PAPER

A Novel Method for the Bi-directional Transformation between Human Living Activities and Appliance Power Consumption Patterns

Xinpeng ZHANG[†a)], **Yusuke YAMADA**[†*], ***Nonmembers***, **Takekazu KATO**[†], ***and*** **Takashi MATSUYAMA**[†], ***Members***

SUMMARY This paper describes a novel method for the bi-directional transformation between the power consumption patterns of appliances and human living activities. We have been proposing a demand-side energy management system that aims to cut down the peak power consumption and save the electric energy in a household while keeping user's quality of life based on the plan of electricity use and the dynamic priorities of the appliances. The plan of electricity use could be established in advance by predicting appliance power consumption. Regarding the priority of each appliance, it changes according to user's daily living activities, such as cooking, bathing, or entertainment. To evaluate real-time appliance priorities, real-time living activity estimation is needed. In this paper, we address the problem of the bi-directional transformation between personal living activities and power consumption patterns of appliances. We assume that personal living activities and appliance power consumption patterns are related via the following two elements: personal appliance usage patterns, and the location of people. We first propose a *Living Activity - Power Consumption Model* as a generative model to represent the relationship between living activities and appliance power consumption patterns, via the two elements. We then propose a method for the bidirectional transformation between living activities and appliance power consumption patterns on the model, including the estimation of personal living activities from measured appliance power consumption patterns, and the generation of appliance power consumption patterns from given living activities. Experiments conducted on real daily life demonstrate that our method can estimate living activities that are almost consistent with the real ones. We also confirm through case study that our method is applicable for simulating appliance power consumption patterns. Our contributions in this paper would be effective in saving electric energy, and may be applied to remotely monitor the daily living of older people.

key words: *pattern transformation, i-Energy, human living activity*

1. Introduction

In recent years, demand-side smart energy management systems have attracted attention for their ability to manage the peak power consumption and total electric energy in a household to reduce the electricity cost and emissions of the greenhouse gas. For this purpose, we have been proposing a novel demand-side energy management system named "*Energy on Demand* (EoD)" [1] that manages power consumption in demand-sides, such as houses, offices, or buildings. The EoD mediates demand power requests from appliances taking into account both available energy sources and appliance priorities to keep user's quality of life (QoL). For example, the EoD might decline to supply limited electrical power to appliances of low priorities.

For the demand-side energy management systems, including our EoD, it is important to predict the appliance power consumption patterns for a user's life to establish a plan of electricity use [2], and to estimate the priorities for each power request from the appliances to keep QoL. It is assumed that the priority of an appliance should be decided dynamically according to its usage in user's personal living activities. For example, TV is important while a person is "watching a TV program," IH cooker is important while a person is "cooking." Consequently, to estimate real-time appliance priority, we need to estimate real-time living activities. In this paper, as the first step towards constructing the EoD, we address the problem of the bi-directional transformation between personal living activities and power consumption patterns of appliances.

As the basis for solving the problem, we establish a *Living Activity - Power Consumption Model* (LAPC model) as a hierarchical probabilistic generative model to represent the relationship between personal living activities and appliance power consumption patterns. We then propose methods on the LAPC model for the bi-directional transformation between personal living activities and appliance power consumption patterns, including (1) the generation of appliance power consumption patterns from given living activities, and (2) the estimation of living activities from measured appliance power consumption patterns. Since the LAPC model simulates the probability distribution of appliance power consumption patterns for given a living activity, the generation can be implemented simply by random sampling of the appliance power consumption according to the distribution. The estimation which is the inverse of the generation, is achieved by using Bayesian inference on the LAPC model to estimate posterior probabilities of living activities from measured appliance power consumption patterns.

We construct the LAPC model with several sub models hierarchically to relate living activities to appliance power consumption patterns via appliance usage patterns and the location of people. The main difficulties that we are facing in constructing the model are caused by the following two

Manuscript received May 21, 2013.
Manuscript revised October 31, 2013.
[†]The authors are with the Graduate School of Informatics, Kyoto University, Kyoto-shi, 606–8501 Japan.
[*]Presently, with Sharp Corporation.
a) E-mail: xpzhang@i.kyoto-u.ac.jp
DOI: 10.1587/transinf.E97.D.275

ambiguities. (1) The ambiguity of living activities. People might perform two or more living activities simultaneously. For example, someone likes to listen to a TV program while cooking; someone cleans a house while washing clothes using a washing machine. We cope with this ambiguity by explicitly defining main and sub living activities in the LAPC model. (2) The ambiguity of the usages of appliances. The operations on appliances performed by a person can be estimated from power consumption patterns of the appliances. Also, the operations can be related to the living activities of the person. However, the relationships between the appliance operations and personal living activities vary according to personal appliance usage patterns. For instance, someone cooks a meal using an induction cooker; someone heats instant food as a meal using a microwave. We deal with this ambiguity by construct sub probability models in the LAPC model to represent the relationships between human living activities and appliance usages.

The rest of the paper is organized as follows. Section 2 explains the LAPC model. Section 3 presents the method for generating appliance power consumption patterns from given living activities, and the method for estimating living activities from appliance power consumption patterns Sect. 4 reports the experimental results. Section 5 reveals related work. Section 6 concludes the paper.

2. Living Activity - Power Consumption Model

In this section, we describe a *Living Activity - Power Consumption Model* (LAPC model) as a Generative Model [3] to represent the relationship from living activities to appliance power consumption patterns. Figure 1 depicts the structure of the LAPC model. To perform a living activity l, a person moves to a location r, and then operates and uses a set $\mathbf{A}$ of appliances. Let $\mathbf{Q}$ denote the set of the operation states of each appliance in $\mathbf{A}$. The set $\mathbf{W}$ of appliance power consumption patterns of each appliance in $\mathbf{A}$ are then generated by $\mathbf{Q}$. We represent the relationship from l to $\mathbf{W}$ through learning probabilities $P(\mathbf{Q}|l)$, $P(\mathbf{W}|\mathbf{Q})$, and $P(r|l)$, in the LAPC model, as we will discuss in detail later in this section. The model is effective for generating $\mathbf{W}$ from l readily. We implement a method for generating $\mathbf{W}$ from l according to $P(\mathbf{Q}|l)$ and $P(\mathbf{W}|\mathbf{Q})$ available in the model, in Sect. 3.1. The model is also effective for estimating l from $\mathbf{W}$ by using Bayesian inference. We propose a method for estimating l from $\mathbf{W}$, through estimating posterior probabilities $P(\mathbf{Q}|\mathbf{W})$ and $P(l|\mathbf{Q})$ based on the model using Bayesian inference, in Sect. 3.2 Consequently, the LAPC model is effective for the bi-directional transformation between l and $\mathbf{W}$.

