Learning a Context-aware Personal Model of Appliance Usage Patterns in Smart Home

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***Abstract*—To conserve electricity, we have been proposing to control the power consumption of home electrical appliances according to their priority. In a household, appliances are used in performing activities of daily life (ADLs), e.g. cooking, bathing, sleeping, etc. It is assumed that the priority of an appliance changes dynamically according to its usage context of ADLs in a household; it also varies depending on the personal appliance usage habits of each household. In this paper, towards evaluating appliance priority, we learn a personal model of appliance usage patterns, which is aware of the context of ADLs, from appliance power consumption patterns.**

***Index Terms*—appliance usage pattern, activity estimation.**

I. Intoduction

Energy shortage and global warming are two of the current global crises. As one solution of the two crises, demand-side home energy management systems (HEMS) [1] have grabbed the spotlight due to their abilities for reducing electricity use and cutting power peak. Recently, we have been proposing a novel HEMS named "Energy on Demand (EoD)" [2] that controls the power consumption of eletrical appliances according to their priority under a limited power supply. We assume that the priority of an appliance should be decided dynamically in the context of activities of daily life (ADLs), such as cooking, bathing, sleeping, and so on. For example, suppose that IH heater is usually used in cooking, TV is used in cooking sometimes, and bathroom light is seldom used in cooking. It is natural to assume that IH heater has a higher priority than TV and bathroom light in cooking. Furthermore, appliance priority varies depending on household due to the different appliance usage habits of each household. For example, if household h_a always turns on TV while cooking and household h_b seldom turns on TV while cooking, we then assume the priority of TV for h_a is higher than that for h_b.

Towards estimating appliance priority in the context of ADLs, we address two tasks in this paper: (ADL Estimation) Estimate ADLs, e.g. cooking, bathing, sleeping, etc., happening at a household from appliance power consumption patterns; (ADL Analysis) Learn a personal model of appliance usage patterns in the context of ADLs for each household. By solving the two tasks, we could analyze the appliance usage patterns in each ADL within a household to decide appliance priority; we also could compare the appliance usage patterns of different households to detect abnormal appliance usages. Chen et al. [3] mine representative appliance usage patterns based on the time of day from appliance power consumption patterns in a household. However, appliance usage patterns depend on ADLs directly, not the time of day. Ellegård et al. [4] collects data including appliance power consumption patterns and ADL sequences, and then visualize the data to analyze the relationships between ADLs and appliance usages. It is hard to collect such data from each household. Therefore, we solve ADL estimation for learning a ADL-aware personal model of appliance usage patterns. Two main ADL estimation approaches exist [5]: camera-based approach, and wearable sensor-based approach. Camera-based approach monitors the behaviors and the locations of inhabitants using cameras. Some households resist the approach because of the invasiveness of camera. Sensor-based approach captures human physical movements using sensors to estimate ADLs. However, ADLs involving same physical movements cannot be identified by the approach. Milenkovic et al. [6] estimate two types of office worker activities at a desk including works using a computer and works not using a computer from the power consumption of a computer. In contrast, we solve a more complicated problem that estimates 14 types of ADLs listed in Table I from appliance power consumption patterns in home.

To estimate ADLs from appliance power consumption patterns, it is needed to know how appliances are used for performing ADLs. That is, we must do the two tasks concurrently: ADL estimation and personal appliance usage patterns learning. We refer to a topic model LDA [7] that is originally developed for text analysis to accomplish the two tasks together. LDA is a generative model that generates words for a document from the latent topics of the document. LDA is widely used for finding topics in documents while learning the distributions over words for each topic [8]. In our case, ADLs and appliances correspond to topics and words in LDA, respectively. We extend LDA to represent two kinds of simultaneity that multiple ADLs happen simultaneously, and multiple appliances are used simultaneously for the ADLs at a time. LDA finds topics in a document, each of which is represented by a distribution over words. As another extension, we describe an online estimation method to assign a label to each ADL to represent their meaning definitely. To assign labels of ADLs for each household, our method first trains a base model that represents the general appliance usage patterns of each ADL. Our method then estimates ADLs online from appliance power consumption patterns for each household using the base model and a personal model. The personal model is initialized to the base model at the beginning, and is updated for each household sequentially using newly obtained data. Increasingly, the personal model changes to represent the

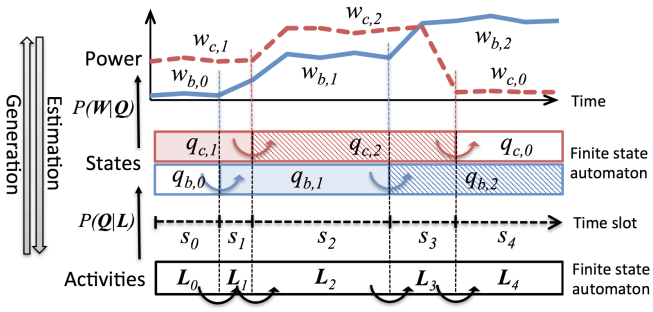

Fig. 1. An example of the AP model.

