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Identification of In-Home Appliance Types Based on Analysis of Current Consumption Using Energy Metering Circuit

Tin Trung Tran, Trung Xuan Pham, Jong-Wook Kim*

Abstract : One of the important applications of activity sensing in the home is energy monitoring. Many previous methodologies for detecting and recognizing household appliances have been proposed. This paper presents an approach that uses an energy metering circuit (EMC) to classify and identify the various electrical devices in home based on root-mean-square (RMS) consumed current value. EMC gathers the RMS current values created by appliance state transition (e.g., on to off) and apparatus operating process. In this paper, an identification algorithm is proposed to detect a change in current levels using the standard deviation of current signals and their average values. In addition, characteristic of the appliance is extracted concerning four feature parameters concerning the number of current levels, the minimum level, the maximum level, and signal-to-noise ratio (SNR) of them. Experiment results validate the reliable performance of the proposed identification method for 11 representative appliances.

Keywords : RMS consumed current, Identification, Monitoring, Energy meter

Ⅰ. Introduction

The appliance identification has been studied and applied for power monitoring aimed to reduce energy consumption during energy usage. The classification and device identification must guarantee the accuracy and reliability. In particular, these works are performed based on detecting the appliance state transition (e.g., on to off) and the apparatus operation process by analyzing the changes in levels of power metrics (e.g., active and reactive power) or raw data (i.e., voltage and current signals).

The previous studies have been developed as Appliance Load Monitoring (ALM) aimed to perform detailed energy sensing and to provide the energy usage information. Most research on in-home appliances has concentrated on ALM from two approaches: Intrusive Load Monitoring (ILM) and Non-intrusive Load Monitoring (NILM). NILM method that laid foundation has been performed by Hart [1]. Since then, NILM algorithm has been developed by many studies with different combinations such as nearest neighbor [2-4].

Recent studies on NILM have spent a majority of time consuming to identify the representative values such as active power, reactive power, RMS current and RMS voltage. In [5-7], identification appliance methods using analysis of power consumption signatures have been proposed. In general, the framework of

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NILM approach includes data acquisition module, extraction of appliance feature, inference, and learning (load identification). Accordingly, detection methods for the electrical events have been proposed in [8, 9] to detect and characterize the events as the appliance feature extraction.

In NILM method, the voltage and current values are measured in order to compute the power metrics. Then, based on computed power metrics the electrical events of an appliance such as the appliance state transition (e.g., on to off and vice versa) are detected. To perform load disaggregation, Artificial Neural Network (ANN) and Hidden Markov Model (HMM) are the most popular algorithms to learn and detect the appliance state transition [10,11]. Robert et al. [12] proposed an interesting approach for detecting a certain appliance and its operation states based on measurable parameters by using Factorial Hidden Markov Model (FHMM) to identify multiple appliances at the same time.

Numerous studies with off-line training approach have used the load power data for extracting the consumed power signatures to label the appliances.

In fact, the change in magnitude of RMS current consumption leads to the change in the power consumption. Therefore, analyzing the changes in the magnitude level of the RMS current consumption during operation of the appliance allows achieving better recognition rate and lower identification time.

The primary goal of this paper is to propose the method for identifying the individual appliance via analyzing the RMS current consumption. The present approach is measuring the level information and signal-to-noise ratio of RMS current signal by the proposed EMC and analyzing some practically measurable parameters (i.e., the total number, minimum and maximum of the estimated current levels and SNR of the current signal) in order to recognize and distinguish the appliance from the others by

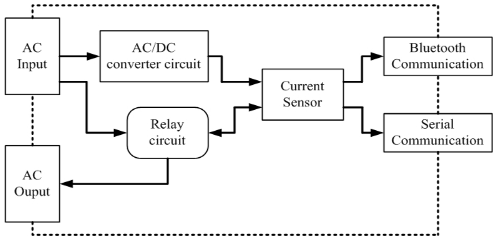

Fig. 1 Proposed EMC design

the observed current consumption features. In general, magnitude levels of current consumption depend directly on the appliance type and operation mode of the appliance, which will be obvious from measurement results. The contribution of this study is, therefore, the ability to gain the identification performance in the energy monitoring system.

The paper is organized as follows. Section 2 describes the data acquisition system and the proposed data processing for appliance identification. Section 3 explains the reliable algorithm for recognizing the appliance type based on detecting the event of level transition on RMS current consumption. Section 4 summarizes and mentions the present study and future work.