We establish the generation model by constructing the following sub models. Section 2.1 describes a Personal Living Activity Model to formally define living activities including activities happening simultaneously. Section 2.2 presents a Personal Appliance Usage Model to represent the relationship between living activities and appliance usages. Section 2.3 describes an Appliance Operation State Model

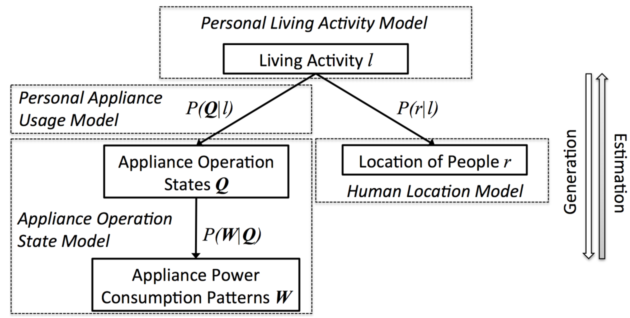


Fig. 1 The structure of our LAPC Model.

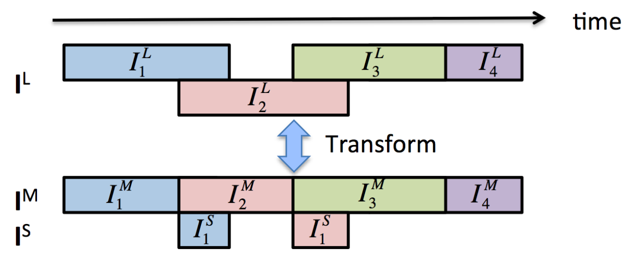


Fig. 2 A example of two representations of a living activity sequence.

to represent the relationship from appliance operation states to appliance power consumption patterns. Section 2.4 introduces a Human Location Model [4] proposed by the authors for estimating the location r of a person based on the person's operations on appliances.

We discuss the details of each sub model in the following subsections.

2.1 Personal Living Activity Model

A living activity could be represented by a label representing the type of the activity, such as cooking, washing, or watching TV, with a time duration indicating when the activity happens. Let $< l_i, b_i, e_i >$ denote a living activity I_i, where l_i is the label of I_i, b_i and e_i are the start time and end time of I_i, respectively.

Living activities happen consecutively in our day life, such as a people has a dinner, watches TV, takes a shower, and then goes to bed. Furthermore, multiple activities might happen simultaneously, such as a people might watches TV while he/she is having a dinner. Consequently, living activities might switch while overlapping. We represent a sequence of living activities using a *flat description*: $\mathbf{I}^L = \{I_1^L, I_2^L, \ldots, I_Q^L\}$. Figure 2 depicts an example of the flat description. Since overlap and time-gaps of multiple activities exist in the flat description, it is difficult for us to estimate such a sequence of living activities.

To solve the problem, we introduce another *main-sub description* to represent a sequence of living activities by restricting overlap and time-gaps, which is more easy to estimate. We represent a sequence of living activities, using a combination of a main activity sequence $\mathbf{I}^M = \{I_1^M, I_2^M, \ldots, I_K^M\}$, and one or more sub activity sequence $\mathbf{I}^{S_j} = \{I_1^{S_j}, I_2^{S_j}, \ldots, I_N^{S_j}\}$. Figure 2 depicts an example of the main-sub description. A main activity means the activity mainly performed by a people at a certain time, and it depends on the location of the people. We give a constraint that no time-gap exists between any two nearby main activities. A sub activity might happen parallel with a main activity in the background, and it does not depend on the location of the people. For example, A people starts the main activity "washing" at the place where the washing machine is. Later, the people moves to the kitchen, performs the main activity "cooking" while "washing" is ongoing. However, "washing" becomes a sub activity at the kitchen now. There might be time-gaps in $\mathbf{I}^{S_j}$ because no sub activity happens in some time duration. As depicted in Fig. 2, the sequence $\mathbf{I}^L$ and the combination of $\mathbf{I}^M$ and $\mathbf{I}^{S_j}$ can be transformed to each other. In this paper, we deal with the case of a main activity sequence with a simultaneous sub activity for the estimation of living activities. However, our method could be extended to deal with multiple sub activity sequences easily.

People always perform some activities one after another consecutively in a certain order at home. For example, people usually eat food after cooking, and dry our hair after taking a shower. People also usually do some activities simultaneously, such as watching TV while eating foods. On the other hand, some activities rarely happen together, such as taking a shower and cooking. We use the following two probabilities to represent the transition and co-occurrence relationships between activities. Let $I_{i-1} =< l_{i-1}, b_{i-1}, e_{i-1} >$ and $I_i =< l_i, b_i, e_i >$ denote two consecutive activities, $P(l_i = l_f | l_{i-1} = l_g)$ is then the transition probability from activity of l_g to that of l_f. Let $[b_i, e_i]$ be the time duration when $I_i =< l_i, b_i, e_i >$ happens, $P(l_i = l_g, l_j = l_f | [b_i, e_i] \cap [b_j, e_j] \neq \emptyset)$ is then the co-occurrence probability between activities of l_g and l_f. The duration time of a type of activity is also an important property. We define duration time distribution $P(\tau_i | l_i = l_g), \tau_i = e_i - b_i$ of activities of l_g, to represent the property.

2.2 Personal Appliance Usage Model

Generally, an appliance a_c has various of operation states $q_1^c, q_2^c, \ldots, q_M^c$. Here, we define an Personal Appliance Usage Model to represent the relationship from a living activity l_g to an appliance a_c that is used (at work) in l_g using a probability $P(a_c|l_g) = P(q_{on}^c|l_g)$, where q_{on}^c denote the operation states of at work. Since the appliances that are used in each activity vary from each people, $P(a_c|l_g)$ should be obtained for each person particularly through learning. We discuss how to learn $P(a_c|l_g)$ at the end of this section. $P(a_c|l_g)$ is used in the method for estimating living activities which will be presented in Sect. 3.2.

An appliance is working with the transitions from one state to another. The transitions are triggered by manual operations of people or automatic controls of the appliance. We represent the relationship from a living activity to the operation states of an appliance using the following probabilities. The probabilities are used in the method for generating appliance power consumption which will be described in Sect. 3.1.

- $P(q_i^c = q_j^c | l_j = l_k, q_{i-1}^c = q_h^c)$: The transition probability from state q_h^c to state q_j^c of appliance a_c in the time duration where activities of l_k happen. The probability is computed by dividing the number of times where activity of q_j^c happens behind activity of q_h^c, by the count of activities of q_h^c.
- $P(\tau_i^c | l_j = l_k, q_i^c = q_h^c)$: The duration time distribution of q_h^c of a_c under activity l_k. To obtain the distribution, we construct a histogram showing the proportion of the time duration of a state that fall into each length of the duration time. We then convert the histogram into a distribution function, such as a normal distribution function.
- $P(q_{k,m=1}^c = q_i^c | l_j = l_k)$: The distribution of the beginning state $q_{k,m=1}^c$ of a_c in activity l_k. This distribution is computed by dividing the number of activities of l_k whose beginning state is q_i^c, by the total number of activities of l_k.

When sufficient learning data can be given in advance for a particular person, it is better to obtain $P(a_c|l_g)$ by learning for the person. However, it is difficult to perform the learning for each person in some situations. For the situations, instead of learning for each person, we can decide $P(a_c|l_g)$ for every person based on the functions of appliances. Let $P_f(l_g|a_c)$ denote the probability that a_c can be used in activity l_g according to its function. $P_f(l_g|a_c)$ can be decided manually. We then compute $P(a_c|l_g)$ using the following equation.

$$P(a_c|l_g) = \frac{P_f(l_g|a_c)P(a_c)}{P(l_g)} \tag{1}$$

By assuming $P(a_c)$ and $P(l_g)$ as uniform distributions, we obtain $P(a_c|l_g) = C \cdot P_f(l_g|a_c)$ where C is a normalization constant making $\int P(a_c|l_g)\mathrm{d}a_c = 1$.

