

A Method of Appliance Detection Based on Features of Power Waveform

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Abstract

We propose a method to detect the model, location and activity of a conventional home electric appliance. Waveforms of current consumed by appliances vary according to their configurations and activity. We define feature parameters for detecting the status of appliances. A current detector, microcomputer and transmitter are equipped in a power outlet in order to measure consumed current, calculate the feature parameters, and transmit the results to a home server. Feature parameters of appliances in the home are learned and stored in a home server in advance. The home server compares the feature parameters of known appliances with the received feature parameters to detect an appliance's model and activity. User could control appliances from out of the house via the Internet.

1. Introduction

A variety of intelligent home appliances and home networks have been introduced. If home appliances are connected via a home network, we can control them remotely. ECHONET[1], OpenPLANET and LonWorks [2] are typical home network specifications. In such a specification, the home appliance is equipped with a communication device and an API in order to connect it to the home network. However, this increases the cost of home appliances and forces the user to trade-in conventional home appliances for newer appliances. Consequently, this approach places an undue burden on the users. Therefore, it is highly desirable to provide a means to connect and control conventional home appliances. Furthermore, from the viewpoint of energy management, forgetting to turn off the power and meeting standby power requirements become problems. Moreover, these problems may lead to the danger of fire, so for the sake of safety it is necessary to control conventional home appliances. As high-energy appliances such as a clothes irons, hair dryers, electric heaters and lighting equipment have very simple configurations, the cost of a network de-

vice is clearly reflected in the price. Therefore, even disregarding the risk of fire hazard and high energy consumption, it is difficult to comply with home network standards. People do not use clothes irons, hair dryers, and portable electric heaters at the same location each time. In order to control such appliances without using any additional device, it is necessary to first detect the location and power state of the target appliance. X10 is a good standard of home automation, but when the appliance is relocated, a different appliance might be controlled.

Let's look at some of the previous studies. Several methods have been introduced to detect the power state and position of devices. One such method involves detecting a power state by sending video and sound with a video camera and microphone. This method needs to take pictures constantly in order to detect the power state, so it fails when the power state of a controlled appliance is visually imperceptible. For position detection in a home, various methods have been proposed, such as those based on ultrasonic or IR sensors[8], RFID[7], barcodes[5, 3] and so on. These methods need to attach additional devices to appliances, and many sensors are also required. Controlling conventional home appliances does not require absolute coordinates but just the connected outlet and room position, since it's only possible to control the power on-off state or perform control via infrared remote control.

Our proposed method uses power outlets with a current detector, microcomputer and transmitter. Waveforms of current consumed by appliances vary according to the particular model. We define feature parameters to detect appliances based on waveforms. This method calculates feature parameters based on measured consumed current and transmits the results to a home server that controls the appliances in the home[4, 6]. Feature parameters of known appliances are learned and stored in the home server in advance. The home server compares the feature parameters of known appliances with the received feature parameters to detect the model and its activity. Appliances are controlled from outside of the house via the Internet and the home server.

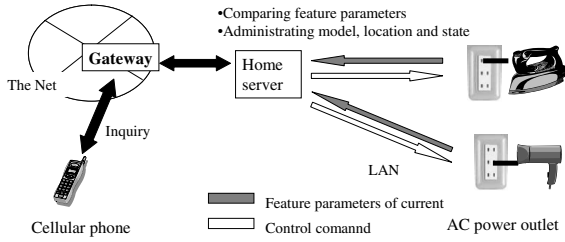


Figure 1. System overview

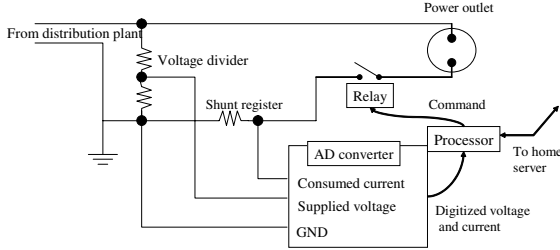


Figure 2. Power outlet

2. Proposed method

In this section, we give an overview of our system and the configuration of a power outlet.

2.1. Overview of system

Figure 1 shows the system for detecting the model, location and power state of home appliances.

Power outlets convert current and voltage from analog to digital and then calculate feature parameters. Next, the feature parameters are transmitted to the home server via local area network. The home server receives feature parameters of appliances connected to power outlets and compares them with feature parameters already learned. Learning is performed when the appliance is first used in the home. The home server detects the model, location and power state of an appliance by comparing its feature parameters and sending a control command to the power outlet when needed, such as when the system detects that the user has forgotten to turn off the power.

2.2. Power outlet

The proposed method installs functions to process the current and control the power line in a home's power outlets. The configuration of the power outlet is shown in Fig.2.

