Home Appliance Load Disaggregation Using Cepstrum-Smoothing-Based Method

Seongbae Kong, Youngwook Kim, Rakkyung Ko, and Sung-Kwan Joo

**Abstract — ***Various load disaggregation methods have been developed for monitoring home appliance loads to save energy in a smart home. Most of load disaggregation methods are designed to focus on the on/off events of single appliance. In reality, however, multiple appliances can be turned on/off simultaneously. Load disaggregation can be complicated by the simultaneous on/off events of multiple appliances. This paper presents a cepstrum-smoothing-based load disaggregation method to effectively deal with the simultaneous on/off events of multiple appliances. Further, a data acquisition system is developed to obtain only the characteristic signals of appliances and to filter the noise inputted from the power supply. Test results are provided to demonstrate the effectiveness of the proposed cepstrum-smoothing-based load disaggregation method[1].*

Index Terms — Non-intrusive Load Monitoring, Load Disaggregation, Cepstrum Smoothing, Signal Features

I. INTRODUCTION

Various sensing approaches have been developed for monitoring home appliance loads to save energy in a smart home [1], [2]. In general, monitoring methods of home appliances can be divided into two categories: distributed direct sensing and non-intrusive load monitoring (NILM) [3]-[5]. The distributed direct sensing attempts to monitor an appliance by placing a sensor between the power outlet and the appliance. This distributed direct sensing requires high cost and high installation complexity of a large number of sensors. As an alternative to distributed direct sensing, however, NILM has received increased attention because of its low cost and low installation complexity of a single-point sensor.

[1] This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2013R1A1A2057969).

This research was supported by the MSIP (Ministry of Science, ICT and Future Planning), Korea, under the ITRC (Information Technology Research Center) support program (NIPA-2014-H0301-14-1006) supervised by the NIPA (National IT Industry Promotion Agency).

S. Kong is with the School of Electrical Engineering, Korea University, Seoul, 136-713, Republic of Korea (e-mail: kong8306@korea.ac.kr).

Y. Kim is with the School of Electrical Engineering, Korea University, Seoul, 136-713, Republic of Korea (e-mail: ugi0283@korea.ac.kr).

R. Ko is with the School of Electrical Engineering, Korea University, Seoul, 136-713, Republic of Korea (e-mail: uranium92@korea.ac.kr).

S. -K. Joo is with the School of Electrical Engineering, Korea University, Seoul, 136-713, Republic of Korea (e-mail: skjoo@korea.ac.kr).

A single-point sensor with NILM can be widely installed at various homes for monitoring home appliance loads. In particular, the appliance load disaggregation method can be integrated into smart home energy management systems (HEMSs) to provide consumers the detailed energy consumption information at the appliance level [6], [7].

In NILM, electrical events can be identified by examining the appliance load signatures such as the power, voltage, and current signals obtained from a sensor. The changes in the on/off status of home appliances normally generate inherent appliance characteristics. Among the various available appliance load characteristics, a change in the electromagnetic interference (EMI) noise is found to be able to effectively classify the changes in the on/off status of specific types of appliances [3]. Analog filters such as low-pass and high-pass filters, and a data logger with a high sampling rate are required to obtain voltage signals because the EMI noise of home appliances exists within the high-frequency components of the voltage signal ranging from tens to hundreds of kilohertz [4]. Classification of the home appliance load by sensing voltage signals utilizes the frequency of the periodic signal generated by the electric motor and the switching-mode power supply (SMPS) that is contained within the appliance [4], [5].

Most of load disaggregation methods using voltage signals are designed to focus on the on/off events of single appliance [8]. In reality, however, multiple home appliances can be turned on/off simultaneously. A TV and a set-top box, a computer and a monitor, and air conditioners and compressor usually operate at the same time. Load disaggregation can be complicated by the simultaneous on/off events of multiple appliances. The classification performance of most load disaggregation methods is influenced by the simultaneous on/off events of multiple appliances.

Cepstrum analysis is effective for detecting the periodic patterns in a frequency spectrum [9], [10] and it has been applied to various areas such as speech and image processing. In addition, the frequency characteristics of a signal with harmonics can be effectively analyzed using the cepstrum method. The SMPS within an appliance often generates distinct EMI noise during its operation. The generated noise is added to the voltage signal to which the home appliances are electrically connected. Features for the load disaggregation can then be extracted from the existing EMI noises within the voltage signal. In this paper, the cepstrum analysis technique is adopted to extract the useful features from the voltage signal.

Contributed Paper
Manuscript received 12/31/14
Current version published 03/30/15
Electronic version published 03/30/15.

This paper presents a cepstrum-smoothing-based load disaggregation method to effectively deal with the simultaneous on/off events of multiple appliances. In this paper, the features extracted from the smoothed cepstrum [11] of the voltage signal generated by a home appliance is shown to be critical for improvement in the classification performance of the proposed load disaggregation method when there is simultaneous on/off event of multiple appliances.

This paper is extended from a preliminary work [12], [13]. The remainder of this paper is organized as follows. In Section II, the voltage signal instrumentation for NILM is presented. The cepstrum-smoothing-based load disaggregation method is proposed in Section III. In Section IV, the implementation and home appliance test results are presented. In Section V, the conclusions and future work are presented.