Ⅱ. Research Methodology

1. Energy meter circuit design

The authors analyzed and evaluated the appliance recognition capability based on the differences in magnitude of RMS current [13]. With this motivation, in this literature, the prototype DAQ system uses the distributed energy meter for gathering the RMS current of individual appliance for identifying the residential appliances type based on detecting the level differences in magnitude of the RMS current.

The structure of EMC with main components, including an energy sensor, relay circuit, AC/DC converter, and two communication methods is shown in Fig. 1. The communication interfaces are used in the proposed design of EMC, which are both serial and Bluetooth communications.

Measuring the RMS current consumption is fully implemented by the energy sensor MCP39F501. During the measurement of RMS current, analog current signal is amplified through programmable gain amplifier (PGA) and subsequently converted to digital signal by a Delta sigma analog-to-digital converter (ADC) with 24 bits and a coherent sampling algorithm to lock the sampling rate to the line frequency. When RMS current calculation is performed with 2^N current samples, its expression is given as

$$Irms = \sqrt{\frac{\sum_{n=0}^{2^N-1}(i_n)^2}{2^N}} \qquad (1)$$

where i_n donates the current value, and N in 2^N is the number of line cycles.

2. Feature Exaction

The data used in this study are collected from the prototype EMC. Accordingly, the EMC acquires RMS current consumption as raw data for an individual home appliance. Afterward, the raw data is extracted and analyzed by programs running on a computer. To obtain the derived RMS current consumption, the program running on a computer for signal processing is designed to transmit and receive the data via serial communication between the EMC and the computer. For data transmission, a data packet containing the raw data and power metrics is transmitted to the computer through serial port RS-232.

The proposed system is set to measure and gather RMS current consumption of such real residential appliances as a fan, lamp, TV, PC, refrigerator, and the like as shown in Fig. 2. The gathering and extracting raw data aims to build the database of RMS current pattern of each device used for experiments. Based on the distinct current value profile of the appliance, the identification algorithm performs

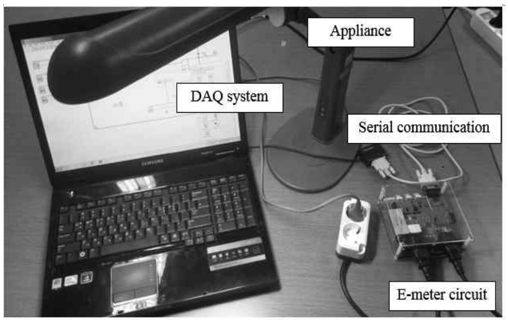

Fig. 2 The proposal system

analyzing characteristic of the current signal to detect on/off or multi-mode operations of the different devices.

Fig. 3 shows measured current magnitude profiles of the 11 popular and representative in-home appliances that are used for experiments The RMS current consumption patterns describe the current of individual appliances in their operating process and on/off state of transition.

3. Proposed Measures for Appliance Identification

The recent approach for current signature recognition has been proposed to solve the identification problem with current consumption of total load [14-16]. To identify appliance types based on analyzing the characteristic of RMS current magnitude, four measurable current level features are proposed in this paper; the total number, the minimum and maximum values, and the SNR of the estimated current levels.

RMS current levels of the appliance being measured will apparently vary depending on the consumption power and the number of operation modes. Therefore, in this study, the minimum and maximum current levels are estimated using average current magnitude (as defined I_{avg}) and its standard deviation (as defined I_{std}). To this end, a simple and reliable approach is used by sliding a window of size N over the recent current magnitude values to compute the I_{avg} and I_{std}. That is, I_{avg} can be

