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

Takekazu Kato*, Hyun Sang Cho**, Dongwook Lee**,
Tetsuo Toyomura***, and Tatsuya Yamazaki***
*Graduate School of Infomatics, Kyoto University,
Yoshida Honmachi 36-1, Sakyo-ku, Kyoto-shi, Kyoto, Japan
(E-mail: t.kato@ieee.org)
**Digital Media Lab., IT Convergence Campus, Korea Advanced Institute of Science and Technology
Seoul 115, Republic of Korea
(E-mail: haemosu@icu.ac.kr)
**National Institute of Information and Communications Technology
3-5 Hikaridai, Seika-cho, Soraku-gun, Kyoto, 619-0289, Japan
(E-mail: yamazaki@nict.go.jp)

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 communication network) within the home network. Furthermore, we demonstrate a prototype home energy management system and examples of services based upon appliance recognition.

Index Terms – Home Energy Management System (HEMS), Home Network, Power Sensing Network, Appliance Recognition.

1. Introduction

We propose a novel home network system that 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***ommunication ***T***echnologies) to provide assertive services, such as home energy management system, 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 [5][6] and DLNA [7] have been proposed for IT appliances and audio-visual appliances, and ECHONET [8] is a protocol for home appliances.

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 to use a ***C***ommunication and ***E***nergy ***C***are ***U***nit (***CECU***) coupled with an appliance recognition method. ***CECU*** is an intelligent outlet equipped with voltage and current sensors, a power control circuit for appliances, and a network module. It can measure the voltage values and the current values. This system recognizes appliances plugged into ***CECU*** from measured voltage current values. Thanks to ***CECU***s and the appliance recognition system, the legacy appliances can be integrated into the home network without any modifications.

The appliance recognition method has been proposed. Patel et al. [3] proposed an appliance detection and classification by extracting electric noise when the appliances were turned on/off. However, it requires accurate and expensive power sensors because it should analyze high-frequency electric signal on power line for extracting noise. Saitoh et al. [2] and Serra et al. [4] used some typical feature of the alternating current system, a peak value, a peak to average ratio, phase of the current signal wave for recognize appliances. However, it is difficult to stable extract these features, because electric signal includes noise and signal pattern is variable according to a load of measured appliance.

We propose PCA based feature extraction from electric signals for stable extraction against noise and load variations. The extracted features are classified by support vector machine [11] techniques. Furthermore, we used one-class SVM [12] for detecting unregistered appliances.

This paper first describes overview of the ***Bit-Watt*** system. Second, we propose an appliance recognition method based on information collected by ***CECUs***. Then, we show the experimental results of the appliance recognition method. Finally, we demonstrate a prototype home energy management system an application of our system.

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

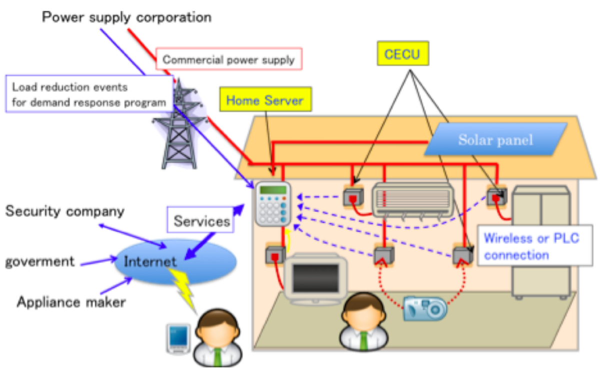


Fig. 1 *Bit-Watt* system.

Fig. 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 plugged appliances, and sends these values 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 server provides services to the user by managing the appliances based upon the collected information.

By connecting ***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 detection of broken appliances.