The power outlet has a current detect resister, AD converter, microcomputer and relay. If digitized waveforms are transmitted from many power outlets to the home server, the home server receives a vast amount data and data traffic is increased. Thus, the power outlet system calculates and transmits feature parameters, not waveforms.

3. Features of current

In this section, we discuss the relationship between current and the features defined by our method. We define five parameters based on observation results of the current consumed by actual appliances.

3.1. Current amplitude

We can represent current amplitude in several forms. These include peak value I_{peak} , average value I_{avg} and root-mean-square(r.m.s.) value.

Calculating the r.m.s. value requires a lot of computational effort by the microcomputer in the power outlet. Thus, the r.m.s. value is not used in order to minimize calculation load. Thus, only I_{avg} is used as a feature parameter. In order to obtain the peak-average ratio R_{pa} discussed in the next section, peak value I_{peak} is also calculated.

$$\begin{aligned} I_{avg} &= \sum i/p \\ I_{peak} &= \max i \end{aligned} \quad (1)$$

where i means sampled value and p means number of sample points per half AC cycle.

3.2. Current form

Features that present current forms include the well-known crest factor ($CF = I_{peak}/I_{rms}$) and form factor ($FF = I_{rms}/I_{avg}$). In order to calculate these parameters, I_{rms} mentioned above should also be calculated. Thus, we define peak-average ratio R_{pa} instead of crest factor and form factor.

$$R_{pa} = CF \cdot FF = I_{peak}/I_{avg} \quad (2)$$

3.3. Current timing

When the load is not pure resistance, a distortion of current and phase difference between current and voltage is observed. We define the parameters peak time difference T_d , turn-on time T_{on} and peak delay factor F_p in order to represent the timing of the passage of current.

$$T_d = T_{I_{peak}} - T_{V_{peak}} \quad (3)$$

where $T_{I_{peak}}, T_{V_{peak}}$ are the peak times of current and voltage measured from when an AC cycle starts.

$$T_{on} = (T_{I_{end}} - T_{I_{start}}) \quad (4)$$

$$F_p = (T_{I_{peak}} - T_{I_{start}})/(T_{I_{end}} - T_{I_{start}}) \quad (5)$$

where $T_{I_{start}}, T_{I_{end}}$ are the times of current turn-on and turn-off. These parameters are shown in Fig.3. This method uses the five parameters mentioned above as feature parameters.

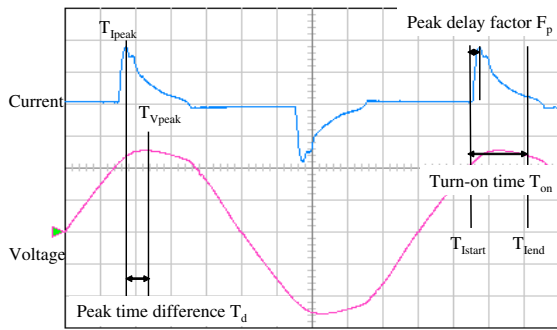


Figure 3. Current timing

4. Processes

In this section, we discuss calculation of the feature parameters mentioned above and the detection process based on feature parameters at the home server.

4.1. Calculation process of feature parameters

Feature parameters are calculated at the power outlet by the following steps:

1. Processor receives the digitized value of the current and voltage.
2. Processor calculates the average I_{avg} of several cycles. When this I_{avg} does not changes by 10 percent from when features parameters were last sent, repeat from Step 1.
3. Calculate the other four parameters. Feature parameters are averages for several cycles as well as I_{avg} .
4. Feature parameters are sent to the home server.
5. The control command from the home server is received, which controls the relay to turn on or off the power line.
6. Repeat from Step. 1.

The feature parameters use the average of several cycles in order to avoid the influence of noise and to reduce the time of transmitting feature parameters. The value of 10 percent in Step 2 is chosen by giving consideration to the voltage fluctuation and transition of power consumption when appliances change their state.

4.2. Detecting model, location and state

The home server detects the model, location and state of appliances based on feature parameters sent from power outlets. Learning feature parameters is performed when the appliance is first used in the home. From the next time the home server receives feature parameters of appliances connected to power outlets, they are compared with the feature parameters already learned. The following steps are used for learning:

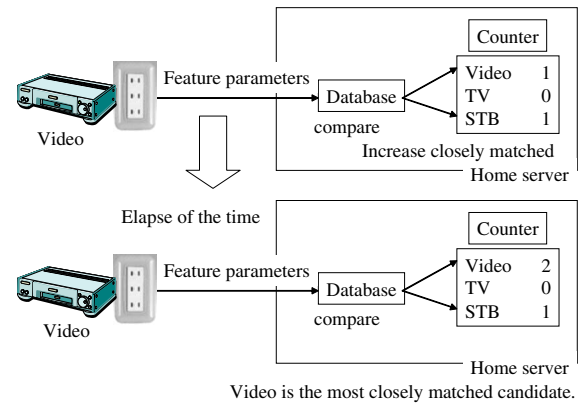


Figure 4. Detection process

1. User sends command to learn to the home server and inputs the model name of the appliance.
2. Connect the appliance to the power outlet.
3. The home server stores feature parameters in the database.
4. After using the appliance for a while, its operation modes, such as hot or cold operation of a hair drier, typically change. Therefore, a number of feature parameters are stored.
5. Stop learning.

