A Method for Recognizing Living Activities in Homes using Positioning Sensor and Power Meters

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***Abstract*—To realize smart homes with sophisticated services including energy-saving context-aware appliance control in homes and elderly monitoring systems, automatic recognition of human activities in homes is essential. Several daily activity recognition methods have been proposed so far, but most of them still have issues to be solved such as high deployment cost due to many sensors and/or violation of users' feeling of privacy due to use of cameras. Moreover, many activity recognition methods using wearable sensors have been proposed, but they focus on simple human activities like walking, running, etc. and it is difficult to use these methods for recognition of various complex activities in homes. In this paper, we propose a machine learning based method for recognizing various daily activities in homes using only positioning sensors equipped by inhabitants and power meters attached to appliances. To efficiently collect training data for constructing a recognition model, we have developed a tool which visualizes a time series of sensor data and facilitates a user to put labels (activity types) to a specified time interval of the sensor data. We obtain training samples by dividing the extracted training data by a fixed time window and calculating for each sample position and power consumptions averaged over a time window as feature values. Then, the obtained samples are used to construct an activity recognition model by machine learning. Targeting six different activities (watching TV, taking a meal, cooking, reading a book, washing dishes, and other), we applied our proposed method to the sensor data collected in a smart home testbed. As a result, our method recognized 6 different activities with precision of about 85% and recall of about 82%.**

I. Introduction

In recent years, various sensing devices including smartphones have been on the market and widespread. These sensing devices make it possible to sense various contexts in households, not only environmental information such as temperature and humidity but also human activities and device usage conditions. It is expected that automatic recognition of human activities enables various daily living support services including energy-saving context-aware appliance control in homes [1] and elderly monitoring systems [2]. Such services, however, require high recognition accuracy for many different activities. There are many studies which utilize various sensing technologies and machine learning based methods to recognize human activities in homes. There are several activity recognition systems using fixed cameras such as [4], [5]. However, these systems may decrease users' comfort level since they violate the users' privacy feeling (a feeling of being monitored) by cameras. There are some studies (e.g., [6]) which attach contact sensors to objects like cups and dishes and recognize complex activities like making coffee, making pasta, etc. However, contact sensors must be attached to almost every object, and it will be too costly for use in general homes. Many activity recognition methods using wearable sensors are proposed (e.g., [7]). However, they focus on simple human activities like walking, running, etc. and it is difficult for these methods to use for recognition of various complex activities in homes.

In this paper, we propose a method for recognizing various human activities in homes, which suppresses deployment cost and does not violate users' privacy feeling by using only positioning sensors and power meters. The proposed method targets various in-home daily activities (our final goal is to recognize all of the following activities: cooking, taking a meal, cleaning rooms, washing clothes, taking bath, having a wash, washing dishes, going to washroom, reading a book, studying, changing clothes, makeup, conversation, telephoning, watching TV, listening music, gaming, using PC, outing, and returning home).

In the proposed system, we construct an activity recognition model by applying a machine learning algorithm to sensor logs collected in a target home. To easily obtain training data set from all the data collected in a home, we have developed a tool which visualizes temporal variation of sensor logs consisting of locations of inhabitants, power consumption of each home appliance collected with positioning sensor and power meters. The tool has a function which allows a user to easily attach a label representing activity type to a specific time interval of sensor logs. It also has a function to play back video of each room in the target home so that the user can intuitively confirm what activity actually happens in the video while investigating the sensor value variation in the specified time interval. Each sensor log of a time interval with a label is extracted and stored as training data. Then each training data is divided into samples by a fixed time window (e.g., 5 minutes) and position and power consumptions averaged over time window are calculated as feature values of each sample. Finally, extracted samples with features are used to construct an activity recognition model by associating the features with the label (activity type). Among several machine learning algorithms, we employed SVM (Support Vector Machines) to construct the model.

To evaluate accuracy of the proposed recognition method, we collected sensor data in a smart home testbed (consisting of one bed room, one living room with kitchen, bathroom, washroom, etc.) which was constructed in Nara Institute of Science and Technology (NAIST) and derived accuracy of recognizing six different activities (watching TV, taking a meal, cooking, reading a book, washing dishes, and other) by applying the proposed method to the collected data. As a result, we confirmed that our proposed method recognizes 6 different activities with precision of about 85% and recall of about 82%. We also show that degrading positioning accuracy to some extent does not affect the activity recognition accuracy so much.

