Current Sensor Based Home Appliance and State of Appliance Recognition

Takeshi Saitoh *, Tomoyuki Oasaki *, Ryosuke Konishi *, and Kazunori Sugahara *

Abstract: This paper presents a current sensor-based home appliance and its state recognition method for intelligent outlets. Our system has three main functions: remote control, monitoring, and power supply schedule management. This research focuses particular on the monitoring function. To recognize the appliance and the state of the appliance, we extract ten features based on a measured current signal. In the experiment, we gather a number of signals with various appliances, and find that features $I_{max}$, $I_{avg}$, and $I_{peak}$ yield valid recognition results of 84.3%, 86.4%, and 90.3% for classifying the state of the appliance into three categories. Moreover, sufficient recognition rates of 97.4%, 97.7%, and 99.0% are obtained by consideration of three candidates.

Key Words: appliance recognition, state of appliance recognition, intelligent outlet, current signal.

1. Introduction

As information technology develops and spreads, not only computers or mobile phones but also home appliances will have communication capabilities. Once the appliance is connected to the home network, it can be remotely controlled by us, such as from the office or a travel destination.

Already, ECHONET and OpenPLANET have been intended for white goods [1],[2]. ECHONET, an acronym of Energy Conservation and HOMecare NETwork, was designed to control home appliances directly and will connect to home electronic devices through a gateway. OpenPLANET [2] was developed by Shikoku Electric Power Co., Inc. Using the network, this system can observe and control electrical appliances in homes, factories and buildings in real time from any location. These systems use Ethernet, IEEE1394 and wireless LAN as communication devices. Therefore, it is necessary to equip these networks with the appropriate communication device in order to control an existing product that does not have the communication capability.

Our aim is to develop a multi-functional outlet called the intelligent outlet, which has the remote control, monitoring and scheduling management functions. The details are described in section 2.2.

This paper is organised as follows. The next section describes the related research and our approach. Section 3 describes the intelligent outlet in detail. The proposed recognition method is described in section 4. The experiment is described in section 5. The conclusion is discussed in section 6.

2. Related Research and Our Approach

2.1 Related Research

For the remote control and monitoring of home appliances, Hart developed the non-intrusive appliance load monitoring system [3]. His system determines the energy consumption of individual appliances that are turning on and off in an electric load based on detailed analysis of the current and voltage of the total load. Yoshimoto et al. also worked on the development of a non-intrusive load monitoring system that did not require installation in the building [4]. They proposed the method for using Neural Networks (Sigmoid Function Networks; SFN) to recognize an appliance by the pattern of its high frequency signals that flow in the gateway of the home power supply. In their system, the device need not be attached to each appliance, and it can be built cheaply. In their experiment, they employed five appliances, the inverter air conditioner, inverter refrigerator, incandescent lamp, fluorescent lamp and television. However, neither the kind nor the number of appliances used in the actual home was discussed. Murata et al. proposed another method for applying a Support Vector Machine (SVM) and Radial Basis Function Networks (RBFN) [5] to obtain high accuracy and improve Yoshimoto’s method. In their experiment, they employed five appliances similar to [4] and ten appliances. Moreover, they published another result [6]. In [6], they employed nineteen appliances that are used in the actual home and applied SFN, SVM and RBFN. Nakamura et al. proposed the method for recognising the current signal pattern, which was measured by a monitor and the Hidden Markov Model (HMM) [7]. Their device need not be installed in the building. In their experiment, eight appliances of six different kinds were used. Ito et al. proposed the recognition method for the appliance, the connecting location and load state based on the measured power consumption of the appliance [8]. They used 33 appliances in their experiment. Inagaki et al. proposed the non-intrusive load monitoring based on integer programming [9]. Their method measures the master current value including multiple appliances and estimates the number of appliances by using the least-squares method. However, in their method, when an appliance with a small current amplitude and an appliance with a large current amplitude operate at the same time, estimation error is common in the appliance with the small current amplitude. In their experiment, 21 modes with nine appliances were used.

