracted the following features for training models: 3 features from position data (median values of the segment), 10 features from home appliances' power consumption data (median values of the segment), 12 features from current consumption (median value of the segment), 8 features from ECHONET Lite ready appliances statuses (mode value of the segment), 3 features from ECHONET Lite incompatible appliances statuses (mode value of the segment), 7 features from motion sensor's data (whether it reacted at least once in the segment), and 1 feature from virtual motion sensor's data (whether it reacted at least once in the segment). We change the target of prediction according to each analysis method as follows.

A. Multi-class classification for predicting activity occurrence time

1) Analysis method: We construct a model to predict the time (from present) when the target activity occurs next.

TABLE III
ACTIVITY OCCURRENCE RECALL BY DIFFERENT ELAPSED TIME

	Bathing	Teeth Cleaning	Cleaning Room	Cleaning Bathroom	Cooking	Playing Game	Long Go Out	Laundry	Makeup
Now	0.750	0.149	0.000	0.000	0.735	0.522	0.921	0.004	0.207
∼10min	0.004	0.037	0.010	0.093	0.078	0.000	0.051	0.101	0.186
10∼30min	0.033	0.200	0.061	0.125	0.064	0.214	0.242	0.189	0.000
30∼60min	0.110	0.072	0.191	0.248	0.169	0.369	0.200	0.194	0.122
1∼2hour	0.147	0.209	0.075	0.235	0.118	0.219	0.060	0.247	0.048
2∼3hour	0.103	0.163	0.094	0.000	0.104	0.071	0.012	0.029	0.000
	Eating	Working On PC	Reading Book	Short Go Out	Sleeping	Using Smartphone	Washing Dishes	Face Washing	Watching TV
Now	0.594	0.682	0.406	0.094	0.931	0.551	0.210	0.208	0.242
∼10min	0.455	0.000	0.048	0.019	0.047	0.035	0.181	0.228	0.074
10∼30min	0.154	0.000	0.032	0.176	0.079	0.201	0.207	0.057	0.110
30∼60min	0.141	0.052	0.021	0.095	0.214	0.144	0.191	0.000	0.124
1∼2hour	0.268	0.077	0.072	0.148	0.241	0.039	0.178	0.113	0.206
2∼3hour	0.067	0.126	0.056	0.113	0.115	0.034	0.088	0.143	0.104

TABLE IV
TABLE OF ACTIVITY OCCURRENCE RECALL WITHIN THE SPECIFIED TIME

	Bathing	Teeth Cleaning	Cleaning Room	Cleaning Bathroom	Cooking	Playing Game	Long Go Out	Laundry	Makeup
∼10min	0.002	**0.103**	0.000	**0.129**	**0.155**	0.000	**0.190**	**0.138**	0.040
∼30min	0.031	**0.238**	**0.256**	**0.222**	**0.157**	0.204	0.144	**0.284**	**0.270**
∼1hour	0.052	**0.266**	**0.327**	**0.271**	**0.260**	0.259	**0.325**	**0.238**	0.113
	Eating	Working On PC	Reading Book	Short Go Out	Sleeping	Using Smartphone	Washing Dishes	Face Washing	Watching TV
∼10min	**0.474**	**0.004**	**0.150**	0.015	**0.078**	**0.064**	**0.301**	0.133	**0.118**
∼30min	**0.538**	**0.001**	**0.082**	0.092	0.032	**0.268**	**0.370**	**0.399**	**0.164**
∼1hour	**0.564**	**0.053**	**0.226**	**0.270**	**0.307**	**0.399**	**0.370**	**0.450**	**0.246**

Specifically, the learning model is built with sensor data as explanatory variables and the time of the activity occurrence as an objective variable. In this method, the time of the next activity occurrence is specified as 7 time ranges (classes): "Now," "occur within 10 minutes," "occur between 10 and 30 minutes," "occur between 30 and 60 minutes," "occur between 1 and 2 hours," "occur between 2 and 3 hours," and "occur after more than 3 hours passed (or not occur)." We construct a classification model for each activity type so that the occurrence time of any type of activity can be predicted.