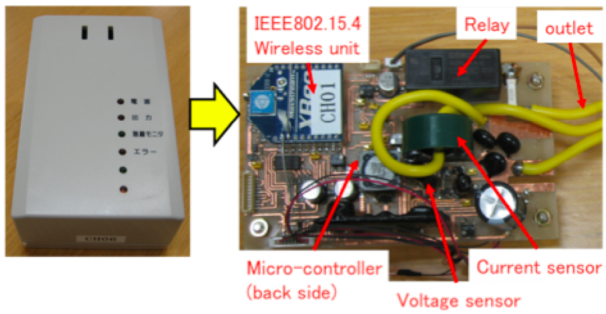


Fig. 2 *CECU* (*C*ommunication and *E*nergy *C*are *U*nit)

Fig. 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 captures current values and voltage values, calculates some features of plugged appliance for appliance recognition, and sends the features to the home server. Additionally, the micro-controller can turn on/off the plugged appliance by the relay switch. ***CECU*** connects to the home server via IEEE802.15.4 wireless connection (like ZigBee® [9]). Other wireless technologies or power line communication (PLC) [10] can also be used for the connection between ***CECU*** and the home server.

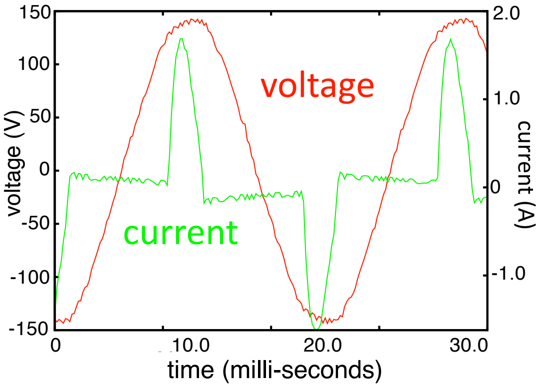
3. Appliance Recognition from Electric Current Signals

3.1. Feature Extraction for Appliance Recognition

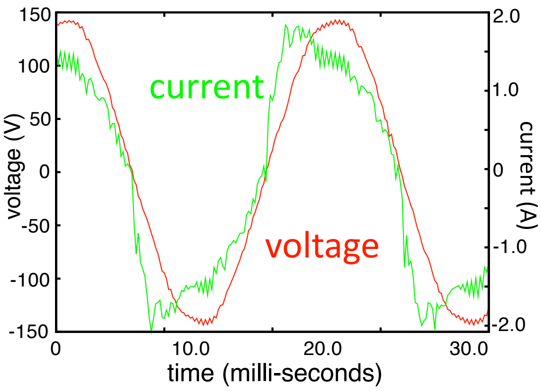
Since home power-lines use alternating current (AC), the voltage and current take wave-shape signals. We believe that an appliance can be identified by comparing the wave-shape because they are different for each appliance, as shown in Fig. 3.

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.



(a) LCD monitor



(b) Microwave oven

Fig. 3 Examples of the evolution of voltage and current signals over time for two different electrical appliances.

So, 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 $\mathbf{e}_j = \left[e_{j,1},\cdots,e_{j,S}\right]^T$ be the j-th eigenvector. The eigenvectors $\mathbf{e}_0,\mathbf{e}_1,\cdots,\mathbf{e}_{K-1}$ are stored in a table in the micro-controller in advance.

The micro-controller segments the current signal for each AC-cycle by detecting zero-crossing of the voltage signal. Then, it calculates feature values of the current signal by inner-product between the segmented current signal and the eigenvectors. The detail process is following.

1. Wait until zero-crossing of the voltage signal is detected.
2. Define the sampling counter $s := 1$;
   initial value of the sum of squared current values $I_{SS} := 0$;
   and the inner-product with the eigenvector $\mathbf{e}_j$
   $f_j := 0 \quad (j = 1,\cdots,K)$
3. Sample the voltage value $v(s)$ and current value $i(s)$.
4. $I_{SS} := I_{SS} + i^2(s)$,
   $f_j := f_j + i(s)e_{j,s}\,(j = 1,\cdots,K)$
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 on the data collected by a ***CECU***, it can be quickly calculated by the micro-controller. Furthermore, this process can be implemented as an exclusive logical circuit. Even in this case, the basis vector for feature extraction can be modified by updating the tables.

