Advanced Science and Technology Letters
Vol.111 (COMCOMS 2015), pp.282-289
http://dx.doi.org/10.14257/astl.2015.111.54

Non-intrusive Load Monitoring for Home Energy Usage with Multiple Power States Recognition

Seungwoo Lee[1], Byunghun Song[1], Youngmin Kwon[1] and Ji-hyo Kim[2]

[1] Korea Electronics Technology Institute. Seongnam-si, Korea,
{seungwoo.lee, bhsong, ymkwon}@keti.re.kr
[2] Omnisystem. Co., Seoul, Korea, jhkim1@omnisystem.co.kr

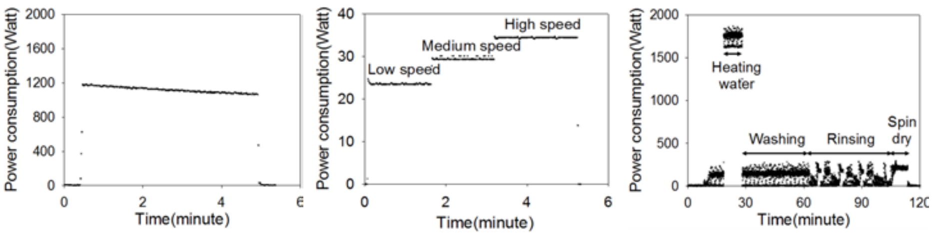
Abstract. Active study has recently been conducted on Non-intrusive Load Monitoring (NILM) system to construct a cost-efficient household energy management framework. The conventional method, however, is not easily applicable to appliances that exhibit a complex operating mode or multiple states of power consumption. In this paper, we propose a NILM system that considers especially *multiple* power states of appliance. The proposed system profiles the power state of appliances based on the distribution of the real power and apparent power of the device. We utilize the state transition probability between power states, and use Hidden Markov model (HMM) for power state recognition.

Keywords: Home Appliance Recognition, Load Disaggregation, Multi-state Appliance, Non-Intrusive Load Monitoring

1 Introduction

Awareness of the energy usage of home appliances is an effective leverage to encourage household residents to save energy [1], [2]. Active research has been conducted to address issues of energy awareness related to home appliances, especially in terms of reducing management costs. Non-intrusive Load Monitoring (NILM) or Non-intrusive Appliance Load Monitoring (NALM) approach recognizes working appliances and estimates their individual energy consumption by monitoring the power draw measured at a single point. Accordingly, the NILM-based mechanism is easy to install and cost-effective because it only requires a single usage of a power meter for measurement of the whole domain. However, these schemes generally suffer from low accuracy of appliance recognition, as well as low accuracy on load disaggregation

ISSN: 2287-1233 ASTL



(a) Microwave oven (Type-1) (b) electric fan (Type-2) (c) laundry machine (Type-3)

Fig. 1. Power measurement of home appliances

To deal with this problem, previous work on NILM has specifically tried to improve the accuracy of appliance recognition. Some studies have used external sensors or devices to detect the binary (i.e., on/off) status of an appliance [3], [4]. Others identify appliances using various pattern recognition techniques [5], [6]. However, most previous still work on appliance recognition has assumed that an electric appliance has a simple set of operating states (i.e., on/idle/off) and consumes constant power in operation. Here, this assumption is arguable because many appliances—such as plasma TVs, washing machines, and rice cookers—have several operating modes and multiple power states.

In this paper, we propose a NILM technique that specifically considers home appliances with *multiple* power states. Our system uses a single point of sensing without additional sensors; hence, it inherits the advantages of the conventional NILM approach. To disaggregate loads accurately among the appliances, we propose a method to profile and recognize the power state of appliances based on the distribution of the real power and apparent power of the device. We specifically consider the transition probability between power states in multi-state appliances, and use HMM to recognize the state accurately.

2 Preliminary Findings: Multiple Power States

We conducted preliminary experiments to analyze the power consumption patterns of several home appliances. Fig. 1 shows the results of these experiments. Based on the power patterns of the appliances, we categorize the devices into three groups. The first group, Type-1, comprises the appliances that consume a constant amount of power continuously when activated. Devices in this group have a binary power state, where they are either active or idle.