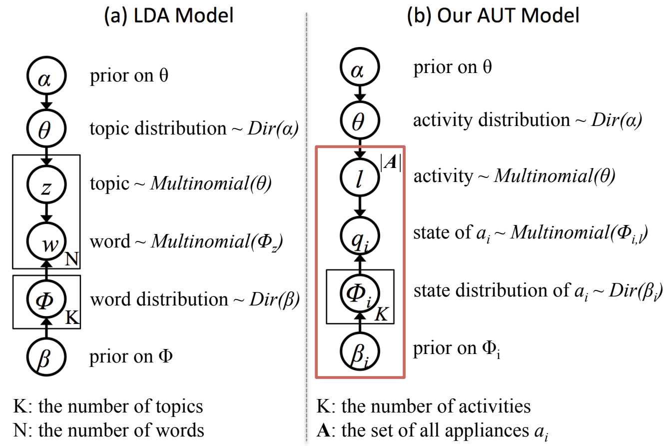

Fig. 2. Plate notations for (a) LDA model, and (b) our AUT model.

ADL-aware appliance usage patterns of each household.

We evaluate our method on real-life datasets collected at a smart house. The evaluation results show that a personal model of ADL-aware appliance usage patterns can be obtained for each household using our method. Our contribution of the ADL estimation can also be applicable to remote monitor of the daily living of older people.

II. Proposed Models and Methods

In this section, we describe the *Activity - Power Model* (AP model) for relating activities to appliance power consumption patterns sequentially along time. Fig. 1 illustrates an example of the AP model including two appliances a_b and a_c. An appliance a_i has multiple operation states $q_{i,j}, j = \{0, 1, ..., M_i\}$, e.g. on and off of a light. At time slot s_0, to perform a set $\mathbf{L}_0$ of activities, each appliance a_i is used on the operation state $q_{i,j}$; and then each $q_{i,j}$ generates the power consumption pattern $w_{i,j}$. We assume that if the operation states of all appliances stay constant then the activities do not change. We partition a next time slot at the ending of each operation state of each appliance. At the next time slot s_1 of s_0, the set $\mathbf{Q}_1 = \{q_{b,1}, q_{c,1}\}$ of the operation states are generated by activities $\mathbf{L}_1$, the power consumption patterns of appliances a_b and a_c are then generated by $q_{b,1}$ and $q_{c,1}$ respectively.

We establish the AP model hierarchically using an AOS model representing $P(w|q)$ for each appliance, and a AUT model representing $P(\mathbf{Q}|\mathbf{L})$, at each time slot.

A. Appliance Operation State Model

Each operation state $q_{i,j}$ of appliance a_i generates a distinguishable power consumption pattern $w_{i,j}$. The AOS model generates the power consumption pattern $w_{i,j}$ for each operation state $q_{i,j}$ of an appliance a_i using a dynamic system $D_{i,j} = P(w_{i,j}|q_{i,j}) \sim N(\mu_{i,j}, \sigma_{i,j})$, which complies with a normalized distribution. We obtain every dynamic system of an appliance by learning, previously. We then estimate operation states from power consumption patterns based on the dynamic systems using Bayesian inference. We omit the detail of the estimation here due to space limitations.

