Current Sensor based Non-intrusive Appliance Recognition for Intelligent Outlet

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Abstract: This paper presents the current sensor based non-intrusive appliance recognition method for intelligent outlet. Our system has two main functions; one is the remote control function of power supply through the Internet. The other is monitoring function observe the state of appliance. In this paper, the monitor function is especially focused. To recognize the state of appliance, we extract nine features based on measured current signal. In the experiment, we gathered a number of signals with various appliances, and found that three features I_{peak}, I_{avg}, and I_{rms} yield valid recognition results of 81.3%, 84.0%, and 87.4% for classifying the state of appliance into three categories.

1. Introduction

The number of products with communication capability will be available at our home by the development of IT technology in not only a computer or a cellular phone but home appliance. By the appliances' being connected with the home network becomes possible, we can control the appliance from remote place. There are ECHONET and OpenPLANET on the home network intended for the white goods [1], [2]. These use Ethernet, IEEE1349, and wireless LAN etc. as a communication device. Therefore, it is necessary to equip these with the communication device to control an existing product that doesn't have the communication capability.

Our aim is to develop the intelligent outlet which has the remote monitoring function of appliance to analysis state and to reduce the standby electricity. The system that alerts to unplug the appliance by gathering and analyzing of electric power information was proposed. Yoshimoto et al. proposed the non-intrusive load monitoring system by Neural Networks [3]. Murata et al. proposed the method for determining the on-off operation of appliance with support vector machine [4], [5]. Moreover, Ito et al. proposed a system of appliance detection and control using power consumption measurement [6]. Nakamura et al. also proposed load monitoring system of electric appliances based on Hidden Markov Model [7].

However, the recognition method of individual state of appliance is not treated to the control or monitoring. Then, this paper proposes the method for recognizing the state of the appliance and the appliance for a number of appliances.

2. System configuration

The system configuration of developed intelligent outlet is shown in figure 1. In this figure, the red line means the voltage flow, and the blue line means the signal flow. This system is composed of a Peripheral Interface Controller (PIC) which is a kind of micro controller, a relay circuit to control on-off of power supply, and a current sensor that measures the amount

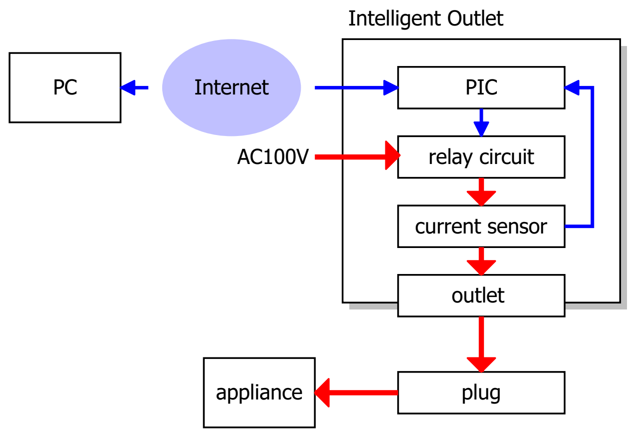


Figure 1. System configuration.

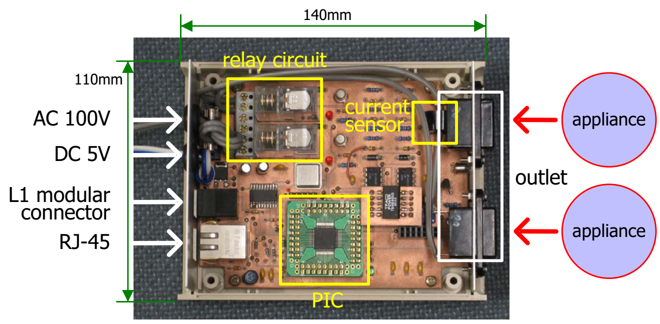


Figure 2. System overview.

of the current that flows to the appliance. The state of the system can be obtained through the Internet.

The overview of developed prototype system is shown in figure 2. The dimension of prototype system is 110(W) × 140(H) × 46(D) mm. Though, this system is used as the posterior device, the type of the embedded in wall is also in our target. Our system is consisted of two outlets, two current sensors, two relay circuits and one PIC. We use CTL-6-V-Z as current sensor made by U.R.D. co., Ltd, and PIC18F67J60 made by Microchip Technology Inc.

