Implementation and Evaluation of Analog-PIR-Sensor-Based Activity Recognition

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Abstract: These days, smart home applications such as concierge service for residents, home appliance control, and so on are attracting attention. To realize these applications, we need a system which recognizes various human activities accurately with a low cost device. There are many studies on the activity recognition in a smart home. We also have proposed an activity recognition technique in a smart home by utilizing digital-output-PIR (passive infrared) sensors, door sensors, and power meters. However, the study has an unsolved issue: we cannot distinguish similar activities happening at the same place, for example, “eating” and “reading” while 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 different activities in the same place. Our technique recognizes user’s activity by utilizing machine learning with frequency components of the sensor’s output as features. However, because the number of features used in ALPAS is 1000 for each analog PIR-sensor, a large capacity memory is required. To reduce the number of features, we select a part of the sensing data. We call the starting point of the selected data as starting frequency (SF) and ending part as ending frequency (EF). We searched SF and EF using a grid search, and evaluated the recognition accuracy. We evaluated the proposed technique in a smart home testbed. In the evaluation, five participants performed four different activities while sitting on a sofa. As a result, we achieved F-Measure: 63.9% when the EF is 1.4 Hz, and F-Measure: 50% or lower when the SF is 9.9 Hz or higher.

Key Words: activity recognition, analog PIR sensor, machine learning, feature reduction, grid search.

1. Introduction

Thanks to the progress of ubiquitous computing technology, there is a strong anticipation to realize smart daily life support systems such as an energy saving home appliance control system [1],[2], a care-taking system for senior citizen, and a concierge system [3],[4] in a smart home. In particular, the concierge service attracts attention. For example, voice assistants such as Google Home by Google and Amazon Echo by Amazon have been put into practical use one after another. Thus, we strongly believe that the technology to accurately recognize detailed living activities of a resident is essential to provide comfortable concierge service in the future.

There are many studies on activity recognition in a smart home [5],[6]. These studies estimate user activities utilizing acoustic sound captured or the usage of electric appliances in the smart home. In addition, we worked on the development of the activity recognition technique by utilizing an ultrasonic-sound-based indoor positioning system, watt meters attached to each appliance, passive infrared (PIR) sensors, and door sensors [7],[8]. In these studies, we defined the following requirements: (i) various types of living activities are recognized, (ii) a small number of low-cost sensors are used, (iii) the privacy exposure of the residents is low, and (iv) the activities of the residents are recognized tag-free. Based on the requirements, we developed the activity recognition techniques.

However, these studies have an unsolved issue: we cannot recognize activities when a user performs different activities at the same location, e.g. the user performs eating and reading while sitting on a sofa. Since this misclassification may stir up the service degradation of concierge, we need to develop a technique to solve this issue. This issue arises from the characteristic of the techniques used where we estimate the activity of a 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 is cooking. 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], a wearable sensor, or a smartphone [11],[12]. Camera-based approaches estimate a user’s activity by utilizing an image processing technique. However, these approaches intrude the user’s privacy, which does not fulfill Requirement (iii). On the other hand, wearable sensor and smartphone based approaches utilize an accelerometer-based activity recognition technique. Nevertheless, these approaches require users to carry a 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 aforementioned challenges, we...
introduce ALPAS\(^1\): analog-output-PIR-sensor-based activity recognition technique which recognizes different activities happening at the same location. An analog output PIR (analog PIR) sensor is a sensor which recognizes the activity of a 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. A digital PIR sensor is a sensor which is widely used for home appliance control and estimating the trajectory of inhabitants in a smart home [13]. A digital PIR sensor outputs 1 when the user exists near the sensor, while the sensor outputs 0 when the user does not exist. Compared with a digital PIR sensor, Analog PIR sensor outputs high voltage when 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 user’s activity by utilizing 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). An analog PIR sensor itself is a low-cost sensor and is placed at a 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 (iii). An analog PIR sensor does not require the user to carry any device, which fulfills requirement (iv). Therefore, the proposed system allows us to realize an activity recognition system that fulfills all the requirements (i)–(v).

