Personalized Energy Auditor: Estimating Personal Electricity Usage

Seungwoo Lee*, Daye Ahn**, Sukjun Lee*, Rhan Ha**, and Hojung Cha*

*Department of Computer Science
Yonsei University
Seoul, Korea
{seungwoo, sjlee, hjcha}@cs.yonsei.ac.kr

** Department of Computer Science
Hongik University
Seoul, Korea
{dayeahn, rhanha}@cs.hongik.ac.kr

***Abstract*—The goal of energy monitoring and eco-feedback systems is to induce energy consumers to change their behaviors to achieve a more sustainable way of life. Comprehensive research and commercial solutions provide energy consumers with information about overall energy costs or appliance-level energy usage. However, in order to better promote spontaneous energy saving with an eco-feedback system, personalized information is required. The conventional solutions cannot identify the energy usage of an individual user in a shared residential environment. In this paper, we propose the Personalized Energy Auditor, which estimates personal energy usage at home. Our system monitors and analyzes appliance usage, as well as the energy cost of the daily activities of residents. The system then estimates personal energy usage automatically, by linking appliance usage data with the individual user. Our system was installed in residential homes, and the experimental results indicate that it accurately estimates personal energy usage.**

Keywords—eco-feedback; home energy monitoring; load disaggregation; indoor tracking

I. INTRODUCTION

Energy crisis has become an immensely important issue worldwide. In order to preserve the environment through reduction in CO2 emissions, much research and effort have been devoted in many areas to reduce energy consumption. A number of studies have monitored real-time energy consumption and provided users with information on energy feedback as a basic method of spontaneously reducing their energy consumption [1, 2]. A variety of energy meters and in-home displays (IHD) [3, 4] have recently been released in commercial markets to promote spontaneous energy saving by showing detailed and accurate usage information.

Existing studies and commercial devices and products have limited functionality in measuring energy consumption within households. There is as yet no comprehensive means of providing information on how much energy a home occupant consumes on an individual basis. Existing studies merely provide users with real-time information on whole-house or appliance-level energy consumption. Therefore, such systems can hardly offer direct answers to questions such as, "*How much energy have I used today?*" or "*Who is an 'energy hog' in my house?*" As a result, individual occupants are left to work out the answers on their own. For example, in an environment that accommodates a number of residents, such as dormitories and house sharing situations, individual energy consumption, which is the information that users would be interested in, cannot be easily extracted from the total energy consumption. Accordingly, to provide individual users with meaningful and highly relevant information, our study aims to suggest answers to the question, "*Who used how much energy in which device?*"

The primary goal of our work is to estimate user-centric energy consumption in environments with multiple occupants. The proposed system informs users of their energy consumption each device, and it also provides a method to infer the hourly energy consumption of individuals. To accomplish this, a smart meter is used to establish an infrastructure for real-time energy monitoring. Then, our system collects user-context information, such as the user's occupancy and room-level location automatically, using a smartphone and doorway sensors. Based on the collected energy and user information, the relationship between an individual device and the user is analyzed. The total energy consumption is then segmented into that of individual users.

The proposed system makes the following contributions:

- To the best of our knowledge, ours is the first system to automatically identify the energy consumption of individual users in shared residential environments.
- An automatic power state recognition and classification method is proposed to monitor and disaggregate the loads of individual devices in real time.
- Based on data collected using smartphones and doorway sensors, the study proposes a non-intrusive occupant tracking system.
- Finally, our study suggests an algorithm that learns the relationship between individual user and device, based on the collected information on energy consumption and user contexts, and then estimates the energy consumption per user.

II. RELATED WORK

A. Eco-Feedback System

Energy usage information enables consumers to understand their usage of resources and calculate potential energy savings [5]. Hence, studies have been conducted to estimate appliance-level electricity consumption at home [2, 6]. Also, diverse types of energy-aware products [3, 4] are now available on the market. These approaches, which aim to create awareness of energy usage and reduce environmental impact, are often called *eco-feedback* technology. The basic assumption of eco-feedback systems is that people, in general, lack awareness of their energy usage, and they will act in more environmentally beneficial ways if they are provided with better energy usage information. Recently, to maximize the transformative potential of feedback information, personalized feedback has gone beyond the disaggregation of energy usage to personal appliances, locations, and times of use by linking consumption to specific individuals [7].