On its side, the home server calculates the root-mean-square of the current values $I_{RMS} = \sqrt{\frac{I_{SS}}{S}}$ and normalized features $\hat{f}_j = \frac{f_j}{I_{RMS}\left|\mathbf{e}_j\right|} \quad (j = 1,\cdots,K)$ from when it receives f_j and I_{SS} from ***CECU***.

3.2. Appliance Recognition for Bit-Watt system

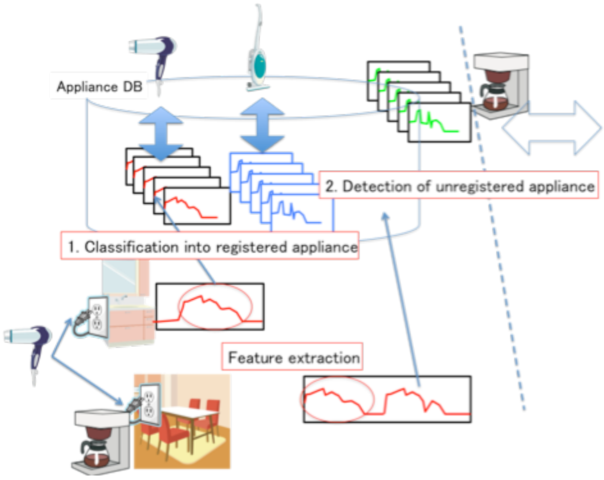


Fig. 4 Appliance Recognition

Fig. 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 them to 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 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. For the classification, we used a support vector machine (SVM) [11] with a Gaussian kernel. For the detection, we used one-class SVM [12]. The one-class SVM is an extension of SVM for one-class classification problems. It is trained from only positive examples (registered class), and it classifies an input pattern into positive (registered class) or negative (unregistered).

4. 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.

4.1. Experimental Environment

Table 1 Target appliances.

No.	Name	Effective power (W)	Apparent power (VA)	Power factor
1	CRT TV	41	66	0.62
2	DVD Player	17.4	25.3	0.68
3	HDD Recorder	40.9	59.5	0.68
4	LCD TV 1	44.1	60.8	0.72
5	LCD TV 2	136.1	141	0.96
6	PC	23.6	36.6	0.64
7	Air conditioner	490.9	567.8	0.86
8	Cleaner 1	883.7	908.6	0.97
9	Cleaner 2	186.1	455.6	0.4
10	Rice cooker	246.4	248.8	0.99
11	Dryer 1	428.4	476.2	0.89
12	Dryer 2	1244.2	1276.1	0.97
13	Dryer 3	774.6	798.7	0.96
14	Refrigerator 1	98	134.8	0.72
15	Refrigerator 2	101.4	129.2	0.78
16	Desk fan 1	12.8	15.1	0.84
17	Desk fan 2	28.9	38	0.76
18	Iron 1	1134.3	1169.1	0.97
19	Iron 2	427.6	448.3	0.95
20	Washing machine	115.6	123	0.93
21	Incandescent lamp	26.3	41.4	0.63
22	Microwave oven 1	1032.7	1078.9	0.95
23	Microwave oven 2	733.1	750.7	0.97
24	Pot 1	1110.8	1135.6	0.97
25	Pot 2	733.1	750.7	0.97

Table 1 shows information of the target appliances, name, effective power, apparent power and power factor. 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 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 stored 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 the home server and the home server recognizes an appliance form the features.

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.

4.2. Classification of Registered Appliances

Table 2 Comparison of the classification results.

	Previous work	original current signal	Proposed method
Classifing into 16 types of appliances	85.5%	99.9%	99.9%
Classifying into the 25 products of appliances	78.0%	95.6%	95.8%

Table 2 shows the classification results for the registered appliances. We evaluated the proposed method compared with previous work [2] and classification using 100 original dimensional vectors. The previous work [2] uses 5 typical features of the alternating current system, a peak value I_{peak}, a peak to average ratio $F_{pta} = \frac{I_{peak}}{I_{avg}}$, the ratio of low-level at one cycle to peak value τ_l, the ratio of high-level at one cycle to peak value τ_h and the gradient angle θ_u of rising edge. The 100 original dimensional vectors are sampled current values within an AC cycle.