II. Voltage Signal Instrumentation

In this section, the hardware configuration for measuring the characteristic signal generated from the motor and/or power supply of a home appliance is described. Fig. 1 shows the appliance's voltage signal acquisition module. A data acquisition device and the appropriate filters are required for the instrumentation of the appliance's voltage signal. Unnecessary EMI noise from the environment is included in the input power. The external electric noise can penetrate into neighboring households because the households living in apartment buildings are at a close electrical distance. The frequency band of the signals obtained from a home appliance is generally 30 kHz–300 kHz. A two-stage LC low-pass filter with cut-off frequency of 5 kHz is designed to remove the external environmental noise.

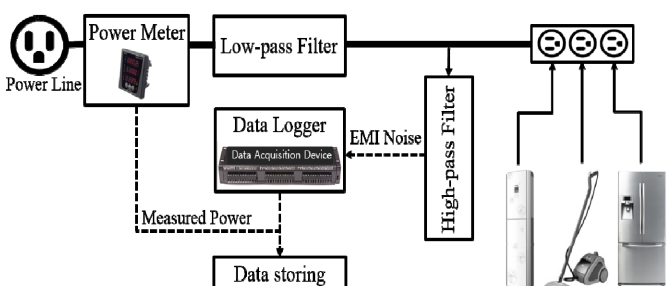

Fig. 1. Overview of the voltage signal acquisition module.

Characteristic signals from home appliances have a relatively small value compared to the main voltage. Therefore, a high-pass filter is utilized to remove the major harmonic components of the main voltage. The magnitudes of the voltage characteristic signals of the home appliances generated from the SMPS module and motor are relatively small. The use of a two-stage RC high-pass filter having a cut-off frequency of 30 kHz is able to acquire the data above 30 kHz. The home appliance voltage data are used to extract feature vectors for classification. An acquisition device with a sufficient sampling rate is needed in order to obtain a high-frequency voltage signal from the home appliance. The data acquisition device generally has an input range voltage of approximately ±10 V.

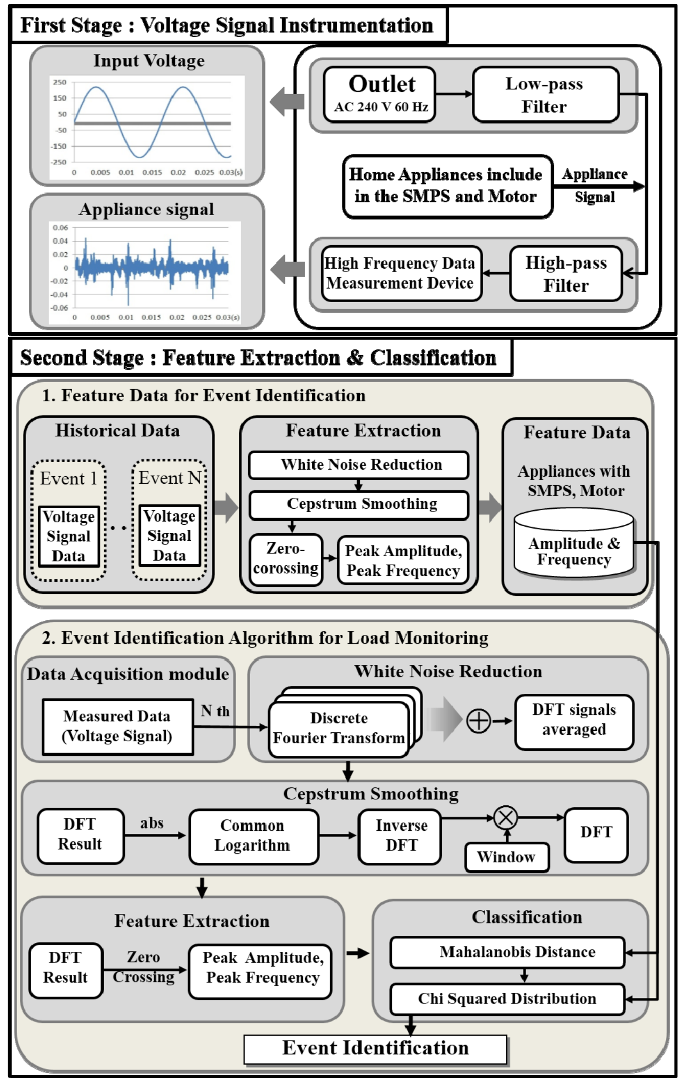

Fig. 2. Overview of the proposed cepstrum-smoothing-based method for NILM.

III. Home Appliance Load Disaggregation Using Cepstrum-Smoothing-Based Method

In this section, a cepstrum-smoothing-based feature extraction method, which is designed to extract the characteristics of home appliances on the basis of the voltage signal acquired from the appliances, is presented. An overview of feature extraction and classification for NILM is shown in Fig. 2. A more detailed description of the proposed NILM method is presented in the following subsections.