In controlling and monitoring appliances, two parameters are important: the measuring device’s installation place relative to the appliance and the physical value it measures.
The device may be installed in roughly three places: (i) inside the appliance, (ii) in the outlet and (iii) near the gateway of the power supply. Type (i) requires the load and cost to set up the device, though it is easy to recognise each appliance. There are various sizes of devices possible in the appliance. If the device is embedded inside the appliance, it does not influence the appliance’s appearance; it is difficult, however, to embed devices inside a small appliance. In addition, devices cannot be embedded in an existing appliance, and an external device alters an appliance’s appearance. With type (ii) and (iii), the appliance by itself is recognised, and the number of devices can be small. Since type (ii) can be embedded inside the wall or power strip, it does not influence the appliance’s appearance. With type (iii), it is possible to construct only one device and difficult to recognise two or more appliances at the same time. The prior research scarcely mentions these problems. Type (ii), meanwhile, has the advantage that the target of recognition is only one appliance, although more devices are needed in comparison to type (iii).

The measured physical value can be divided roughly into three kinds: (I) the electric power signal, (II) the voltage and current signals and (III) the current signal. Phase information can be calculated by measuring both the voltage and current. Measuring only the current (III) can be done at the lowest cost.

2.2 Approach

As mentioned above, our system employs type (ii) and (III); that is, the installation place is in the outlet, and the measured physical value is the current signal. Moreover, the main target of most traditional research is to recognise the appliance, and its states, except on-off, are not reported in detail. Though, two literatures [3],[9] discuss for two or more states of the appliance. In [3], Hart proposed state recognition based on the states transition graph. In [9], Inagaki et al. also proposed state recognition method. However, both literatures employed type (iii) and this is a difference of this research. This paper proposes not only a recognition method for the appliance but also a recognition method for the state of the appliance by using only the current signal.

The overview of the developed system called an intelligent outlet is shown in Fig. 1. In this figure, the thin solid line means the network line, the thick solid line means the voltage line and the thick dotted line means the measured signal line. Use in a home or office network is assumed. Our system is composed of several intelligent outlets connected to appliances and the home server that manages these intelligent outlets. The intelligent outlet is composed of several current sensors to measure the current that flows to the appliance, several relays that control the on-off state and a Peripheral Interface Controller (PIC), which is a kind of micro-controller that controls and communicates with the intelligent outlet. Via the Internet, the user can gain access to the home server from the outside by using a PC or mobile terminal, such as a cellular phone, and can acquire the state of the appliances.

Our system achieves three functions.

- Remote control function on the Web to turn connected appliances on or off.

Using this function, the user can turn off an appliance from the outside if he forgot to turn it off. Moreover, he can turn on the heater before coming home on a cold winter day, making the home warm for his arrival.

- Monitor function to observe the state of connected appliances from the Web.

The user can check on the welfare of someone in the target home, for instance, the living situation of a solitary elderly person, by monitoring the use state of appliances.

- Power supply schedule management function by server.

This function can contribute to saving power effectively by automatically turning off an appliance, such as the displays in a school computer room at night.

In the first of the three above-mentioned functions, remote control, the user determines whether an appliance should be on or off; hence, the intelligent outlet need not determine the on-off status by itself. This function is then easy to implement. Similarly, the third function, schedule management, requires the server to send the control signal to the intelligent outlet, but the user operates the management instruction of the server. Therefore, this function is as easy to implement as the first function. On the other hand, the monitor function should recognise the appliance and the state of the appliance from the current signal measured by the intelligent outlet. There are a few methods to recognize the state of the appliance only by the current signal. Given the second function’s complexity, this paper is especially focused on the second monitor function.

3. Intelligent Outlet

3.1 Prototype System

The developed prototype of the intelligent outlet is shown in Fig. 2. The size of the prototype is 110mm (W) × 140mm (H) ×
46mm (D). Though this system is not embedded, the development of an embedded type is also possible. The basic composition is as follows. Our system used the PIC18F67J60 built into the Ethernet controller made by Microchip Technology, Inc., the current sensor CTL-6-V-Z made by U.R.D. Co. and the relay GR2-1 made by OMRON Corp. The AC power, DC power and connected terminals such as the Ethernet connector are installed on the left side of the case.

3.2 Current Signal

The current sensor does not acquire the current signal directly, and the current that flows to the connected appliance through the sensor is converted into the voltage. Based on this voltage value, the signal is inputted into the input pin of the PIC A/D converter through the full-wave rectifier circuit and non-inverting amplifier circuit of the operational amplifier and converted into a value of zero or greater. Our system uses the 10-bit A/D converter. The maximum voltage that can be measured in the system is 3.3V and the resolution voltage is 3.2mV.