When learning data of a person is available, we learn $P(a_c|l_g)$ for the person according to the rate $f(c, g)$ of the number of the activities of label l_g using a_c to the total number of the activities of l_g in the learning data, using Eq. (2).

$$P(a_c|l_g) = (1 - \lambda(c)) \cdot P(l_g|a_c) + \lambda(c) \cdot f(c, g) \tag{2}$$

$$\lambda(c) = log\frac{|\mathbf{I}^L|}{|\{I_i^L : a_c \text{ is used in } I_i^L\}|}/log|\mathbf{I}^L|$$

Here, $\mathbf{I}^L = \{I_i^L, i \in Z_{>0}\}$ is the set of the living activities existing in the learning data. Basically, if appliance a_c is frequently used in living activities of l_g, then we assume $P(a_c|l_g)$ is high. That is, a high $f(c, g)$ leads to a high $P(a_c|l_g)$. However, some appliances, such as "air conditioner," "air fan," etc., work in almost all types of living activities. These appliances do not contribute as much to the meaning of each type of living activities as an appliance used in a certain type of living activity, such as "IH cooker" used in "cooking." Therefore, we give $f(c, g)$ a weight $0 < \lambda(c) \leq 1$, which is low if a_c is used in many living activities. On the other hand, these appliances might be useful for some types of living activities, which is represented by $P(l_g|a_c)$. Finally, we decide $P(a_c|l_g)$ according to both $f(c, g)$ and $P(l_g|a_c)$ as shown in Eq. (2). We compare the learned $P(a_c|l_g)$ with the appliance function based $P(a_c|l_g)$ in the experiments discussed in Sect. 4.

2.3 Appliance Operation State Model

We define the representation of the relationship from appliance operation states to appliance power consumption patterns using hybrid dynamic systems.

Each operation state q_i^c of appliance a^c, including the state of "Power OFF," generates a distinguishable power consumption pattern w_i^c. The power consumption patterns for each operation state q_i^c of an appliance a_c is represented using a dynamic system $D_i^c = P(w_i^c|q_i^c)$. In this paper, we assume that each dynamic system complies with a normalized distribution model, as below.

$$P(w_i^c|q_i^c) \sim N(\mu_i^c, \sigma_i^c) = \frac{1}{\sqrt{2\pi}\sigma_i^c} e^{-\frac{(w_i^c-\mu_i^c)^2}{2\sigma_i^{c\,2}}} \tag{3}$$

It is possible to model each dynamic system more exactly using a approximate method, such as a Kalman filter [5]. However, we observe that most of the appliances can be represented by normalized distributions. We obtain every dynamic system of an appliance by learning, previously.

2.4 Human Location Model

The relationship between a living activity l and appliance power consumption patterns W is affected by location r of people, as depicted in Fig. 1. We assign $P(r|l)$ manually according to room layout, as explained at the first of Sect. 2. In this section, we introduce a Human Location Model of a state space model proposed by the authors [4], for estimating the location r of a person through observing operations on appliances performed by the person.

The basic idea of the model is as follow. A person moves to a location near an appliance, and then operates and uses the appliance. The artificial operation changes the operation state of the appliance. Consequently, the power consumption pattern of the appliance also changes. Later, the person moves again to the location near another appliance, and then operates the appliance, repeatedly. We can observe the artificial operation on appliance a_c from the power consumption patterns of a_c, as explained in Sect. 2.3. We then can estimate the location of a person according to the locations where a_c can be operated.

Let r_t represents the location of a person at time tick t. We obtain the probability distribution $P(r_t)$ using a particle filter algorithm [6] based on the model. We then decide the location r_t which generates the largest $P(r_t)$ as the location of the person at time tick t.

3. Bi-directional Transformation on LAPC Model

In this section, we describe the methods for the bi-directional transformation between personal living activities and power consumption patterns based on our LAPC Model.

3.1 Generating Power Consumption Patterns from Personal Living Activities

Given an activity sequence $\mathbf{I}^L = \{I_1^L, I_2^L, \ldots, I_Q^L\}, I_k^L =< l_k^L, b_k^L, e_k^L >$ represented by the flat description, we propose a method to generate the power consumption patterns at each second for each appliance, using the LAPC model.

We present the method as follow. For each appliance a (The label c of appliance a_c is removed for clarity here):

For each $I_k^L =< l_k^L, b_k^L, e_k^L >, 1 \leq k \leq Q$:

(1) Let $m \in Z_{>0}$ denote the index of the operation states of a in l_k^L. Decide the beginning state $q_{k,m=1}$ according to $P(q_{k,m=1} = q_i|l_k^L) > 0$ randomly, set the start time $s_{k,m=1} = b_k^L$ for $q_{k,m=1}$.

(2) Decide the duration time $\tau_{k,m}$ of state $q_{k,m}$ according to $P(\tau_{k,m}|l_k^L, q_{k,m})$ randomly, set the end time $e_{k,m} = s_{k,m} + \tau_{k,m}$ for $q_{k,m}$.

- If $\tau_{k,m} = 0$, go to (4);
- else if $e_{k,m} > e_k^L$, set $e_{k,m} = e_k^L$, go to (4).

(3) Let $m = m + 1$, decide the next state $q_{k,m}$ according to $P(q_{k,m}|l_k^L, q_{k,m-1}) > 0$ randomly, set $s_{k,m} = e_{k,m-1} + 1$ *sec*, go to (2).

(4) If $P(q_{k,1}|l_k^L) \cdot \prod_{2\leq j\leq m} P(q_{k,j}|l_k^L, q_{k,j-1}) > \beta$, output the generated sequence $\mathbf{I}_k$ consisting of the operation states $q_{k,j}, 1 \leq j \leq m$, for l_k^L.

Output: $\mathbf{I} = \{\mathbf{I}_1, \mathbf{I}_2, \ldots, \mathbf{I}_Q\}$.

The method selects operation states and the time duration of the states randomly to constitute each sequence $\mathbf{I}_k, 1 \leq k \leq Q$. At step (4), the product of the beginning state probability and the state transition probabilities of every consecutive operation states pair in sequence $\mathbf{I}_k$ is computed. If the product is larger than a threshold value β, the method outputs the sequence; otherwise, it regards the sequence as inappropriate and generates the sequence again.

Multiple activities might happen simultaneously in $\mathbf{I}^L$. For different activities, different operation states of an appliance might be generated. Consequently, multiple different operation states of an appliance might overlap in time in $\mathbf{I}$ outputted at above. However, for an appliance, only one operation state can exist at a time. The method only remains the operation state whose average power consumption is the largest at each time tick for each appliance in $\mathbf{I}$. The average of the power consumption of each operation state of each appliance are available in the dynamic systems described in

Sect. 2.3. Finally, the method outputs a operation state sequence without overlap for each appliance.