A. White Noise Reduction

The voltage signal data acquired from a home appliance include the main voltage signal, the major harmonic components of the voltage signal, and external noise that has not been completely removed. The voltage signal of an appliance is vulnerable to white noise because the voltage magnitude of an appliance is small. In order to reduce the noise accompanying a signal voltage, the average of the discrete Fourier transform (DFT) spectrum is calculated. After the average data, which represent random noise components, are removed, the signal peak in voltage signal characteristics of the appliance can be clearly seen.

B. Cepstrum Smoothing

The cepstrum is defined as the inverse Fourier transform of the logarithm of the power spectrum of a signal [9]. Cepstrum analysis was first introduced in 1963, and it was originally used to analyze the echoes within seismic signals produced from earthquakes [10].

The characteristics of home appliance voltage signals can be obtained more effectively by using the cepstrum method because the cepstrum characterizes the periodic patterns in a signal with harmonics. In order to perform the cepstrum analysis, the voltage signals $x(n)$ are transformed into the frequency domain by using the FFT, and their spectrum is obtained as follows:

$$X_m[k] = \sum_n x(n) e^{-j\frac{2\pi}{N}kn} \quad , \; 0 \le k < N \tag{1}$$

After the FFT is applied, the cepstrum method transforms the information present in the spectrum into the quefrency domain. The term "quefrency" represents the independent variable of the cepstrum [14]. The cepstrum representation can be obtained by taking the inverse Fourier transform of the logarithm of the absolute value of magnitude of the Fourier-transform of a signal as follows:

$$\tilde{x}(n) = \frac{1}{N} \sum_{k=0}^{N-1} \log \left| X_m[k] \right| e^{j\frac{2\pi}{N}kn} \quad , \; 0 \le n < N \tag{2}$$

Rectangular window is used for inverse-transform for the smoothed spectrum after weighting in the cepstrum domain. $w(m)$ is given by:

$$w(m) = \begin{cases} 1 & if \quad 0 < j < m \;, \quad 0 \le j < n \\ 0 & otherwise \end{cases} \tag{3}$$

$$Y_m[k] = DFT\,[w(m) \cdot \tilde{x}(n)] \tag{4}$$

Cepstrum-smoothing can be expressed as follows:

$$Y_m = DFT\,[w(m) \cdot IDFT \; \log(\left| X_m \right|)] \tag{5}$$

where Y_m is the frequency spectrum of the cepstrum-smoothing result, $w(m)$ is an n-point rectangular window, and X_m is the average of the DFT spectrum values.

The cepstrum can be obtained by taking the inverse DFT of the logarithm of the absolute value of the DFT of a voltage signal. Then, the n-point rectangular window is applied to truncate the cepstrum. The unnecessary quefrency components of a voltage signal can be removed by applying the rectangular window to the cepstrum of the voltage signal. The cepstral, i.e., the spectral of the smoothed cepstrum is obtained by computing the DFT of the truncated cepstrum.

C. Feature Extraction

There are different peaks in the smoothed cepstrum of the voltage signal generated by each different appliance. Therefore, the features are extracted from the smoothed cepstrum to determine which appliances change the on/off status. In this study, the frequency and amplitude of the dominant peaks in the smoothed cepstrum of the voltage signal generated by each appliance are selected to form a feature vector representing the individual home appliance. The frequency and amplitude of the dominant peaks are obtained by a zero-crossing method.

D. Classification

The operating appliances can be classified according to the feature vector, i.e., the frequency and amplitude of the dominant peaks in the smoothed cepstrum. Also, a centroid vector for each appliance is obtained by computing the average of feature vectors for the appliance in the training data set. In this research, Mahalanobis distance (MD) and chi-squared distribution are applied to classify which appliances turn on or off. The operating appliances are classified by finding the smallest Mahalanobis distance between a centroid vector and the feature vector of the new electrical event. The range of the Mahalanobis distance is limited by using the chi-squared distribution in which a confidence level is applied. The Mahalanobis distance calculation and the confidence-interval application of the chi-squared distribution of the n-dimensional multivariate normal distribution function N (μ, $\sum$) for the selected feature vectors for the i-th appliance in the training data set are described as follows:

$$(x_i - \mu_i)^T \textstyle\sum_i^{-1} (x_i - \mu_i) < X_n^2(\alpha) \tag{6}$$

where x_i denotes the feature vectors of the peak by the selected i-th appliance, μ_i is the average of the feature vectors for the i-th appliance in the training data set, $\sum_i$ is the covariance of the feature vectors for the i-th appliance in the training data set, $X_n^2(\alpha)$ is the value of the chi-squared distribution having a degree of freedom P and a significance level of $\alpha\%$.

E. New Appliance Registration

A new appliance, which is not included in the initial training data set, can be installed at home. The procedure for registering a new installed home appliance is shown in Fig. 3.

A candidate is designated as a new appliance if consistent power use increases due to the occurrence of an electrical event and the voltage features of the electrical event are unable to be determined as a home appliance by using the proposed classification method. If electrical events with the same feature vector and similar power usage occur more than three times, the user is notified of the determination of a new appliance.

