ALPAS: Analog-PIR-sensor-based Activity Recognition System in Smarthome

Yukitoshi Kashimoto, Masashi Fujiwara, Manato Fujimoto, Hirohiko Suwa, Yutaka Arakawa, Keiichi Yasumoto
Graduate School of Information Science, Nara Institute of Science and Technology
Ikoma, Nara 630-0192, Japan
Email: {kashimoto.yukitoshi.km3, fujiwara.masashi.fe8, manato, h-suwa, ara, yasumoto}@is.naist.jp

***Abstract*—These days, smart home applications such as a concierge service for residents, home appliance control and so on are attracting attention. In order to realize these applications, we strongly believe that we need a system which recognizes the various human activities accurately with a low cost device. There are many studies which work on the activity recognition in the smarthome. Moreover, we also have proposed the activity recognition technique in the smarthome by utilizing the digital-output-PIR sensor, door sensor, watt meter. However, the study has the challenge: we cannot distinguish between the similar tiny activities at the same place: "eating" and "reading" with sitting on a sofa. In order to cope with this challenge, we introduce ALPAS: analog-output-PIR-sensor-based activity recognition technique which recognizes the detailed activities of the user. Our technique recognizes the activity of the user by utilizing the machine learning. We evaluated the proposed technique in a smarthome which belongs to the authors' university. In the evaluation, three subjects performed four different activities with sitting on a sofa. As a result, we achieved F-Measure: 57.0%.**

I. Introduction

Thanks to the progress of ubiquitous computing technology, there is a strong anticipation to realize the smart daily life support system such as the energy saving home appliance control[1][2], care-taking system for senior citizen, and concierge system[3][4] in smarthome. In order to realize these applications, we need to develop a technique which recognizes the various activities of human accurately with low cost device.

There are many studies which work on the activity recognition in smarthome[5][6]. These studies estimate the activity of the user by utilizing an acoustic sound captured or the usage of electric appliances in smarthome. In addition, we have worked on the development of the activity recognition technique by utilizing ultrasonic-sound-based indoor positioning, watt meter attached to each appliance, Passive Infra-Red (PIR) sensor, and door sensors[7][8]. In these studies, we have defined the requirements: "(i)Abstract and various types of living activities are recognized," "(ii) Low-cost and a small number of sensors are used," "(iii) Low privacy exposure of the residents is realized," and "(iv) Tag-free activity recognition." Based on the requirements, we have developed the activity recognition techniques.

However, these studies have a challenge: we cannot recognize the activity when the user performs different activities at the same location, e.g. the user performs "eat" and "read" with sitting on a sofa. Since this misclassification may stir up the service degradation of smart home applications, we need to develop a technique to solve this challenge. This challenge arises from the characteristic of the techniques. In those techniques, we estimate the activity of user by utilizing the correlation between the activity and location, i.e. when the user exists in the kitchen area, we estimate that the user "cooks." Thus, we need to develop a system which recognizes the activities even though the user performs them at the same location, which we define as an additional requirement: "(v) Different activities at the same location are recognized."

In order to recognize the multiple activities at the same location, we can assume to utilize a camera[9][10], wearable sensor or smartphone[11][12]. In the camera approach, we estimate the user's activity by utilizing the image processing technique. However, the camera approach intrudes the user's privacy, which does not fulfill Requirement (iii). On the other hand, the wearable sensor and smartphone approach utilize accelerometer inside and activity recognition technique. Nevertheless, these approaches demand the user to carry the device, which does not fulfill Requirement (iv). Thus, we need to develop a new technique which fulfills all requirements.