B. Home Occupant Sensing and Tracking

Occupancy detection or presence sensing is an essential element to infer the daily activities of users. Occupancy detection is widely used in many pervasive computing areas [8, 9]. Motion sensors such as passive infra-red (PIR), ultrasonic sensors are commonly used to detect occupants, but these sensors are not capable of identifying individual occupants or counting the number of occupants.

Several studies [10–13] have been conducted to solve the occupant identification problem. Vision-based image processing techniques [10] are used to identify individuals, but people may not be willing to install cameras in their homes for privacy reasons [12]. Mobile devices or wearable devices such as RFID tags [11] can also solve the identification problem, although carrying or wearing devices is intrusive or burdensome for some users. Meanwhile, the Doorjamb [13] tracking system was proposed using low-cost doorway sensors. The system employs two ultrasonic range finders to measure the height and the walking direction of the person passing through. Doorjamb provides room-level tracking without privacy-invasive sensors or wearable devices. The scheme has, however, a limited ability to identify users since occupants of similar height cannot be distinguished.

In our work, we also employ doorway sensors for non-intrusive occupant tracking. We reduce the ambiguity of occupant identification by using the opportunistic Wi-Fi-based locating system and improve the accuracy of walking direction using two PIR sensors.

III. MOTIVATION AND CHALLENGES

As a preliminary experiment to analyze the characteristics of individual energy usage in the home, we collected the presence patterns of users, as well as the amount of energy consumed in two homes, for a period of one month. We recorded the energy usage in real time by attaching energy metering devices on appliances. The recorded information was reported daily to the users, who then manually annotated their energy usage.

Figure 1 shows the average time of each user's stay in the home and the usage information acquired from each appliance, with user annotation. The results indicate that the amount of energy consumed by each individual varied by a factor of ten or more, even in the same home, and that there was a great deviation between individuals' energy usage. Moreover, the appliances that each individual used were widely different. Some appliances such as televisions, microwaves, and coffee machines were shared by all occupants, whereas the laptop and audio and speaker were used by one individual. This shows that each individual tends to use each electronic appliance

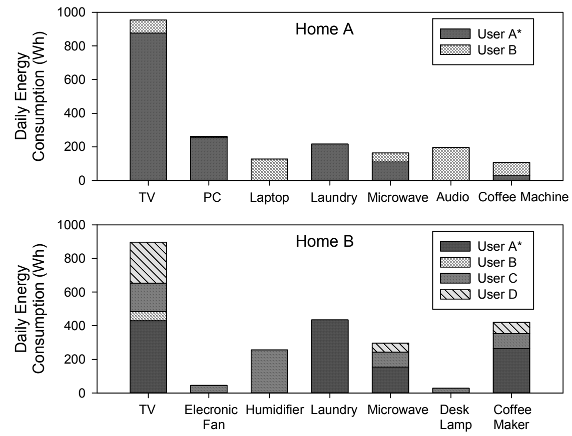


Fig. 1. Appliance Usage According to Occupants in Two Homes

differently, suggesting that advanced techniques such as context-aware energy management, forecasting of daily electricity demand, or home automation, should be applied to each user separately.

However, in order to extract individual energy usage in a shared residential environment, the occupant who actually uses the appliance should be identified. This is, practically speaking, a difficult task to achieve because there is no explicit evidence indicating which user has activated which appliance. Therefore, a technique should be developed to detect the user by collecting user context information and inferring from observation. Here, we suppose that an appliance should be near (i.e., within the same room) to a user to activate it. Also, the background appliances such as the refrigerator, which is always on regardless of the presence of a user, should be distinguished from the user-interactive appliances that need to be activated directly by a user. Generally, user-interactive appliances are activated either by direct contact or by remote control through an infra-red (IR) sensor. The appliance has to be in the same room because of the limited range of the IR. Thus, the user of each appliance is inferred based on the information on user location in a spatial unit and usage monitoring of the appliances.