B. Appliance Usage Topic Model

We develop an AUT model that represents $P(\mathbf{Q}|\mathbf{L})$ in each time slot. The AUT model is extended from a topic model LDA [7] that was originally developed for text. Fig. 2 depicts the plate notations of the LDA model and our AUT model. LDA generates words for a document from the latent topics of the document. In LDA, multiple topics exist in a document with a topic distribution; for each word in the document, a topic is generated from the topic distribution, and then the word is generated from the specific word distribution of the topic. We regard each time slot as a document, and regard the operation state of each appliance in a time slot as a word. We then can use LDA to describe the multiple activities happening in a time slot, which correspond to the multiple topics existing in a document. However, the structure of LDA is not suitable for representing the relationship between activities and appliances. We extend LDA to our AUT model. In AUT, multiple activities happen simultaneously in a time slot with an activity distribution θ; for the operation state q_i of each appliance a_i, an activity l is generated from $Multinomial(\theta)$, and then q_i is generated from the activity-specific operation state distribution $Multinomial(\phi_{i,l})$ of a_i and l. In LDA, a topic-specific word distribution is computed over all words. Each word in a document is generated sequentially according to a topic-specific word distribution. A same word might be generated multiple times in a document. In AUT, an activity-specific operation state distribution is computed over all operation states for each appliance; The operation state of each appliance in a time slot is generated simultaneously according to the operation state distributions of each appliance.

Given the set $\mathbf{Q}_s$ of the operation state $q_{i,j,s}$ of each appliance a_i and the set of labels L'_s of activities at each time slot s, our task is to compute the expected operation state distribution $\widehat{\phi_{i,k}}$ of each appliance a_i and each activity l_k. We use Gibbs sampling to accomplish the task similarly to the method [9] for learning LDA. Let $l_{i,j,s}$ denote the activity generating the operation state $q_{i,j,s}$ of appliance a_i at time slot s. Firstly, we train the probability of $l_{i,j,s}$. The operation state of each appliance remains unchanged within a time slot. Therefore, we assume that the probability of $l_{i,j,s}$ never changes within a time slot. We sample activities generating each operation state at a time slot only for the first time unit, e.g., the first second, of the time slot. Let $N_{i,j,k,s}$ be the number of times that the operation state $q_{i,j}$ of appliance a_i was assigned to activity l_k in the sampling for the first time unit of time slot s, and let d_s be the length of time slot s. We then define $N_{i,j,k,s}d_s$ as the count the operation state $q_{i,j}$ of appliance a_i was assigned to the activity l_k at time slot s. Consequently, $N_{i,j,k} = \sum_s(N_{i,j,k,s}d_s)$ is the count the operation state $q_{i,j}$ is assigned to activity l_k at every time slot, and $N_{k,s} = \sum_i \sum_j(N_{i,j,k,s}d_s)$ is the count an operation state is assigned to activity l_k at time slot s. Given the current state of all but one variable $l_{i,j,s}$, the conditional probability of $l_{i,j,s}$ is given by:

$$p(l_{i,j,s} = l_k, |\mathbf{L}_s^{-i,j,s}, \mathbf{Q}_s, \alpha, \beta) = \frac{N_{k,s}^{-q_{i,j,s}} + \alpha_k}{\sum_k(N_{k,s}^{-q_{i,j,s}} + \alpha_k)} \times \frac{N_{i,j,k}^{-q_{i,j,s}} + \beta_{i,j,k,s}}{\sum_j(N_{i,j,k}^{-q_{i,j,s}} + \beta_{i,j,k,s})} \quad (1)$$

Here, $-q_{i,j,s}$ denotes that the count does not include the current assignment of operation state $q_{i,j}$ at time slot s. The target activity l_k at time slot s is restricted to belong to the activities of the labels in L'_s. The probability is larger if many of the other operation states except $q_{i,j}$ at time slot s are assigned to the activity l_k, and if many of the operation states $q_{i,j}$ at other time slots are assigned to the activity l_k. We set all $\alpha_k = 1.0$ and $\beta_{i,j,k,s} = 0.01$ in this paper.

a) Weighting Schemes: It is assumed in Equation 1 that each appliance operation state is equally important in calculating the conditional probability. However, the operation states of some appliances that exist for a long time are unimportant for identifying ADLs. For example, appliances that have been forgotten to be turn off are not actually used for performing ADLs; appliances that work all the time, e.g. refrigerator, aircon, ventilation fan, etc., do not contribute much for any particular ADL. We assign a weight $w_{i,j}$ to each appliance operation state $q_{i,j}$ to differentiate their importance for estimating ADLs, similarly to the weighting schemes [10] for LDA. Given a dataset of duration of T $[sec]$, then

$$w_{i,j} = log_2 \frac{T\ [sec]}{usage\ duration\ [sec]\ of\ q_{i,j}}, \quad (2)$$

where $w_{i,j}$ is subject to $1.0 \leq f_{i,j} \leq 15.0$ in order to avoid overfitting. We then replace $N_{i,j,k,s}$ by $N_{i,j,k,s}w_{i,j,k}$ in Equation 1.