After the operation state sequence of an appliance is obtained, the method generates the power consumption patterns for the appliance, using the dynamic systems proposed in Sect. 2.3. More precisely, for each operation state q_i^c of appliance a^c in the obtained sequence, the method obtains the power consumption patterns w_i^c at each time tick through a random sampling on distribution $P(w_i^c|q_i^c) \sim N(\mu_i^c, \sigma_i^c)$. At last, by summing up the power consumption amount of every appliance, the power consumption pattern of the whole family is available.

3.2 Estimating Personal Living Activities from Power Consumption Patterns

We present the method for estimating living activities from appliance power consumption patterns based on the LAPC model.

3.2.1 Estimating Appliance Operation States

To estimate the living activities during a period $< 0, T >$, the method first estimates the operation states from the power consumption patterns during the period for each appliance. Let $\mathbf{W}_T^c = \{w_1^c, w_2^c, \ldots, w_T^c\}$ be the sequence of the power consumption patterns w_t^c of appliance a_c at each time tick $0 \leq t \leq T$. The method estimates the operation state q_t^c for w_t^c at t, by finding the operation state having the maximal likelihood that correspond to the power consumption pattern from time tick $t - J$ to $t + J$. We set $J = 5$ *sec* in the experiments described in Sect. 4.

$$q_t^c = q_i^c = \arg\max_i P(q_i^c|w_{t-J}^c) \ldots P(q_i^c|w_{t+J}^c) \tag{4}$$

The dynamic systems $P(w_t^c|q_i^c)$ are available in the LAPC model, as discussed in Sect. 2.3. $P(q_i^c|w_t^c)$ is computed based on the dynamic systems using Bayesian inference as below.

$$P(q_i^c|w_t^c) = \begin{cases} \frac{P(w_t^c|q_i^c)P(q_i^c)}{P(w_t^c)} = D \cdot P(w_t^c|q_i^c) & (1 \leq t \leq T) \\ 1 & (otherwise) \end{cases} \tag{5}$$

Here, $P(q_i^c)$ and $P(w_t^c)$ are assumed as uniform distributions, and D is a normalization constant making $\int P(q_i^c|w_t^c) \mathrm{d}q_i^c = 1$. After the operation state at each t is obtained, consecutive identical operation states are integrated together to obtain the time duration of each operation state. Finally, we can obtain a sequence of consecutive time duration of operation states.

3.2.2 Estimating Living Activities

We describe the estimation of living activities from the sequences of operation states of every appliance. We starts with cutting the period $< 0, T >$ into several time duration $\{I_1, I_2, \ldots, I_K\}$, at the end time of each operation state of each appliance, as illustrated in Fig. 3. In each time duration $I_k, 1 \leq k \leq K$, only one operation state exists for each appliance. We assume that one main activity happens at each I_k, and at most one sub activity might happen simultaneously with the main activity. Let $\mathbf{Q}_k = \{q_k^1, q_k^2, \ldots, q_k^O\}$ be the set of the operation states of each appliance in $\{a_1, a_2, \ldots, a_O\}$ that appear in I_k. Let r_k be the room where the people stays at for the longest time during I_k. It is unnecessary to know the precise location of people at each time tick in the method, as we will discuss later in this section. We first formally define the problem of estimating personal living activities, at below.

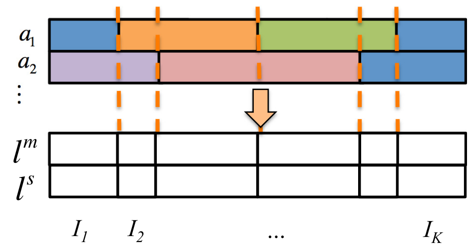


Fig. 3 Cutting a period by the ending of each appliance state.

Problem 1: Given the following inputs, (1) set $\mathbf{L}$ of the preliminarily defined candidate living activities, e.g. "cooking," "Cleaning," "Bathing," etc. (2) the sequence of time duration $\{I_1, I_2, \ldots, I_K\}$, (3) the set $\mathbf{Q}_k = q_k^1, q_k^2, \ldots, q_k^O$ of the operation states of each appliance and the location r_k of the people during each time duration $I_k, 1 \leq k \leq K$, we estimate a combination of a main activity l^m and a sub activity l^s most likely happens in each time duration I_k, as the equation at below.

$$(l^m, l^s)_k = \arg\max_{(l^m \in \mathbf{L}, l^s \in \mathbf{L} \cup L_{null})} P(l^m, l^s|\mathbf{Q}_k, r_k), \tag{6}$$

where L_{null} denotes no living activity happens.

To estimate Eq. (6), we do the following convention based on the LAPC model using Bayesian inference.

$$\begin{aligned} P(l^m, l^s|\mathbf{Q}_k, r_k) &= \frac{P(\mathbf{Q}_k, r_k|l^m, l^s)P(l^m, l^s)}{P(\mathbf{Q}_k, r_k)} \\ &= \frac{P(\mathbf{Q}_k|l^m, l^s)P(r_k|l^m)P(l^s|l^m)P(l^m)}{P(\mathbf{Q}_k, r_k)} \end{aligned} \tag{7}$$

Note that, we assume that sub activities are independent to the location of people, as explained in Sect. 2.1. $P(r_k|l^m)$ is given previously according to l^m and room layout. For example, "cooking" is performed at "kitchen," therefore we assign $P(kitchen|cooking) = 1$. $P(l^s|l^m)$ is the probability that a sub activity might happen simultaneously with a given main activity, which can be given manually according to the contents of each activity. As an example, we assign $P(Cleaning|Bathing) = 0$ because cleaning might not happen during bathing. $P(\mathbf{Q}_k, r_k)$ is the probability that $\mathbf{Q}_k$ and r_k could be observed, which is unrelated to l^m and l^s. We replace $P(\mathbf{Q}_k, r_k)$ by a normalization constant γ making

$\int P(l^m, l^s|\mathbf{Q}_k, r_k)\mathrm{d}l^m\mathrm{d}l^s = 1$. $P(l^m)$ is the prior distribution of the main activities, which is assumed to be a uniform distribution here. Consequently, we only have to estimate $P((Q)_k|l^m, l^s)$.

By assuming that the usage probabilities of each appliance are independent with each other, we compute $P((Q)_k|l^m, l^s)$ using the following equation.

$$\begin{aligned} &P((Q)_k|l^m, l^s) \\ &= P(q_k^1|q_k^2, \dots, q_k^O, l^m, l^s)P(q_k^2|q_k^3, \dots, q_k^O, l^m, l^s) \\ &\quad \dots P(q_k^O|l^m, l^s) \\ &= \prod_{1\le c\le O} P(q_k^c|l^m, l^s) \end{aligned} \tag{8}$$

We discuss how to compute $P(q_k^c|l^m, l^s)$ for each appliance a_c. If an appliance is powered off, it is meaningless to any living activity. Let $q_k^c = OFF$ denote that a_c is in the state of powered off during time duration I_k, then we set

$$P(q_k^c = OFF|l^m, l^s) = 0.5 \tag{9}$$

For other operation states of a_c, we calculate $P(q_k^c|l^m, l^s)$ by subtracting the probability that a_c is used in neither l_m nor l_f from 1, as the following equations.

$$P(q_k^c|l^m = l_g, l^s = l_h) = 1 - (1 - P(a_c|l_g))(1 - P(a_c|l_h)) \tag{10}$$

$P(a_c|l_g)$ can be decided by learning for each people particularly, or be decided based on appliance function for any people, as discussed in Sect. 2.2.