II. Related Work

Many studies about indoor activity recognition have been conducted. Activity recognition studies can be roughly categorized into two methods: processing images taken by video cameras, and using various sensors, such as pressure and contact sensors.

Brdiczka et al. [8] proposed a technique for recognizing living activities inside a smart home. Their study used an ambient sound sensor and a 3D video tracking sensor, and achieved recognition rates ranging from 70% to 90% for both individual activities, such as working and naps, and activities performed by more than one person, such as conversations and games. However, their method requires a specific camera and microphone and places the residents at risk to privacy exposure. In addition, the recognition accuracy of their method is not enough as many other activities are left unrecognized.

Kasteren et al. [9] designed a system for recognizing living activities such as eating, watching TV, going out, using the toilet, taking showers, doing the laundry, and changing clothes in a smart home embedded with door sensors, pressure-sensitive mats, float sensor, and temperature sensor. The recognition accuracy of their system ranges from 49% to 98%. It can recognize many activities, but it has a high initial costs and low recognition accuracy depending on the type of activities.

Chen et al. [6] designed a system for recognizing complex living activities such as making coffee, cooking pasta, watching TV, taking a bath, and washing hands in a smart home embedding contact, motion, tilt and pressure sensors. Their system achieved a recognition accuracy greater than 90%. However, this method requires many sensors and overall system cost will be high.

Activity recognition methods that use wearable accelerometers have already achieved accuracies greater than 90% for simple actions such as walking, sitting, running and sleeping [10]. However, using wearable accelerometers to recognize abstract or complex activities has not yet been proposed. The method of Bao et al. [11] can recognize 20 activities, such as watching TV, cleaning, and working, using five wearable accelerometers. However, the burden on users is heavy because it requires a user to wear five sensors. Maekawa et al. [12] focused on the magnetic field generated by home appliances when used, and proposed a method of recognizing the living activities, such as watching TV, shaving, the operation of the mobile phone, brushing of teeth and cleaning, using a wearable magnetic sensor. However, their approach is limited to actions associated with the operation appliances and their recognition accuracy is only approximately 75%.

To overcome the limitations in the aforementioned studies, we propose a daily living activity recognition method that has low initial costs, low privacy exposure, and uses only power meters and indoor positioning sensors that are expected to become widely-used in the future. In addition, our system aims to achieve high recognition accuracy for a range of simple and abstract activities that cover the basic daily living activities in a home.

III. Activity Recognition in Homes: Requirements and Sensors Used

As we already addressed in Sect. I, the following requirements must be satisfied in activity recognition in homes.

(1) Abstract and various types of living activities are recognized.

(2) Low-cost and a small number of sensors are used.

(3) Low privacy exposure of the residents is realized.

Basic steps to solve these requirements are described as follows. To satisfy requirement (1), we target the twenty daily living activities such as "cooking" and "taking a meal" to cover the basic activities in the home. For requirements (2) and (3), we use only indoor positioning sensors and power meters. The following subsection contains the definitions of living activities and the types of sensor data collected.

A. *Definition of living activity*

We describe the target living activities in this section. According to the Statistic Bureau, Ministry of Internal Affairs and Communications in 2011, the main activities within one day is classified into the 20 types shown in Figure 1. The activities are classified as primary activities (i.e., physiologically necessary activities such as sleeping and eating), secondary activities (i.e., mandatory activities in social life such as working and housework), and tertiary activities (i.e,. activities in during times that can be used freely). In addition, a detailed classification method with 6 large classifications, 22 middle classifications, and 90 small classifications of action within one day are also defined. We refer to these definitions in our study, and we extracted the 20 activities as targets of our living activity recognition method: cleaning rooms, washing clothes, taking bath, having a wash, washing dishes, going to washroom, reading a book, studying, changing clothes, makeup, conversation, telephoning, watching TV, listening music, gaming, using PC, outing, and returning home.

B. *Collection of sensor data*

In this subsection, we describe the sensors used in our study. Data is collected by a person living in the smart home shown in Figure 2 (Experimental housing facilities of 1 bed room and 1 living room with kitchen built in the Nara Institute of Science and Technology). In the smart home, power meters, ambient sensors (i.e. temperature, humidity, illumination, human sensors embedded in different places), ultrasonic positioning sensor, door sensors, faucet sensors are deployed. In the proposed method, we use only power meters and ultrasonic positioning sensor for living activity recognition. Sensor data acquired by both sensors are sent by ZigBee and automatically stored in a server. We describe details of each sensor below.