IV. PERSONALIZED ENERGY AUDITOR

This section presents the details of the personalized home energy auditing system. Figure 2 presents an overview of the proposed system. The system consists of the following components. First, smart meters are deployed for measuring the energy consumption of individual appliances in real time. The system monitors the state of the appliances, such as the amount of energy consumption, activation time, and types of appliance. Second, an in-home occupant tracking system collects user context information, consisting of the room-level trace of occupants using personal mobile phones and sensors that are mounted at each doorway. Then, the system links the energy usage of occupants using the indoor trace and historical usage data. Finally, our system provides feedback information on energy usage to the relevant user. Here, we assume that the system has prior information about the deployed location of sensors, such as smart meter and doorway sensors, and accesses the room-level Wi-Fi fingerprint maps. The following sections describe the functionality and algorithm for each component in detail.

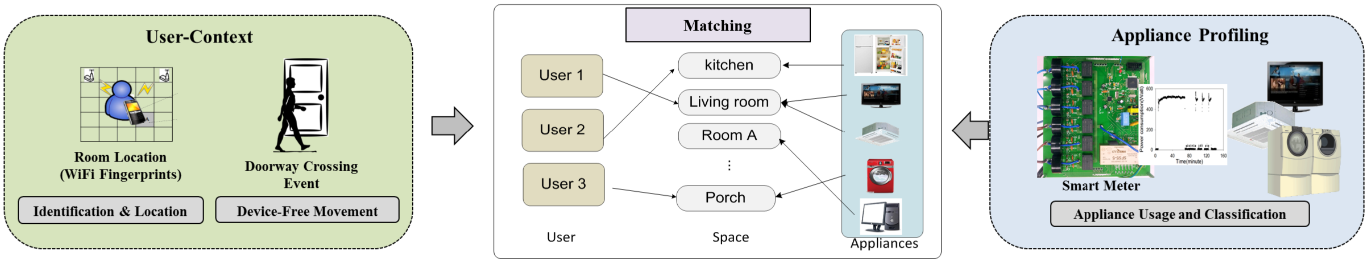


Fig. 2. System Overview

A. *Real-time Appliance Usage Monitoring*

In our system, energy metering devices are responsible for measuring the energy usage of appliances and delivering sensed data to the home energy management (HEM) server.

Recognizing activation of appliances: Once a smart meter is installed, it starts to measure the power draws of appliances and periodically reports metering data to the HEM. Since most electronic appliances consume a small amount of power, called standby power, even when they are switched off, the system has to distinguish the on or off state of the appliance by monitoring its power draw. With the collected power draws, the HEM produces a power profile of the individual appliance using the DBSCAN [15], which is a density-based clustering algorithm. After power profiling, the minimum clustered value of the power draw of the appliance is regarded as the power consumption in standby mode because active mode operation requires a high power draw. Finally, the HEM determines that an appliance is activated when the current power of the appliance is larger than power of standby mode.

Appliance classification: Our system aims to disaggregate power consumption of appliances according to the energy consumer. To accomplish this, we classify home appliances, based on their usage pattern, into three types: *background appliances*, *shared appliances*, and *personal appliances*. Background appliances such as refrigerators are activated regardless of an occupant's presence. The load from these appliances is not disaggregated to an individual occupant, whereas the loads from other appliances are disaggregated into users who have activated the appliances. Here, the system classifies the background appliances based on the activation dependency with occupants. Also, the shared appliance and the personal appliance are differentiated according to the correlation coefficient with the occupant.

B. *In-home Occupant Tracking System*

Wi-Fi-based user identification and locating system: Since a mobile device (e.g., a smartphone) is personally owned and carried by a user, it can be used to identify the owner by checking the location of the device. Also, we used a Wi-Fi-based positioning system (WPS) [14] to obtain the location of the user. If the user stays in a certain indoor space, a mobile device registers received signal strength (RSS) similar to radio from the surrounding Wi-Fi access points (APs). We used the Tanimoto coefficient to compare the similarities of RSS vectors. The system determines that an occupant is located in place a at time t, if $s(f_t, f^a) \leq \varepsilon$, where the similarity function $s(\cdot)$ is based on the Tanimoto coefficient, f_t is the Wi-Fi fingerprint of RSS vectors at time t, f^a is trained Wi-Fi fingerprints at place a in advance, and ε is a given threshold. With the Wi-Fi fingerprints technique, a mobile device can periodically estimate the room-level location of a user. However, in home environments, it is not always guaranteed that the location of a mobile device corresponds with the location of the device owner. To filter out the inconsistent location of the mobile phone, the location obtained from the WPS is used to estimate the user location only when the movement of a mobile device is detected (Figure 3). The movement of a mobile phone is estimated using the built-in three-axis accelerometer. The system determines that a mobile device is being used or carried if $|G_t| - |G_{t-1}| > \varphi$, where G_t is the acceleration sample at time t and φ is the pre-defined threshold (i.e., 0.1m/s^2).