Since this paper emphasises a device whose purpose is to recognize not only the appliance but also the state of that appliance, the device must acquire details of the signal. Therefore, it is preferable to measure one cycle signal rather than multiple cycles. The number of samples that were measured at a time in our program was \( M = 80 \). When the commercial frequency is 60Hz, the sampling frequency to measure the signal for one cycle at a time becomes \( M \times f_s = 4.8k\text{Hz} \). Then, we set the sampling frequency \( f_s = 4.44k\text{Hz} \) to measure the signal. Therefore, our system measured the signal for 18ms at a time.

Figure 3 shows typical signals that were measured to the fan and LCD display three times, respectively. The horizontal axis is the number of samples, and the vertical axis is the voltage. In this research, we tried to recognise the appliance and the state of the appliance using these signals.

### 4. Proposed Method

The flowchart of our method is shown in Fig. 4. The phase shifting is first applied to the input signal. Next, ten features are extracted, and these features are normalised. The recognition method is applied at the end of our method, and the appliance and the state of the appliance are obtained. Details of each process are as follows.

#### 4.1 Phase Shifting

Even if the same appliance and the same state are measured, the phase of the signal is different, as shown in Fig. 3. It is suitable to obtain the coordinate phase for the feature extraction described later. Then we apply the phase shifting process.

Here, the acquired original signal is denoted by \( x(i) \), and the signal after phase shifting and selecting only one cycle signal is denoted by \( y(i) \).

This process is based on the maximum value \( \max(x(i)) \), as shown in Fig. 5(a). The number of samples in a cycle \( N \) is 74 from the sampling frequency \( f_s = 4.44k\text{Hz} \). The signal is shifted \( p \) samples to the left. That is, the following equations are applied.

\[
\begin{align*}
\{ y(j) = x(i) & \quad j_1 = 1, 2, \cdots, N - p, \\
& \quad i_1 = p, p + 1, \cdots, N, \\
\{ y(j) = x(i) & \quad j_2 = N - p + 1, \cdots, N, \\
& \quad i_2 = 1, 2, \cdots, p - 1.
\end{align*}
\]

The diagram of this operation is shown in Fig. 5 (b). As a result, the shifted signal starts from the maximum value, as shown in Fig. 5 (c). Figure 6 shows two shifted signals of Fig. 3.

#### 4.2 Feature Extraction

The appliance is classified into four types: the resistance circuit, motor circuit, rectification circuit and the combination of
these circuits. The current signal of the resistance circuit is similar to the sine wave of the voltage. The power circuit is often delayed behind the voltage, so that this circuit has induction, and this signal is distorted a little. The rectification circuit has a sharp wave and short energising time. Based on \( y(i) \), we extract ten features described as follows.

There are three typical features to explain the current signal: a peak value \( I_{\text{peak}} \), an average value \( I_{\text{avg}} \) and a root mean square value \( I_{\text{rms}} \). These values are calculated with the following equations.

\[
I_{\text{peak}} = \max_{i \in N} y(i) \tag{1}
\]

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

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

Here, \( N \) is the number of samples of one cycle. The relationship between these three features and \( y(i) \) is shown in Fig. 7 (a). Moreover, we extract three features: a crest factor \( CF \), a form factor \( FF \) in which a time concentration of the signal and a peak-to-average ratio \( F_{\text{pfa}} \). These values are calculated with the following equations.

\[
CF = \frac{I_{\text{peak}}}{I_{\text{rms}}} \tag{4}
\]

\[
FF = \frac{I_{\text{rms}}}{I_{\text{avg}}} \tag{5}
\]

\[
F_{\text{pfa}} = CF \cdot FF = \frac{I_{\text{peak}}}{I_{\text{avg}}} \tag{6}
\]

These six features are used in [8].

Moreover, this paper defines four other features: the low-level ratio \( r_L \), the high-level ratio \( r_H \), the rising edge angle \( \theta_{r}[\text{deg}] \) and the falling edge angle \( \theta_{f}[\text{deg}] \). \( r_L \) and \( r_H \) are defined by \( r_L = N_L/N \) and \( r_H = N_H/N \), respectively, where \( N_L \) is the number of samples in which \( y(i) < t_L \) is satisfied, and \( N_H \) is the number of samples in which \( y(i) > t_H \) is satisfied. In this research, we experimentally set \( t_L = 0.1I_{\text{peak}} \) and \( t_H = 0.8I_{\text{peak}} \). \( \theta_{r} \) is the angle between \( U_L \) and \( U_H \), where \( U_L \) is the lowest point when \( y(i) > t_L \) and \( U_H \) is the highest point when \( y(i) < t_L \). Similarly, \( \theta_{f} \) is the angle between \( D_L \) and \( D_H \), where \( D_L \) is the highest point when \( y(i) < t_H \) and \( D_L \) is the lowest point when \( y(i) > t_L \), as shown in Fig. 7 (b).