Fig. 1. Examples of living activity classification

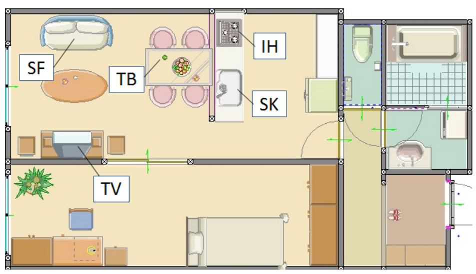

Fig. 2. Floor plan of smart home used in the experiment

1) Ultrasonic positioning sensor: The ultrasonic positioning sensor consists of an ultrasonic transmitter called TAG, and receivers. The receivers are mounted on the ceiling of each room in the smart home as shown in Figure 3. An ultrasonic sensor transmitter, shown in right of Figure 4, is attached to the resident (e.g., in chest pocket), and senses his/her position. The position estimation error is less than 50cm as the nominal value, but in a stationary state of the sensor, we confirmed that the error is within approximately 5cm. The sampling frequency is 2 Hz.

2) Power meter: The power meter shown in left of Figure 4 can collect data from one consumer electronic (100v) per sensor. The sampling period is 30 seconds (2 times per minute). Data are indicated of real number more than 0 in watts (2 decimal places). In addition, there are CT sensors that measure the power consumption of the equipment such as water heaters and lighting. We also used CT sensors in this study.

IV. Living Activity Recognition Method

In this section, we describe our method for recognizing living activities. The proposed method recognizes the daily living activities by machine learning. The process of applying machine learning is composed of the following three steps. (1) Acquisition of training data to be used for learning, (2) extraction of the feature values of the training data acquired, (3) construction of a recognition model for living activities. In the following subsection, we describe the details of these steps.

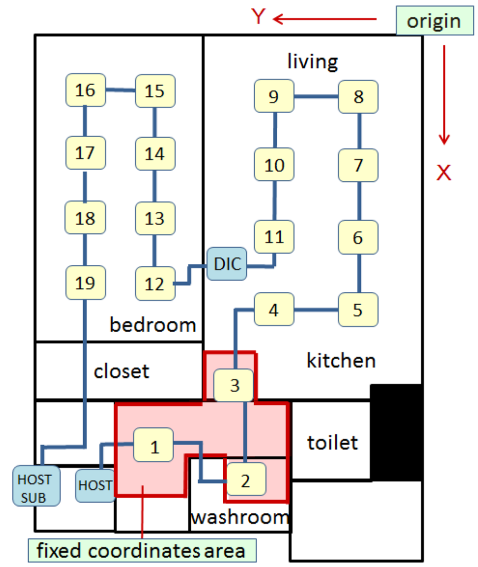

Fig. 3. Receivers location of the ultrasonic positioning sensor

Fig. 4. Power meter and Transmitter of the ultrasonic positioning sensor

A. Acquisition of Training Data

For machine learning, the system needs the training data which have the correspondence between the living activities and the sensor data in advance. We have developed a living activity labeling tool to easily obtain the training data. Figure 5 shows a screen shot of the developed living activity labeling tool. This tool supports the labeling of living activity and visualizing of multiple heterogeneous sensing data collected in a smart home. This tool extracts the data for arbitrary time interval from the accumulated sensor data, and shows graph of various types of sensor data (Power consumption of each home appliance, temperature and humidity of each room, etc.). In addition, it can visualize the movement track of the resident with TAG on the floor plan image by using the information obtained from the ultrasonic position sensor. Furthermore, it integrates a function of synchronously displaying the corresponding video recorded as ground truth, and we can use the labeling function which links arbitrary time interval of sensor data to a specific activity with easy user operation: (1) select the sensor button associated with the action, (2) select a time interval by dragging on the graph, and (3) select the corresponding label of the living activity.