C. Online Estimation

We describe an online estimation method using the AUT model for ADL estimation and for learning a ADL-aware personal model of appliance usage patterns for each household. We say that two households are of the same type if similar parts, such as a living room, a bedroom, a kitchen, and a bathroom, form each house. We define 14 labels of ADLs previously as presented in Table I. For a group of households of the same type, we do the following. We collect a dataset including ADL sequences of the 14 ADLs and appliance power consumption patterns from several households of the group. We identify appliances in different households by the type and the location of each appliance, such as kitchen light, or restroom air fan. The dataset should cover all the appliances existing in all the households of the group and all the 14 ADLs. Firstly, we train a base model that consists of the expected operation state distributions $\widehat{\phi^b_{i,k}}$ for all appliance a_i and all activity l_k using the dataset:

$$\widehat{\phi^b_{i,j,k}} = \frac{\sum_s(N_{i,j,k,s}w_{i,j}d_s + \beta_{i,j,k,s})}{\sum_i(\sum_s(N_{i,j,k,s}w_{i,j}d_s + \beta_{i,j,k,s}))}. \quad (3)$$

A high probability $\phi^b_{i,j,k}$ is generated if operation state $q_{i,j}$ is used long for the activities of l_k, and if operation state $q_{i,j}$ seldom appears in other activities. For example, Fig. 4 (a) presents an example of a base model $\widehat{\phi^b}$. For each appliance and each ADL, the sum of the probabilities $\widehat{\phi^b_{i,j,k}}$ of all operation states is 1.0.

A base model represents the ADL-aware general appliance usage patterns for a group of households. However, the personal appliance usage patterns of each household vary. It is insufficient to estimate ADLs for each household using the base model only. Our online estimation method estimates ADLs for each household of a group using the base model $\widehat{\phi^b}$ with a personal model $\widehat{\phi^p}$. We set $\widehat{\phi^p_{s=0}} = \widehat{\phi^b}$ at the first time slot $s = 0$. At each time slot s, our method performs the following two steps.

(Step 1) *ADL Estimation*: Estimates ADLs happening at time slot s for the household on the AUT model, by setting $\beta_{i,j,k,s} = \phi^p_{i,j,k,s}\lambda^p + \phi^b_{i,j,k}\lambda^b$. With the setting of $\beta_{i,j,k,s}$, our method combines the base model and the personal model with weight λ_b and λ_p respectively as the prior $\beta'_{i,j,k,s}$ of the current operation state distribution $\phi_{i,j,k,s}$ of time slot s.

$$\phi_{i,j,k,s} = \frac{N_{i,j,k,s}w_{i,j,k,s} + \beta'_{i,j,k,s}}{\sum_i(N_{i,j,k,s}w_{i,j,k,s} + \beta'_{i,j,k,s})}. \quad (4)$$

Here, $w_{i,j,s=0}$ is initialized using the weight computed on the base model, and $w_{i,j,s}$ is updated using the newly obtained data sequentially. We set $\lambda_b = \lambda_p = 0.5 * \beta$ to let the base model and the personal model contribute equally, in this paper. We was referring to online LDA [8] for using past posterior as the current prior. As the ADLs happening at time slot s, our method outputs the combination of the ADLs having the maximal likelihood $p'(l_{i,j,s} = l_k) = \theta_{i,s}\phi_{i,j,k,s}$ for each appliance a_i.

$$\theta_{i,s} = \frac{N_{k,s} + \alpha_{k,s}}{\sum_k(N_{k,s} + \alpha_{k,s})}, \quad (5)$$

where $N_{k,s} = \sum_i \sum_j(N_{i,j,k,s}w_{i,j,k,s})$.

(Step 2) *Personal Model Update*: The personal model $\widehat{\phi^p_{i,j,k,s+1}}$ for the next time slot is updated by incorporating the posterior $\phi_{i,j,k,s}$ of current time slot:

$$\widehat{\phi^p_{i,s+1}} = (\widehat{\phi^p_{i,s}} + \phi_s d_s)/(1 + \sum_s d_s) \quad (6)$$

Increasingly, the personal model $\widehat{\phi^p}$ is adapted to represent the ADL-aware appliance usage patterns of each household.

TABLE I
THE LABEL AND THE DESCRIPTION OF EACH OF THE 14 PREDEFINED ADLS.