In order to cope with the above mentioned challenges, we introduce ALPAS[1]: Analog-output-PIR-sensor-based activity recognition technique which recognizes the detailed activities of the user. An analog output PIR (Analog PIR) sensor is a sensor which recognizes the activity of the user, even though he/she performs different activities at the same location. Moreover, Analog PIR is easily deployed by converting the ordinary digital output PIR (Digital PIR) sensor. Digital PIR sensor is a sensor which is widely used for home appliances control in smarthome. Digital PIR sensor outputs "1" when the user exists close to the sensor, while the sensor outputs "0" when the user does not exist. Compared with Digital PIR sensor, Analog PIR sensor outputs high voltage when the user exists near the sensor, while the sensor outputs low voltage when the user does not exist. Moreover, the sensor outputs high frequency signal when the user moves rapidly. Based on this difference, our proposed system recognizes the activity of the user by utilizing the machine learning, which fulfills Requirement (v). Above all, the proposed system recognizes the user's activity even when the user performs different activities at the same location, which fulfills Requirement (i). Analog PIR sensor itself is low-cost sensor and should be placed to the particular place at which multiple activities occur, which fulfills Requirement (ii). The proposed system does not capture any image or sound of the user, which fulfills Requirement

[1]ALPAS: **A**na**L**og **P**ir-sensor-based **A**ctivity recognition **S**ystem

1550-445X/17 $31.00 © 2017 IEEE
DOI 10.1109/AINA.2017.33

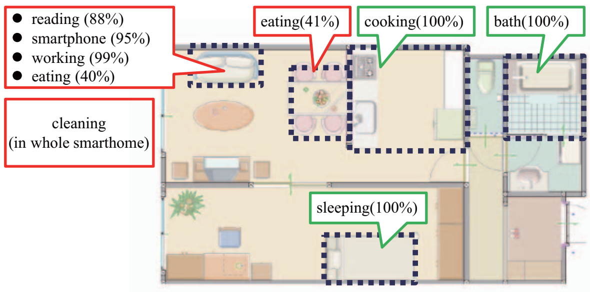

Fig. 1. Correlation between position and activity
(Each number shows the ratio of the activity that occurs the position.)

(iii). Analog PIR sensor does not demand the user to carry any device, which fulfills Requirement (iv). Therefore, the proposed system enables us to realize the activity recognition system that fulfills the all requirements (i)–(v).

We evaluated the proposed technique in a smarthome which belongs to the authors' university. In the evaluation, three subjects performed four different activities with sitting on a sofa. As a result, we achieved F-measure: 57.0%.

II. Related work

Many studies on the activity recognition in the smarthome have been reported. We introduce the related works on activity recognition in smart home in the following two parts: "Activity recognition by utilizing the correlation between the activity and location" and "Motion-recognition-based activity recognition."

A. Activity recognition with activity-location-correlation

There are many studies which estimate the user's activity by utilizing the correlation between the activity and location of the user[13][14]. That is, if the user exists in the kitchen, the system estimates that the user cooks.

Kasteren et al.[13] designs 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.[14] designs 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.

Ueda et al.[7] introduces the activity recognition system in smarthome by utilizing the ultrasonic-sensor-based indoor positioning system and wattmeter attached to each home appliance. Nevertheless, the system demands the user to carry an ultrasonic transmitter, which is obtrusive to the user.

Kashimoto et al.[8] estimates the user's activity based on the correlation between the user's position and activity by utilizing Digital PIR sensor. However, their technique cannot distinguish the above mentioned activities, since there is little difference of the user's position and power consumption when he/she performs them with sitting on the sofa. Figure 1 illustrates the correlation between the user's position and activity. For "cooking," "bathroom activities," and "sleeping," most activities occur at the same location. On the other hand, "reading," "smartphone," "working," and "eating" occur at the sofa. Thus, this technique cannot distinguish these activities.

B. Motion-recognition-based activity recognition

In order to recognize the multiple activities at the same location, we can assume to utilize a camera[9][10], wearable sensor or smartphone[11][12].