Our system estimates the user’s activity by utilizing a machine learning technique with frequency components of the sensor’s output as features. As a result of recognizing four types of activity using ALPAS, we found that activities can be recognized with an accuracy of 57.0%. However, because the number of features used in ALPAS is 1000 per one analog PIR-sensor, a large capacity memory is required. Hence, to put the proposed system into practical use, it is necessary to reduce the number of features. To reduce the number of dimensions of a feature vector, we select a part of it. We call the starting point of the selected data as starting frequency (SF) and the ending part as ending frequency (EF). We adopt a grid search to investigate the transition of the recognition accuracy by changing SF and EF of frequency spectrum intensity used as a feature vector, and investigate SF and EF which can reduce the number of dimensions of features without deteriorating the recognition accuracy. We evaluated the proposed technique in a smart home testbed. In the evaluation, five participants performed four different activities while sitting on a sofa. As a result, we achieved F-Measure 63.9% when the EF is 1.4 Hz, and F-Measure 50% or lower when the SF is 9.9 Hz or higher.

Our major contribution is that we have realized the low-cost, device-free, and accurate activity recognition system that utilizes an analog-output PIR sensor. Specifically, we first developed the analog-output PIR sensor. Since we just customize a commercial digital PIR sensor that has generally used now, the cost is quite low. The second contribution is that we succeeded to distinguish similar human activities occurred in the same location. In this paper, we target activities performed alone on the sofa: eating, using a PC, reading a book, and using a smartphone. We selected lower accuracy activities from previous studies [7],[8],[14], which actually happened in the previous experiments. These activities could not be recognized with a power consumption sensor and a location sensor. The third contribution is that we succeeded to suppress the size for training data by investigating the correlation between the bandwidth of frequency feature and the recognition accuracy. From these contributions, the proposed method has practical value.

2. Related Work

Many studies on the activity recognition in a smart home have been reported. We introduce related work 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.

2.1 Activity Recognition with Activity-Location-Correlation

There are many studies which estimate a user’s activity by utilizing the correlation between the activity and location of the user [15],[16]. That is, if the user exists in the kitchen, the system estimates that the user cooks.

Kasteren et al. [15] design 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 sensors, and temperature sensors. The recognition accuracy of their system ranges from 49% to 98%. It can recognize many activities, but it has high initial cost and low recognition accuracy depending on the type of activities.

Chen et al. [16] design 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 embedded with contact, motion, tilt, and pressure sensors. Their system achieved recognition accuracy greater than 90%. However, this method requires many sensors and overall the system cost will be high.

Ueda et al. [7] introduce an activity recognition system in a smart home by utilizing an ultrasonic-sensor-based indoor positioning system and power meters 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] estimate a user’s activity based on the correlation between the user’s position and activity by utilizing a 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

\(^1\) ALPAS: AnaLog output-Pir-sensor-based Activity recognition System

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Fig. 1 Correlation between position and activity (each number shows the ratio of the activity that occurs the position).
performs them while sitting on a 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, using a smartphone, working, and eating occur at the sofa. Thus, this technique cannot distinguish these activities.

2.2 Motion-Recognition-Based Activity Recognition

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

There are several studies which estimate a user’s activity by utilizing camera. Hoey et al. [9] estimate a user’s activity by utilizing an image processing technique and partially observable Markov decision process. Fiore et al. [10] estimate the activity of a user who walks inside the building by utilizing cameras and an image processing technique. However, the installing cost of the cameras, which the user has to set up in every room in the building and cables which connect between the cameras and the processing server becomes burden on the user. Also, Kashimoto et al. [8] and Nakagawa et al. [14] are concerned about invasion of privacy caused by using cameras. Therefore, we also suppose that some people do not like being recorded by cameras.

Wearable sensor approaches estimate the activity of a user by utilizing mobile devices such as a smartphone, smart watches, and so on [11]. Mase et al. [12] have proposed a technique to estimate the user’s activity such as walking, running, and sitting by utilizing an accelerometer and a 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.

2.3 Approach of Analog PIR Sensor-Based Activity Recognition

In order to solve open issues in the previous studies, we aim to develop an activity recognition system by utilizing analog PIR sensors, which has advantages of low installation and operation cost, and low privacy intrusion. The proposed system allows us to recognize the user’s activity accurately, even though he/she performs different activities in the same place. Additionally, we can realize the proposed system just by converting a 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 1.

(i) various types of living activities are recognized.
(ii) a small number of low-cost sensors are used.
(iii) the privacy exposure of the residents is low.
(iv) the activities of the residents are recognized tag-free.
(v) Different activities at the same location are recognized.