The second group, Type-2, represents appliances that exhibit multiple operating modes, but consume a constant amount of power at each operating mode. For instance, electric fan, shown in Fig. 1(a), has three different operating modes. The Type-2 devices usually operate in a mode set by user; hence, the power consumption is stable until the operating mode changes.

The last group of appliances, Type-3, has sequential power modes. The laundry machine, shown in Fig. 1 (c), belong to this group. Type-3 appliances have a sequence of operation modes that consume different amounts of power depending on the state. For example, the laundry machine sequentially performs a washing process, a rinsing process, followed by a spin dry process. Due to these sequential power states, a conventional NILM system is not really applicable in this case, and significantly degrades the overall accuracy of appliance recognition and load disaggregation.

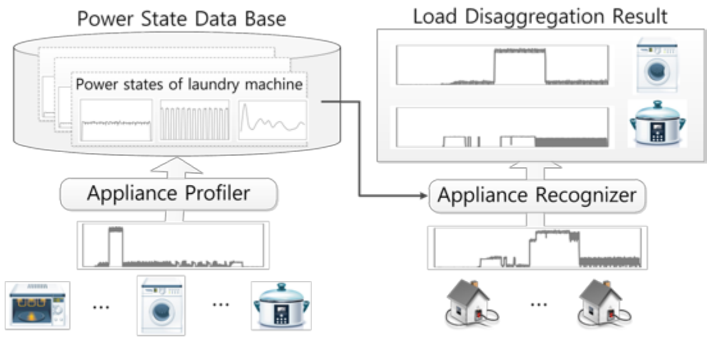


Fig 2. System overview

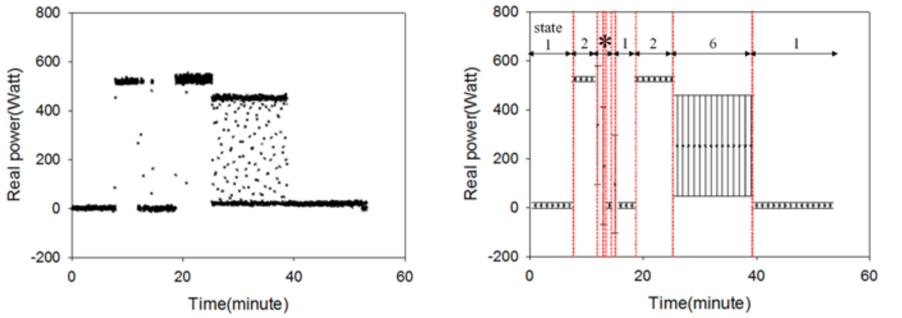
3 Non-Intrusive Load Disaggregation System

The objective of the proposed system is to recognize the power states of appliances with multiple operating modes, and accordingly disaggregate the power consumption (i.e., loads) of appliances. Our approach uses both the distribution of power consumption and the transition probability between the power states of appliances. We profile the power state of appliances using the distribution characteristics of real power, as well as the apparent power consumption of appliances. In order to recognize appliance with multiple power state accurately, the transition probability between the power states is computed based on the profile data. Finally, the proposed system recognizes the power state of appliances with HMM. Fig. 2 gives an overview of the proposed system. The system comprises an appliance profiler and appliance recognizer. The appliance profiler trains the appliance characteristics as a set of power, while the appliance recognizer detects the appliance state for load disaggregation.

3.1 Profiling appliances

To generate the profile of the appliance state, the appliance profiler (1) performs signal segmentation to detect the steady-states, (2) extracts meaningful features to generate a state signature of each steady-state, (3) clusters the steady-states into representative groups (i.e., power state)

Steady-state detection. First, the signal is segmented into steady-states by measuring the difference among the sequences of consecutive samples. To determine the segmentation point within consecutive samples, we modified the MinMaxSteady-State algorithm [7]. Given the sequence of samples s, i.e., $\boldsymbol{s_t} = (\boldsymbol{x_{t-W+1}}, \dots, \boldsymbol{x_t})$, at time *t* with window *W*, the scheme estimates the similarity between $\boldsymbol{s_t}$ and $\boldsymbol{s_{t-W}}$ as follows:



(a) original power trace (b) generated Power states

Fig 3. Profiling the rice cooker

$$f(s_t, s_{t-W}) = \begin{cases} Stable, & if\ d_{max} < \varepsilon\ and\ d_{min} < \varepsilon \\ Unstable, & else \end{cases}, \tag{1}$$

where d_{max} is the difference between $max(s_t)$ and $max(s_{t-W})$, $\mathrm{d}_{\min}$ the difference between $min(s_t)$ and $min(s_{t-W})$, and ε the threshold of the similarity. The sequence of samples is considered as the steady-state if the scheme produces *stable*. When the scheme produces *unstable*, we filter out the signal, since it is not viable for representing the characteristics of the appliance.

Feature extraction. We then extract the meaningful features of the steady-state to generate a state signature. We defined the state signature $\vec{\boldsymbol{f}}$ using the features of the distribution of power consumption, expressed as:

$$\vec{f} = (\mu_{real}, \sigma_{real}, \mu_{app}, \sigma_{app}), \tag{2}$$

where μ is the average, σ the standard deviation, and *real* and *app* indicate the real power and the apparent power, respectively. The apparent power is useful in distinguishing appliances that consume similar amounts of real power.

Clustering power states. Finally, the appliance status is represented as a finite set of power states. We cluster the steady-states with similar signatures into a representative group, i.e., *power state*. To estimate the similarity between two states, we use the Hellinger distance [8], which represents the distance of two distributions. The metric is computed as:

$$H(s_i, s_j) = 1 - \sqrt{\frac{2\sigma_i\sigma_j}{\sigma_i^2+\sigma_j^2}}\, e^{-\frac{1}{4}\frac{(\mu_i^2-\mu_j^2)^2}{\sigma_i^2+\sigma_j^2}}, \tag{3}$$

where μ_i and σ_i are the average and standard deviation of s_i.

3.2 Recognizing appliances

Based on the profile data, the appliance recognizer uses HMM to determine the current status of each appliance in terms of power state, and disaggregates the power consumption in real time. In general, HMM infers the hidden states from the observations, using the observation probability as well as the state transition probability. Both the real and the apparent power consumptions are observed in our system. We compare the power distribution derived from the combined power state of appliances with overall power distribution in a house. Here, the similarity is regarded as the observation probability of HMM.

State transition probability. We compute the state transition probability based on the profile data. In case of the appliance with multiple power states (Type-3), we use a specific set of operations to compute the transition probability since the appliance exhibits a regular pattern of sequential operation. For example, a rice cooker repeats cyclic operations, such as heating, pressure, and cooking. By using the transition matrix, the system accurately recognize the sequential states of rice cooker. On the other hand, the transition probability of Type-1 and Type-2 appliances cannot be computed, because the operation mode is manually changed by user. Therefore, we use uniform distributions in the state transition probability.

Observation probability. This metric is the possibility that a certain combination of power states represents the observed power consumption in a target place (i.e., house). We first generated the state signature of current steady-state. The problem is, then, to decompose the current power consumption into a combination of power states. Given the profile F and the state signature of current power consumption $\vec{\boldsymbol{f}}_{\boldsymbol{c}}$, we find the observation probability of the appliance status S, expressed as follows:

$$S \otimes F = \begin{bmatrix} s_{11} & \cdots & s_{1j} \\ \vdots & \ddots & \vdots \\ s_{i1} & \cdots & s_{ij} \end{bmatrix} \otimes \begin{bmatrix} \vec{f}_{11} & \cdots & \vec{f}_{1i} \\ \vdots & \ddots & \vdots \\ \vec{f}_{j1} & \cdots & \vec{f}_{ji} \end{bmatrix} \cong \vec{f}_c, \tag{4}$$

where s_{ij} indicates the recognized power state, $\vec{f}_{ij}$ the *j-th* state signature of the *i-th* appliance, and $\otimes$ the composition operation of two distributions. Here, $s_{ij} = \sum_{k=1}^{j} s_{ik} = 0$ or 1 and $\sum_{u=1}^{i}\sum_{v=1}^{j} s_{uv}$ is unknown. In other words, one appliance cannot be set to multiple power states at the same time, and the system should infer the number of acting appliances.