In Eq. (7), we do not consider the relationships between the living activities in two consecutive time duration. However, we should also consider the transition probability between living activities. Figure 4 illustrates the dependent relationships existing between two consecutive time duration. We estimate living activities in $l_k, 2 \le k \le K$ using the following equation extended from Eq. (7).

$$\begin{aligned} &P(l_k^m, l_k^s|\mathbf{Q}_k, r_k, l_{k-1}^m, l_{k-1}^s) = \\ &\frac{P((Q)_k|l_k^m, l_k^s)P(r_k|l^m)P(l_k^s|l_k^m, l_{k-1}^m, l_{k-1}^s)P(l_k^m|l_{k-1}^m, l_{k-1}^s)}{P(\mathbf{Q}_k, r_k)} \end{aligned} \tag{11}$$

Equation (11) can be computed similarly to Eq. (7), except that we need to estimate $P(l_k^m|l_{k-1}^m, l_{k-1}^s)$. For the best, the probability should be assigned according to the transition probabilities between living activities, the lengths of I_{k-1} and I_k, and the duration distributions of each living activity. In this paper, we decide the two probabilities only according to the transition probabilities between living activities for clarity. We estimate that the activity after "cooking" tends to be "meal."

3.2.3 Summary of the Estimation Method

We summarize our method for estimating personal living activities from appliance power consumption patterns in the following:

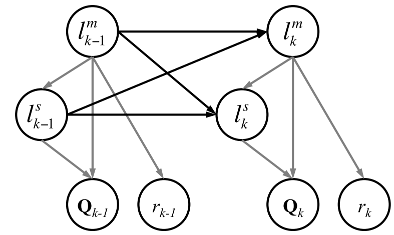


Fig. 4 Dependent relationships among living activities.

- Decide a set $\mathbf{L}$ of candidate living activities.
- Decide $P(r_k|l^m)$ according to the layout of the house.
- Decide $P(l^s|l^m)$ according to the contents of each activity.
- Decide $P(a_c|l_g)$ for each activity a_c and each living activity l_g based on learning or appliance function, using the model proposed in Sect. 2.2.
- For time duration I_k
  1. Obtain the set $\mathbf{Q}_k = q_k^1, q_k^2, \dots, q_k^O$ of the operation states of each appliance in $\{a_1, a_2, \dots, a_O\}$ from the power consumption patterns of the appliances, using the dynamic systems proposed in Sect. 2.3.
  2. Obtain the location r_k of the person using the human location model introduced in Sect. 2.4.
  3. Estimate a main activity $l^m \in \mathbf{L}$ with a sub activity $l^s \in \mathbf{L}$ using Eq. (11).

We describe our method at above as a offline method to estimate living activities during a period. Actually, our method can work both online and offline. Our method can obtain $\mathbf{Q}_k = q_k^1, q_k^2, \dots, q_k^O$ and r_k immediately from the real-time power consumption patterns of each appliance, at Step 1 and Step 2 described at above, respectively. Therefore, our method can do real-time estimation of living activity.

In our method, the list of appliances, the list of candidate living activities, and the probabilities $P(a_c|l_g)$ based on appliance functions, can be shared by houses of different layout. However, our method also requires the room layout and the locations of each appliance to obtain the location of people. The location of people is necessary for estimating main activities. It is difficult to apply our method for practical use under such a strict requirement. As a future work, we plan to improve our method by removing the requirement. A possible solution is that estimate the combination of simultaneous living activities which having the maximum likelihood for generating the combination of the operation states of each appliance.

4. Experiments

We first evaluate the method for estimating personal living activities from appliance power consumption patterns in Sect. 4.2. We can use the human location model proposed by the authors [4] to obtain the location of a people in the method, as explained in Sect. 2.4. The model has been confirmed through experiments that it can estimate the location

Table 1 The probabilities $P(a_c|l_g)$ of each appliance in each activity for evaluating day 1 of A.

$P(a_c\|l_g)$*	Outing	Sleeping	Dining	Bathing	Personal hygiene	Cooking	Cleaning	Laundry	Chore	Job	Entertainment	Watching TV	Having a rest	Converstation	$\lambda(c)$
TV	0 / 0	0 / 0	0 / 0.10	0 / 0.03	0 / 0.01	0 / 0.02	0 / 0.04	0 / 0.02	0 / 0	0 / 0.01	0.25 / 0.20	0.75 / 0.25	0 / 0	0 / 0	0.10
Air Conditioner	0 / 0	0 / 0	0.50 / 0.18	0 / 0.01	0.04 / 0.06	0 / 0.01	0.07 / 0.06	0 / 0.01	0.11 / 0.11	0.13 / 0.11	0.13 / 0.09	0.13 / 0.11	0.33 / 0.25	0.50 / 0.50	0.02
Living room light	0 / 0	0 / 0	0 / 0.05	0 / 0.06	0.04 / 0.07	0 / 0.01	0.07 / 0.09	0 / 0.05	0.11 / 0.11	0.13 / 0.16	0.13 / 0.13	0.13 / 0.14	0.33 / 0.25	0.50 / 0.50	0.11
Bedroom light	0 / 0	0 / 0	0 / 0	0 / 0	0.04 / 0.06	0 / 0	0.07 / 0.06	0 / 0	0.11 / 0.11	0 / 0	0 / 0	0 / 0	0.33 / 0.25	0 / 0	0
Refrigerator	0 / 0	0 / 0	0 / 0.09	0 / 0.03	0 / 0.02	0.04 / 0.05	0 / 0	0 / 0.04	0 / 0	0 / 0.02	0 / 0.05	0 / 0.06	0 / 0	0 / 0	0.09
Corridor light	0 / 0	0 / 0	0 / 0	0 / 0	0.04 / 0.06	0 / 0	0.07 / 0.06	0 / 0	0.11 / 0.11	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0
Kitchen light 1	0 / 0	0 / 0	0 / 0.07	0 / 0.04	0 / 0.02	0.22 / 0.23	0.07 / 0.09	0 / 0.03	0.11 / 0.11	0 / 0.05	0 / 0.03	0 / 0.05	0 / 0	0 / 0	0.10
Kitchen light 2	0 / 0	0 / 0	0 / 0.12	0 / 0	0 / 0.01	0.22 / 0.24	0.07 / 0.04	0 / 0	0.11 / 0.11	0 / 0	0 / 0	0 / 0.10	0 / 0	0 / 0	0.25
Pot	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0.07 / 0.08	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0
Microwave oven	0 / 0	0 / 0	0.50 / 0.25	0 / 0	0 / 0.02	0.22 / 0.15	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0.04	0 / 0	0 / 0	0.52
IH Cooker	0 / 0	0 / 0	0 / 0.14	0 / 0	0 / 0	0.22 / 0.18	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0.09	0 / 0	0 / 0	0.43
Restroom light	0 / 0	0 / 0	0 / 0	0 / 0	0.26 / 0.11	0 / 0.02	0.07 / 0.02	0 / 0	0.11 / 0.11	0 / 0	0 / 0.02	0 / 0.08	0 / 0.25	0 / 0	0.73
Lavatory light	0 / 0	0 / 0	0 / 0	0.25 / 0.17	0.26 / 0.33	0 / 0	0.07 / 0.06	0.14 / 0.08	0.11 / 0.11	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0
Bathroom light	0 / 0	0 / 0	0 / 0	0.75 / 0.50	0.04 / 0.07	0 / 0	0.07 / 0.03	0 / 0.15	0.11 / 0.11	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0.41
Dryer	0 / 0	0 / 0	0 / 0	0 / 0	0.26 / 0.11	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0.83
Cleaner	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0.40 / 0.35	0 / 0.08	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0	0.83
Washing Machine	0 / 0	0 / 0	0 / 0	0 / 0.16	0 / 0.03	0 / 0	0 / 0.11	0.86 / 0.47	0 / 0	0 / 0.04	0 / 0.08	0 / 0.02	0 / 0	0 / 0	0.32
Notebook PC	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0.01	0 / 0.01	0 / 0	0 / 0.07	0 / 0	0.75 / 0.61	0.50 / 0.40	0 / 0.07	0 / 0	0 / 0	0.35