In order to fulfill requirement (i), the proposed system recognizes user’s activity even when the user performs different activities at the same location. For requirement (ii), Analog PIR sensor itself is low-cost sensor and should be placed to the particular place at which multiple activities occur. For requirement (iii), the proposed system does not capture any image or sound of the user. For requirement (iv), we adopt the PIR sensor, which does not require the users to carry any mobile device. For requirement (v), we need to develop an analog PIR sensor that has an analog output which fluctuates in accordance with the user’s activity. As mentioned, the proposed system allows us to realize the activity recognition system that fulfills all the requirements 1–5.

3. Analog-PIR-Sensor-Based Activity Recognition

3.1 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. An analog PIR sensor outputs the electric signal which corresponds to a user’s activity. The sensor outputs a large amplitude wave when a user exists near the sensor. The sensor outputs a high frequency signal when a 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 a classifier, which is generated by a machine learning technique, and store the result into the database: Activity DB.

3.2 Basic Study on Analog PIR Sensor

In order to adopt an analog PIR sensor, we conducted a preliminary experiment and studied the sensor. In the experiment, a participant moved fast or slowly in front of the analog PIR sensor. The distance between the participant and the sensor was about 90 cm. Then, we observed the output of the analog PIR sensor. Figure 3 shows the output signal when the participant moves fast. Figure 4 shows the output signal when the participant moves slowly. In both figures, the upper graph illustrates the raw signal of the analog PIR sensor, while the lower graph the frequency component of the output signal. By comparing these two figures, we confirmed that we can recognize lively activities such as eating from the higher component of frequency. On the other hand, we recognize slow activity such as reading from the lower component of frequency.

3.3 Implementation of Analog PIR Sensor

Our proposed system requires an analog PIR sensor. However, most popular PIR sensors on the market have digital-output, and there is no analog-output PIR sensor that allows us to introduce with low cost. Then, we decided to convert a digital PIR sensor on the market to an analog one in a simple manner. By adopting this technique, we utilize the current digital PIR sensor that has been already installed in our smart home, and realize the proposed system with small installation cost. Figure 5 illustrates the analog PIR sensor which we developed. Figure 6 illustrates the block diagram of the analog-output PIR sensor. Initially, this sensor was a digital-output PIR sensor. The 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 converted it to an analog sensor by modifying the wiring of the circuit board inside. We can capture analog signal output from the output port of the pyroelectric element. However, the output signal is weak to be captured. Therefore, as shown in the Fig. 6, we capture slightly amplified analog signal from an output port of the first operational amplifier.

3.4 Activity Recognition by Utilizing Machine Learning

In this section, we describe the details of our activity recognition technique. Our system estimates a user’s activity by utilizing a machine learning technique.

3.4.1 Process of machine learning

We apply machine learning with the following three phases: In the first phase, we acquire training data for learning. In the second phase, we extract a feature vector from the data. In the third phase, we generate an activity recognition classifier from the extracted features.

(Phase 1) Acquisition of the training data

In order to conduct machine learning, we need to obtain 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 vector extraction

In “Phase 2,” we extract the feature vector for machine learning in the following two steps: First, we divide the sensor data by a particular time-window. Second, we extract a feature vector for each time-window. 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 an activity recognition classifier from the dataset that we have obtained in “Phase 1” and the
feature vector that we have processed in “Phase 2.” In order to generate the classifier, we have used scikit-learn\(^3\), which is famous as machine learning library for Python. scikit-learn has various machine learning and classifier algorithms. For our research, we have selected Random Forest classifier empirically.

### 3.4.2 Feature vectors

In our proposed system, we selected a frequency feature for each time-window. We extracted the frequency component between 0 Hz and 50 Hz by utilizing FFT. In our research, we have applied the time-window by 10 s, also the sliding-window for 1\( \mu \)s empirically. Because of the time-window width, the frequency resolution is 0.1 Hz. Therefore, the number of dimensions of feature vectors is 1,000 per Analog PIR sensor. When installing a lot of analog PIR sensors in a smart home, the number of features increases, and it causes massive memory usage. It leads to higher cost. In order to put our proposed system into practical use in the smart home, we need to reduce the number of dimensions of features. As was shown in the results of basic study on the analog PIR sensor in Section 3.2, the frequency component which the analog PIR sensor outputs is unique for each activity. For instance, when a user performs eating, the user’s body moves relatively quickly, the analog PIR sensor outputs the signal including high frequency. In our research, we selected the frequency component of optimal band for analog-PIR-based activity recognition. The frequency component of optimal band means the frequency component between starting-frequency (SF) and ending-frequency (EF), which is shown in Fig. 7. We need to adjust SF and EF which does not cause lower recognition accuracy. In order to adjust these frequencies, we use a grid search technique.