We can see that the proposed method achieved accuracy of **99.9%** when it classifies into 16 types of appliances and **95.8%** when it classifies into 25 products of appliances respectively. Classification into the 25 products is more difficult than classification into 16 types, because the test data includes same type but different products of appliances. They have similar shapes of current signal wave. Against this difficulty our method achieve accurate classification rate. 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).

4.3. Detection of Unregistered Appliances

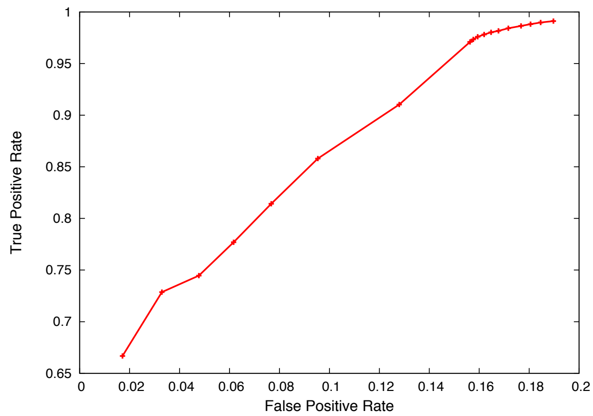


Fig. 5 ROC curve: detection rates for unregistered appliances against parameter changes.

This section presents 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. Fig. 5 shows the detection results as an ROC curve, which indicates false positive rate and true negative rate while changing the parameters of one-class SVM. The true positive rate means the rate of successful detection for the positive samples (registered appliances) is successfully. On the other hand, the false positive rate means the rate of miss-detection for unregistered appliances. Therefore, the method has good performance if the curve achieve to upper-left in the graph. This result shows that the detection accuracy for unregistered appliances can be optimized by setting parameters for one-class SVM. In the best case, the total detection rate achieved an accuracy of **97.7%**.

5. Home Energy Management based on Appliance Recognition

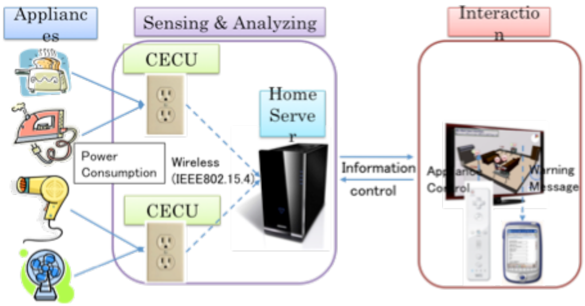


Fig. 6 A prototype of *Bit-Watt* system.

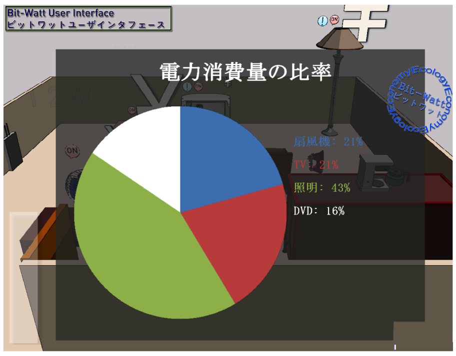
We implemented a prototype to demonstrate the applications of the ***Bit-Watt*** system. Fig. 6 shows the overview of the prototype ***Bit-Watt*** system. It includes ***CECU***s, a home server, and some interaction devices.

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 regular using time is set to the system for each appliance. The system detect irregular usage when an appliance is used longer than the regular time and notify to the user.