4.3 Recognition Methods

Here, we apply both \( k \) Nearest Neighbour (\( k\)-NN) and SVM, which is generally used as a pattern recognition method.

4.3.1 Normalization

For each feature, the observed value is normalised using the \( z \)-score normalisation. That is, we compute the mean \( \mu \) and standard deviation \( \sigma \) and obtain the normalised feature \( f_n \), with \( f_n = (f - \mu)/\sigma \), where \( f \) is the original feature.

4.3.2 \( k\)-NN

\( k\)-NN is amongst the simper of all machine learning algorithms. The training samples are vectors in a multi-dimensional feature space. The space is partitioned into regions by locations and labels of the training samples. A point in the space is assigned to the class \( c \) if it is the most frequent class label among the \( k \) nearest training samples. We use a Euclidean distance. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples. In the actual classification phase, the test sample whose class is not known is represented as a vector in the feature space. Distances from the new vector to all stored vectors are computed, and the \( k \) closest samples are selected. The new vector is classified by a majority vote of \( k \) nearest samples. Here, \( k \) is a positive integer. If \( k = 1 \), then the object is simply assigned to the class of its nearest neighbour, called NN.

4.3.3 SVM

Suppose we are given some training samples \((x_i, c_i)\), where \( c_i \) is either 1 or -1, indicating the class to which the point \( x_i \) belongs. Each \( x_i \) is a \( p\)-dimensional vector. We want to give the maximum-margin hyperplane that divides the points having \( c_i = 1 \) from those having \( c_i = -1 \). Any hyperplane can be written as the set of points \( x \) satisfying \( w \cdot x - b = 0 \), where \( w \) is a normal vector perpendicular to the hyperplane. The parameter \( b \) determines the offset of the hyperplane from the origin along the normal vector \( w \).

We want to choose \( w \) and \( b \) to maximise the margin, or dis-
tance between the parallel hyperplanes that are as far apart as possible while still separating the sample. These hyperplanes can be described by the equation $\mathbf{w} \cdot \mathbf{x} - b$.

Note that if the training samples are linearly separable, we can select the two hyperplanes of the margin in a way that there are no points between them and then try to maximise their distance. By using geometry, we find the distance between these two hyperplanes is $\frac{2}{\|\mathbf{w}\|}$, so we want to minimise $\|\mathbf{w}\|$. As we also have to prevent sample points from falling into the margin, we add the following constraint: $\alpha_i (\mathbf{w} \cdot \mathbf{x}_i - b) \geq 1$, for all $1 \leq i \leq n$.

The optimization problem presented in the preceding section is difficult to solve because it depends on $\|\mathbf{w}\|$, the norm of $\mathbf{w}$, which involves a square root. Fortunately it is possible to alter the equation by substituting $\|\mathbf{w}\|$ with $\frac{1}{2} \|\mathbf{w}\|^2$ without changing the solution. Clearly,

$$\text{minimize} \frac{1}{2} \|\mathbf{w}\|^2, \text{subject to} \ (\mathbf{c}_i (\mathbf{w} \cdot \mathbf{x}_i) - b) \geq 1, 1 \leq i \leq n.$$

Writing the classification rule in its unconstrained dual form reveals that the maximum-margin hyperplane, and therefore the classification rule, can be described by the equation sign($\mathbf{w} \cdot \mathbf{x} - b$).

5. Experiment

5.1 Target Appliances

In this experiment, we collected 28 kinds of appliance used in the office and home, such as the personal computer, the television, the refrigerator and fan, as shown in Table 1. We collected three appliances of each kind, for a total number of 84 appliances. This number of appliances is more than that of the related research described in 2.1. After collecting appliances, we investigated the number of measured states in them and found there are from one to four states except the off state. Thus, the total number of all states is 162 for these 84 appliances.

For 162 states, 20 samples of each of the current signals were measured by using the prototype system. That is, we collected 3240 samples. Since this paper focuses the investigation on an efficient method to recognise the appliance and the state of the appliance, we preserved current signals in PCs measured through the Internet. Then, we extracted ten features and applied the recognition method. This process was done off-line by using a PC.