F. Progress Module

Fig. 4 shows user interface (UI) screenshot of the prototype NILM program. A voltage signal that occurs in a home appliance can be visualized. The frequency-domain value of the voltage signal transformed by the proposed method is shown. Moreover, the amount of power use that a home appliance uses can be shown to the user. The list of home appliances is presented in a text format.

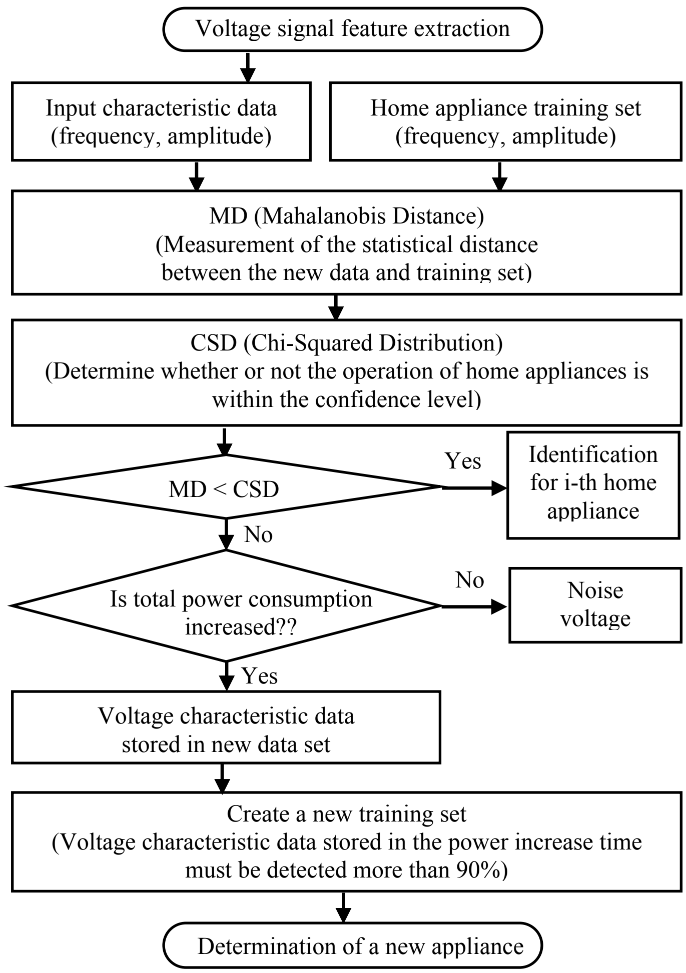

Fig. 3. Proposed new appliance registration procedure.

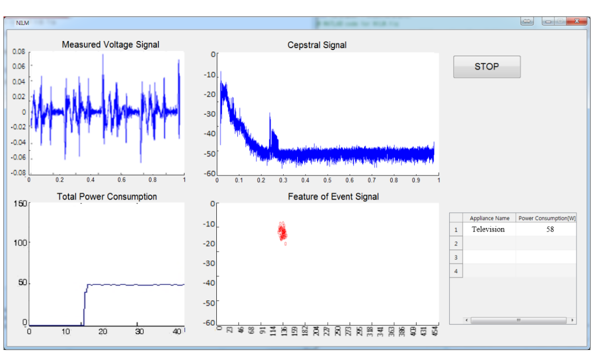

Fig. 4. User-interface screenshot of the implemented prototype NILM program.

IV. Implementation and Home Appliance Test Results

The test results of the proposed cepstrum-smoothing-based method for home appliances are described in this section. A low-pass filter with a 5 kHz cut-off frequency was designed for removing noise, and a high-pass filter with a 30 kHz cut-off frequency was also designed for obtaining the voltage signals of the appliances. Because the characteristic voltage signals that appear in the home appliances are generated by a switching module with a high-frequency component, an acquisition device with a sampling rate of 1 MHz was used in this study.

A two-stage LC low-pass filter for removing outside noise was designed using common-mode inductors and capacitors. In this study, the low-pass filter is used for obtaining a clear appliance signal, thereby improving the performance of the proposed method. However, the proposed method still has good classification performance without the low-pass filter. Also, a two-stage RC high-pass filter for acquisition of a home appliance characteristic signal was designed using resistors and capacitors. Voltage data was acquired using the high-speed voltage measurement device.

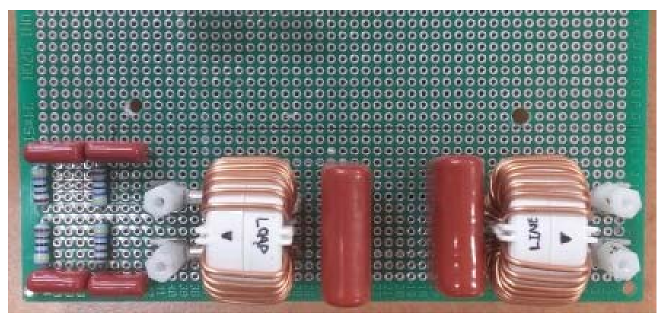

Fig. 5. Implemented filters for data acquisition.

The implemented filters are shown in Fig. 5. The key specifications of the tested home appliances are listed in Table I.