ID	Label	Description
1	cooking	cooking a meal; clearing the table; washing the dishes
2	having a meal	having a breakfast, a lunch, or a dinner
3	bathing	taking a shower or a bath
4	personal hygiene	excepting bathing; going to toilet; washing hands or face; changing clothes...
5	cleaning	cleaning the house
6	laundry	washing clothes and drying clothes
7	housework	any housework except cleaning and washing
8	work	doing something relating to study or job
9	conversation	talking with someone face-to-face, on the phone, or on the Internet...
10	entertainment	reading a book; watching DVD; playing games; listening to music...
11	watching TV	watching or listening TV
12	having a rest	doing nothing; drinking tea or coffee; eating snacks; having a short nap...
13	outing	all members are going outside the house
14	sleeping	all members are sleeping more than 30 minutes

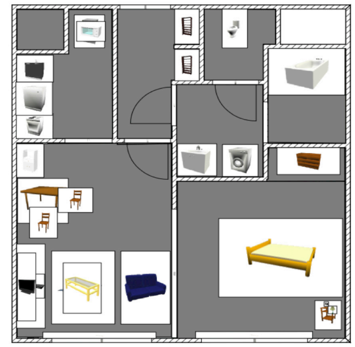

Fig. 3. The room layout and the appliances in the smart house.

(a) A base model learned from A1&B1

	Kitchen light		IH heater		Refrigerator			WC light		WC fan		Bathroom light		Bathroom fan		Dryer		Washing machine		Cleaner		TV		note PC		Aircon	
weight	1.00	5.55	1.00	5.90	1.21	1.00	12.7	1.00	6.81	1.00	1.16	1.00	6.13	1.05	1.00	1.00	10.2	1.00	5.89	1.00	12.1	1.00	2.41	1.00	3.68	1.50	1.00
$\Phi_{i,j,k}$	off	on	off	on	rest	cooling	open	off	on	off	on	off	on	off	on	off	on	off	on	off	on	off	on	off	on	off	on
1 cooking	0.14	0.86	0.22	0.78	0.28	0.70	0.02	1.00	0.00	0.17	0.83	1.00	0.00	0.13	0.87	1.00	0.00	1.00	0.00	1.00	0.00	0.36	0.64	0.97	0.03	0.08	0.92
2 having a meal	0.75	0.25	1.00	0.00	0.20	0.80	0.00	0.50	0.50	0.00	1.00	0.35	0.65	0.02	0.98	1.00	0.00	1.00	0.00	1.00	0.00	0.52	0.48	1.00	0.00	0.07	0.93
3 bathing	1.00	0.00	1.00	0.00	0.35	0.65	0.00	0.62	0.38	0.37	0.63	0.03	0.97	0.12	0.88	0.99	0.01	0.74	0.26	1.00	0.00	0.94	0.06	1.00	0.00	0.02	0.98
4 personal hygien	0.97	0.03	0.99	0.01	0.60	0.39	0.01	0.38	0.62	0.22	0.78	0.98	0.02	0.19	0.81	0.79	0.21	0.98	0.02	1.00	0.00	0.64	0.36	1.00	0.00	0.23	0.77
5 cleaning	1.00	0.00	1.00	0.00	0.24	0.76	0.00	0.97	0.03	0.41	0.59	1.00	0.00	0.00	1.00	1.00	0.00	1.00	0.00	0.14	0.86	0.12	0.88	1.00	0.00	0.09	0.91
6 laundry	0.28	0.72	0.50	0.50	0.46	0.54	0.00	0.98	0.02	0.86	0.14	1.00	0.00	0.67	0.33	1.00	0.00	0.02	0.98	1.00	0.00	0.51	0.49	0.83	0.17	0.46	0.54
7 housework	0.71	0.29	0.91	0.09	0.63	0.33	0.04	0.95	0.05	0.94	0.06	0.40	0.60	0.16	0.84	1.00	0.00	1.00	0.00	1.00	0.00	0.53	0.47	0.97	0.03	0.17	0.83
8 work	1.00	0.00	1.00	0.00	0.48	0.52	0.00	0.99	0.01	0.00	1.00	1.00	0.00	0.01	0.99	1.00	0.00	0.64	0.36	1.00	0.00	0.83	0.17	0.00	1.00	0.03	0.97
9 conversation	1.00	0.00	1.00	0.00	0.39	0.61	0.00	1.00	0.00	0.03	0.97	1.00	0.00	0.04	0.96	1.00	0.00	1.00	0.00	1.00	0.00	0.97	0.03	1.00	0.00	0.15	0.85
10 entertainment	1.00	0.00	1.00	0.00	0.51	0.49	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	0.00	0.67	0.33	0.16	0.84	0.00	1.00
11 watching TV	1.00	0.00	1.00	0.00	0.42	0.58	0.00	0.99	0.01	0.37	0.63	1.00	0.00	0.23	0.77	1.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.06	0.94
12 having a rest	1.00	0.00	1.00	0.00	0.08	0.92	0.00	0.45	0.55	0.33	0.67	1.00	0.00	0.84	0.16	1.00	0.00	1.00	0.00	1.00	0.00	0.06	0.94	1.00	0.00	0.26	0.74
13 outing	1.00	0.00	1.00	0.00	0.46	0.54	0.00	1.00	0.00	0.94	0.06	1.00	0.00	0.96	0.04	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.99	0.01
14 sleeping	1.00	0.00	1.00	0.00	0.52	0.48	0.00	1.00	0.00	0.42	0.58	1.00	0.00	0.33	0.67	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.10	0.90