2) Analysis Result: Table III shows recall (i.e., accuracy in this case) of occurrence time classification result for all activities. The columns show activities and the rows show the time range in which the target activity occurs next. "Now" indicates that the activity is already in progress, "∼10min," "10∼30min," "30∼60min," "1∼2hour," "2∼3hour" indicate the time range during which the activity occurs. In the table, we did not show the case "more than 3 hours" because we are not much interested in this class (the occurrence time is far from present) and the classification accuracy of this class is rather high since the samples classified to this class are many compared to other classes.

We observed that occurrence time "∼10min" for "eating" was predicted with accuracy of 45.5%. This suggests that it is possible to predict eating activity occurrence time to some extent by analyzing sensor data, for example, acquiring the pattern that eating occurs after cooking (resident is in the kitchen). Since everyone follows the activity order of cooking and then eating, the prediction of eating occurrence achieved the highest accuracy among all activities.

The prediction accuracy for other activities is not so high, caused by incorrect learning due to many different occurrence patterns for each activity type in the collected dataset.

B. Before-or-after classification for predicting next activity occurrence time

1) Analysis Method: We found that multi-class classification based method for activity occurrence time prediction is difficult due to its low prediction accuracy. In practical use, it is important to predict if activity occurs within a certain time rather than predicting activity occurrence by time ranges. More specifically, it is more desirable to predict if the target activity occurs within, e.g., 2 hours than predicting the occurrence time range, e.g., between 1 and 2 hours from present. Hence, as another approach, we construct a model to predict whether or not an activity occurs within a specified time. This model has three classes: (1) is already occurring, (2) occurs within the specified time and (3) occurs after the specified time. It is expected that this simplified model can improve the prediction accuracy for all activities. We use 10 minutes, 30 minutes and 1 hour as "the specified time" in constructing models.

2) Analysis Result: Table IV and Fig. 5 show recall (i.e., accuracy) of activity occurrence time classification for 10 min, 30min and 1 hour as the specified time. In the table, the cases of "Now" and "after the specified time" are omitted because we are interested only in "within the specified time."

The columns show activities and the rows show the time range in which the activity occurs. A higher prediction accuracy than the multi-class case is shown in bold font. For example, the eating activity occurring within 10 minutes could be predicted with 47.4% of accuracy.

Comparing Table III with Table IV, the prediction accuracy of the before-or-after classification is higher in most of the activities. Especially the recall of activity occurring within one hour is improved to a great extent.