*Appliance function based probability / Learned probability

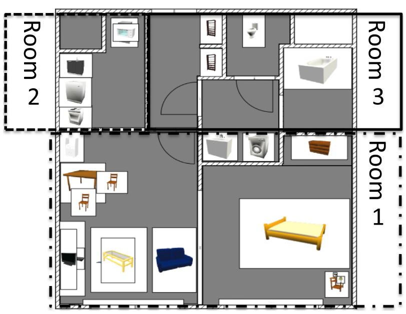


Fig. 5 The room layout and the appliances.

of a people with a high precision in [4]. In the experiments presented in this section, to evaluate our method for estimating personal living activities without the interference of the model, we manually give the room where a people is.

In Sect. 4.3, we evaluate the method for generating power consumption patterns from given living activities by case studies.

4.1 Dataset and Setting

We perform experiments at a smart house where every appliance is connected to the electricity through a smart tap. Figure 5 depicts the layout of the house, and the appliances placed in the house. We indicate the locations in the room in the unit of centimeter. The size of the room is 538×605 cm^2. The first row and the first column of Table 1 list all the 14 labels of living activities and some of the 34 appliances, respectively.

In this paper, we consider the case of a people living alone. We ask three people denoted by A, B, and C, to live in the house for 4 days, 2 days and 5 days, respectively. We ask them to record their living activities per 15 minutes.

4.2 Evaluation of Estimating Living Activities

As explained in Sect. 3.2, the probability $P(a_c|l_g)$ that appliance a_c is used in living activity l_g can be decided by two ways. Firstly, $P(a_c|l_g) = C \cdot P_f(l_g|a_c)$ is assigned according to the functions of appliances. We select a score from $\{0.5, 1.0, 1.5, 2.0, 2.5, 3.0\}$ for each $P_f(l_g|a_c)$. A high score represents the function of a_c is more useful for performing l_g. For example, "TV" is definitely usable for "watching TV," therefore we assign $P_f(watching\ TV|TV) = 3.0$; "TV" is usable for "entertainment," therefore we assign $P_f(entertainment|TV) = 1.0$; each light might be useful for "personal hygiene," therefore we assign $P_f(personal\ hygiene|living\ room\ light) = P_f(personal\ hygiene|bedroom\ light) = \ldots = 0.5$. The appliance function based probability can be applied for estimating living activity of any people. Secondly, $P(a_c|l_g)$ is learned for each participant using Eq. (2). For each participant, to evaluate the data of one day of the participant, we use the data of other days of the participant as learning data. Table 1 presents the appliance function based probabilities, and the learned probabilities for evaluating day 1 of A. The two kinds of probabilities are normalized so that $\sum_{a_c \in \mathbf{A}} P(a_c|l_g) = 1$, respectively. The rightmost column presents the $\lambda(c)$ values of each appliance, as defined in Eq. (2). The $\lambda(c)$ value of "air conditioner" is the lowest because participant A always turned on air conditioner for a long time. The $\lambda(c)$ values of "TV," "living room light," "refrigerator" are also low. Inversely, the $\lambda(c)$ values of "cleaner," "dryer" are the highest. The $\lambda(c)$ values are consistent with the discussions stated in Sect. 2.2. The values in front of and behind of "/" in each cell are the appliance function based probability and the learned probability, respectively. The learned probabilities are quite different from the appliance function based probabilities. For example, A turned on TV while dining. Consequently, the learned $P(TV|dining) = 0.10$, although the appliance function based $P(TV|dining) = 0$. As another example, A turned on TV, air conditioner, washing machine, living room light, kitchen light while bathing in some cases. Similarly, $P(a_c|l_g)$ is also learned for other participants. We observe that the learned probabilities $P(a_c|l_g)$ of each participant are different. For example, C does not turn on TV while bathing, although A and B do so. We omit the learned $P(a_c|l_g)$ of other participants here due to space limitations.

We then estimate the living activities of each of the 4

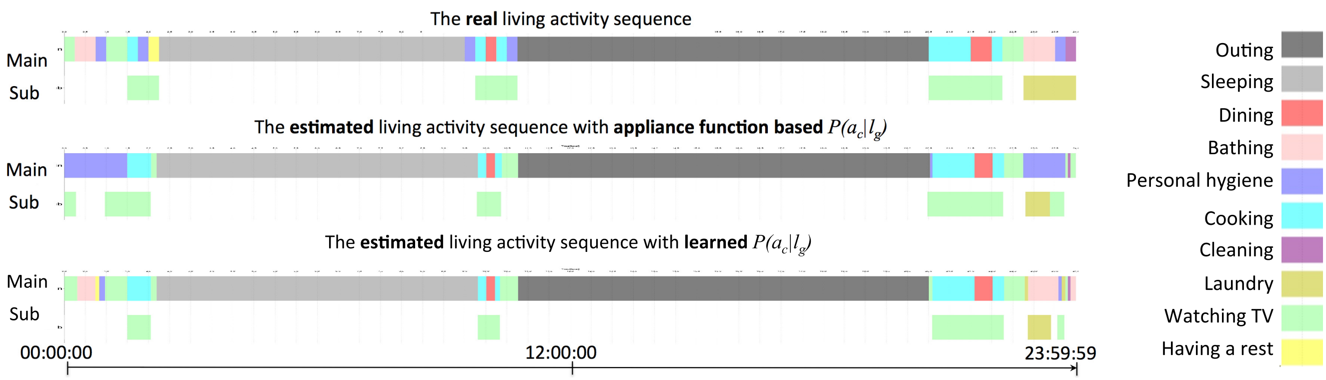


Fig. 6 The sequences of the living activities of A in day1.

Table 2 Recall, precision and F-measure on the estimated living activities.