TABLE I
HOME APPLIANCE SPECIFICATIONS

Appliance name	Acquisition point	Power dissipation	Model
Television	SMPS	60 W	50 in LED TV
Computer	SMPS	300 W	Desktop PC
Monitor	SMPS	30 W	22 in IPS
Refrigerator	Motor	120 W	Inverter type (BLDC) smart refrigerator
Washer	Motor	230 W	Inverter type (BLDC)
Vacuum cleaner	Motor	700 W	Normal AC motor

The voltage signal data were acquired at a sampling rate of 1 MHz for 0.5 s. Voltage signals, which are collected using a data acquisition device, are transformed into the frequency domain by using the DFT. The obtained voltage signal is then processed for about 1.5 s.

In order to reduce the noise signal, the average of the DFT spectrum is computed by summing over five iterations. The voltage signal of a home appliance is converted by the cepstrum method. Fig. 6 illustrates the process in which voltage signal is transformed to the smoothed cepstrum in multiple steps.

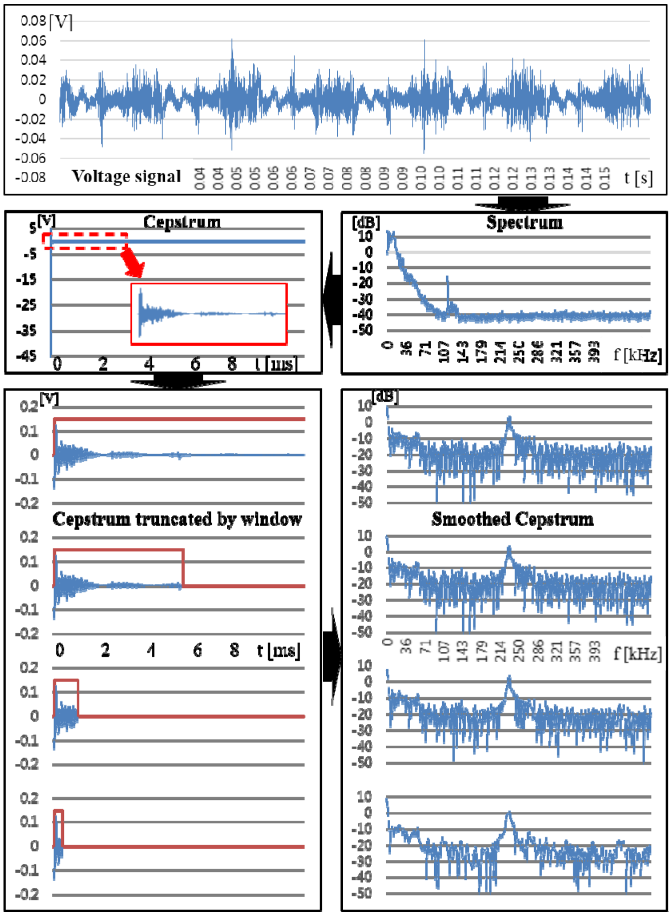

Fig. 6. Example of cepstrum smoothing using the measurement data.

Fig. 7 shows a comparison of results obtained by the proposed cepstrum-smoothing-based method (left) and the simple DFT (right) for refrigerator, and washer. Additionally, the amplitude of the peak frequency is different depending on the spectrum of a specific appliance. These characteristics increase the complexity of the appliances' feature acquisition algorithm. The cepstrum method can be used to reduce the variance of the home appliance peak signal in the DFT spectrum. Further, cepstrum-smoothing can be used to handle the similar peak size of characteristic signals from different appliances by reducing the characteristic downward sloping at low frequencies.

Each home appliance has different frequency characteristics. The washer signal has the majority of frequencies in the low-frequency band due to the operation of the inverter electric motor. The low-frequency band signal is also generated by the refrigerator by the operation of the inverter electric motor. However, different frequency components from the washer are present. When a refrigerator and a washer are operated simultaneously, the location of the refrigerator peak in the DFT spectrum moves more than when using the cepstrum method. In addition, the washer may possibly be classified as a different appliance because the magnitude of the peak of the washer is relatively lower than that obtained by the cepstrum method. Fig. 10 shows the feature value of single/multiple appliance operation extracted from the simple DFT and the cepstrum method.