(b) A personal model learned for C using the base model presented in (a)

1 cooking	0.24	0.76	0.33	0.67	0.51	0.48	0.01	1.00	0.00	0.42	0.58	1.00	0.00	0.42	0.58	1.00	0.00	1.00	0.00	1.00	0.00	0.50	0.50	0.98	0.02	0.69	0.31
13 outing	1.00	0.00	1.00	0.00	0.47	0.53	0.00	1.00	0.00	0.33	0.67	1.00	0.00	0.30	0.70	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.82	0.18
14 sleeping	1.00	0.00	1.00	0.00	0.47	0.53	0.00	1.00	0.00	0.32	0.68	1.00	0.00	0.38	0.62	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.80	0.20

Fig. 4. A base model and a personal model.

For example, Fig. 4 (b) presents an example of the personal model $\widehat{\phi_i^b}$ which is updated from the based model presented in Fig. 4 (a). The base model is obtained from a datasets collected from households where Kitchen light and IH heater are used often in cooking. The personal model is learned for a household that often cooks instant food only and seldom uses the two appliances in cooking. Our online estimation method successfully learns the personal model for the household, in which the probabilities of the state "on" of the two appliances in cooking are lower than those in the base model.

III. EXPERIMENTS

In this section, we conduct experiments to evaluate our online estimation method for ADL estimation; we also show some examples of the ADL-aware appliance usage patterns learned using our method. We perform experiments at a smart house where every appliance is connected to the electricity through a smart tap. A smart tap collects the power consumption of an appliance per 2-3 seconds. Fig. 3 depicts the layout of the house, and the appliances placed in the house. There are 19 appliances in the smart house. Some appliances are listed in the first row of Fig. 4 (a).

We ask four families denoted by A, B, C, and D to live in the house for 7 days, respectively. Three families have only one member, and one family has two members. We ask them to record living activities in the unit of minute every day.

A. Evaluation of ADL Estimation

We first train a base model using the datasets of some families, and then use the base model to estimate ADLs for each family. Family A and family B used all the 19 appliances, and performed all the 14 types of ADLs. We use half of each of the datasets of A and B, denoted by A1 and B1, to train the base model. The other halves denoted by A2 and B2 are used for evaluation later. Figure 4 (a) presents the base

	Recall	Precision	F-measure
	A2		
base	0.817	0.845	0.831
base+personal	0.815	0.849	0.832
	B2		
base	0.848	0.777	0.811
base+personal	0.871	0.802	0.835
	C		
base	0.679	0.484	0.566
base+personal	0.690	0.483	0.568
	D		
base	0.875	0.697	0.776
base+personal	0.880	0.701	0.781

Fig. 5. Recall, precision and F-measure on estimated ADLs.