There are several studies which estimate the user's activity by utilizing camera. Hoev et al.[9] estimate the user's activity by utilizing the image processing technique and partially observable Markov decision process. Loran et al.[10] estimate the activity of the user who walks inside the building by utilizing the stereo camera and image processing technique. However, the installation cost of the cameras, which the user has to set up in every room in the building, and cable which connects between the camera and the processing server becomes burden on the user.

Wearable sensor approaches estimate the activity of the user by utilizing mobile devices such as a smartphone, smart watches and so on[11]. Mase et al[12] has proposed a technique to estimate the user's activity such as "walk," "run," and "sit" by utilizing the accelerometer and gyroscope attached to the user.

However, the wearable sensor approach has a challenge that the sensor can just estimate the activities which has strong correlation with the user's posture. Moreover, the user always has to carry the device and change the battery, which is obtrusive to the user.

C. Approach of Analog PIR sensor-based activity recognition

In order to solve the challenges in the previous studies, we aim to develop an activity recognition system by utilizing Analog PIR sensor, which has features of low installation and operation cost, and low privacy intrusion. The proposed system enables us to recognize the user's activity accurately, even though he performs different activities with sitting on a sofa. Additionally, we can realize the proposed system just by converting the digital-output PIR sensor to an analog one in a simple manner.

In other words, we need to develop an activity recognition system which fulfills the requirements (i)–(v) mentioned in Chapter I.

- Req 1: Abstract and various types of living activities are recognized.
- Req 2: Low-cost and a small number of sensors are used.
- Req 3: Low privacy exposure of the residents is realized.
- Req 4: Tag-free activity recognition
- Req 5: Different activities at the same location are recognized.

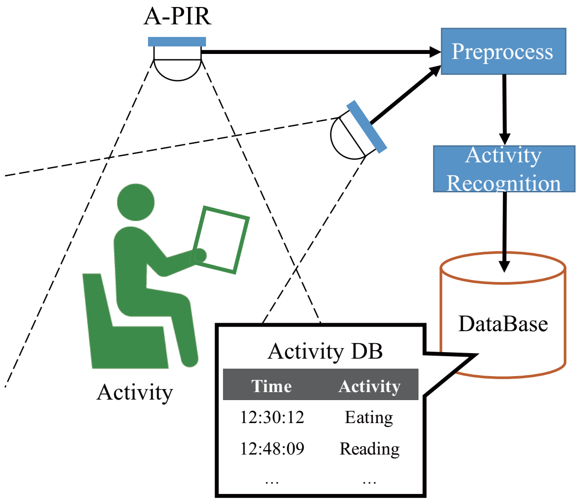

Fig. 2. System overview

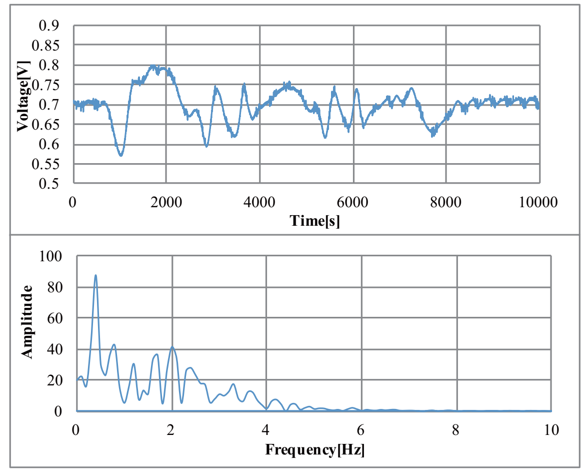

Fig. 3. Output of Analog PIR sensor when the user moves fast (Upper graph: raw signal, Lower graph: frequency component)