The current sensor transduces the current signal that flows to connected appliance into the voltage signal. This signal is transduced the positive value through the Op Amp and non-inverting amplifier, and input to the A/D converter of PIC. Here, we set the resolution of A/D converted to 10 bit. Then, we can measure the voltage signal of 3.3V in the maximum voltage and the resolution 3.2mV. Moreover, we set the sampling frequency to 4.4 kHz. The number of samples that can be measured at a time is 80 samples, that is, 1.33 seconds according to the specification of our system. The commercial

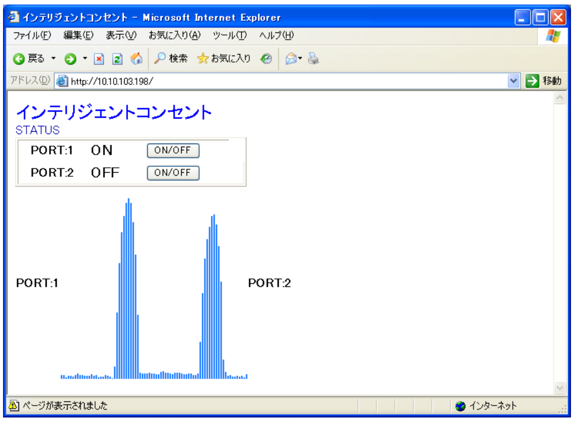
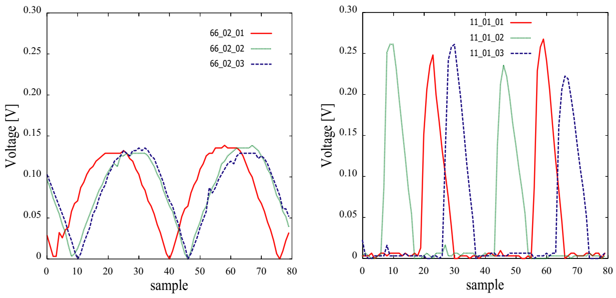


Figure 3. Browser window.



(a) fan (b) LCD display

Figure 4. Signals before phasing.

frequency in west Japan is 60 Hz. Then, the data at almost one cycle can be observed by measuring one time.

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Figure 3 shows the browser window of our system. In the upper part of this window, there is an ON/OFF switch of the relay. In this figure, one port is ON and the signal of this port is displayed in the lower part of this window. The other is OFF and its signal is not displayed. If the user turns on the switch of port 2, the signal port 2 is displayed.

Figure 4 shows the result of the measurement to a fan and a LCD display each three times. The horizontal axis indicates the number of samples and the vertical axis indicates the voltage value. This paper describes the method for recognizing the category and the state of the appliance from these signals.

3. Recognition algorithm

The flowchart of our algorithm is shown in figure 5. We first apply the phase shifting to obtain coherent signal. Next, we extract nine features. Then, we apply the normalization process, and the nearest neighbor method to recognize the state of appliance. The details of each process are described in the following sections.

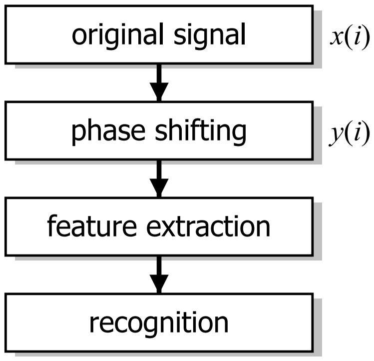
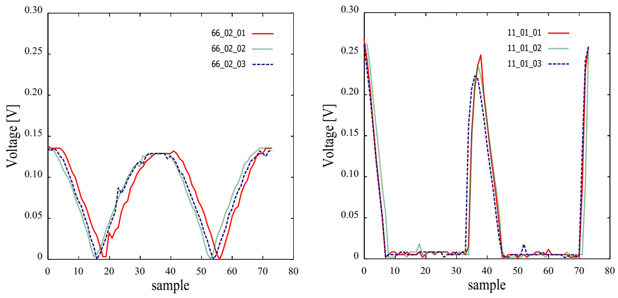


Figure 5. Flowchart of recognition algorithm.



