Appliance Recognition from Electric Current Signals for Information-Energy Integrated Network in Home Environments

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Abstract. We are developing a novel home network system based upon the integration of information and energy. The system aims to analyze user behavior with a power-sensing network and provide various life-support services to manage power and electric appliances according to user behavior and preferences. This paper describes an electric appliance recognition method using power-sensing data measured by **CECU** (**C**ommunication and **E**nergy **C**are **U**nit) which is an intelligent outlet with voltage and current sensors to integrate legacy appliances (which are incompatible with a communications network) with the home network. Furthermore, we demonstrate a prototype home energy management system and examples of services based upon appliance recognition.

Key words: Home Energy Management System (HEMS), Home Network, Power Sensing Network, Appliance Recognition

1 Introduction

We propose a novel home network system which integrates information and power networks[1], which we call the Bit-Watt system. Our system aims to manage the energy and electrical appliances in home environments by using ICT (**I**nformation and **C**ommunications **T**echnologies) to provide assertive services, such as home energy management, home safety and health-care, according to user behavior and preferences estimated from power consumption and the state of appliances in home environments. For this purpose, the system requires a framework for collecting information on the appliances and controlling their states.

Recently, intelligent appliances and home networks have been made available commercially, making it possible to monitor and control appliances remotely. The HAVi[2, 3] and DLNA[4] have been proposed for IT appliances and audio-visual appliances, and ECHONET[5] is a protocol for home appliances.

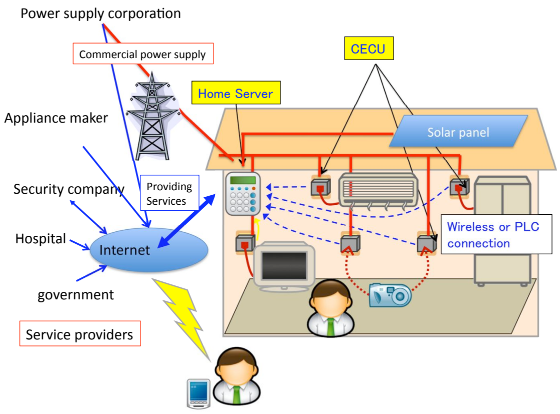


Fig. 1. Bit-Watt System

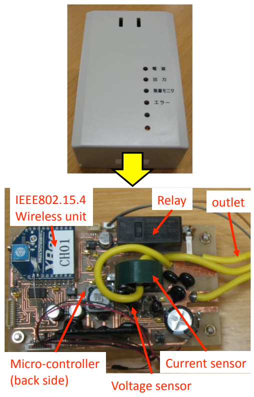


Fig. 2. CECU

Presently, to use a home network, appliances have to be implemented with these protocol-stacks. In other words, when a user uses legacy appliances in his/her home, the user has to modify the appliances or buy new appliances instead. Furthermore, it is sometimes difficult to implement the protocols for some simple appliances because of size and cost limitations.

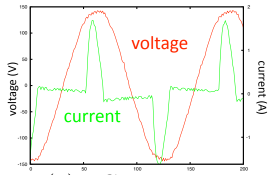
To solve these problems, we propose **CECU** (**C**ommunication and **E**nergy **C**are **U**nit) and an appliance recognition method by using **CECU**. **CECU** is an intelligent outlet with voltage and current sensors, a power control circuit for appliances, and a network module. It can measure the voltage and current values; our system recognizes appliances plugged into **CECU** from measured the voltage and current values. In our system, the legacy appliances can be integrated into the home network without any modifications.

This paper describes an appliance recognition method by using **CECU** as the basis of an information-energy integrated network system. Furthermore, we demonstrate a prototype home energy management system as an application of our system.

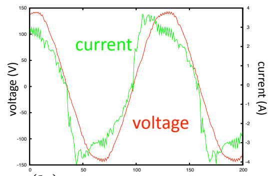
2 Bit-Watt System: Information-Energy Integrated Network System

2.1 Overview of the Bit-Watt System

Figure 1 shows an overview of the information-energy integrated network system, which we call the Bit-Watt system. The Bit-Watt system consists of **CECU**s, a home server, and a UI controller. **CECU** is attached between the home outlet and appliances, measures the voltage and current values of the attached appliance, and sends them to the home server. It can control an appliance according to commands from the home server. The home server collects power information on the appliances from **CECU**s to identify them and their status. The home