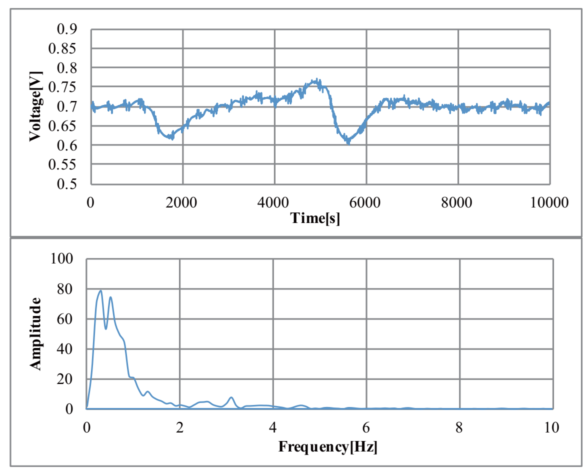

Fig. 4. Output of Analog PIR sensor when the user moves slowly (Upper graph: raw signal, Lower graph: frequency component)

In order to fulfill Req 1, the proposed system recognizes the user's activity even when the user performs different activities at the same location. For Req 2, Analog PIR sensor itself is low-cost sensor and should be placed to the particular place at which multiple activities occur. For Req 3, the proposed system does not capture any image or sound of the user. For Req 4, we adopt the PIR sensor, which does not demand the user to carry any mobile device. For Req 5, we need to develop Analog PIR sensor that has an analog output which fluctuates in accordance with the user's activity. Above the all, the proposed system enables us to realize the activity recognition system that fulfills the all requirements 1–5.

III. Analog-PIR-sensor-based activity recognition

A. System overview

Figure 2 illustrates an overview of the Analog-PIR-sensor-based activity recognition system. Our system consists of Analog PIR sensor, the preprocessing module, activity recognition module and activity database. Analog PIR sensor outputs the electric signal which corresponds to the user's activity. The sensor outputs the large amplitude wave when the user exists close to the sensor. The sensor outputs the high frequency signal when the user moves fast. Our system processes the signal in the following three steps: First, the signal from the PIR sensor is treated in the preprocessing module to be divided into a particular time window and applied the window function. Second, we extract the frequency feature by utilizing Fast Fourier Transform (FFT). Finally, we estimate the user's activity by utilizing the classifier, which is generated by machine learning technique, and store the result into the database: Activity DB.

B. Basic study on Analog PIR sensor

In order to adopt Analog PIR sensor, we have conducted a preliminary experiment and studied Analog PIR sensor. In the experiment, a subject moved fast or slowly in front of Analog PIR sensor. The distance between the subject and sensor was about 50cm. Then, we observed the output of Analog PIR sensor. Figure 3 shows the output signal when the user moves fast. Figure 4 shows the output signal when the user moves slowly. In both figures, the upper graph illustrates the raw signal of Analog PIR sensor, while the lower graph does the frequency component of the output signal. By comparing these two figures, we confirmed that we can recognize lively activities such as "eat" from the higher component of frequency. On the other hand, we recognize slow activity such as "read" from the lower component of frequency.