(a) fan (b) LCD display

Figure 6. Signals after phasing.

3.1 Phase shifting

Even if it is the same appliance and the same state, the phase of the measured signal might be different as shown in figure 4. It is preferable to obtain coherent signal. Then, we apply the phase shifting process. Here we call the measured signal on original signal $x(i)$, and applied phasing signal that took out only one cycle on target signal $y(i)$. The target signal is shifted based on the peek value in original signal. Figure 6 shows the target signal form that applies the phasing process to figure 4.

3.2 Features

This paper applies recognition process to recognize the category of appliance and its state, by using the following nine features calculated from $y(i)$.

There are a peak value I_{peak}, an average value I_{avg}, and a root mean square value I_{rms} as a typical features of the current. These values are calculated as follow equations.

$$I_{peak} = \max_{i \in N} y(i) \tag{1}$$

$$I_{avg} = \frac{1}{N} \sum_{i=1}^{N} y(i) \tag{2}$$

$$I_{rms} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} y(i)^2} \tag{3}$$

Where, N is a number of samples of one cycle. Moreover, there are a crest factor CF, a form factor FF in which a time concentration of the signal, and a peak to average ratio F_{pta}. These values are calculated as follow equations.

$$CF = \frac{I_{peak}}{I_{rms}} \tag{4}$$

$$FF = \frac{I_{rms}}{I_{avg}} \tag{5}$$

$$F_{pta} = \frac{CF}{FF} = \frac{I_{peak}}{I_{avg}} \tag{6}$$

In this research, we define three another features, the ratio of low-level at one cycle to peak value r_l, the ratio of high-level at one cycle to peak value r_h, and the gradient angle θ_u[deg] of rising edge.

3.3 Recognition method

The recognition process is applied the well-known method, the Nearest Neighbor method after applying normalization. For each feature, the observed values are normalized using the average μ and standard deviation σ.

4. Experiment

In this experiment, each signal of 20 samples of 243 all states was measured from 94 appliances used the office and household as the personal computer, the television, the refrigerator, the fan, as shown in table 1. For instance, if the fan has two rotational speeds (strong mode and weak mode), we can measure three states; off state, strong mode, and weak mode.

Here, we excluded 55 states that the current hardly flows while turned off. Figure 7 and figure 8 show two states, off state and on state, of the washing machine and cleaner, respectively. Observing figure 7(a) and figure 8(a), both signal values are almost zero, and it is difficult to discriminate each other. However, observing figure 7(b) and figure 8(b), these are on state and it is easy to discriminate each other.

We classified into three kinds that showed 188 measured states in the following. In table 1, the number of state #1 denotes 243 all states included 55 states, and the number of state #2 denotes 188 states.

1. 188 categories considered all states of each appliance to be another category.
2. 94 categories considered to be one category without distinguishing state of each appliance.
3. 35 categories in which appliance was classified by kind

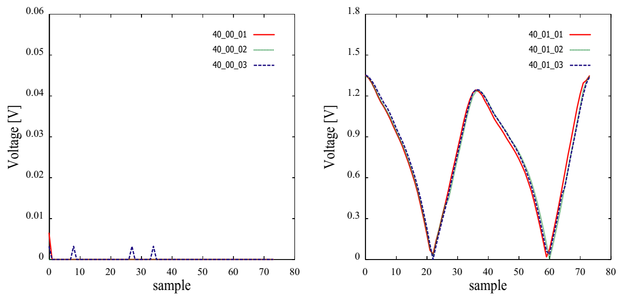
We applied the leave-one-out method to obtain high recognition accuracy with a few data. Namely, out of 20 samples for each category, 19 samples are a training set and the remaining one sample is a recognition set. By varying one sample, the total number of recognition trials is 20 for each category. The resulting recognition rate with nine all features was 76.3%, 80.5%, 85.5%, into 188 categories, 94 categories, and 35 categories, respectively.