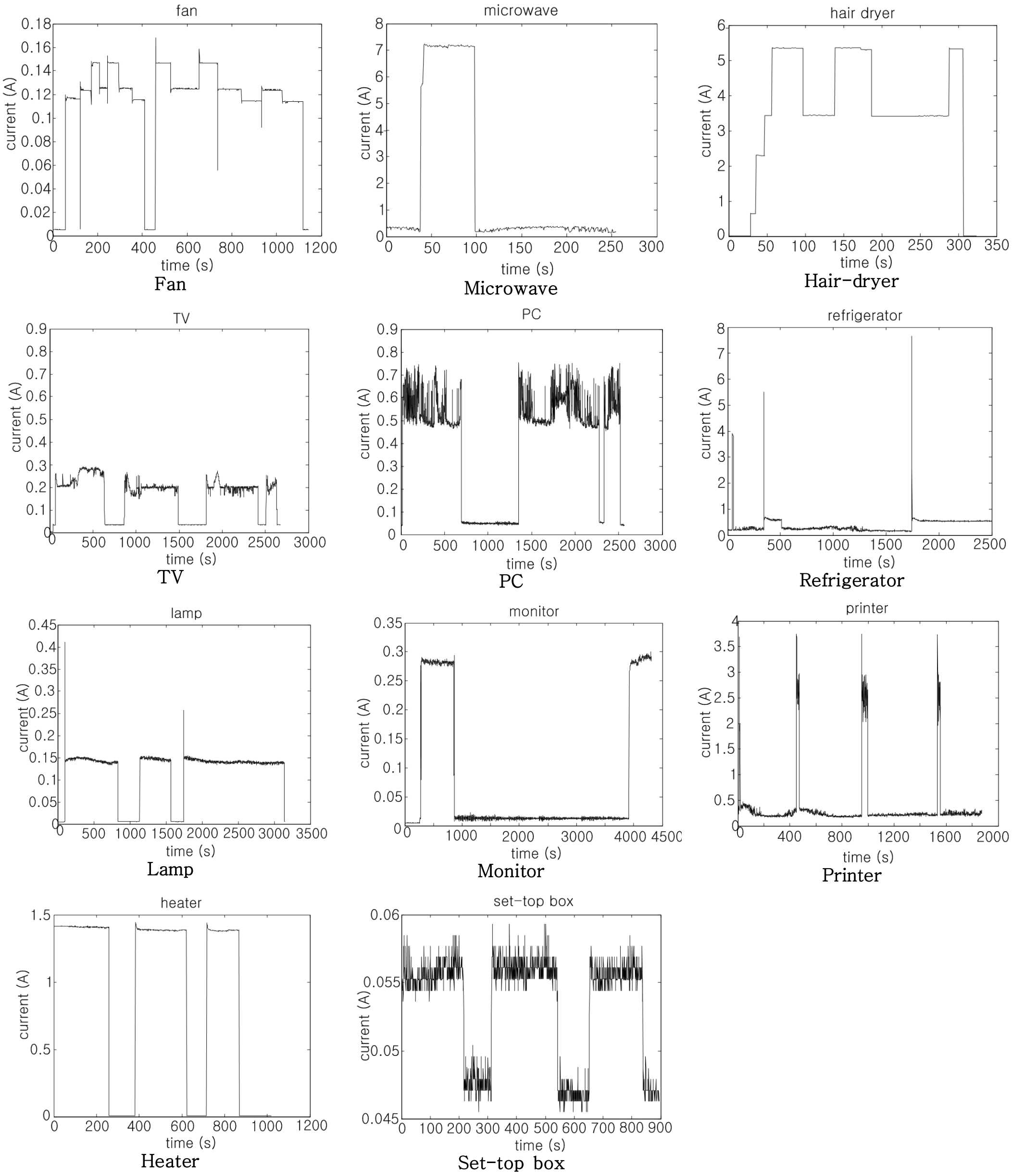

Fig. 3 Patterns of RMS current levels for 11 residential electric appliances measured

calculated by averaging a series of recent current values from the present time to the previous N-1th sample time, as shown in Equation 2. Then, I_{std} can be attained by calculating the standard deviation for the windowed data, as presented in Equation 3.

$$I_{avg}[kT] = \frac{1}{N}\sum_{i=1}^{N} I[(k-i)T] \tag{2}$$

$$I_{std}[kT] = \sqrt{\frac{\sum_{i=1}^{N} I^2[(k-i+1)T]}{N} - I_{avg}^2[kT]} \tag{3}$$

where $I[kT]$ is the signal of RMS current magnitude at the k-th sampling instance, T is the sampling time, and N denotes the size of windowed data.

To record the RMS current value at the moment when the current magnitude leaps to the other operation level, average standard deviation (ASD), I_{std}^{avg}, is newly proposed like the following

$$I_{std}^{avg}[kT] = \frac{1}{M}\sum_{i=1}^{M} I_{std}[(k-i)T] \tag{4}$$

where M is the size of the window for averaging the latest standard deviation values, and I_{std} is presented in Equation 3. The ASD value allows detecting a sudden change in current magnitude level, which will be explained in the following section.