		A-1	A-2	A-3	A-4	B-1	B-2	C-1	C-2	C-3	C-4	C-5	Average
wo/learning	Recall	20/26=0.77	15/18=0.83	20/22=0.91	15/18=0.83	9/14=0.64	7/9=0.78	6/12=0.5	10/12=0.83	13/19=0.68	10/19=0.53	16/21=0.76	0.746
	Precision	23/24=0.96	22/25=0.88	26/28=0.93	22/26=0.85	9/16=0.56	7/12=0.58	9/12=0.75	14/14=1.0	18/21=0.86	11/17=0.65	25/33=0.76	0.784
	F-measure	0.85	0.85	0.92	0.84	0.60	0.67	0.60	0.91	0.76	0.58	0.76	0.758
w/learning	Recall	22/26=0.85	15/18=0.83	19/22=0.86	15/18=0.83	9/14=0.64	8/9=0.89	6/12=0.5	10/12=0.83	14/19=0.74	10/19=0.53	16/21=0.76	0.771
	Precision	28/31=0.9	20/20=1	24/27=0.88	21/30=0.7	10/21=0.48	8/11=0.73	9/13=0.69	14/14=1.0	22/25=0.88	13/16=0.81	24/28=0.86	0.786
	F-measure	0.87	0.91	0.87	0.76	0.55	0.80	0.58	0.91	0.80	0.64	0.81	0.773

days of A using the method proposed in Sect. 3.2, with the appliance function based $P(a_c|l_g)$ and the learned $P(a_c|l_g)$, respectively. Similarly, we also estimate the living activities for each day of B, and for each day of C. As an example, Fig. 6 depicts the real living activity sequences and the estimated living activity sequences, in day 1 from 00 : 00 : 00 to 23 : 59 : 59 of A. Each color represents a type of the living activities exemplified on the right side. At a glance, the sequence estimated with the learned $P(a_c|l_g)$ is quite consistent with the real one. Our method also successfully estimated simultaneous living activities, such as A watches TV while cooking, and A washes clothes while bathing. Compared to the sequence estimated with the learned $P(a_c|l_g)$, the sequence estimated with the appliance function based $P(a_c|l_g)$ fails to estimate "bathing" happened around 00 : 30 and that happened around 23 : 00. The appliance function based probabilities of air conditioner, living room light, in "bathing" are 0, as presented in Table 1. The appliance function based probabilities of these appliances in "personal hygiene" are not 0. Participant A turned on these appliances while bathing. Therefore, our method with the appliance function based probabilities regards "bathing" as "personal care" by mistake. However, through learning the usage probabilities of these appliances in each living activity for A, our method can correctly estimate "bathing."

We quantitatively evaluate our method using a recall and a precision. Given an real living activity l_a, we check the set $\mathbf{L}_e$ of the estimated living activities appearing in the same time duration as l_a. The set $\mathbf{L}_e$ contains both main activities and sub activities. We do not separate main activities from sub activities, here. If there is a living activity of the same type as l_a in $\mathbf{L}_e$, we regard that l_a is successfully estimated. We then compute recall as the rate of the activities that are correctly estimated in the real living activity sequence. Inversely, given a estimated living activity l_e, we check the set $\mathbf{L}_a$ of the real living activities appearing in the same time duration as l_e. If there is a living activity of the same type as l_e in $\mathbf{L}_a$, we regard that the estimated activity l_e is correct. We then compute precision as the rate of the correct activities in the estimated living activity sequence. Table 2 presents recall, precision, and F-measure for each day of A, B, and C, respectively. The values in front of and behind of "/" in each cell of "Recall" are the number of the correctly estimated activities and the total number of the real activities, respectively. The values in front of and behind of "/" in each cell of "Precision" are the number of the correctly estimated activities and the total number of the estimated activities, respectively. At first, our method generates higher F-measure values with learning personal appliance usage probabilities $P(a_c|l_g)$ in 7 of the 11 days. The average values of recall, precision, and F-measure with learning are 0.771, 0.786, and 0.773. We can say that the experimental results are quite good. On the other hand, the recall and the precision without learning (using appliance function based probabilities $P(a_c|l_g)$) are also satisfactory. Next, we look at the results of each day of each participants. The F-measure values of each day of A are similar. The results of day 1 of B are slightly inferior with learning. We learn day 2 of B for evaluating day 1 of B. Some activities happening in day 1 of B do not happen in day 2 of B. We cannot correctly learn $P(a_c|l_g)$ for B because the learning data is not enough. It is considerable that we could obtain better results for B if we have more learning data. Among the results of the 5 days of C, the results of day 1 are inferior. In day 1, C performed "conversation" and "having a rest." In the two types of activities, no appliance is used specially. Consequently, our method fails to detect the two types of activities. However, the final goal of our work is to estimate the priorities of each

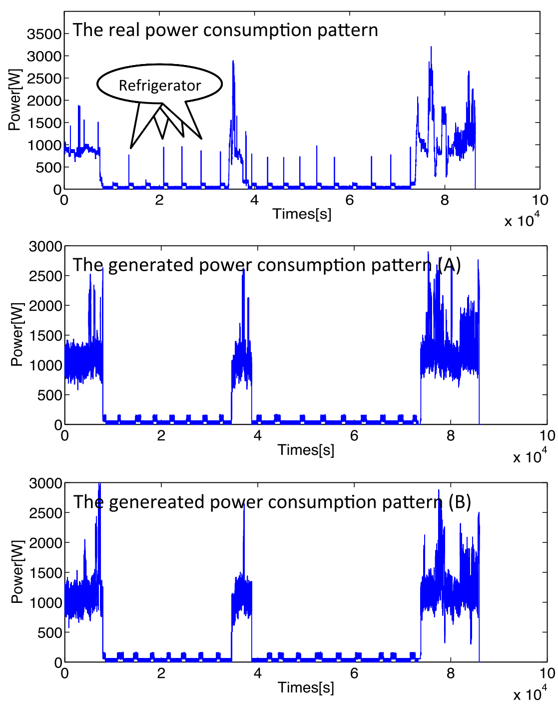


Fig. 7 The real and generated power consumption patterns of day 1 of A.

appliance in each activity. If no appliance is used specially in an activity, we can disregard the activity for our final goal.

We have demonstrated that our method is effective for estimating living activities through the learning of personal appliance usage probability $P(a_c|l_g)$. However, it is hard to collect labeled data from each user for the learning. On the other hand, our method also can estimate living activities to a satisfactory extent for any user with the appliance function based probability $P(a_c|l_g)$. As a future work, we first construct our LAPC model with the appliance function based probability $P(a_c|l_g)$ as a general model that can be applied for all users; we then do online learning of the personal appliance usage probability $P(a_c|l_g)$ for each user while estimating living activities on the general model. Increasingly, the general model is updated to a personal model for each user.