(a) LCD monitor



(b) micro-wave oven

Fig. 3. Examples of the voltage and current signals

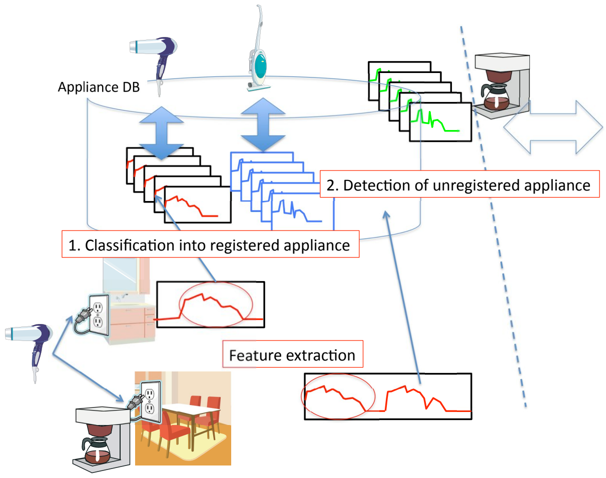


Fig. 4. Appliance Recognition

server provides services to the user by managing the appliances based upon the collected information.

by attaching **CECU** and the home server into home environments, our system can integrate an information network and energy network without remodeling existing appliances and home environments. Furthermore, the home server can connect to the Internet as a home gateway and cooperate with service providers. For examples, security companies can provide home safety services, hospitals can province health care services and appliance makers can provide the appliance information for appliance recognition and detecting broken appliances.

Figure 2 shows a prototype of **CECU**. The prototype includes a voltage sensor, a current sensor, a relay circuit, and a micro-controller. The micro-controller functions to convert analog signals from the sensors to digital values, extract signal features, and control the relay. **CECU** connects with the home server via IEEE802.15.4 wireless connection (like ZigBee[6]). Other wireless technologies or power line communication (PLC)[7] can also be used for the connection between **CECU** and the home server.

2.2 Feature Extraction for Appliance Recognition

Since home power-lines use alternating current (AC), the voltage and current take wave-shape signals. We believe that the appliance can be identified through comparing features of the shape because they are different for each appliance, as shown in Fig. 3.

However, it is difficult to incorporate recognition processes into **CECU** because of size and cost limitations. On the other hand, it is also difficult to directly send voltage and current values to the home server because a large amount of data is required for shape comparison.

To solve this problem, we implemented the recognition process as cooperation between **CECU** and the home server. **CECU** extracts a few features from the measured voltage and current values, and the home server recognizes the appliance from these features by comparing them with an appliance-feature database.

Here, the features should be small in number and easy to extract via the micro-controller in **CECU**. We consider sampled values for the electric current of each AC cycle as a high-dimensional vector and extract features through dimension reduction techniques using principal component analysis (PCA).

In the learning process, training vectors of electric current signals are given for all target appliances in advance, and eigenvectors are calculated by PCA from these training vectors. Then, a few eigenvectors with the maximum eigenvalues are selected as basis vectors for feature extraction.

During the recognition process, **CECU** extracts features with an inner product between the input vector of the current signal and basis vectors and sends them to the home server. Furthermore, training and input vectors are normalized by the root mean square of the vectors to eliminate changes in the wave-shape caused by differing loads of appliances.

Concrete processes for feature extraction in **CECU** are implemented as follows.

Let S be the sample number of voltage/current signals for each AC cycle, K be the dimension of extracted features, and $\mathbf{e}_j = \{e_{j,1}, \cdots, e_{j,S}\}$ be the j-th eigenvector. The eigenvectors $\mathbf{e}_0, \mathbf{e}_1, \cdots, \mathbf{e}_{K-1}$ are stored to a table in the micro-controller in advance.

1. Wait until zero-crossing of the voltage signal is detected.
2. Define the sampling counter $s := 1$, sum of squared current values $I_{SS} := 0$ and features $f_j := 0 (j = 1, \cdots, K)$
3. Sample the voltage value $v(s)$ and current value $i(s)$.
4. $I_{SS} := I_{SS} + i^2(s); f_i := f_i + i(s)e_{j,s}(j = 1, \cdots, K)$
5. If $s < S$ then $s := s + 1$ and go to Step 3; otherwise, go to Step 6.
6. Send I_{SS} and $f_j(j = 1, \cdots, K)$ to the home server and go to Step 1.

Since this process requires simple sum-of-product operations only by **CECU**, it can be quickly calculated by the micro-controller. Furthermore, the process can be implemented as an exclusive logical circuit. Even in this case, the feature can be modified by updating the basis vectors table.

The home server calculates the root-mean-square of the current values $I_{RMS} = \sqrt{\frac{I_{SS}}{K}}$ and normalized features $\hat{f}_i = \frac{f_i}{|\mathbf{e}_i| I_{RMS}} (i = 1, \cdots, K)$ from when it receives f_i and I_{SS} from **CECU**.