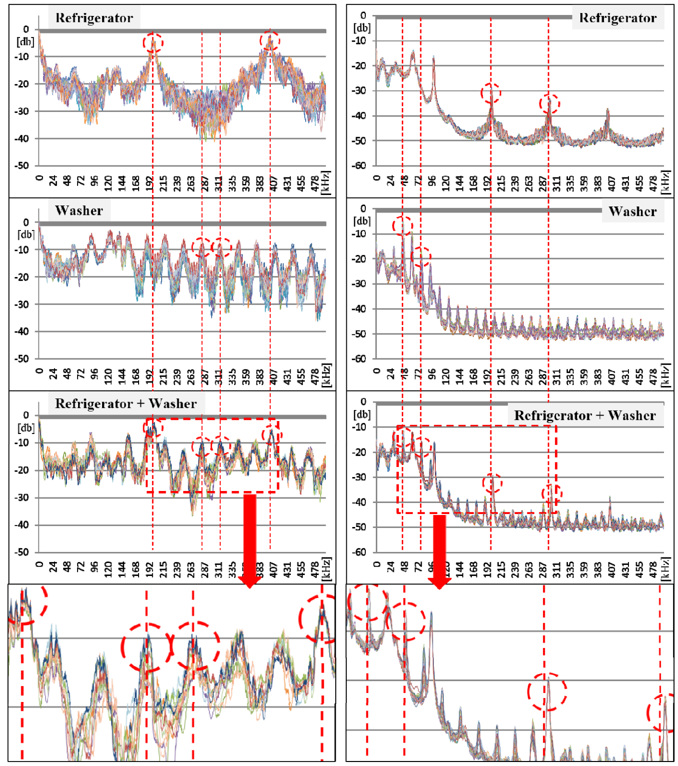

Fig. 7. Results of the proposed cepstrum-smoothing-based method (left) and the simple DFT (right) [Refrigerator, Washer].

Fig. 8 shows a comparison of results obtained by the proposed cepstrum-smoothing-based method (left) and the simple DFT (right) for television, and monitor. For the computer signal, a strong signal is clearly present. In contrast, the television has a clear strong signal clearly, but the two peaks overlap. For the monitor, the amount of power use is small because of the relatively small signal. Therefore, there is a case in which the signal of the monitor cannot be determined owing to the noise that occurs when two or more devices operate. Using the proposed cepstrum-smoothing-based method, it is possible to identify the device even if there is peak nearby noise because peak amplitude value is large.

Fig. 9 shows the feature value extracted from the simple DFT and the cepstrum method. The peak amplitude of the simple DFT is different for each home appliance. Therefore, it is impossible to determine whether the operation of the home appliance is based on specific values. However, the peaks of the home appliances using the cepstrum method are greater than -15 dB, and the instrument used in this study can observe the electric home appliance operation. For a single home appliance, several peaks can occur, and all peak information is stored in the database, but the representative (or dominant) peak is used for classification.

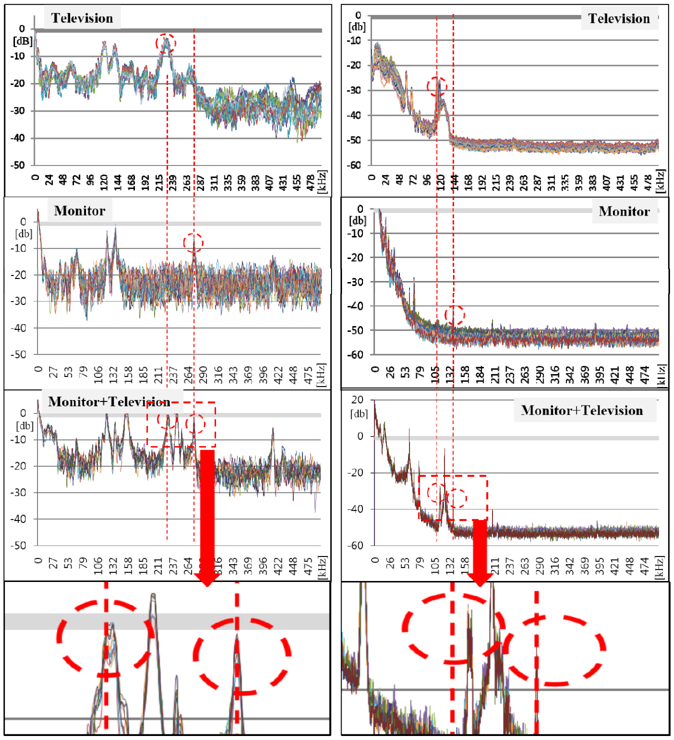

Fig. 8. Results of the proposed cepstrum-smoothing-based method (left) and the simple DFT (right) [Television, Monitor].

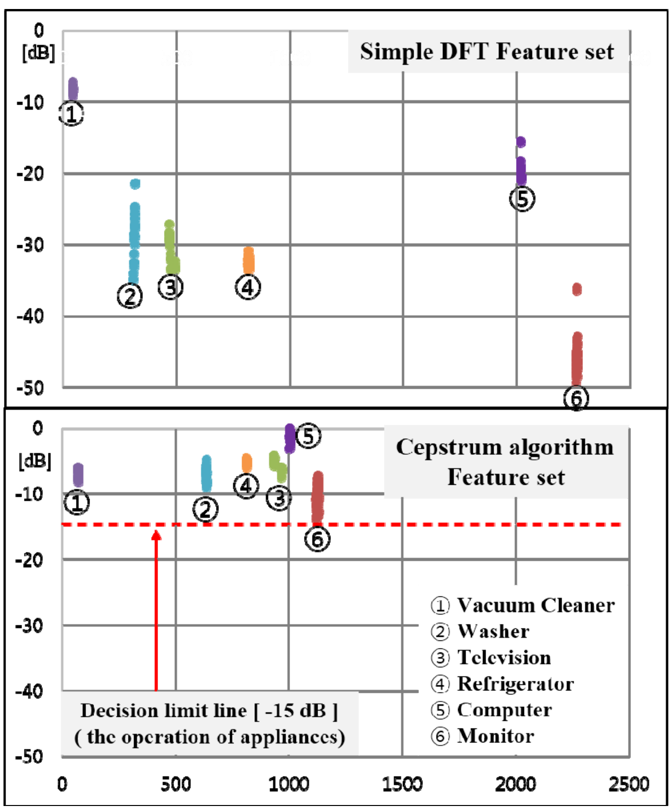

Fig. 9. Scatterplot of voltage feature (peak frequency and amplitude).