The typical signals are shown in Fig. 8 through Fig. 11. Figure 8 shows three states of the rice cooker: off mode, thermal insulation mode and rice cooking mode. Figure 9 shows three states of the dehumidifier: off mode, air cleaning mode and dehumidification mode. Figure 10 shows four states of the fan: off mode, low mode, middle mode and high mode. Figure 11 shows four states of the radio cassette recorder: off mode, waiting mode, CD play mode and radio mode. As seen in these figures, off mode has a value of almost zero. Hence, it is easy to distinguish the off state from other states of each appliance. Thus, this paper does not consider the off state.

In this experiment, we classified the 162 states into three categories as follows.

- C162: 162 categories, where each state of each appliance is considered to be a separate category.
- C84: 84 categories, one for each distinct appliance, with all states for the same appliance belonging to the same category.
- C28: 28 categories in which each appliance was classified by function. For instance, three types of fans are classified into one category.

<table>
<thead>
<tr>
<th>No.</th>
<th>appliance</th>
<th>number of states</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>desktop PC</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>laptop PC</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>CRT display</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>LCD display</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>laser printer</td>
<td>3</td>
</tr>
<tr>
<td>6</td>
<td>laser printer</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>televisions</td>
<td>3</td>
</tr>
<tr>
<td>8</td>
<td>projector</td>
<td>3</td>
</tr>
<tr>
<td>9</td>
<td>digital video camera</td>
<td>3</td>
</tr>
<tr>
<td>10</td>
<td>video cassette recorder</td>
<td>3</td>
</tr>
<tr>
<td>11</td>
<td>radio cassette recorder</td>
<td>3</td>
</tr>
<tr>
<td>12</td>
<td>refrigerator</td>
<td>3</td>
</tr>
<tr>
<td>13</td>
<td>rice cooker</td>
<td>3</td>
</tr>
<tr>
<td>14</td>
<td>pot</td>
<td>3</td>
</tr>
<tr>
<td>15</td>
<td>coffee maker</td>
<td>3</td>
</tr>
<tr>
<td>16</td>
<td>washing machine</td>
<td>3</td>
</tr>
<tr>
<td>17</td>
<td>vacuum cleaner</td>
<td>3</td>
</tr>
<tr>
<td>18</td>
<td>dehumidifier</td>
<td>3</td>
</tr>
<tr>
<td>19</td>
<td>drier</td>
<td>3</td>
</tr>
<tr>
<td>20</td>
<td>electric shaver</td>
<td>3</td>
</tr>
<tr>
<td>21</td>
<td>heated toilet seat</td>
<td>3</td>
</tr>
<tr>
<td>22</td>
<td>electric carpet</td>
<td>3</td>
</tr>
<tr>
<td>23</td>
<td>fan</td>
<td>3</td>
</tr>
<tr>
<td>24</td>
<td>kotatsu</td>
<td>3</td>
</tr>
<tr>
<td>25</td>
<td>telephone</td>
<td>3</td>
</tr>
<tr>
<td>26</td>
<td>battery charger of cellular phone</td>
<td>3</td>
</tr>
<tr>
<td>27</td>
<td>game console</td>
<td>3</td>
</tr>
<tr>
<td>28</td>
<td>desk lamp</td>
<td>3</td>
</tr>
<tr>
<td>total</td>
<td></td>
<td>84</td>
</tr>
</tbody>
</table>

Table 1 Appliance list.
5.2 Recognition Result

We collected 3240 samples, which are enough data. However, the number of samples in each state is 20, which is not enough. Consequently, we applied the leave-one-out cross-validation method to obtain high recognition accuracy with few data. Namely, we divided the 20 samples into two groups, nineteen samples for training and one for recognition. The resulting average recognition rates of 20 trials are defined as the recognition rate.

Here, we carried out two experiments: (1) analysis of the effective method that obtained a high recognition rate based on each method and (2) analysis of the effective feature.

5.2.1 Analysis of effective method

By using all ten features described in 4.2, three recognition methods of NN (k = 1), k-NN (k = 3) and SVM were applied. The results were recognition rates of 88.1%, 87.3% and 86.4% in C28; 83.7%, 82.6% and 82.3% in C84; and 78.9%, 78.0%
and 78.4% in C162. As seen, NN obtained the highest recognition rate in all categories. Here, we tested various k values from 1 to 20 and set k = 3, where we can obtain the highest recognition rates for k-NN. The radial basis function (RBF) was used as a kernel function of SVM to apply SVM in this experiment.