To solve this problem, we define the depth d as the number of appliance in operation, computed as $d = \sum_{u=1}^{i}\sum_{v=1}^{j} s_{uv}$. We consider that the maximum difference of d is 1 between the previous status S at time *t-1* to status S, and the current status S at time t. That is, the states of multiple appliances cannot be changed simultaneously. The method finds the observation probability P as:

$$\mathrm{P}(S_x) = H\left(S_x \otimes F, \vec{f}_c\right), \tag{5}$$

where S_x is a variant from the previous status S within $d \leq 1$. In other words, the current status can be generated by changing one appliance's state from the previous one. We regard the status S_x as one state of HMM in our system.

Power state recognition. The proposed system uses HMM to recognize the power states of each appliance. We find the optimal status of appliance which produces the maximum product of state transition probability and observation probability. In order to find the optimal status, we use a forward algorithm which is a kind of Dynamic Programming. Given the transition probability $\boldsymbol{a}$, and the observation probability $\boldsymbol{b}$, the probability of state $\boldsymbol{\delta}$ is expressed as:

$$\delta_t(j) = max_{1\leq i\leq N}\, \delta_{t-1}(i) a_{ij} b_j(\vec{f_t}), \tag{6}$$

where $\delta_t(j)$ indicates the probability of state j at time t, i the previous state, N the number of states, and $\vec{f_t}$ the observed power signature of whole house at time t. The optimal status S' is expressed as:

$$S' = \arg\max_{1\leq i\leq N} \delta_t(i). \tag{7}$$

This means that the appliance status at time t is the state with the highest probability. Our method looks for the optimal appliance status recursively in real time.

Load disaggregation. The power consumption is now disaggregated into each appliance based on the recognized status S. We used a simple metric of ratio among the power consumptions of each appliance. For instance, if the total power consumption is 110W and the system recognizes three appliances in operation—state A (10W), state B (20W), and state C (70W)—the power consumption ratio is 1:2:7. The disaggregated power of each appliance is then 11W, 22W, and 77W, respectively. We used this ratio metric, instead of the direct use of power, to handle the error from unstable states.

4 Evaluation

We evaluated each component of the proposed system using two experimental setups: single appliance recognition and a multiple version of this recognition. The system was also validated with real deployment in a household. For single-point sensing, we deployed Energy Monitoring Node [9], which contains a split-core current

Table 1. Home appliances used in the experiments.

Appliance	**Appliance description**			**State recognition accuracy**		
	Number of states	Real power (W)	Apparent power (W)	Recall (%)	Precision (%)	OA (%)
Microwave oven	2	[1100,1200]	[1100,1250]	100	100	100
Coffeepot	2	[1650,1700]	[1700,1750]	100	100	100
Refrigerator	2	[0,100]	[0,150]	100	100	100
Air conditioner	2	[0,500]	[0,550]	99.7	99.6	99.7
Hair dryer	4	[200,1450]	[350,1500]	99.8	99.9	99.8
Rice cooker	6	[20,550]	[20,600]	90.7	97.3	96.9
Laundry machine	5	[0,1800]	[0,1850]	94.8	90.3	90.8

transformer and voltage adaptor to measure current and voltage. Table 1 shows the

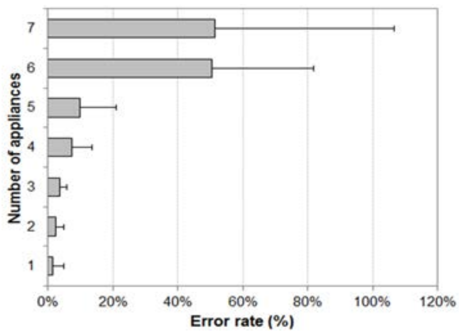


Fig 4. Load disaggregation accuracy according to the number of appliances.

appliances used in the experiments.