However, the overall prediction accuracy is still not high

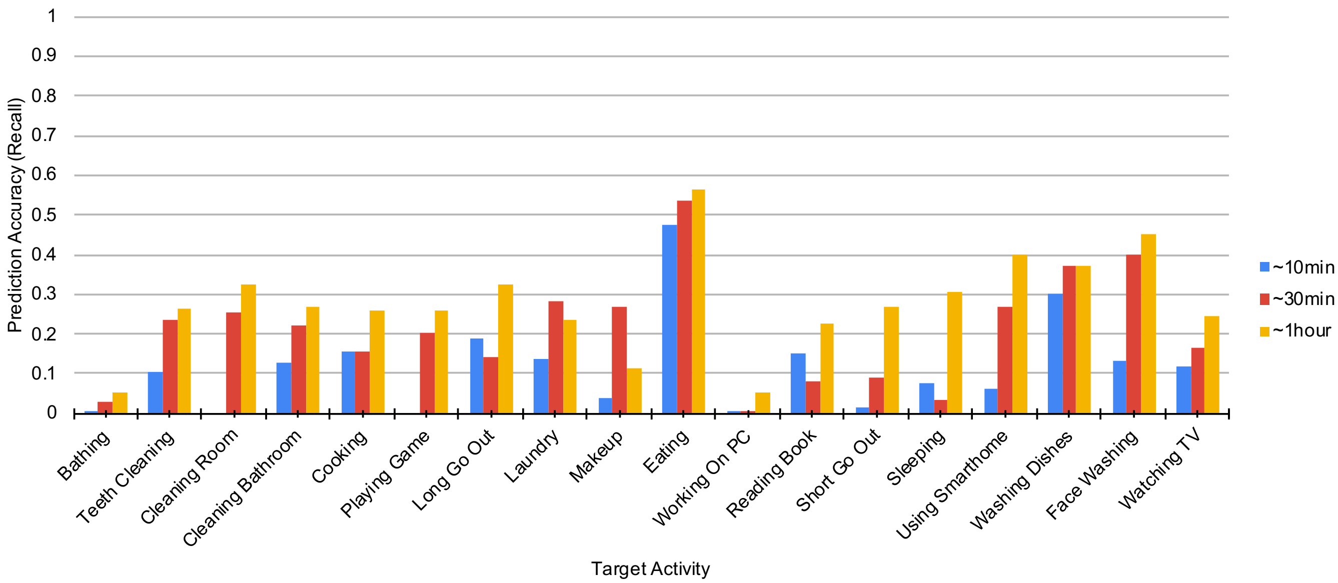

Fig. 5. Graph of Activity Occurrence Recall within the Specified Time

enough for practical use. This result suggests that the activity occurrence patterns are rather irregular in the collected dataset. In our data collection experiments, we instructed participants to do all of the target activities, because activity prediction models could not be constructed unless all activities take place. However, this instruction might have caused difference in activity patterns from those in actual life, making prediction difficult. In this experiment, we analyzed the data rounded in each 10 second time window, but prediction accuracy might be improved by directly analyzing raw sensor data with finer temporal granularity.

VII. Conclusion

In this paper, we proposed two methods to construct LSTM-based models to predict the occurrence time of activities of daily living (ADL). The first method constructs a multi-class classifier which outputs one of the time ranges (elapsed time from present). This method resulted in low prediction accuracy due to insufficient amount of training data and the irregularity of the occurrence time of activities. In the second method, we constructed a before-or-after classifier to judge if the target activity occurs within a specified time or not. With this model, we could achieve much better accuracy than the first model, although the absolute accuracy is not so high for practical use.

In the experiment, as training data, we used simple statistical features (e.g., median, mode, etc.) calculated for samples with 10 second time window. By using finer resolution data, the accuracy could be improved. Investigating this is part of the future work. The experiment in this work collected only limited number of activities because of short experiment period, thus the prediction accuracy was low. To improve the accuracy, we are planning to collect sensor data in the general households for longer period of time by developing and deploying a simple and inexpensive data collection system consisting of a gateway and set of different sensors.

Acknowledgement

This work was in part supported by JSPS KAKENHI Grant Numbers 16H01721 and 17KT0080.

References

[1] Z.-H. Wu, A. Liu, P.-C. Zhou, and Y. F. Su, "A bayesian network based method for activity prediction in a smart home system," in *Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on*. IEEE, 2016, pp. 001 496–001 501.

[2] K. Moriya, E. Nakagawa, M. Fujimoto, H. Suwa, Y. Arakawa, A. Kimura, S. Miki, and K. Yasumoto, "Daily living activity recognition with echonet lite appliances and motion sensors," in *Pervasive Computing and Communications Workshops (PerCom Workshops), 2017 IEEE International Conference on*. IEEE, 2017, pp. 437–442.

[3] W. Sasaki, M. Fujiwara, H. Suwa, M. Fujimoto, Y. Arakawa, A. Kimura, T. Miki, and K. Yasumoto, "Daily living activity recognition through time series analysis of data obtained with echonet lite appliances and motion sensors (in japanese)," *Workshop of Social System and Information Technology (WSSIT18)*, 2018 (in Japanese).

[4] Y. Kim, J. An, M. Lee, and Y. Lee, "An activity-embedding approach for next-activity prediction in a multi-user smart space," in *Smart Computing (SMARTCOMP), 2017 IEEE International Conference on*. IEEE, 2017, pp. 1–6.

[5] I. Fatima, M. Fahim, Y.-K. Lee, and S. Lee, "A unified framework for activity recognition-based behavior analysis and action prediction in smart homes," *Sensors*, vol. 13, no. 2, pp. 2682–2699, 2013.

[6] V. Jakkula and D. J. Cook, "Mining sensor data in smart environment for temporal activity prediction," *Poster session at the ACM SIGKDD, San Jose, CA*, 2007.

[7] K. Ueda, M. Tamai, and K. Yasumoto, "A method for recognizing living activities in homes using positioning sensor and power meters," *the 2nd IEEE PerCom Workshop on Smart Environments: Closing the Loop (SmartE 2015)*, 2015.

[8] L. Song and Y. Wang, "3d accurate location stream tracking and recognition using an ultrasound localization system," in *Proceedings of the 2011 International Conference on Indoor Positioning and Indoor Navigation (IPIN2011)*, 2011, pp. 1–4.

[9] F. Chollet *et al.*, "Keras," https://keras.io, 2015.