Generating the trace for device-free movement: To provide a seamless tracking system, the system has to trace the device-free movement of occupants. We installed doorway sensors to generate the traces of the occupants while they were not carrying a mobile phone. The doorway sensor consists of two PIR sensors to detect the moving direction of person crossing the doorway and an ultrasonic sensor to measure the height of the individual, in order to differentiate between individuals. The sensors are mounted at the top of a doorway, as shown in Figure 4. The sequence of detected times of two PIR sensors, which are mounted to detect opposite directions, indicates the direction of movement of the crossing person. The ultrasonic sensor measures the person's height. When the doorway is empty, the sensors measure the distance d_{floor}

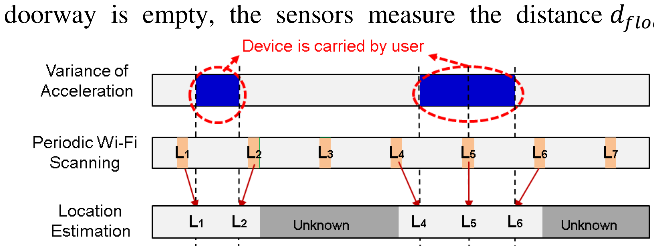


Fig. 3. Wi-Fi-Based Locating System

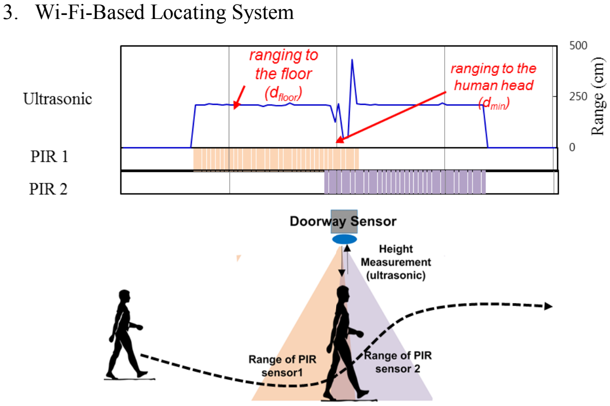


Fig. 4. Doorway Sensor for Detecting Crossing Person

from the floor to the sensor. While a person is crossing the doorway, the ultrasonic sensor continuously measures the distance to the top of the head d_h. The distance to the head of the crossing person is a minimum measurement d_{min}, *and the height of the crossing people* h *is evaluated as* $h = d_{floor} - d_{min}$. If both of the PIR sensors detect a person from r_{in} to r_{out}, the sensor generates an event $E_i = (t_i, h_i, r_{in}, r_{out})$, where t_i is the timestamp of the crossing event and h_i is estimated height, and r_{in} and r_{out} are corresponding rooms.

Seamless in-home tracking system: To bridge the gap between locations that are intermittently obtained using WPS and the detected doorway events, the system decides which person has caused each doorway event. Since the doorway events may include measurement error and ambiguity when occupants have similar height, we estimated the location of each user based on probability. At the beginning, an occupant's location is estimated from his/her mobile device. For example, given a set of rooms $R = \{ r_1, r_2, \dots, r_n\}$, the movement of the mobile device owned by occupant p^1 is detected at time t. The mobile device also scans Wi-Fi fingerprints f_t; then we estimate the location of p^1 as follows:

$$L_t(p^1) \approx \arg_{r_i} max\ s\big(f_{r_i}, f_t\big) \cdot p(r_i),\ (r_i \in R), \quad (1)$$

where $L_t(p^1)$ denotes the location of occupant p^1 at time t, $s(\cdot)$ is a similarity function based on the Tanimoto coefficient, f_{r_i} is the RSS Wi-Fi fingerprint vectors of room *i,* and $p(r_i)$ is the probability that an occupant stays in room r_i. The probability $p(r_i)$ is prior probability, which is derived from previous events using doorway sensors. Having room-level location of each occupant based on Wi-Fi fingerprints, the HEM continuously updates the location of an occupant by selecting the highest probability of room whenever the HEM receives the events from the doorway sensors. For example, if a doorway sensor generates a new event $E_k = (t_k, h_k, r_i, r_j)$, then the probability that an occupant p^1 has crossed from r_i to room r_j is estimated as follows:

$$p\big(\ L_{t_k}(p^1) = r_j\ \big) = p\big(L_{t_{k-1}}(p^1) = r_i\big) \cdot \varphi \cdot\ p\big(O = p^1 \big| H = h_k\big),$$
$$\varphi = \frac{\#\ of correct\ detections}{\#\ of\ doorway\ crossing\ events}, \quad (2)$$

where φ denotes the accuracy of crossing event detection using two PIR sensors. $p(O = p^1 \mid H = h_k)$ is the probability of occupant O *is* p^1 *given a height measurement, which is estimated as follows:*

$$p(O = p^1 \mid H = h_k) = \frac{p(H=h_k|O=p^1)}{\sum_{o=\emptyset,p^1,\dots p^N} p(H=h_k|O=o)}, \quad (3)$$

where $\emptyset$ *denotes the unoccupied state.* $p(H = h_k|O = \emptyset)$ means the *false positive probability.* $p(H = h_k|O = p^1)$ is evaluated in Section V. B.

C. *User-level Load Disaggregation*

The power consumption of each appliance is now disaggregated for each occupant based on the observation of user location, the type of appliance, and historical usage.

Correlation between occupants and appliances: We analyze the relation between the appliances and occupants to classify the appliance type (i.e., background, shared, or personally owned appliances). First, we define the activation dependency coefficient D_{a_i,p_j} between occupant and activation of the appliance as follows:

$$D_{a_i,p_j} = \frac{\#\ activation\ of\ a_i\ while\ p_j\ is\ located\ in\ room\ r_a}{total\ activation\ counts\ of\ a_i}, \quad (4)$$

where a_i denotes appliance *i,* p_j is occupant j, and r_a is the room in which appliance a_i is located. The dependency indicates the users who used the appliance most or the ownership of the appliance. The ownership can be estimated by comparing the dependency with each occupant. With $D_{a_i,\emptyset}$ a value that denotes the probability that an appliance a_i is activated when room r_a is empty, appliances are classified into background appliances and others. We also define the correlation between activating time and occupants as follows:

$$C_{a_i,p_j} = \frac{stay\ time\ of\ p_j\ while\ a_i is\ operating}{total\ operating\ time\ of\ a_i}. \quad (5)$$

The correlation C_{a_i,p_j} infers the interactions between occupants and user. It is used to disaggregate loads from sharing appliances to individual occupants.

Evaluation of individual energy usage: After classifying the type of each appliance, the system disaggregates the real-time energy load to the occupants. The loads from background appliances are provided to the user as shared energy loads instead of individual energy usage. The load from personally owned appliances, including leakage energy consumption (i.e., standby power), belongs to their owners, whereas loads from shared appliances are distributed to co-located occupants by linking the location of occupants at the time when an appliance is activated. We used the activation time of an appliance instead of length of active time to discern the actual user because some appliances such as washing machines, air conditioners, microwaves, and rice cookers do not need continuous interactions with the user; thus, they often stay in active mode while they are operating. If multiple users are present in the same room with active appliances, loads from the appliances are proportionally disaggregated according to correlation C_{a_i,p_j}. The accuracy of disaggregation is evaluated in the following section.

V. Personalized Energy Auditor

A. *System Deployment*

We deployed the system at two homes, and the experiments were conducted for three weeks at one home and five weeks at the other. The homes are occupied by multiple residents: two in Home A and four in Home B.

TABLE I. Experimental Settings

	Home A	**Home B**
Number of residents	2 persons	4 persons and a pet
Height of each resident	155cm(User A), 168cm(User B),	158 cm(User A), 176 cm(User B), 169 cm(User C), 179 cm(User D)
Experiment duration	5 weeks	3 weeks
Installed Smart Meter	3	4
Installed Doorway Sensors	6	7