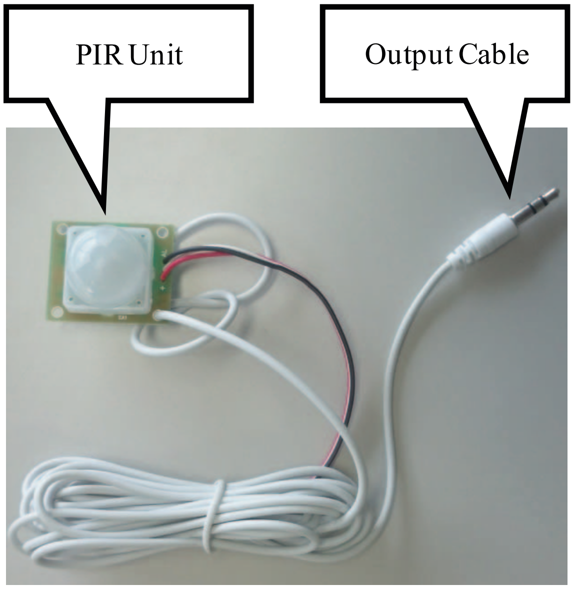

Fig. 5. Analog PIR sensor

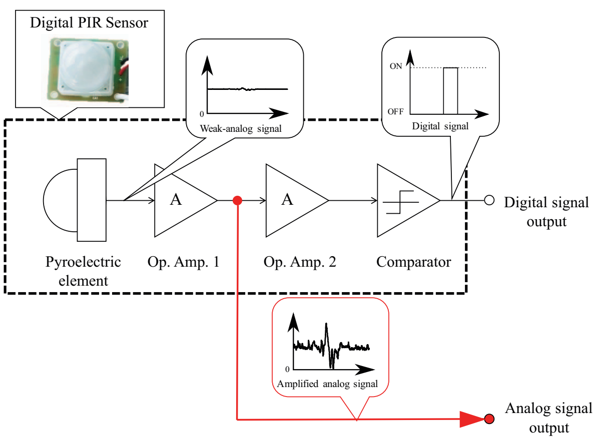

Fig. 6. Block diagram of Analog PIR sensor

C. Implementation of Analog PIR sensor

Our proposed system requires Analog PIR sensor. However, most popular PIR sensors on the market are digital-output, and there is not any analog-output PIR sensor that allows us to introduce with low cost. Then, we have decided to convert Digital PIR sensor on the market to the analog one in a simple manner. By adopting this technique, we utilize the current digital PIR sensor that has been already installed in smarthome, and realize the proposed system with small installation cost. Figure 5 illustrates Analog PIR sensor which we have developed. Figure 6 illustrates the block diagram of the analog-output PIR sensor. Initially, this sensor was a digital-output PIR sensor[2]. Digital PIR sensor consists of a pyroelectric element, two operational amplifiers and a comparator. Because of weak output signal from pyroelectric element, two operational amplifiers amplify the signal. Then, the comparator converts the amplified signal into the digital (On/Off) signal. Then, we have converted it to Analog sensor by modifying the wiring of the circuit board inside. We can capture analog signal output from the output port of pyroelectric element. However, the output signal of pyroelectric element is weak to be captured. Therefore, as shown in the Figure 6, we capture slightly amplified analog signal from an output port of the first operational amplifier.

D. Activity recognition by utilizing machine learning

In this section, we describe the details of our activity recognition technique. Our system estimates the user's activity by utilizing the machine learning technique. We conduct the machine learning with the following three phases: In the first phase, we acquire the training data for learning. In the second phase, we extract the feature vector from the data. In the third phase, we generate the activity recognition classifier from the extracted features.

(Phase 1) Acquisition of the training data: In order to conduct the machine learning, we need to obtain the training data which contains the pair of the sensor data and activity labels. In our research, we annotate the label to the data manually.

(Phase 2) Feature vectors extraction: In "Phase 2," we extract the feature vector for the machine learning in the following two steps: First, we divide the sensor data by a particular time-window. Second, we extract the feature vector for each time window. In our research, we have applied the time-window by 10 seconds empirically. We have selected the frequency feature of the sensor output which is calculated by FFT.

(Phase 3) Activity recognition model generation: In "Phase 3," we generate the activity recognition classifier from the dataset that we have obtained in "Phase 1" and feature vector that we have processed in "Phase 2." In order to generate the classifier, we have used Weka[3], which is famous as a machine learning and data mining tool. Weka has various machine learning and classifier algorithms. For our research, we have selected Random Forest classifier empirically.

IV. Evaluation

We conducted the evaluation to measure the performance of the proposed system.