### 4. Evaluation

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

#### 4.1 Evaluation Method

From our study, we selected four target activities: eating, using a PC, reading, and using a smartphone which the user often performs while sitting on a sofa. Figure 8 describes the evaluation environment. We installed five PIR sensors around the sofa. We attached one analog PIR Sensor on the ceiling above the sofa, and installed the other sensors with four tripods respectively at right and left and front and back of the sofa so that the sensors capture a movement of the user’s hand and body. Five participants, four males and one female in 20’s, participated in the evaluation. A participant performed the above four activities while sitting on the sofa between 6 min and 16 min.

\(^3\) scikit-learn: http://scikit-learn.org/
The proposed system achieved higher accuracy than our previous work [14]: 39.3% for all combinations. Therefore, we think that the robustness of the proposed system is high enough against different activities.

Table 2 shows the recognition accuracy of each pattern.

| Person | Sensor Position | Seating pos: center of the sofa | F-Measure |
|--------|-----------------|-------------------------------|-----------|
| Person 1 | On ceiling and right | 65.4% | 56.1% |
| Person 2 | On ceiling and left | 70.4% | 50.3% |
| Person 3 | On ceiling and front | 72.8% | 45.8% |
| Person 4 | On ceiling and back | 73.9% | 49.6% |
| Person 5 | On ceiling and left | 48.3% | 54.0% |
| Person 6 | On ceiling and front | 52.2% | 51.5% |
| Person 7 | On ceiling and back | 59.6% | 54.3% |
| Person 8 | On ceiling and right | 59.7% | 55.5% |
| Person 9 | On ceiling and left | 48.8% | 59.9% |
| Person 10 | On ceiling and front | 47.6% | 62.0% |
| Person 11 | On ceiling and back | 56.3% | 67.2% |
| Person 12 | On ceiling and right | 54.1% | 64.5% |
| Person 13 | On ceiling and left | 62.7% | 80.4% |
| Person 14 | On ceiling and front | 67.5% | 83.0% |
| Person 15 | On ceiling and back | 70.4% | 83.2% |
| Person 16 | On ceiling and right | 77.3% | 86.4% |
| Person 17 | On ceiling and left | 56.2% | 57.3% |
| Person 18 | On ceiling and front | 61.1% | 52.5% |
| Person 19 | On ceiling and back | 64.1% | 53.8% |
| Person 20 | On ceiling and right | 67.1% | 61.1% |

In this experiment, we evaluated average recognition accuracy for 40 patterns with different number of participants, seating position, and sensor position. As a result, we obtained the lowest accuracy of 45.8%, and the highest accuracy of 86.4%. Although there is variation in the recognition accuracy, the proposed method achieved higher accuracy than our previous work [14]: 28% for all combinations. Therefore, we think that the robustness of the proposed system is high enough against the difference of the target environment. More specifically, when confirming the recognition rate of each activity in detail regarding the 40 patterns, we achieved the lowest accuracy of 30.7% when Person 4 sitting on the far right side of the sofa was eating. Also, we achieved the highest accuracy of 96.9% when Person 2 sitting on the far right side of the sofa was reading. Although there is variation in the recognition accuracy caused by combination of individuals and events, we confirmed that the proposed system exceeded the recognition accuracy in previous work [14]. Therefore, we believe that the robustness of the proposed system is high enough against different activities.