TABLE II. ACCURACY OF DOORWAY SENSORS

	Precision	***Recall***
Height Detection	0.96	0.86
Direction	0.94	0.98

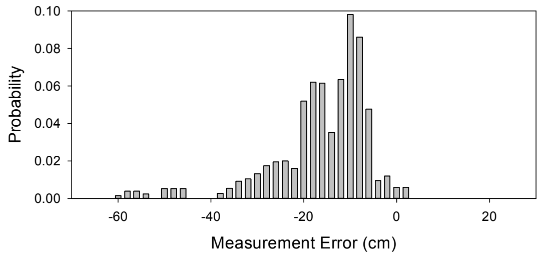


Fig. 5. Probability Density Function (PDF) of Height Measurement Error

B. *Performance of Doorway Sensor*

First, we evaluated the accuracy of the measurement of the height and direction of movement of the person crossing the doorway. For a preliminary experiment, we installed a doorway sensor at the entrance of our laboratory with nine occupants. During two days, more than 200 crossing events were detected. Table II shows the accuracy and sensitivity of the proposed doorway sensor. The *precision* and *recall* are evaluated as follows:

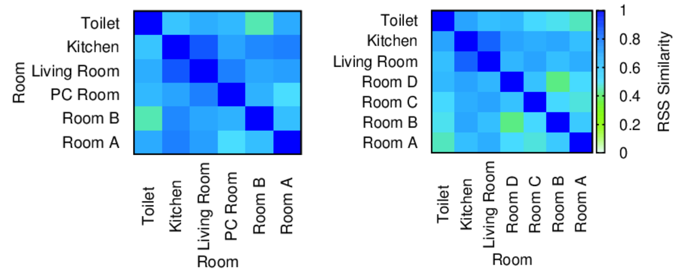
$$Precision\ \left(\frac{TP}{TP+FP}\right) = \frac{counts\ of\ correct\ detections}{counts\ of\ total\ detection},$$

$$Recall\ \left(\frac{TP}{TP+FN}\right) = \frac{counts\ of\ correct\ detections}{counts\ of\ ground\ truth\ events}.$$

For detecting direction using two PIR sensors, most transitions were correctly detected, as the recall value is above 98% in Table II. However, our sensors failed to detect the few events in which more than two occupants were crossing the doorway simultaneously because the PIR sensor cannot count the number of persons in the vicinity. Also, if people are present near both sides (in/out) of the doorway, the estimation of direction of movement may be inaccurate. In height estimation, 14% of height measurements were out of the effective range from 100 *cm* to 190 cm (false negative). Figure 5 shows the probability density function of measurement error. The PDF of the measurement noise was asymmetric and biased and the measured height was often smaller than the true height of the crossing person. The measurement error can be caused by many factors, including the pose of the walking person, multipath fading, low sampling frequency of the sensors, and so on.

C. *Performance of Occupant Tracking*

Next, we evaluated the accuracy of the Wi-Fi fingerprint-based positioning system in the home environments. In our experiments, after collecting the Wi-Fi fingerprint vector, a mobile phone compared the current fingerprints with the fingerprints of the target place, which was trained *a priori*. Then, the decision was made to locate a mobile phone in the room that had the most similar RSS vectors. Figure 6 shows the similarity of normalized RSS vectors collected in the two homes. Apparently, in most cases, an RSS vector for a room is distinct from other RSS vectors. Only the similarity between kitchen and living room is relatively high because there is no physical wall between the two spaces. In our experiments, the Wi-Fi based location system yielded more than 91% accuracy.