A. Evaluation method

From our preliminary study, we selected four target activities: "eat," "read," "PC," and "Smartphone" which the user often performs with sitting on a sofa. Figure 7 describes the evaluation environment. We installed two PIR sensors: one sensor on the ceiling above the sofa and the other sensor on the wall aside the sofa so that the sensors capture the movement of

[2]Digital PIR sensor, http://akizukidenshi.com/catalog/g/gM-02471/

[3]Weka: http://www.cs.waikato.ac.nz/ml/weka/

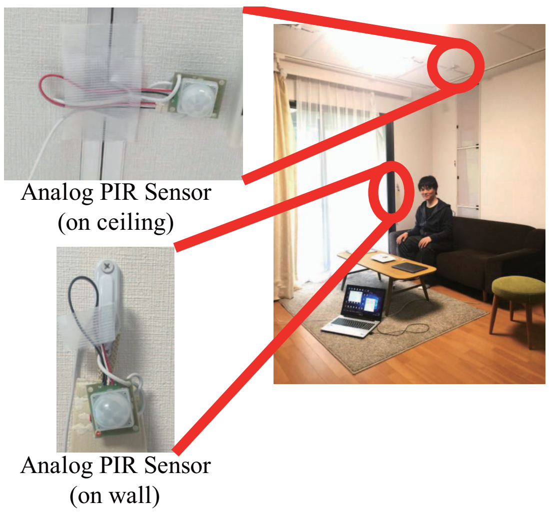

Fig. 7. Evaluation environment

the user's hand and body. Three subjects, 20-years-old males, participated in the evaluation. A subject performed the above four activities with sitting on the sofa between 6–16 minutes.

After collecting the data, we annotated the activity labels to it. As the feature vector, we selected the frequency component of Analog PIR sensor. We describe the procedure of the feature extraction as followings:

1) Sampling the sensor data
2) Dividing the sensor data with the time-window
3) Sliding the time-window

In the first step, we captured the sensor data with 1.0 msec sampling interval. We recorded each activity between 6 min.–16 min. In the second step, we divided the data into 10 second time-window. After that, we applied Hamming window to the data empirically. We extracted the frequency component between 0–50 Hz by utilizing FFT. In the third step, we moved the sliding window for 2.5 seconds, which we determined empirically. In the fourth step, we repeated the Step 1–3 for the all data. By utilizing the feature vector extracted from the above mentioned steps, we generated the classifier model for the activities: "Eat," "PC," "Read," and "Smartphone."

We conducted three evaluations: Evaluation 1: 10-fold cross-validation, Evaluation 2: Leave-one-day-out cross-validation, and Evaluation 3: Leave-one-person-out cross-validation. In Evaluation 1: 10-fold cross-validation, we evaluated that the selected frequency component was enough to distinguish the activities. In Evaluation 2: Leave-one-day-out cross-validation, we evaluated the adaptability of the proposed system to a new day's data. In Evaluation 3: Leave-one-person-out cross-validation, we evaluated the adaptability of the proposed system to a new person.

B. Result and Discussion

TABLE I
CONFUSION MATRIX FOR FOUR ACTIVITIES

	Eat	PC	Read	Smartphone
Eat	345	105	64	4
PC	104	717	220	159
Read	107	317	632	144
Smartphone	59	226	206	579

TABLE II
EVALUATION RESULT FOR 10-FOLD CROSS-VALIDATION

Eval. item	Eat	PC	Read	Smartphone	Weighted Avg.
Precision	56.2%	52.4%	56.4%	65.3%	57.9%
Recall	66.9%	59.5%	52.6%	54.3%	57.0%
F-Measure	60.9%	55.6%	54.3%	59.1%	57.0%

1) Evaluation result for 10-fold cross-validation: Table I shows the confusion matrix for "Evaluation for 10-fold cross-validation." Each row in the confusion matrix describes the activity which the user performs in the evaluation. Each column describes the predicted activity. Table II shows the Precision, Recall, and F-Measure for each activity. Precision is the ratio of retrieved instances that are relevant. Recall is the ratio of relevant instances that are retrieved. We obtained F-Measure from the following equation.