In addition, we found that our proposed system can recognize more accurately than Kashimoto et al. [8] and Nakagawa et al. [14]. These studies recognize activities: eating 28.0%, reading 2.5% and using a smartphone 14.6%. Kashimoto et al. [8] estimate the user’s activity based on the correlation between the user’s position and activity by utilizing digital PIR sensor. Nakagawa et al. [14] estimates activity using the user’s position and power consumption of home appliances, and the acceleration of the user. However, their techniques cannot distinguish the above mentioned activities, since there is little difference of the user’s position and power consumption when he/she performs them while sitting on the sofa. On the other hand, our technique estimates the user’s activity from the Analog PIR sensor output that changes in accordance with activity. As a result, our method shows average accuracies of eating 70.9%, using a PC 63.1%, reading 60.0% and using a smartphone 56.6%. We achieved higher accuracies than the accuracies of previous studies [8],[14]. Especially, those of Person 4 are higher overall as shown in Table 3. However, the other person’s accuracy is low for using in the real environment. Improving the activity recognition accuracy of the proposed system is our future work. And also, the comparison between these two studies is our future work.
living in a smart home. Even our current system can recognize multiple persons’ activities individually in limited situations that they are staying at different spaces where PIR sensors are deployed, in the smart home. However, in the situation that multiple persons’ activities take place at the same space like on a sofa, the current system cannot distinguish their activities because the analog PIR sensors cannot distinguish infrared light obtained from them. Supporting multiple persons’ activity recognition is our future work.

4.2.2 10-fold cross-validation with reduction in frequency features of higher frequency component

Figure 9 shows the shift of activity recognition accuracy when the classifier was generated by using frequency components between 0 Hz and EF Hz. Figure 9 reported that the average F-Measure took the highest value 63.9% when EF is 1.4 Hz. When EF is higher than 1.4 Hz, the recognition accuracy converges to 57%. Figures 3 and 4 in Section 3.1 show that most frequency components are between 0 Hz and 2.0 Hz. We confirmed that using the frequency component higher than 2.0 Hz as feature leads to low accuracy. Also, since higher frequency components are not necessary in our proposed system, it saves a lot of memory and storage. Table 4 shows the confusion matrix when EF is 1.4 Hz. Table 5 shows the Precision, Recall and F-Measure when EF is 1.4 Hz. Compared with the average F-Measure in Section 4.2.1, we confirmed that setting EF to 1.4 Hz leads to the reduction in the number of feature and improves the recognition accuracy.

4.2.3 10-fold cross-validation with reduction features of lower frequency component

Figure 10 reported the evaluation result of a grid search about SF. Figure 10 showed the shift of activity recognition accuracy when the classifier was generated by using frequency component between SF and 50 Hz. Figure 10 reported that the recognition accuracy becomes lower than 50% when SF is set to 9.9 Hz or higher. Table 6 shows the Precision, Recall and F-Measure when SF is 9.9 Hz. Table 6 shows that the average F-Measure was 48.2%. Eating had the best average F-Measure 58.7%. This result shows that the frequency feature of eating does not lower frequency components. On the other hand, the average F-Measure of the other three activities are less than 50% using a PC was 47.8%, reading was 48.8%, and using a smartphone was 48.3%. Compared with Fig. 2 in section 4.2.1, we confirmed that the recognition accuracy of using a smartphone decreases especially. Table 7 shows the confusion matrix when setting SF to 9.9 Hz. Compared with the confusion matrix in Section 4.2.1, we confirmed the increase in the rate which using a smartphone is incorrectly recognized as using a PC or reading. These results show that the frequency feature of using a smartphone has lower frequency components than using a PC and reading. Therefore, the reduction in frequency features of lower frequency component leads to decrease of the recognition accuracy of using a smartphone.

5. Conclusion

In this paper, we developed an analog-output-PIR-sensor-based activity recognition technique which can recognize different activities happening at the same location. Our technique recognizes a user’s activity by utilizing the machine learning with the frequency components of the sensors’ output as features. To reduce the number of features, we selected a part of the features between the starting point, starting frequency (SF), and the ending point, ending frequency (EF). We searched SF and EF using a grid search, and evaluated the recognition accuracy. In the evaluation, five participants performed four different activities while sitting on a sofa. As a result, we achieved F-Measure: 63.9% when the EF is 1.4 Hz, and F-Measure: 50% or lower when the SF is 9.9 Hz or higher. In addition, we plan to conduct four future studies. The first study is the discussion on the performance with more participants. The second study is the discussion on the appropriate parameters for the machine learning. The third study is the discussion on the selection of the feature vector. The final study is the discussion on individ-
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