In addition, as shown in Fig. 3, the RMS current pattern of PC contains sharp and noisy signals, which is quite peculiar. Therefore, to obtain another feature, SNR of the current signal, I_{snr}, is calculated by ratio between I_{avg} and I_{std} with the following expression

$$I_{snr}[kT] = \frac{I_{avg}[kT]}{I_{std}[kT]} \tag{5}$$

III. Appliance Identification with Experiment Data

This paper focuses on developing the proposed identification algorithm with consideration of various measures provided in Section 2.3. The identification algorithm is composed of four steps, which is explained below.

First, a profile of RMS current consumption is measured and collected by the DAQ system as described in Section 2.1 and 2.2. Subsequently, I_{avg}, I_{std}, and I_{std}^{avg} for each RMS current are calculated to detect a new RMS current magnitude level.

Second, I_{std} is compared with I_{std}^{avg} to detect

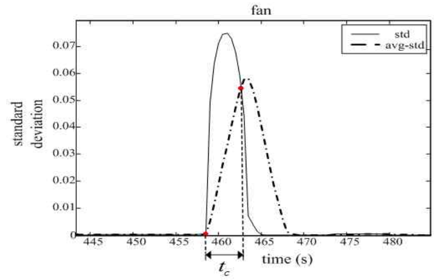

Fig. 4 Measurement of transition time using current magnitude values

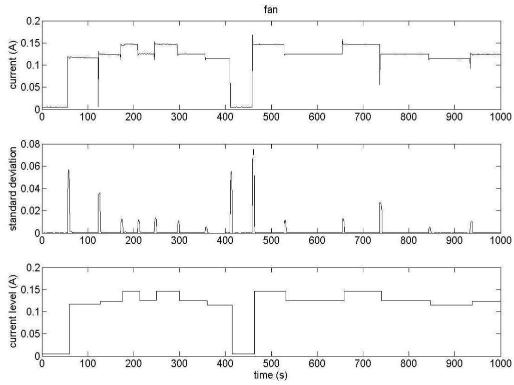

Fig. 5 Extraction of current magnitude levels with experiment data for a fan

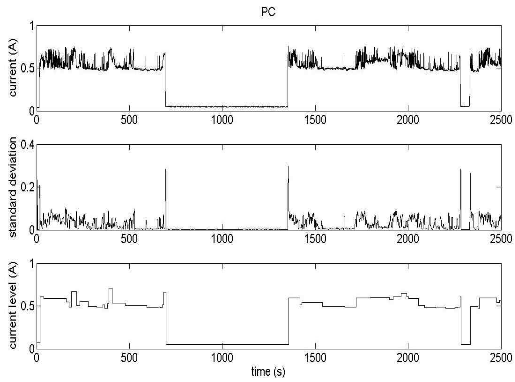

Fig. 6 Extraction of current magnitude levels with experiment data for a PC

a change in current magnitude level. If the present current magnitude changes abruptly, I_{std} will be greater than $K*I_{std}^{avg}$ where K denotes coefficients for I_{std}^{avg}, i.e., the latest

Table 1. Four practicable measurable parameters associated with the current magnitude levels

Appliance	Estimated Current Levels	No. of Level	Average Current SNR
Lamp	5.4mA - 142.9mA	2	173.76
TV	34.1mA - 214mA	2	157.93
PC	49.9mA - 543.4mA	2	64.83
Printer	232mA - 2.55A	2	89.18
Microwave	307.2mA - 7.16A	2	704.60
Monitor	4.9mA - 13.2mA - 283.4mA	3	68.11
Refrigerator	4.0mA - 558.4mA - 3.848A	3	68.69
Fan	4.9mA - 115.0mA -124.5mA - 46.5mA	4	3963.67
Hair-dryer	5mA - 641.2mA -2.30A - 3.42A - 5.34A	5	1510.7
Heater	4.8mA - 1.39A	2	1362.061
Set-top box	47mA - 56mA	2	129.25

short-time pattern of I_{std}. Then, as the signal is stabilized, I_{std} will be quickly smaller than I_{std}^{avg}. The proposed algorithm records the two moments and calculates time duration between them, which is called the transition time t_c, as shown in Fig. 4 where K is set to 1. In the case that an actual level change occurs, the transition time will be longer than that of mere noise signals. A good criterion for the appropriate transition time is determined 3 seconds after experiments with our appliances.