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

Table II reported that the average F-Measure was 57.0%. "Eat" had the highest F-measure: 60.9%, while "PC" was 55.6%, "Read" was 54.3%, and "Smartphone" was 59.1% respectively. When the user performed "Eat," the user moved rapidly, which bred the evident difference on the frequency. Meanwhile, the frequency feature difference between "PC," "Read," and "Smartphone" achieved the particular performance. In summary, we confirmed the effectiveness of the machine learning technique by utilizing the frequency feature.

In addition, it is assumed that we achieved better activity recognition performance than Kashimoto et al.[8]. Kashimoto et al. estimates the user's activity based on the correlation between the user's position and activity by utilizing Digital PIR sensor. However, their technique cannot distinguish the above mentioned activities, since there is little difference of the user's position and power consumption when he/she performs them with sitting on the sofa. On the other hand, our technique estimates the user's activity from Analog PIR sensor output that changes in accordance with the activity. The comparison between these two studies is our future work.

2) Leave-one-day-out cross-validation: Table III reported the evaluation result of "Leave-one-day-out cross-validation." We confirmed that we classified the user's activities with average F-Measure: 36.6% by utilizing the proposed technique. The lower F-Measure compared with "Evaluation of 10-fold cross-validation" derived from the activities' difference between days. For example, at one day the subject ate rice, while at another day he ate noodle. This difference bred the

TABLE III
EVALUATION RESULT FOR LEAVE-ONE-DAY-OUT CROSS-VALIDATION

Eval. item	Eat	PC	Read	Smartphone	Weighted Avg.
Precision	51.5%	36.3%	27.5%	45.7%	38.2%
Recall	62.4%	53.2%	19.8%	31.8%	38.6%
F-Measure	54.3%	43.2%	22.5%	36.3%	36.6%

TABLE IV
EVALUATION RESULT FOR LEAVE-ONE-PERSON-OUT CROSS-VALIDATION

Eval. result	Eat	PC	Read	Smartphone	Weighted Avg
Precision	50.3%	37.6%	31.2%	31.9%	36.0%
Recall	56.9%	45.6%	23.2%	23.2%	36.0%
F-Measure	50.8%	40.7%	26.7%	26.7%	35.0%

different feature vector patterns, which resulted in lower score. Meanwhile, we can improve the recognition performance by categorizing eating activities. For example, we can make the categories such as "Eating: noodle" or "Eating: rice."

3) Leave-one-person-out cross-validation: Table IV reported the evaluation result of "Leave-one-person-out cross-validation." Table IV also reported that we achieved the average F-Measure: 35.0%. Compared with "Leave-one-day-out cross-validation," there is little difference between them. As a result, we confirmed that we estimate the new user's activity by utilizing the proposed method.

V. CONCLUSION

In this paper, we have developed an analog-output-PIR-sensor-based activity recognition technique which can recognize the detailed activities of the user. Our technique recognizes the activity of the user by utilizing the machine learning and frequency component of the sensor's output. We evaluated the proposed technique in the smarthome. In the evaluation, three subjects has performed four different activities with sitting on the sofa. As a result, we achieved F-Measure: 57.0% for 10-fold cross-validation, which we consider as comparably higher score. However, for the Leave-one-day-out or Leave-one-person-out, we achieved lower scores compared with it. Thus, we consider to adopt additional feature such as time-series pattern of the output signal that is characteristic to each activity and improve the performance. In addition, we plan to conduct four future studies. First study is the discussion on the performance with more subjects. Second study is the discussion on the appropriate parameters for the machine learning. Third study is the discussion on the selection of the feature vector. Final study is the discussion on the individual difference between sensors.

VI. ACKNOWLEDGMENTS

This work is partly supported by the Japanese Government Monbukagakusho: JSPS KAKENHI Grant Number 16H01721 & 16K00126.