B. Extraction of Feature Value

Feature value is a data that is effective to identify the activities. In the proposed method, we get the feature value from the sensor data of the time interval which is labeled by the living activity labeling tool, as follows. First, we collect

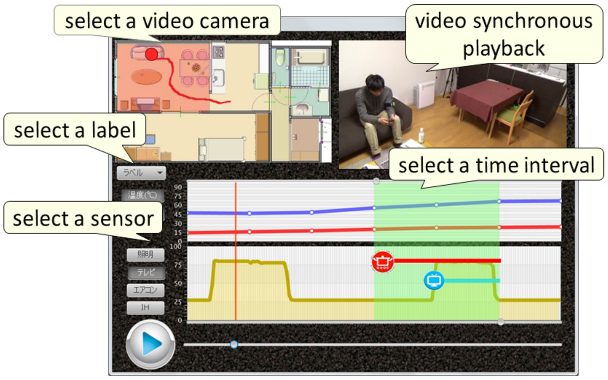

Fig. 5. Daily living activity labeling tool

data set for living activities, then, divide each data by a fixed time interval (window) into samples, and calculate the feature value for each sample which is required to machine learning. We set 5 minutes to time window when dividing each data, since 5 minutes interval achieved the best recognition accuracy in the preliminary experiment with various lengths of time windows. As the feature value, we use the average value of power consumption of each power meter to identify the usage of the corresponding home appliance, and the median value for the position data to mitigate the influence of outliers caused by errors in the ultrasonic sensor.

C. *Construction of Living Activity Recognition Model*

We constructed a machine learning model using feature values of sensor data labeled by the developed labeling tool as training data. In the proposed method, we employ SVM (Support Vector Machines) which is one of the popular pattern recognition algorithms. In SVM, a separation plane which maximizes the distance from each data point is computed to divide the given data set into two classes. To recognize more than two types of activities using SVM, we construct a recognition model for each of the activities and combine all the constructed models so that the given data is classified into one of the activities.

V. EXPERIMENTAL EVALUATIONS

To evaluate the performance of the proposed method, we collected data of daily living activities in the smart home shown in Fig. 2. Below, we describe an overview of experiments and results of evaluation.

A. *Overview of Experiments*

The experiment targeted to recognize six types of activities which occur frequently in a home: watching TV, taking a meal, cooking, reading a book, washing dishes, and other. Two participants (both males in twenties) lived in the smart home for three days each. Data were collected for a total of six days. Each of the participants wore an ultrasonic position transmitter and they performed normal daily activities. In Figure 2, locations of the appliances and furniture that were used for the activities are shown. The TV is located in the area marked “TV” and the participant watched TV while sitting on the sofa, “SF”. The participant cooked using the IH heater, “IH”. Meals were taken on the dining table, “TB”. Finally, dishwashing was done in the sink, “SK”.

After collecting the data, we labeled the sensor data according to activity type using the living activity labeling tool shown in Figure 5. The recorded video was used as ground truth. A total of 150 minutes of sensor data were labeled for each activity. Then, we extracted 30 samples with the feature values from the 150 minutes data by dividing it by 5-minute time window. We used position data and power consumption data for TV and IH cooking heaters, as training data, and we constructed an activity recognition model by applying the SVM algorithm to the extracted samples with feature values. We constructed three different activity recognition models: a model using both the location and the power consumption data, that using only the location data, and that using only the power consumption data. We evaluated these three activity recognition models in terms of recognition accuracy. We prepared 30 samples for each activity as test data used for evaluation where the samples were extracted in the same way as the training data.

In addition, we carried out another experiment with the same configuration as above by degrading the accuracy of the position estimation. In this experiment, the whole space in the smart home is divided by square-shaped cells whose side is 2-meter and 1-meter long, as shown in Figure 6 and we deliberately adjusted the position estimated by the ultrasonic positioning sensor to the center of the cell including the estimated position. Then, we evaluated the influence in the activity recognition accuracy by the degraded position estimation accuracy.

B. *Experimental Results*

Tables I and II show the results when using the activity recognition model constructed using both position and power consumption data. In the confusion matrix in Table I, the rows show the actual activities while the columns show the activities predicted by the activity recognition model. Table II shows the Precision, Recall, and F-measure for each of the living activities. Precision is the ratio of the correct samples to all the samples recognized as a specific living activity. Recall is the ratio of the samples recognized as a specific activity to all the samples of the activity. The F-measure is the harmonic mean of Recall and Precision as shown in the following equation:

$$F = \frac{2\text{Recall} \cdot \text{Precision}}{\text{Recall} + \text{Precision}}$$