Fig. 5 and 6 exemplify extraction of current amplitude levels from current magnitude data for a fan and a PC, which are contrasts to each other. In each figure, the top subfigure represents the profile of original current RMS values; the middle one is the standard deviation I_{std} calculated by (3) with the window size of 10, and at the bottom shows the profile of estimated current magnitude levels attained by setting $K=2$, $t_c=3$. As can be seen in the standard deviation profiles, peak signals are much more salient for the fan than for PC, which results in a better match between original and extracted magnitude levels.

In contrast, significant perturbation occurs in the current magnitudes of PC owing to the multiple application software running in processors of PC. Therefore, the sharp peaks in the derived standard deviation contain numerous local current amplitude levels, which correspond to the same degree, i.e., on the state. At this point, the local magnitude levels varying within a small range need to be clustered and updated into the single one at the next step.

Third, once a new current level is detected, the algorithm compares it with the ones found so far to update the estimated current levels. If a new current level, e.g., I_j, is regarded matching best with one of the previously estimated current levels, e.g., I_l, with their difference below $\alpha\%$ of the maximum current level, I_l is updated by weighted average of both levels in such a way that

$$I_l^{'}=\frac{I_jT_j+I_lT_l}{T_j+T_l},\ T_l^{'}=T_l+T_j \tag{6}$$

where $I_l^{'}$ and $T_l^{\prime}$ denote the newly updated current level and duration time respectively, and T_j is the duration time for I_j.

Finally, the proposed algorithm refers to an

Table 2. Four identification rule types of information relevant with current magnitude levels

Current Level Value	Range 1		Range 2	Range 3
Total number (Rule 1)	1	2	3	4 ~
	Set-top box	TV, Printer, PC, Microwave, Lamp, Heater	Refrigerator, Monitor	Fan, Hair-dryer
Minimum (Rule 2)	0 ~ 10mA		10mA ~ 100mA	100mA ~
	Fan, Hair-dryer, Lamp, Monitor, Set top box, Heater		TV, PC	Refrigerator, Printer, Microwave
Maximum (Rule 3)	0 ~ 0.5A		0.5 ~ 5A	5A ~
	Fan, TV, Lamp, Monitor		Refrigerator, PC, Printer, Heater	Microwave, Hair-dryer
Average SNR (Rule 4)	0 ~ 100		100 ~ 1000	1000 ~
	Refrigerator, PC, Printer, Lamp, Monitor		TV, Microwave, Lamp, Set-top box	Fan, Hair-dryer, Heater

Table 3. Identification numbers assigned to appliances

Appliance	Fan	Hair-dryer	Printer	Lamp	Microwave	Monitor	PC	Refrigerator	TV	Set-top box	Heater
Id. no	1	2	3	4	5	6	7	8	9	10	11

identification rule table with the four feature parameters concerning the current levels attained so far such as their total number, maximum, and minimum current levels and average SNR of the current. Then, each feature parameter suggests a set of matched appliance types as a candidate list, and the device which appears most often in the four resultant records are selected as an identified one.

To this end, database concerning the four parameters needs to be constructed for the representative home appliances by either experiments or specification data, which is provided in Table 1.

Based on Table 1, we can make the identification rule table concerning appropriate value ranges as shown in Table 2. While the current magnitude levels are detected online by EMC, each current feature parameter is compared with the parameter range of the corresponding rule enrolled in Table 2, and the resultant sets of matched appliance types are attained as the temporary candidates for the appliance connected to EMC. Among them, the device common to all the four criteria is the identification output. For instance, assume that we are not aware of the connected in-home device and the four feature parameters along with their candidate appliances are attained from Table 3 like the following

- Total number of level is 2: TV, Printer, PC, Microwave, Lamp
- Minimum level is 0.06A: TV, PC
- Maximum level is 0.7A: Refrigerator, PC, Printer
- Average SNR of level is 75: Refrigerator, PC, Printer, Lamp, Monitor

Among the four candidate lists, in this case study, it is apparent that PC is the only appliance common to all the lists, which fulfills all the four criteria. Subsequently, the result indicates that the appliance identified in this case is the PC with the probability of 100% as identification rate.