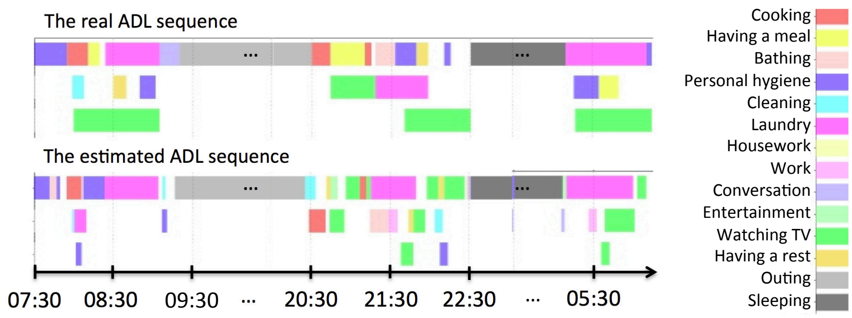

Fig. 6. The ADL sequences of one day of A.

model $\widehat{\phi^b}$ learned from A1 and B1. The row "weight" presents the weight evaluated for each appliance operation state. The states "off" of almost all appliances and the state "cooling" of refrigerator have the lowest weight 1.0. That is, these states seldom contribute for performing any ADL. By contrast, the state "on" of IH heater, bathroom light, washing machine, and cleaner own very high weight. Next, we look at the probability $\phi_{i,j,k}$ of each appliance operation state and each ADL. As discussed in Section II-B, the probabilities are proportional to the the weight of the state and the usage duration of each state in each ADL. The shadowed cells denote the highest probabilities of the state "on" of each appliance among all ADLs. For example, the probability of "on" of kitchen light in cooking is the highest among all ADLs. The results reveal that the appliance is usually and especially used for a long time in cooking. Similarly, the probability of bathroom light in bathing, that of washing machine in laundry, and that of TV in watching TV are the highest, respectively. On the other hand, the probabilities of "on" of aircon in all ADLs excepting outing are not much different. The probabilities of "cooling" of refrigerator, those of "on" of WC fan, those of "on" of bathroom fan, are also similar, respectively. The results mean that these appliances are used in almost all ADLs.

Using the base model, we do ADL estimation and learn a personal model for each of A2, B2, C and D. As an example, Figure 4 (b) presents a part of the personal model $\widehat{\phi^p}$ learned for C. C always only cook instant food and does not use the appliances in Kitchen often. This appliance usage habit is successfully captured in the personal model, so that the probability of kitchen light and that of IH heater in cooking are much lower than those in the base model, respectively. C also does not use aircon often every day. The probabilities of "on" of aircon are low. C turns on WC fan and Bathroom fan while going out. The probabilities of "on" of the two appliances in outing are higher than those of the base model. In this manner, our online estimation method can learn a personal model reflecting the ADL-aware appliance usage patterns for each household.

We quantitatively evaluate the ADLs estimated for each family. We estimate ADLs for each family in two manners: (1) using a base model only; (2) using a base model and a personal model. Fig.5 presents the recall, precision, and F-measure computed on every minute in the time duration of each dataset for all ADLs. The base model is trained from A1 and B1. The F-measure values of using the base model and a personal model are higher for each dataset. The average of the F-measure values of all datasets is 0.754, which is very high. As an example, Fig. 6 depicts the real ADL sequence and the estimated ADL sequence of one day of A. Each color represents a type of ADL. The simultaneous ADLs in a sequence are depicted in three lines without order. The estimated ADL sequence is quite consistent with the real ADL sequence. This day is a weekday. Only one member is in family A. Family A weeks up early in the morning, cooks and eats food, goes out after finishing laundry around $9:00$. Family A comes back to home around $20:30$, and then cooks food, has a meal while watching TV, takes a bath while doing laundry, and goes to bed around $22:30$. We conclude from the above results that our method can estimate ADLs accurately, and that learning a personal model is effective for ADL estimation.

Real ADL \ Estimated ADL	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0.77		0.03	0.02		0.02	0.02	0.01	0.03		0.07	0.01		
2	0.11	0.02	0.01	0.05	0.03	0.10	0.02	0.07	0.02	0.06	0.38	0.09	0.01	0.02
3			0.93	0.01		0.03								
4			0.02	0.68		0.09	0.02	0.03	0.04		0.02	0.03		0.05
5	0.14	0.01	0.03	0.09	0.45	0.04		0.03		0.02	0.01	0.04	0.10	0.01
6			0.02	0.02		0.83		0.02	0.02		0.06	0.02		
7	0.01		0.25	0.16		0.34			0.04		0.04	0.02	0.01	0.11
8			0.02	0.03	0.01			0.40	0.24	0.04	0.12	0.02	0.05	0.06
9			0.08	0.10	0.03	0.01			0.13	0.02		0.02	0.08	0.54
10	0.07					0.06		0.06	0.04	0.65	0.01		0.03	0.06
11	0.06		0.02	0.04	0.02	0.09					0.72	0.03		
12			0.13	0.14		0.03		0.03	0.20		0.04	0.22	0.05	0.16
13				0.02								0.02	0.93	0.02
14				0.02					0.01			0.03		0.92

Fig. 7. Confusion matrix for real and estimated ADLs.