Table II lists the spreads of the amplitudes of the peaks of home appliances. A lower spread value of the peak amplitudes can help improve the home appliance recognition rate. The cepstrum method more effectively reduces the spread of the

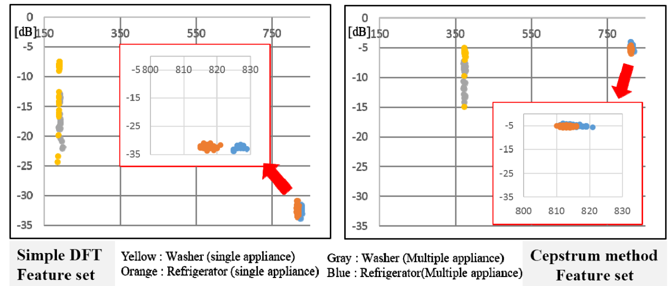

Fig. 10. Scatterplot of voltage feature of single/multiple appliance operation (peak frequency and amplitude).

home appliance peak signal when compared with the DFT spectrum. There may be an increase in the variance of the peak amplitudes of the vacuum cleaner depending on its operation mode. Because the vacuum cleaner has relatively high amplitude values at the peak in comparison with other home appliances, the effectiveness of the logarithm operation in the cepstrum method tends to be decreased. Unlike other home appliances, the variance of the peak amplitudes of the vacuum cleaner increases after the cepstrum method is applied. Because the increase in the variance of the peak amplitudes of the vacuum cleaner in the spectrum is relatively small, the vacuum cleaner can also be effectively classified by using the proposed method.

TABLE II
AMPLITUDE VARIANCE OF EACH APPLIANCES' PEAK

Appliance name	DFT spectrum peak frequency variance	Cepstrum method peak frequency variance
Television	3.87	0.65
Computer	0.62	0.46
Monitor	3.38	2.25
Refrigerator	0.44	0.10
Washer	12.78	9.07
Vacuum cleaner	0.18	0.41

Table III summarizes a comparison of classification performance of the proposed cepstrum-smoothing-based method and the simple DFT. The proposed method shows better classification performance than the simple DFT for both the operation of single appliance and the simultaneous operation of multiple appliances. Especially when multiple appliances simultaneously operate, the classification performance of the proposed method is better.

TABLE III
CLASSIFICATION PERFORMANCE OF THE SIMPLE DFT AND THE PROPOSED METHOD

	Classification performance of the simple DFT	Classification performance of the proposed method
Operation of Single Appliance	97.54%	98.95%
Simultaneous Operation of Multiple Appliances	91.21%	96.37%

Fig. 11 shows the results for the new appliance registration. The feature set of the vacuum cleaner is deleted from training data set. The new appliance registration algorithm attempts to check whether the vacuum cleaner operates, and a new appliance is registered. The signal with the feature is extracted by the proposed method, but the turn-on signal of the appliance is not observed. The training data closest to the vacuum cleaner are the data for the washer, but the data are outside the chi-squared distribution decision range; thus, it becomes an unknown appliance.

The amount of power use increases when operating the vacuum cleaner. The feature related to the vacuum cleaner is registered as a new appliance because the feature was confirmed 98% during operation of the vacuum cleaner, and the user is notified of the determination of a new appliance.

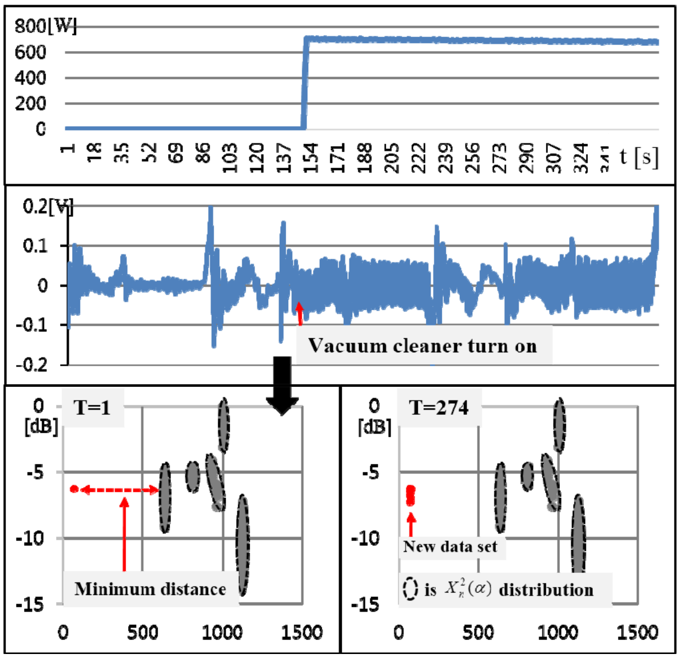

Fig. 11. Registration test of a new electric home appliance.