As shown in Table II, when both position and power consumption data were used, the proposed method recognized living activities with Precision, Recall, and F-measure of 85.05%, 81.67%, and 81.06% on average, respectively. When focusing on the F-measure of each activity, “watching TV” is the highest with about 89.55% of F-measure, while “washing dishes” resulted in the lowest F-measure of about 74.57%. For “watching TV”, the highest F-measure is owing to a big feature on the power consumption of the TV and the position data of the sofa in the living room when the user is watching TV. The reason why precision of “watching TV” was not 100% is that a small number of the activities were mistakenly classified to “reading a book”. The proposed method could not distinguish

TABLE I. CONFUSION MATRIX IN THE CASE OF USING BOTH THE POWER CONSUMPTION AND POSITION INFORMATION

	cooking	taking a meal	washing dishes	watching TV	reading a book	other
cooking	24	0	6	0	0	0
taking a meal	0	30	0	0	0	0
washing dishes	0	8	22	0	0	0
watching TV	0	0	0	30	0	0
reading a book	0	0	0	4	26	0
other	0	7	1	3	4	15

TABLE II. EVALUATION RESULTS IN THE CASE OF USING BOTH THE POWER CONSUMPTION AND POSITION INFORMATION

living activity	Precision(%)	Recall(%)	F-measure(%)
cooking	100.00	80.00	88.89
taking a meal	66.67	100.00	80.00
washing dishes	75.86	73.33	74.57
watching TV	81.08	100.00	89.55
reading a book	86.67	86.67	86.67
other	100.00	50.00	66.67
average	85.05	81.67	81.06

TABLE III. CONFUSION MATRIX IN THE CASE OF USING ONLY THE POSITION INFORMATION

	cooking	taking a meal	washing dishes	watching TV	reading a book	other
cooking	28	0	2	0	0	0
taking a meal	0	30	0	0	0	0
washing dishes	5	7	18	0	0	0
watching TV	0	0	0	19	11	0
reading a book	0	0	0	21	9	0
other	0	6	1	6	1	16

TABLE IV. EVALUATION RESULTS IN THE CASE OF USING ONLY THE POSITION INFORMATION

living activity	Precision(%)	Recall(%)	F-measure(%)
cooking	84.85	93.33	88.89
taking a meal	69.77	100.00	82.19
washing dishes	85.71	60.00	70.59
watching TV	41.30	63.33	50.00
reading a book	42.86	30.00	35.30
other	100.00	53.33	69.56
average	70.75	66.67	66.09

"reading a book" while turning on TV from "watching TV". On the other hand, for "washing dishes", not small number of the activities were mistakenly classified to "cooking" or "taking a meal". This is because some of "cooking" activities included precooking behavior which does not use IH heater, and they were difficult to be distinguished from "washing dishes".

Tables III and IV show the confusion matrix and the recognition accuracy result, respectively, by the model constructed using only the position data. Average precision, recall, and F-measure of all living activities were about 70.75%, 66.67%, and 66.09%, respectively, which are lower than when using both position and power consumption data. The F-measure of the "cooking" and "taking a meal" were relatively high (88.89% and 82.19%, respectively), however, those of "reading a book" and "watching TV" were low (50.00% and 35.30%, respectively). This is because the activities of "reading a book" and "watching TV" happened in the same place (i.e., sofa), so it was difficult to distinguish those activities with only position information.

Tables V and VI show the confusion matrix and the recognition accuracy results by the model constructed using only the power consumption data. Average precision, recall, and F-measure of all living activities were about 29.80%, 42.78%, and 31.87%, which are the lowest among all the three models. These results indicate that activities of watching TV and cooking can be recognized with relatively high accuracy by using only power consumption data, however, activities without using power like "reading a book" and "taking a meal" are difficult to recognize without position information.

C. Evaluations with Degraded Positioning Accuracy

The smart home we used for the above experiments is equipped with a highly accurate position estimation system using ultrasonic sensors, but it is too costly to be used in general homes at present. Then, assuming the use of the indoor positioning system of lower cost (e.g., systems using infrared sensors, iBeacon, etc.), we intentionally degraded accuracy of estimated positions. For the degradation purpose, the whole space in the smart home is divided by square-shaped cells whose side is 2-meter or 1-meter long, as shown in Figure 6 and we adjusted the position estimated by the ultrasonic positioning sensor to the center of the cell including the estimated position. Then, we evaluated the influence in the activity recognition accuracy by the degraded position estimation accuracy. Tables VII and VIII show the evaluation results for the cases with 2m and 1m cells, respectively.