(a) Home A (b) Home B

Fig. 6. Similarity of Wi-Fi RSS Vectors According to Space

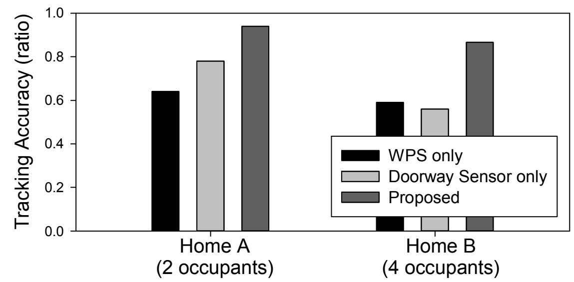


Fig. 7. Accuracy of In-home Tracking

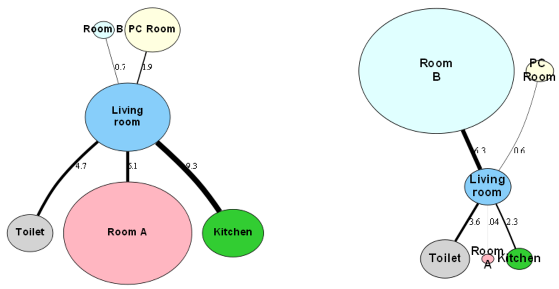
Figure 7 shows the tracking results based on WPS and crossing events using the doorway sensors. To compare the results with actual movement, occupants manually annotated each event and their activities during a week. The WPS-only showed low accuracy in both homes because of the device-free movement of occupants. In the case of the doorway sensor-only system, over 81% of indoor movements were correctly tracked in Home A, whereas the accuracy of indoor tracking using sensors in Home B was only 58% because Home B had four residents, and three out of four had similar heights, within a range of 10 cm. This increased the ambiguity of tracking. Moreover, many false positives for crossing events occurred in Home B because the PIR sensor also detected the movement of a pet. However, the proposed system, which combines WPS and doorway crossing events, improved tracking accuracy up to 94% and 87% at Home A and Home B, respectively.

D. *Relations between Space and Occupants*

Based on the trace of each occupant at home, we analyzed the relationship between rooms and occupants. Figure 8 shows the daily mobility of each occupant. The size of the node indicates the time the occupant stayed in each room; the thickness of the line indicates the frequency of transitions between rooms. Using this mobility graph, dependency between room and occupants can be estimated. For example, the largest node indicates the personal room of each occupant. Also, a homemaker (User A) visits almost all rooms in the house, including the kitchen, living room, and even other personal rooms for cleaning, whereas other occupants usually visit only a few rooms, namely their own, the living room, and the toilet.

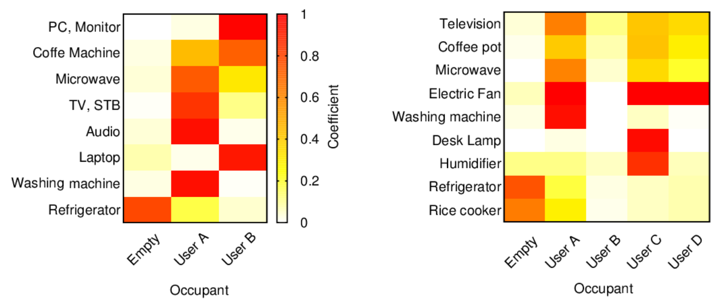
E. *Appliance Classification with Power Profiling*

The system classified the appliances into three groups based on the correlation coefficient between appliance and the room location of each occupant. Figure 9 shows the relationship between usage of appliances and each occupant. The high value of the dependency coefficient with empty indicates a



(a) User A (Home A) (b) User B (Home A)

Fig. 8. Daily In-Home Mobility Pattern of Occupants (Home A)



(a) Home A (b) Home B

Fig. 9. Dependency between Appliance Usage and Each Occupant

TABLE III. ACCURACY OF PERSONALIZED LOAD DISAGGREGATION

	Accuracy (%)							
	TV	***PC & Monitor***	***Laptop***	***Laundry***	***Microwave***	***Audio***	***Coffee Machine***	***Total***
Home A	91%	93%	98%	92%	92%	100%	87%	95%
	TV	***Electric Fan***	***Humidifier***	***Laundry***	***Microwave***	***Desk Lamp***	***Coffee Pot***	***Total***
Home B	86%	100%	94%	100%	89%	100%	79%	88%

background appliance; hence, appliances such as refrigerators and rice cookers are classified as background appliances because they can operate without interaction from co-located users. The coefficient for each occupant and an appliance implies the occupants who used the appliance the most or ownership of the appliance.

F. Estimating Individual Energy Usage

Finally, we evaluated the accuracy of individual electricity usage. We compared our estimated usage with user annotated data. Table III shows the accuracy of user-level load disaggregation based on correlation. The overall error rate of the proposed system is less than 5% and 12% at Home A and Home B, respectively. The results indicate that our system indeed provides accurate and personalized energy feedback information.

VI. CONCLUSION

In this paper, we proposed a personalized load disaggregating system that estimates an individual's electricity usage in a shared residential environment. To infer the actual user of each device, the system monitors appliance usage in real time and the room-level location of occupants. To collect the individual user locations, we proposed a seamless tracking system in the home environment by combining the WPS locating system with doorway crossing sensors. Our system links the energy usage of each appliance with the individual user, based on the relationship between appliances and users, and traces of location; it then provides personalized feedback information to the user.

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