The following steps are used for detecting:

1. The home server waits for feature parameters sent from power outlets.
2. When feature parameters are received, they are compared with other feature parameters in the database to find the model whose feature parameters correspond to the received feature parameters as a detection candidate. Feature parameters are affected by calculation timing and voltage variation, so this comparison has a certain margin of error.
3. When there are several models with matched feature parameters, increase the counter that counts the number of matched parameters. Wait for the next feature parameters and repeat from Step. 2. Figure4 shows this process.
4. The most closely matched candidate model is regarded as the true model, and the appliance connected to the power outlet transmits its feature parameters.
5. The power state of the appliance is also determined from the feature parameters.

5. Evaluation

In this section, we discuss the evaluation of our method.

5.1. Conditions

First, learn the feature parameters of all appliances for up to several minutes, for example, until the thermostat mode

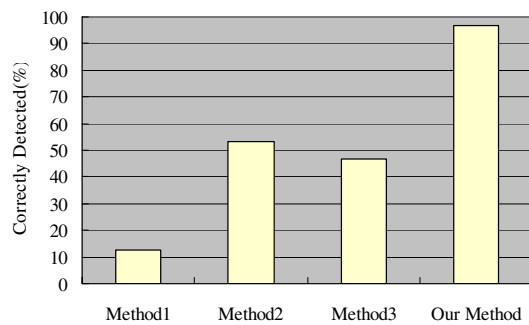


Figure 5. Evaluation results

changes when the load is a clothes iron. Feature parameters are determined from the average of 10 cycles. The effective SNR of the AD converter is 77 dB and Peak SNR is 69 dB. Maximum current range is fixed at 20 A.

The appliances tested are 33 ordinary home appliances: four hair dryers, two clothes irons, one futon dryer, one air conditioner, five items of lighting equipment, two air purifiers, three televisions, four VCRs, five other AV devices, two computers, one food mixer, one vacuum cleaner, one shaver and one cellular phone charger. Every appliance is tested 10 times for up to 3 minutes. The criteria for evaluation is whether the model of the machine can be detected consistently for 3 minutes.

5.2. Results

We compared our method with other methods. Figure 5 shows the results. Method 1 uses only I_{avg} . The home server identifies the appliance with the latest I_{avg} . Method 2 uses only I_{avg} and the home server identifies the appliance by determining the most closely matched candidate with all I_{avg} received as well as our detection method described in section 4.2. Method 3 uses the feature parameters that our method uses but only uses the latest parameters. Our method uses feature parameters and identifies the appliance by determining the most closely matched candidate with all of the feature parameters received.

Method 1 could identify only four appliances accurately. In nearly every case this method could not correctly identify the appliance. This poor performance is due to the current amplitudes of many appliances being close to each other.

Method 2 detects more appliances than method 1, but this method has almost the same results as method 1 when the appliance current is constant because only a few parameters are received. Thus, using only the current value is insufficient for identifying appliances.

Method 3 also detects more appliances than method 1 because the five parameters are different among appliances, especially when the appliance has a rectifying circuit since rectifying circuits tend to generate many distinctive waveforms. However, when there are appliances that have similar circuits in a home, they cannot be identified correctly.

This evaluation criteria is whether the appliance is detected consistently within 3 minutes. When the feature parameters don't match the appliance's feature parameters by accident due to noise, calculation timing, or the comparison's margin of error, the result is treated as a misdetection.

Our method uses the change of waveform to find the most closely matched candidate over time, thus avoiding the misdetection that occurs with the other three methods described above. Our method also cannot detect the appliance model when two hair dryers of the same power are kept turned on because they generate only a few similar feature parameters. However, since our method detects the load as a hair drier, this is not a critical matter from a practical standpoint. There are few high-power resistance loads in a home. Consequently, our method is practical.

All of nondetectable states occurred when the load was a cellular phone charger because its current is too low and it drops below the noise floor occasionally.

6. Conclusions

In this paper, we proposed a method to detect the model, location and state of a home appliance by processing its current. Our method aims to use conventional home appliances as smart appliances. This was achieved by calculating the feature parameters of the current of home appliances and comparing them with feature parameters learned in advance and stored in the home server. We intend to extend this method to achieve faster and more accurate detection and combine the method with other control techniques such as infrared remote control.

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