The next experiments were to determine which features among nine features are more effective for recognition. First only one feature was used as the recognition feature. The feature yielding the highest recognition rate was identified and then a second feature with the first feature yielding the highest recognition rate was determined. This process was carried out for all the nine features. The most to least effective features are I_{rms}, I_{avg}, and I_{peak} in this order. Figure 9 shows the result, where three curves (pattern 1, pattern 2, and pattern 3) are shown. As the result, we obtained the highest recognition rate of 81.3%, 84.0%, and 87.4% with three features, into 188 categories, 94 categories, and 35 categories, respectively.

Here, 243 states including off state were classified into three patterns similar to the above mentioned. As the result, each highest recognition rate was 64.1%, and was 66.1%, and 69.1%, respectively. Since the current hardly flows in off, the discrimination with other states is difficult. Then, the recognition rate was decreased.

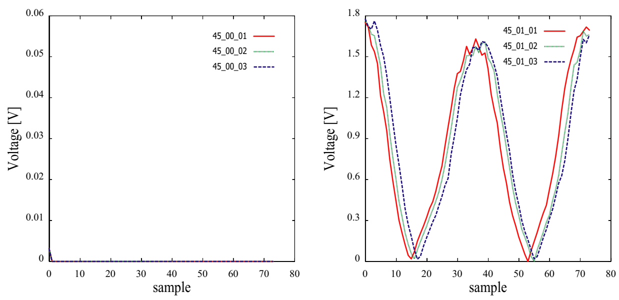
Table 1. Target appliances.

appliance	number of product	number of state #1	number of state #2
desktop PC	3	2	1-2
laptop	3	2	1-2
CRT display	3	2	1-2
LCD display	3	3	2
laser printer	3	3	2-3
ink-jet printer	3	3	2-3
television	3	2-2	1-3
portable television	1	2	2
projector	3	2-3	2-3
projector	1	2	2
digital video camera	3	4	3
video cartridge recorder	3	4	4
radio cassette recorder	3	3-4	2-3
refrigerator	3	2	2
rice cooker	3	3	2
pot	3	2	2
pot	1	2	1
coffee maker	3	2	1
cooking stove	1	4	3
washing machine	3	3	2
portable washing machine	1	2	1
cleaner	3	2	1
dehumidifier	3	2-3	1-2
hair drier	3	3	2
shaver	3	2	2
warm toilet seat	3	2	1-2
heaters			
carbon heater	1	4	3
ceramic heater	1	2	1
stove	1	3	2
electric blanket	1	2	1
electric carpet	3	2	1
electric fan	3	4	3
portable electric fan	1	3	2
kotatsu	3	2	1
telephone	3	2	2
battery charger of cellular phone	3	2	1
game console	3	2-3	1-2
desk lamp	3	2	1
total	94	243	188



(a) OFF (b) ON

Figure 7. washing machine.



(a) OFF (b) ON

Figure 8. cleaner.

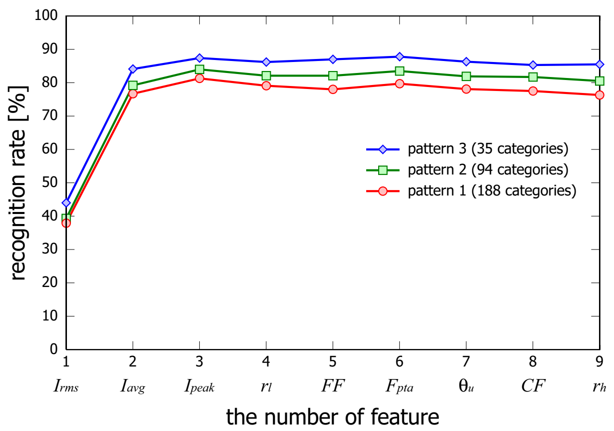


Figure 9. Recognition results.

5. Conclusion

This paper proposes current sensor based non-intrusive appliance recognition method for intelligent outlet. We gathered a number of signals with various appliances, and found that three features I_{peak}, I_{avg}, and I_{rms} yield valid recognition results of 81.3%, 84.0%, and 87.4% for classifying the state of appliance into three categories.

This paper describes the recognition method, then, the future work is implemented proposed method into the intelligent outlet, and work toward practical use of whole system.

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