Next, we look at the performance of our method for identifying each type of ADLs using the base model trained from A1 and B1 and a personal model. Fig. 7 presents the confusion matrix for the real and the estimated ADLs of all

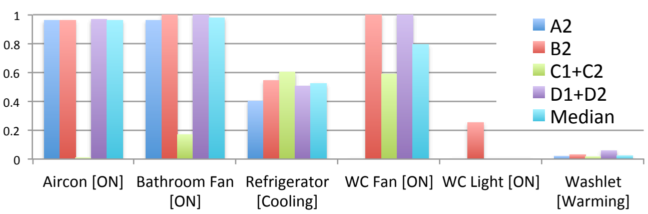

Fig. 8. Rate of the usage duration of each appliance in sleeping.

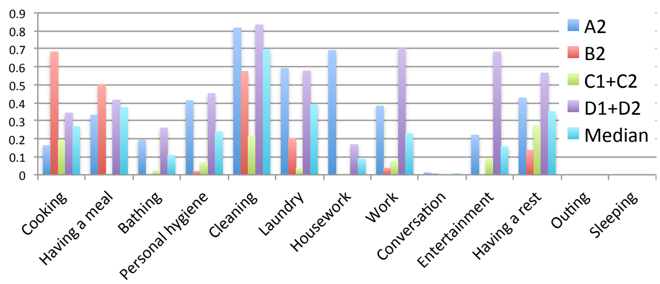

Fig. 9. Rate of the usage duration of TV in each ADL.

the four families. Each cell in a row represents the rate that an ADL was identified as an ADL in every minute. If an real ADL does not appear in the estimated ADLs, we regard the ADL is identified as each of the estimated ADLs; otherwise, the ADL is identified as itself. The IDs of the ADLs refer to those presented in Table I. For example, ID.1 "cooking" was identified as "cooking" with a rate of 0.77. The cell of the largest rate in each row is colored. 11 out of the 14 ADLs, such as cooking, bathing, outing, sleeping, etc., were estimated as itself with the highest rate, respectively. No.2 "having a meal" was estimated as No.11 "watching TV" with the highest rate. The reason is that no appliance is especially necessary for "having a meal" in our smart home. All the families usually "watch TV" while dining. Consequently, "having a meal" cannot be identified by our method, while "watching TV" which happens simultaneously with "having a meal" is identified. Similarly, our method also cannot accurately identify housework and conversation because no appliance is specially used for the two ADLs.

B. Analysis of the Personal Models

We show some interesting examples to show a way for power conservation by comparing the personal models of different households. Fig. 8 depicts the rates of the usage duration of each appliance to the duration of sleeping for each family. The median of the rates of each appliance of the four families is also given. We can observe that only B turns on WC light for a long time while sleeping from Fig. 8. It is possible for B to turn off WC light while sleeping for electricity conservation.

As another example, Fig. 9 depicts the rates of the usage duration of TV to the duration of each ADL. The rate of A in housework is much higher than the corresponding medians. The rate of B in cooking and that of D in work are much higher than their corresponding median, respectively. In this manner, by comparing the usage duration of an appliance under the context of ADLs among several families, it is helpful for each family to discover their overuse of an appliance.

We plan to learn other kinds of ADL-aware personal models, such as the usage duration distribution of each appliance, and the co-occurrence relationships among appliances. It is hopeful that automatic control of appliance power consumption could be developed through analyzing these ADL-aware models.

IV. Conclusion

Towards controlling appliance power consumption according to personal appliance usage habits in the context of ADLs, we addressed the two tasks: estimating ADLs from appliance power consumption patterns, and learning ADL-aware personal appliance usage patterns. It is difficult to solve the tasks for any household because the appliance usage habit of each household is different. To accomplish the tasks, we first train a base model representing the ADL-aware general appliance usage patterns using labeled datasets collected from a few households. We then learn an ADL-aware personal model of appliance usage patterns online for each household through ADL estimation based on the base model.

We confirmed through experiments performed on real life datasets that our method can estimate ADL accurately, and the personal models obtained using our method reflect the appliance usage patterns of each household. We also demonstrated using several case studies that it is possible to discover abnormal appliance usages by comparing the ADL-aware personal models of multiple households.

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