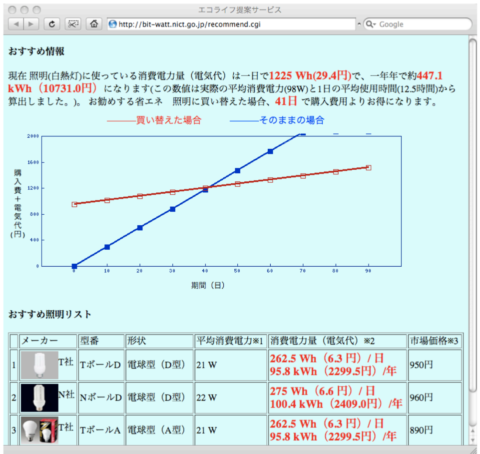
The second service is remote monitoring and control. On the one hand this service provides the status and power consumption for each appliance to the user. On the other hand the user can control appliances in his living room thanks to interaction devices that consist of a display and Wii™ Remote. The third service recommends new ecologically wise replacements for appliances 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 improve users awareness of wasted power consumptions. Fig. 7 shows examples of the services. The system could identify an appliance even if the appliance is plugged into different outlets. Therefore, the system accumulates the total amount of power consumption for each appliance even if the appliance location changes. In addition, the system could recommend replacing an inefficient appliance by a more ecological one. Furthermore, the system warned the user against irregular overuse of an appliance.

(a) monitoring service (detail): It indicates detail information for an appliance (TV), power consumption (12.0W), today's amount of power consumption (0.1 kWh) and electric charge of today (0.0 yen).



(b) monitoring (total): The pi-graph indicates the ratio of power consumptions in whole of this room.



(c) Recommendation: The system recommends new ecologically wise replacements for appliances wasting power consumption by comparing initial cost for new appliance and power-charges (graph) and shows some new appliances with its cost and specifications.

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

6. Conclusion

In this paper, we proposed an appliance recognition method using electrical 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.

References

[1] Yamazaki, T., Jung, J., Kim, Y.J., Hahn, M., Teng, R., Tan, Y., Matsuyama, T.: *Integration of sensor network and energy management system in home and regional community environments*, In proc. of the 4th International Symposium on Energy, Informatics and Cybernetics (EIC 2008), pp. 276–279, 2008.

[2] Saitoh, T., Aota, Y., Osaki, T., Konishi, R. and Sugahara, K.: *Current Sensor based Non-intrusive Appliance Recognition for Intelligent Outlet,* In proc. of the 23rd International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC 2008), pp. 349-352, 2008.

[3] Shwetak N. Patel, Thomas Robertson, Julie A. Kientz, Matthew S. Reynolds, and Gregory D. Abowd: *At the Flick of a Switch: Detecting and Classifying Unique Electrical Events on the Residential Power Line*, In proc. of 9th International Conference (UbiComp2007), pp. 271-288, 2007.

[4] Serra, H., Correia, J., Gano, A.J., de Campos, A.M. and Teixeira, I.: Domestic *Power Consumption Measurement and Automatic Home Appliance Detection*, In proc. of 2005 IEEE International Workshop on Intelligent Signal Processing, pp. 128- 132, 2005.

[5] Higuchi, M., Morioka, R., Inagaki, K., Togashi, A.: *Outline of HAVi*, In PIONEER R&D, vol. 11, no. 2, pp. 39–49, 2001.

[6] HAVi, http://www.havi.org/.

[7] DLNA Alliance, http://www.dlna.org/jp/industry/.

[8] ECHONET CONSORTIUM, http://www.echonet.gr.jp/.

[9] ZigBee® Alliance, http://www.zigbee.org/en/index.asp.

[10] HD-PLC Alliance http://hd-plc.org/.

[11] Corinna Cortes and V.N.Vapnik: *Support-vector networks, Machine Learning,* vol. 20, no. 3, pp. 273-297, 1995.

[12] Scholkopf, B., C. Platt, J., Shawe-Taylor, J., J. Smola, A. and C. Williamson, R.: *Estimating the support of a high-dimensional distribution,* In NEURAL COMPUTATION, vol. 13, no. 7, pp. 1443–1471, 2001.