REFERENCES

[1] J. Scott, A. Bernheim Brush, J. Krumm, B. Meyers, M. Hazas, S. Hodges, and N. Villar, "PreHeat," in *Proceedings of the 13th international conference on Ubiquitous computing - UbiComp '11*. New York, New York, USA: ACM Press, 9 2011, p. 281. [Online]. Available: http://dl.acm.org/citation.cfm?id=2030112.2030151

[2] S. Barker, A. Mishra, D. Irwin, P. Shenoy, and J. Albrecht, "SmartCap: Flattening peak electricity demand in smart homes," in *2012 IEEE International Conference on Pervasive Computing and Communications*. IEEE, 3 2012, pp. 67–75. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6199851

[3] P. Rashidi and A. Mihailidis, "A Survey on Ambient-Assisted Living Tools for Older Adults," *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 3, pp. 579–590, 5 2013. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6399501

[4] J.-T. Kim, J.-Y. Soh, S.-H. Kim, and K.-Y. Chung, "Emergency Situation Alarm System Motion Using Tracking of People like Elderly Live Alone," in *2013 International Conference on Information Science and Applications (ICISA)*. IEEE, 6 2013, pp. 1–4. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6579321

[5] J. Wan, M. J. OGrady, and G. M. P. OHare, "Dynamic sensor event segmentation for real-time activity recognition in a smart home context," *Personal and Ubiquitous Computing*, vol. 19, no. 2, pp. 287–301, 2 2015. [Online]. Available: http://link.springer.com/10.1007/s00779-014-0824-x

[6] C. Belley, S. Gaboury, B. Bouchard, and A. Bouzouane, "Activity recognition in smart homes based on electrical devices identification," in *Proceedings of the 6th International Conference on PErvasive Technologies Related to Assistive Environments - PETRA '13*. New York, New York, USA: ACM Press, 2013, pp. 1–8. [Online]. Available: http://dl.acm.org/citation.cfm?doid=2504335.2504342

[7] K. Ueda, M. Tamai, and K. Yasumoto, "A method for recognizing living activities in homes using positioning sensor and power meters," in *2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops)*. IEEE, 3 2015, pp. 354–359. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=7134062

[8] Y. Kashimoto, K. Hata, H. Suwa, M. Fujimoto, Y. Arakawa, T. Shigezumi, K. Komiiya, K. Konishi, and K. Yasumoto, "Low-cost and Device-free Activity Recognition System with Energy Harvesting PIR and Door Sensors," in *The 2016 International Workshop on Information Flow of Things*, 2016, p. (to appear).

[9] J. Hoey and J. J. Little, "Value-directed human behavior analysis from video using partially observable Markov decision processes." *IEEE transactions on pattern analysis and machine intelligence*, vol. 29, no. 7, pp. 1118–32, 7 2007. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/17496372

[10] 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, 1 2008. [Online]. Available: http://dl.acm.org/citation.cfm?id=1362986.1363069

[11] O. D. Lara and M. A. Labrador, "A Survey on Human Activity Recognition using Wearable Sensors," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 3, pp. 1192–1209, 23 2013. [Online]. Available: http://ieeexplore.ieee.org/articleDetails.jsp?arnumber=6365160

[12] K. Mase, "Activity and location recognition using wearable sensors," *IEEE Pervasive Computing*, vol. 1, no. 3, pp. 24–32, 7 2002. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1037719

[13] T. L. van Kasteren, G. Englebienne, and B. J. A. Kröse, "An activity monitoring system for elderly care using generative and discriminative models," *Personal and Ubiquitous Computing*, vol. 14, no. 6, pp. 489–498, 2 2010. [Online]. Available: http://dl.acm.org/citation.cfm?id=1851896.1851902

[14] L. Chen, C. D. Nugent, and H. Wang, "A Knowledge-Driven Approach to Activity Recognition in Smart Homes," *IEEE Transactions on Knowledge and Data Engineering*, vol. 24, no. 6, pp. 961–974, 6 2012. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5710936