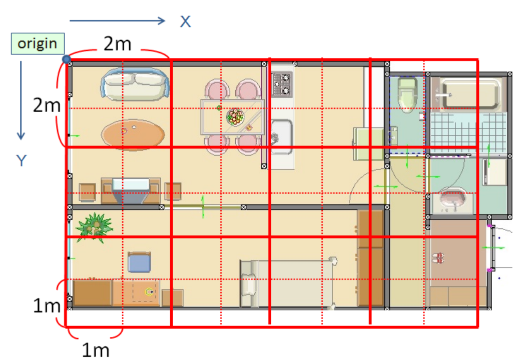

Fig. 6. Degradation of estimated position by cell

The average F-measure for 1m-cell case and 2m-cell case were 79.82%, and 75.86% respectively. This indicates that the recognition accuracy reduces as the position estimation accuracy degrades. However, the degree of reduction is rather small, and the activity recognition accuracy for 2m-cell case is still comparable to that for the best positioning accuracy (Table II). The F-measure of "cooking" for 1m-cell and 2m-cell cases were 93.10% and 76.92%, respectively, and there is a big degradation. This is because it is difficult to distinguish the position between the sink and the IH heater when using 2m-cell. This suggest that accurately recognizing "cooking" requires 1m-cell positioning accuracy.

Throughout the experiment, we confirmed that it is possible

TABLE V. CONFUSION MATRIX IN THE CASE OF USING ONLY THE POWER CONSUMPTION

	cooking	taking a meal	washing dishes	watching TV	reading a book	other
cooking	21	0	0	0	9	0
taking a meal	0	0	0	5	25	0
washing dishes	0	0	0	11	19	0
watching TV	0	0	0	30	0	0
reading a book	0	0	0	4	26	0
other	0	0	0	6	24	0

TABLE VI. EVALUATION RESULTS IN THE CASE OF USING ONLY THE POWER CONSUMPTION

living activity	Precision(%)	Recall(%)	F-measure(%)
cooking	100.00	70.00	82.35
taking a meal	0	0	0
washing dishes	0	0	0
watching TV	53.57	100.00	69.77
reading a book	25.24	86.67	39.09
other	0	0	0
average	29.80	42.78	31.87

TABLE VII. EVALUATION RESULTS IN THE CASE OF THE SEPARATING BY A CELL OF 1M POSITION INFORMATION

living activity	Precision(%)	Recall(%)	F-measure(%)
cooking	96.43	90.00	93.10
taking a meal	75.68	93.33	83.58
washing dishes	73.08	63.33	67.86
watching TV	76.00	100.00	86.36
reading a book	83.87	86.67	85.25
other	76.19	53.33	62.74
average	80.21	81.11	79.82

TABLE VIII. EVALUATION RESULTS IN THE CASE OF THE SEPARATING BY A CELL OF 2M POSITION INFORMATION

living activity	Precision(%)	Recall(%)	F-measure(%)
cooking	90.90	66.67	76.92
taking a meal	62.50	100.00	76.92
washing dishes	60.00	60.00	60.00
watching TV	81.08	100.00	89.55
reading a book	89.66	86.67	88.14
other	100.00	46.67	63.64
average	80.69	76.67	75.86

to recognize various living activities in homes by using a positioning sensor and power meters with sufficiently high accuracy. We also found that the high-accuracy (and high-cost) positioning system is not necessary and a low-cost positioning sensor which can detect a rough position of the resident in the room is enough for living activity recognition.

VI. CONCLUSION

In this paper, we proposed a method for recognizing in-home daily activities from data sensed by a positioning sensor and power meters attached to appliances based on machine learning. In the proposed method, to mitigate users' feeling of being monitored and suppress deployment costs, only data of users' position and power consumptions of appliances are used to construct a recognition model. Experimental results show that the proposed method using SVM can recognize six different activities: cooking, taking a meal, washing dishes, watching TV, reading a book, and other, with a precision of 85.05% and a recall of 81.06%. We also confirmed that sufficiently accurate recognition results are obtained even when degrading accuracy of the positioning sensor to some extent.

As part of future work, we will extend our model to recognize more activity types. Also, we plan to improve recognition accuracy by adding more features like time when activity happens, deviation in the sensor data, and so on.

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