2.3 Appliance Recognition for Bit-Watt system

Figure 4 shows an overview of the appliance recognition process. In this process, **CECU** measures the current signal of the appliance plugged into its outlet, extracts features from the measured signal in an AC cycle, and sends it to

Table 1. Target Appliances

	Name	$P(W)$	$S(VA)$	F		Name	$P(W)$	$S(VA)$	F
1	CRT TV	41.0	66.0	0.62	14	refrigerator 1	98.0	134.8	0.72
2	DVD Player	17.4	25.3	0.68	15	refrigerator 2	101.4	129.2	0.78
3	HDD Recorder	40.9	59.5	0.68	16	desk fan 1	12.8	15.1	0.84
4	LCD TV 1	44.1	60.8	0.72	17	desk fan 2	28.9	38.0	0.76
5	LCD TV 2	136.1	141.0	0.96	18	iron 1	1134.3	1169.1	0.97
6	PC	23.6	36.6	0.64	19	iron 2	427.6	448.3	0.95
7	air conditioner	490.9	567.8	0.86	20	washing machine	115.6	123.0	0.93
8	cleaner 1	883.7	908.6	0.97	21	incandescent lamp	26.3	41.4	0.63
9	cleaner 2	186.1	455.6	0.40	22	microwave oven 1	1032.7	1078.9	0.95
10	rice cooker	246.4	248.8	0.99	23	microwave oven 2	733.1	750.7	0.97
11	dryer 1	428.4	476.2	0.89	24	pot 1	1110.8	1135.6	0.97
12	dryer 2	1244.2	1276.1	0.97	25	pot 2	733.1	750.7	0.97
13	dryer 3	774.6	798.7	0.96					

the home server. The home server recognizes the appliance by comparing the measured features with registered features in the database.

However, it is difficult to register the features for all the different kinds of existing appliances into the the home server database in advance. To solve this problem, the system registers the features as a new appliance when it detects the features of an unregistered appliance. We assume that the features and information of the new appliance can be downloaded from web sites of the appliance maker or service providers for the appliance data via the Internet. The system requires two types of recognition techniques: classification of registered appliances and detection of unregistered appliances. We used a support vector machine (SVM) [8] with a Gaussian kernel for the classification process and a one-class SVM [9] for the detection process. The one-class SVM is an extension of SVM for one-class classification problems, which is classifying an input pattern into a registered cluster or not.

3 Evaluation of Appliance Recognition

In this section, we show the experimental results of the two types of recognition processes; classification of registered appliances and detection of unregistered appliances.

3.1 Experimental Environment

Table 1 shows information of the target appliances, name, effective power $P(W)$, apparent power $S(VA)$ and power factor F. We used 25 appliances for the evaluation. The table shows the name and power consumption for each appliance. Appliances with the same name but different number, such as LCD TV 1 and 2, indicate the same kind of appliances but different products. It is difficult to

Table 2. Comparison of the classification results

	typical features	original vectors	proposed
16 types	85.5%	99.9%	99.9%
25 products	78.0%	95.6%	95.8%

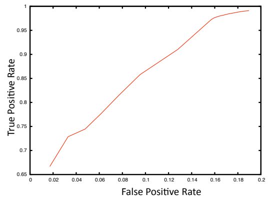


Fig. 5. ROC curve

classify the appliances using typical AC parameters, effective power, apparent power and power factor, because some appliances have similar parameters.

In the experiments, we used 100 samples of training data and 450 samples of test data for each appliance. The total number of training data was $25 \times 100 = 2500$ and the number of test data was $25 \times 450 = 11250$. The test data were different from the training data.

During the learning process, the eigenvectors and eigenvalues were calculated from all training data by PCA and 4 eigenvectors with maximum eigenvalues were selected as basis vectors. The features for each training vector were extracted by the inner product between each training vector and the basis vectors and the SVM was trained from the features of the training data.

The basis vectors were written into the micro-controller in **CECU** in advance. During the recognition process, the features were extracted by **CECU** using the inner product between the input vector and basis vectors. The extracted features were sent to and recognized by the home server.

A PC with Intel Core2 3.0GHz was used as the home server, and PIC18F2550 was used for **CECU**. The sampling rate of the voltage and current values was set to 100 for each cycle. This means $60 \times 100 = 6000$ samples per second.

3.2 Classification of Registered Appliances

Table 2 shows the classification results for the registered appliances. We evaluated the proposed method by comparing results with using 100 original dimensional vectors or 5 typical features of the alternating current system. The 100 original dimensional vectors are sample current values within an AC cycle, and the 5 typical features include the average value of the electric current, peak to average ratio, phase shifting time, available power time within an AC cycle, and peak delay from the start of the current.