V. Conclusion and Future Work

In this paper, a cepstrum-smoothing-based load disaggregation method is proposed for effectively disaggregating load appliances. The features extracted from the smoothed cepstrum of the voltage signal is shown to be important for improving the classification performance of the proposed load disaggregation method when there is simultaneous on/off event of multiple appliances. Also, data acquisition system is developed to obtain only the characteristic signals of appliances by filtering out the external environmental noise. Future research needs to be directed toward the development of a cloud computing-based service for registering a new installed home appliance which is not included in the initial training data set.

References

[1] H. Y. Lam, G. S. K. Fung, and W. K. Lee, "A novel method to construct taxonomy of electrical appliances based on load signatures," *IEEE Trans. Consumer Electron.*, vol. 53, no. 2, pp. 653-660, May 2007.

[2] D. -M. Han and J. -H. Lim, "Design and implementation of smart home energy management systems based on zigbee," *IEEE Trans. Consumer Electron.*, vol. 56, no. 3, pp. 1417-1425, Aug. 2010.

[3] A. Zoha, A. Gluhak, M. A. Imran, and S. Rajasegarar, "Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey," *Sensors*, vol. 12, no. 12, pp. 16838-16866, Dec. 2012.

[4] S. Gupta, M. S. Reynolds, and S. N. Patel, "Electrisense: Single-point sensing using EMI for electrical event detection and classification in the home," *in Proc. ACM International Conference on Ubiquitous Computing*, Copenhagen, Denmark, pp. 139-148, Sep. 2010.

[5] M. Zeifman and K. Roth, "Nonintrusive appliance load monitoring: Review and outlook," *IEEE Trans. Consumer Electron.*, vol. 57, no. 1, pp. 76-84, Feb. 2011.

[6] H. H. Chang, "Non-intrusive demand monitoring and load identification for energy management," *Energies*, vol. 5, no. 11, pp. 4569–4589, Nov. 2012.

[7] Y. -C. Chen, C. -M. Chu, S. -L. Tsao, and T. -C. Tsai, "Detecting users' behaviors based on nonintrusive load monitoring technologies," *in Proc. IEEE International Conference on Networking, Sensing and Control*, Evry, France, pp.804-809, Apr. 2013.

[8] Y. -H. Lin and M. -S. Tsai, "Development of an improved time-frequency analysis-based nonintrusive load monitor for load demand identification," *IEEE Trans. Instrum. Meas.*, vol. 63, no. 6, pp. 1470-1483, Jun. 2014.

[9] E. Gomez, A. Klapuri, and B. Meudic, "Melody description and extraction in the context of music content processing," *J. New Music Res.*, vol. 32, no. 1, pp. 23-40, Mar. 2003.

[10] B. P. Bogert, M. J. Healy, and J. W. Tukey, "The quefrency analysis of time series for echoes," *in Proc. the Symposium on Time Series Analysis*, Providence, USA, pp .209-243, 1962.

[11] C. Breithaupt, T. Gerkmann, and R. Martin, "Cepstral smoothing of spectral filter gains for speech enhancement without musical noise," *IEEE Signal Processing Letters*, vol. 14, no. 12, pp. 1036-1039, Dec. 2007.

[12] S. Kong, Y. Kim, S. -K. Joo, and J. -H. Kim "Cepstrum smoothing - based feature extraction method for electric loads disaggregation," *in Proc. IEEE International Conference on Consumer Electronics*. Las Vegas, USA, pp. 290-291, Jan. 2014.

[13] Y. Kim, S. Kong, R. Ko, and S. -K. Joo, "Electrical event identification technique for monitoring home appliance load using load signatures," *in Proc. IEEE International Conference on Consumer Electronics*. Las Vegas, USA, pp. 296-297, Jan. 2014.

[14] J. Benesty, M. M. Sondhi, and Y. A. Huang, *Springer Handbook of Speech Processing*, Springer: New York, 2008, pp. 166-172

Biographies

Seongbae Kong received his M.S. degree in Electrical Engineering from Korea University, Seoul, Korea, in 2011, He is pursuing Ph.D. degree at Korea University, Seoul, Korea. His research interests include smart device, power IT, electric vehicles and energy forecasting

Youngwook Kim received his B.S. degree in Electrical Engineering from Korea University, Seoul, Korea, in 2010, He is pursuing Ph.D. degree at Korea University, Seoul, Korea. His research interests include smart grid and reliability.

Rakkyung Ko received his B.S. degree in Electrical Engineering from Korea University, Seoul, Korea, in 2014, He is pursuing M.S. degree at Korea University, Seoul, Korea. His research interests include smart grid and energy management system.

Sung-Kwan Joo received his M.S. and Ph.D. degrees from the University of Washington, Seattle, in 1997 and 2004, respectively. From 2004 to 2006, He was an Assistant Professor in the Department of Electrical and Computer Engineering at North Dakota State University. He is currently an Associate Professor in the School of Electrical Engineering at Korea University. His research interests include multi-disciplinary research related to energy systems, involving information technology, optimization, and intelligent systems.