4.3 Evaluation of Generating Power Consumption Patterns

We evaluate the method proposed in Sect. 3.1 for generating power consumption patterns from living activities by case studies. Figure 7 depicts the real power consumption pattern of day 1 of A. Firstly, we learn probability distributions $P(q_i^c = q_j^c | l_j = l_k, q_{i-1}^c = q_h^c)$, $P(\tau_i^c | l_j = l_k, q_i^c = q_h^c)$, and $P(q_{k,m=1}^c = q_i^c | l_j = l_k)$ described in Sect. 2.2, from the other 3 days of A. We then generate power consumption patterns using the method from the real living activities of the day with the learned probability distributions. Figure 7 depicts two generated patterns obtained under the same experimental conditions, which are different because of randomness of our method. Both the two generated patterns are quite similar to the real one. Most of the peaks in the real power consumption patterns are appropriately simulated in the generated patterns. We can say that the method constructed using the LAPC model is useful for simulating appliance power consumption patterns from living activities. On the other hand, the method cannot capture the values of some power consumption peaks. The considerable problems are (1) we do not consider the co-occurrence or exclusive of appliances in the method, and (2) the power consumption of some appliances, such as an air conditioner, change dramatically. Especially, the method cannot simulate the peaks denoted by "Refrigerator" in Fig. 7. These peaks are generated by the activation of the compressor of refrigerator. The dynamic system $P(D_i^c) \sim N(\mu_i^c, \sigma_i^c)$ modeled using a normalized distribution cannot capture such kind of peaks that happen in a very short time during a operation state. We plan to solve the problems in the future.

5. Related Work

Recently, the problem of simulating residential electrical power consumption has attracted much attention. Several models [2], [7] have been proposed for simulating the power consumption of weather-related electrical appliances, such as air-conditioning, ventilation, and lighting, according to temperature, humidity, hux, and so on. Hobby et al. [2] also proposed to simulate the power consumption for other appliances based on the probabilities of starting each appliance at any particular time of an average day which are extracted from American time use survey (ATUS) [8]. The method proposed by Muratori et al. [7] is somewhat similar to our method for simulating appliance power consumption patterns. The method first uses a Markov chain to generate living activity patterns based on the transition probabilities between living activities derived from the ATUS data, and then converts the power consumption during each living activity simply according to the statistical data of the power consumption of each activity. These works do not model the relationship between living activities and appliance power consumption. By modeling the relationship, our method can simulate the power consumption patterns of each appliance in each living activity for each particular person.

On the other hand, few works challenge the problem of estimating living activities from appliance power consumption patterns as we do. As one of the few works, Yoshino et al [9] proposed a method to estimate the activity status of the students in a lab from the power consumption of computers used by the students. They define only 6 activity status beforehand, including "going home," "outing," "working on PC," "having a rest," "meeting," and "attending seminar." They then learn the corresponding relationships between each activity status and the power consumption pattern of the computer used by each student, using a hidden markov model. Finally, they estimate activity status for each student based on the learned corresponding relationships. Compared with this work, we estimate personal living activities from the power consumption patterns of multiple appliances. Obviously, we solve a more realistic and complicated problem.

6. Conclusion and Future Work

In this paper, we addressed the problem of the bi-directional transformation between personal living activities and appliance power consumption patterns. We summarize our contributions in this paper as follows:

- A LAPC model of a generative model for representing the relationship between personal living activities and appliance power consumption patterns.
- A method for generating appliance power consumption patterns from given personal living activities using the LAPC model. Case studies show that the method can accurately simulate appliance power consumption patterns to a satisfactory extent.
- A method for estimating personal living activities from measured appliance power consumption patterns based on the LAPC model. Experiments demonstrate that our method can estimate living activities quite similar to the real ones.

As the future work, we plan to extend our method to estimate living activities of a family of multiple persons. We also plan to evaluate the priorities of appliances according to living activities.

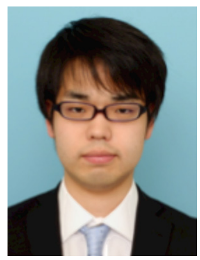
Acknowledgements

This research was supported by JST, CREST.

References

[1] T. Matsuyama, "Creating safe, secure, and environment-friendly lifestyles through i-energy," New Breeze, vol.21, no.2, pp.1–8, 2009.
[2] J. Hobby, A. Shoshitaishvili, and G. Tucci, "Analysis and methodology to segregate residential electricity consumption in different taxonomies," IEEE Trans. Smart Grid, vol.3, no.1, pp.217–224, 2012.
[3] C. Shannon, "A mathematical theory of communication," Bell Syst. Tech. J., vol.27, pp.379–423 and 623–656, July and Oct. 1948.
[4] Y. Yamada, T. Kato, and T. Matsuyama, "Human behavior estimation from power consumption patterns of appliances over smart tap network (in Japanese)," IEICE Technical Report, USN, vol.111, no.134, pp.25–30, 2011.
[5] R.E. Kalman, "A New Approach to Linear Filtering and Prediction Problems," Trans. ASME - Journal of Basic Engineering, no.82 (Series D), pp.35–45, 1960.
[6] G. Kitagawa, "On monte carlo filter and smoother (in Japanese)," Proc. Institute of Satistical Mathematics, vol.44, no.1, pp.31–48, 1996.
[7] M. Muratori, M.C. Roberts, R. Sioshansi, V. Marano, and G. Rizzoni, "A highly resolved modeling technique to simulate residential power demand," Applied Energy, no.107, pp.465–473, 2013.
[8] "American time use survey." http://www.bls.gov/tus/.
[9] T. Yoshino, K. Awahara, S. Izumi, M. Terabe, K. Hashimoto, and T. Suganuma, "Design of living situation estimation system based on observation of power comsuption (in Japanese)," IEICE Technical Report IN, vol.112, no.88, pp.1–6, 2012.

Xinpeng Zhang received BS degree from the School of Software Engineering, Huazhong University of Science and Technology, Wuhan, China, in 2004, the MS and the DS degree in Information Science from the Graduate School of Informatics, Kyoto University, Kyoto, in 2009 and 2012, respectively. He was a researcher at NICT in 2012. He is a researcher at the Graduate School of Informatics, Kyoto University, from 2013. His research interests include data mining, graph mining, information retrieval, and pattern recognition. He is a member of IEEE, IEEE Computer Society, and DBSJ.



Yusuke Yamada received BS degree from the Undergraduate School of Electrical and Electronic Engineering, Kyoto University, Kyoto, in 2011. He received MS degree from the Graduate School of Informatics, Kyoto University, Kyoto, in 2013. He joined Sharp Corporation from April, 2013.

Takekazu Kato received his BS, and DS degree in Okayama University, Japan, in 1997, and 2001, respectively. He is currently a associate professor in the Graduate School of Informatics, Kyoto University. His research interests include pattern recognition, computer vision, and energy Informationization. He is a member of IEEE, IEEE Communications Society, IPSJ, and IEICE.

Takashi Matsuyama received his B.S. degree and D.Eng. in electrical engineering from Kyoto University, Japan, in 1974, 1976, and 1980. He is currently a professor in the Graduate School of Informatics, Kyoto University. His research interests include knowledge-based image understanding, computer vision, cooperative distributed vision, 3D video, and human-machine interaction. He has received nine best paper awards from Japanese and international academic societies including the Marr Prize at the International Conference on Computer Vision in 1995. He is a fellow of the International Association for Pattern Recognition and the Information Processing Society of Japan, and a member of the Japanese Society for Artificial Intelligence, IEICE, and the IEEE Computer Society.