This inference scheme can be numerically implemented using an integer frequency matrix whose rows are appliance identification number

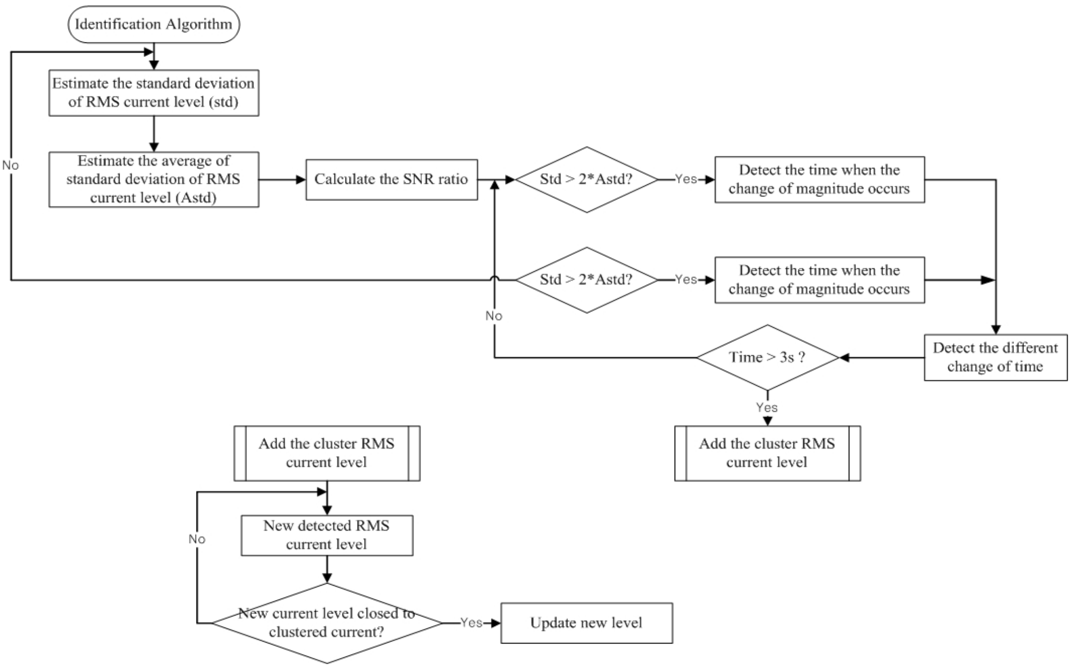

Fig. 7 Flow diagram of the proposed identification algorithm

and its cumulative number of inclusion in the candidate list. At every cycle of inference with the four feature parameters, the appliance whose count number is the largest becomes the identified appliance at that time. In the example above, after the check cycle the count number of PC will be increased by 4, while 3 for Printer and 2 for TV, Refrigerator, and Lamp in the frequency matrix. Therefore, the PC is selected as an identification result.

The proposed algorithm of identification method is shown in Fig. 7. The algorithm is designed with the proposed measures for appliance identification based on RMS current signal as mentioned in Section 2.3. Table 3 summarizes 11 identification numbers assigned to all the appliances considered in this paper.

From the achieved results, the proposed algorithm allows performing appliance recognition easier and simpler with only one EMC and a microprocessor. With the novelty of identification in terms of current level transitions and operating condition of home appliances based mainly on RMS current consumption, the proposed model has no limit in the number of appliances to be measured and not require exhaustive training for each appliance as the previous methods.

IV. Conclusion

In this paper, a new identification algorithm has been proposed to detect and recognize the household appliances only by current signals. The authors focused on developing the identification algorithm based on analyzing and extracting the behavior of RMS current consumption for residential electrical appliances. This paper selected four feature parameters concerning the estimated current levels such as its total number, minimum, maximum, and the SNR as information for inference. By referring to all these parameters, identification analysis was performed to match them with the appliance database.

For preparing to identify the household

appliances, the characteristic of RMS current signals has been analyzed and evaluated from the different appliances through their current profiles. The following three selection steps were performed: (a) calculating the average and standard deviation of current magnitude and its average standard deviation to find a new current magnitude level in real-time; (b) comparing standard deviation and average standard deviation to detect level change; and (c) updating the estimated current levels by matching a new current level with previously estimated current levels. The algorithm was developed based on these selection steps to detect the behavior of the recent RMS current level and identify appliances through matching the corresponding estimated RMS current levels.

In the future work, the server system for the smart home application whose main ingredient is the database with RMS current consumption profile of the different appliance types, will be developed and connected to many EMC. It enables the system to recognize all the connected appliances to EMC. In addition, the system can update information of a new appliance automatically and identify it when it is connected to the system next time.

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