Next, we applied the principal component analysis (PCA) for ten features and experimented with changing the number of principal components used for recognition. The experimental results were shown on the right side of Tables 2–4. NN with ten features and experimented with changing the number of principal components used for recognition. The highest recognition rate is 90.3%. To analyse the recognition result in detail, we computed the Confusion Matrix (CM), which expresses a tendency for wrong recognition. CM is a visualization tool typically used in analysing recognition result. Each column of the matrix represents the instances in a result class, while each row represents the instances in an actual class. One benefit of CM is that it is easy to see if the system is confusing two classes. CM of C28 is shown in Fig. 12. The numbers of the columns and rows express the appliance number shown in Table 1. The numerical values and contrast of each cell indicate the recognition rate. A white empty cell means the recognition rate is 0%. As shown, 17 categories among 28 obtained more than a 90% recognition rate. Oppositely, the appliance No.18 (dehumidifier) obtained the lowest recognition rate of 60%, and No.13 was misrecognised to be the fan. Since this CM looks like the symmetric matrix, it was found that similar appliances were misrecognised mutually.

These results confirmed that NN is the most effective method to recognise the appliance and the state of the appliance.

5.2.2 Analysis of effective features
The next experiments were to determine which features among ten features are more effective for recognition. First, only one feature was used as the recognition feature, and we carried out ten experiments. The feature yielding the highest recognition rate was identified and then a second feature combined with the first feature to yield the highest recognition rate was determined. This process was carried out for all ten features. As a result, we obtained the features in order of recognition effectiveness as follows: Irms, Iavg, Ipeak, r1, FF, θa, CF, r2, θc and Fpme. The recognition results were shown in the left side of Tables 2–4. The more effective features are Irms, Iavg and Ipeak in this order, and three recognition rates of C28, C84 and C162 were 90.3%, 86.4% and 84.3%, respectively, by NN.

5.2.3 Discussion
Here, we evaluate the recognition accuracy and focus on the result that of the three features Irms, Iavg and Ipeak by NN, the highest recognition rate is 90.3%. To analyse the recognition result in detail, we computed the Confusion Matrix (CM), which expresses a tendency for wrong recognition. CM is a visualization tool typically used in analysing recognition result. Each column of the matrix represents the instances in a result class, while each row represents the instances in an actual class. One benefit of CM is that it is easy to see if the system is confusing two classes. CM of C28 is shown in Fig. 12. The numbers of the columns and rows express the appliance number shown in Table 1. The numerical values and contrast of each cell indicate the recognition rate. A white empty cell means the recognition rate is 0%. As shown, 17 categories among 28 obtained more than a 90% recognition rate. Oppositely, the appliance No.18 (dehumidifier) obtained the lowest recognition rate of 60%, and 13% was misrecognised to be the fan. Since this CM looks like the symmetric matrix, it was found that similar appliances were misrecognised mutually.

Although the highest recognition rates of C28, C84 and C162 were 90.3%, 86.4% and 84.3%, this accuracy is not enough. Nonetheless, our system is considered to display several candidates to the user. Figure 13 shows the recognition result by NN where three candidate curves (first, second and third) of
three categories are shown, respectively. The result is that three recognition rates of three candidate cases of three categories were 99.0%, 97.7% and 97.4%, respectively.

As described in 5.1, there are some appliances for which the outputs are changed continuously, such as the dimmer. In these appliances, not the difference of wave shape, but rather the scale, changes into the difference of the output. Here, three features $I_{peak}$, $I_{avg}$, and $I_{rms}$, which were concluded as the effective features in this paper, change by the difference of the scale. Though it is possible to recognize the target appliance if the range of the output divides and each output is measured as the training sample, it is not realistic. Thus, the recognition method for continuously variable appliances remains an important topic for future work.

6. Conclusion

This paper developed an intelligent outlet that has the monitor function to observe from the Web the state of connected appliances and the remote control function on the Web to control the on-off state of connected appliances. This paper focused on recognizing the appliance and the state of the appliance based on the current signal, while a related method had been targeted only for recognizing the appliance. We proposed the phase shifting process and ten effective features. We gathered a number of signals with various appliances and found that three features, $I_{rms}$, $I_{avg}$, and $I_{peak}$, yield valid recognition results of 90.3%, 86.4% and 84.3% for classifying the state of an appliance into three categories. Moreover, adequate recognition rates of 99.0%, 97.7% and 97.4% were obtained by consideration of three candidates.

In our experiment, we did not implement the whole process of how the intelligent outlet and home server should be used. Therefore, a future work will be to implement the proposed method into the intelligent outlet and to work toward the practical use of the whole system.

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References


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