We can see that the proposed method achieved an accuracy of 99.9% for 16 types of appliances and 95.8% for the 25 appliances respectively. This is more accurate than using typical AC features and nearly equivalent to the results of using the 100 original dimensional vectors.

Furthermore, during this experiment, the micro-controller performed the feature extraction within an AC cycle (1/60 seconds).

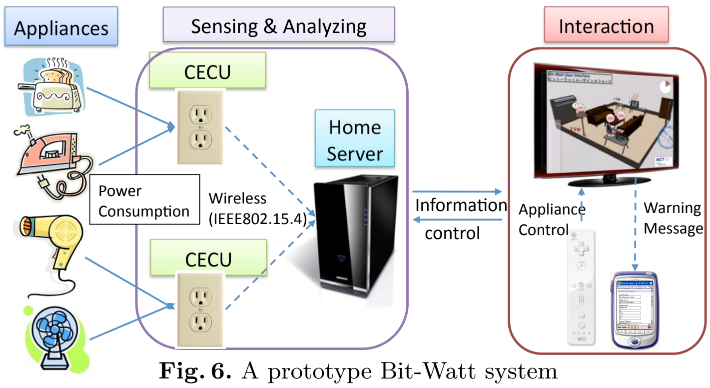


Fig. 6. A prototype Bit-Watt system

3.3 Detection of Unregistered Appliances

Here we show the results of detecting unregistered appliances. In this experiment, one-class SVM was trained from training vectors for 24 appliances, excluding one appliance to act as an unregistered appliance. The results were obtained by detecting the unregistered appliance from test vectors while changing the unregistered appliance. Figure 5 shows the detection results as an ROC curve, which indicates false positive and true negative rates while changing the parameters of one-class SVM. The results show that the detection accuracy for unregistered appliances can be optimized by setting the good parameters for one-class SVM. In the best case, the total detection rate achieved an accuracy of 97.7%.

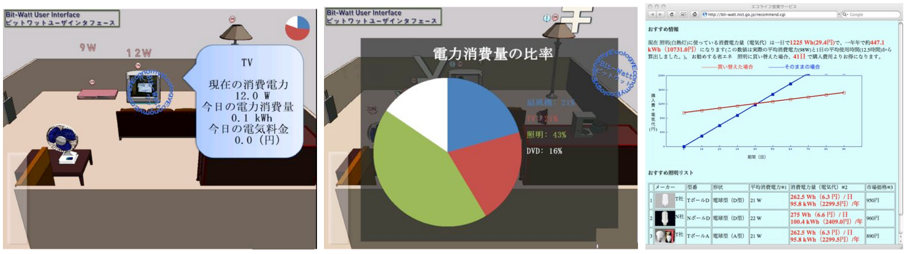
4 Home Energy Management based on Appliance Recognition

We implemented a prototype to demonstrate the applications of the Bit-Watt system. Figure 6 shows the overview of the prototype Bit-Watt system. It includes **CECU**s, a home server, and some interaction devices.

The system provides three services with appliance recognition. The first service is watching over and notification for appliances that users forget to turn off. The second service is remote monitoring and control, which provides the status and power consumption for each appliance to the user and control of the appliance via living room interaction devices that consist of a display and Wii®Remote. The third service is recommendation, which recommends new ecology replacements for appliances with wasting power consumption.

Additionally, the system was demonstrated to the public at the ATR/NICT Open House 2008. During the demonstration, we noted the public response that the Bit-Watt system can make users improved the awareness of the wasted power consumptions.

Figure 7 shows examples of the service results. The system could identify the same appliances even if the appliance connects to different outlets. Therefore, the system could accumulate the total amount of power consumption for each appliance even if the appliance location changed. In addition, the system could



(a) monitoring (detail) (b) monitoring (total) (c) recommendation

Fig. 7. Examples of services on the Bit-Watt system

recommend to replace the inefficient appliance with the new ecology appliance as well as the system. Furthermore, the system warned the user against irregular overuse of the appliance.

5 Conclusions

In this paper, we proposed an appliance recognition method using electric current signals for an information-energy integrated network, and we demonstrated home energy management based upon the proposed system.

We extracted appliance features in **CECU** by PCA and recognized appliances from the features by using SVM. In experiments, we evaluated the proposed method and can confirm that the proposed method achieves accurate classification rate.

For future work, we are considering the development of a framework to register features and information on unregistered appliances when they are detected. Furthermore, we are looking into learning user behavior and preferences from measured power consumptions and the state of the appliances in order to develop assistive services for proactive energy management.

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