Prior to running complicated experiments, we initially validated the functionality of the proposed system in a simple setup; that is, the user is allowed to operate up to one appliance at a time. For this experiment, we generated a set of profiles for the seven appliances in advance, and conducted power state recognition for each appliance. We used a *precision* and *recall* metric to evaluate the accuracy of state recognition. To evaluate the accuracy over whole operation time, we defined the *overall accuracy* (OA) as follows:

$$OA = \frac{1}{T}\sum_{t=1}^{T}\delta(g_t, p_t)\text{, where } \delta(g_t, p_t) = \begin{cases} 1, & if\ g_t = p_t \\ 0, & else \end{cases}, \qquad \textbf{(8)}$$

where g_t and p_t are the states of ground truth and the recognition result at time *t*. As shown in Table 1, the proposed system successfully recognized the power state of single appliances.

Now, we analyzed the performance of the system in relation to the number of appliances in operation. A large number of appliances may derive low accuracy because of the complexity in load disaggregation. Fig. 4 shows the accuracy of the proposed system according to the number of appliances. The system correctly recognized 18±20% of cases throughout all the experiments, although the accuracy decreased as the number of appliances increased. The system derived approximately 51% error if seven appliances were in operation at the same time. The result shows that the system exhibits relative large error if the user operates multiple appliances simultaneously.

5 Conclusion

In this paper, we proposed a NILM system that specifically considers appliances with multiple power states. We defined a power state using the distribution of power consumption. The system first trains the appliance characteristics as a set of power states and computes the state transition probability in offline training. It then uses HMM with power distribution and state transition probability to recognize the power state of multiple appliances. Our experiments showed that the proposed system correctly estimates the power states and energy consumption of multiple appliances.

Acknowledgments. This work was supported by the International Collaborative Energy Technology R&D Program of the Korea Institute of Energy Technology Evaluation and Planning (KETEP) granted financial resource from the Ministry of Trade, Industry & Energy, Republic of Korea (No. 20148530050120), the Technology Innovation Program (10054486, Development of Open Industry IoT (IIoT) Smart Factory Platform and Factory-Thing Hardware Technology) funded By the Ministry of Trade, industry & Energy(MI, Korea), “The Components & Materials Technology Development Program (10043800, Development of Micro Smart Environmental Sensor Measurement Module, Control Chip, and Application Program)” funded by the Ministry of Trade, Industry & Energy (MI, Korea) and the Energy Technology Development Program (2013T100200078, development of integrated demand response system technology for co-residential resources and demonstration of business model) funded by the Ministry of Trade, Industry &Energy (MOTIE, Korea).

References

1. Froehlich, J., Larson, E., Gupta, S., Cohn, G., Reynolds, M.,Patel. S.: Disaggregated End-Use Energy Sensing for the Smart Grid. In IEEE Pervasive Computing, vol. 10(1): 28--39, (2011)
2. Froehlich, J., Everitt, K., Fogarty, J., Patel, S., Landay., J.: Sensing opportunities for personalized feedback technology to reduce consumption. In: CHI Workshop on Defining the Role of HCI in the Challenge of Sustainability (2009)
3. Gupta, S., Reynolds, M. S., Patel, S. N.: ElectriSense: single-point sensing using EMI for electrical event detection and classification in the home. In: 12th ACM international conference on Ubiquitous computing, pp. 139—148 (2010)
4. Jung, D., Savvides. A.: Estimating building consumption breakdowns using ON/OFF state sensing and incremental sub-meter deployment. In: 8th ACM Conference on Embedded Networked Sensor Systems, pp. 225--238 (2010)
5. Ruzzelli, A. G., Nicolas, C., Schoofs A., O′Hare, G. M. P.: Real-time recognition and profiling of appliances through a single electricity sensor. In: 7th Annual IEEE Communications Society Conference on Sensor Mesh and Ad Hoc Communications and Networks, pp. 1--9 (2010)
6. Lin, G., Lee, S., Hsu, J. Y., Jih, W.: Applying power meters for appliance recognition on the electric panel. In: 5th IEEE Conference on Industrial Electronics and Applications, pp. 2254--2259 (2010)
7. Figueiredo, M., de Almeida, A., Ribeiro, B.: Home electrical signal disaggregation for non-intrusive load monitoring (NILM) systems. Neurocomputing, 96(1), 66--73 (2012)
8. Liese, F., Miescke, K.–J.: Statistical Decision Theory. In: Statistical Decision Theory, pp. 1--52, Springer, New York (2008)
9. Open Energy Monitor project, http://openenergymonitor.org/emon/

