Appliance Recognition and Unattended Appliance Detection for Energy Conservation

Gu-Yuan Lin
National Taiwan University

Wan-Rong Jih
National Taiwan University

Jane Yung-jen Hsu
National Taiwan University

Appliance Recognition and Unattended Appliance Detection for Energy Conservation

Shih-chiang Lee and **Gu-yuan Lin** and **Wan-rong Jih** and **Jane Yung-jen Hsu**
Department of Computer Science and Information Engineering
National Taiwan University
Taipei, Taiwan
{r97026, r97131, wrjih, yjhsu}@csie.ntu.edu.tw

Abstract

Providing energy conservation services becomes a hot research topic because more and more people attach importance to environmental protection. This research proposes a framework that consists of four process models: appliance recognition, activity-appliances model, unattended appliances detection, and energy conservation service. Appliance recognition model can recognizes the operating states of appliances from raw sensing data of electric power. An activity-appliances model has been built to associate activities with appliances according to the data of Open Mind Common Sense Project[1]. Using the relationship between activities can help to detect *unattended appliances*, which are consuming electric power but not take part in the resident's activities. After obtain information of appliance operating states and unattended appliances, residents can receive energy conservation services for notifying the energy consumption information. Finally, the experimental results show that dynamic Baysian network approach can achieve higher than 92% accuracy for appliance recognition. Data of activity-appliances model shows most appliances are strong activity-related.

Introduction

Energy-conservation has been a popular issue in recent years. Researches (Pérez-Lombard, Ortiz, and Pout 2008) which analyzed the world energy indicators between 1973 and 2004, state that the primary energy consumption is growing at a higher rate than population, leading to the increase of its per capita value on 15.7%. The efficiency in exploiting energy resources, shown as the relation between final and primary energy, has declined by 7%, especially due to soaring electrical consumption. Meanwhile, the electrical energy consumption is 17.1% in total final energy consumption according to the key world energy statistics 2009[2] of International Energy Agency.

Studies show that there are approximately 5-15% savings if people can acquire the energy information directly (Darby 2006). Traditional electricity meters can provide power consumption information for users, such as voltage, current, impedance, power factors, watt, apparent power, etc. However, these raw sensing data do not bring any clue for users to understand their electricity usage, and therefore cannot help them to improve their knowledge of energy efficiency. Detailed energy information for users could be how much money has been spent while using appliances, what appliances are in used, and so on. Accordingly, residents can have clear picture of every appliances and easily understand the situation of power consumption.

Before we can calculate the cost of using a specified appliance, acquire the detailed power usage for every appliance state will be necessary. To predict whether appliances is in used or not, the relationship between appliance and resident's activity should be modeled. There are many appliances in a house. Consequently, it is not easy to figure out the operating state of every appliance at the same time. This is the first challenge for delivering these detailed energy consumption information to residents. Second, residents perform daily activities are variously and dynamically. It is hard to model the relationship between appliance and activity. Furthermore, the combination of activities and appliances is an exploded number, therefore, correctly detect waste appliances is the third challenge.

This paper proposes a framework to provide energy-saving services. The system collecting electric power information from electrical panels and recognizes the operating states of appliances in real time. User behavior is taking into account to improve the accuracy of appliance state. In addition, this framework builds an activity-appliances model, which associates activities with appliances by a common-sense data collection. According to the activity-appliances model, we can find appliances that do not be used in the current resident's activities, and these appliances are wasting electric power. We named such appliances are *unattended appliances*. Services provide to the user include display unattended appliances to remind the user to turn the appliance off and show how much cost when using an appliance. Such energy conservation service can assist users to manage energy wisely and finally lower overall energy cost.

Related Work

There are two domains of researches which are related to our work, including appliance states recognition, energy conservation issues, and application.

[1] http://openmind.media.mit.edu/

[2] https://www.iea.org/publications/free_new_Desc.asp?PUBS_ID=1199

Appliance Recognition

The researches on appliance recognition problem could be classified into two categories among the difference of sensor devices. One is using smart outlets to measure the electric information of individual appliance. The other is utilizing the power line interface to capture the electric noise and detecting the state change of appliances.

Using Smart Outlets An intuitive method for recognizing appliances is to distinguish the difference between a variety of appliances by using individual electric information. Ito et al. and Saitoh et al. proposed several feature parameters to characterize the power waveform, such as average, peak, crest factor, form factor, etc. They applied nearest neighbors to recognize what appliance was plugged in. Serra et al. divided the power values of all appliances into several power levels, and then identified appliances according to the number of times that the appliance's power reach to each power level. Kato et al. used Linear Discriminant Analysis (LDA) to extract features from power waveform and applied Support Vector Machine (SVM) to classify appliances. Kim et al. used multiple heterogeneous sensors, such as magnetic, light, and audio sensors, to detect operating state and estimate electricity consumption.

However, the sensor deployment of such methods may cause some problems in a real home environment. If they want to identify all appliances in a house, they have to install numerous intelligent outlets or sensors around the environment. This deployment will increase the cost of system and the difficulty of maintenance. Therefore, there are some obstacles to popularize such systems in actual residences.

Using Power Line Interface The other approach for detecting appliances is employing power line interface to acquire the noise of electric events(Patel et al. 2007). They performed Fast Fourier Transformation on the incoming signal to separate the component frequencies and adopt SVM to classify which appliance was being turned on. The purpose of the research was similar to our study. However, the power line interface cannot measure the electricity consumption, which is the most important information for energy management. As a result, this research inspire us to detect the states change of appliances and acquire the energy information simultaneously.

Energy Conservation Issues and Applications

There are several researches on providing services for energy conservation. Here we review two catogries related to our work.

Providing Energy Information and Saving Tips Some work aim to show energy information and tips to users, and facilitate they to do energy-saving behavior. Google PowerMeter is an energy monitoring tool (Google). It intends to help people for saving energy and money by providing energy information via smart meters and energy monitoring devices. Furthermore, they visualize the information, and let user easily review and compare their energy usage with past. In addition to Google PowerMeter, Microsoft also develope a web service called Microsoft Hohm (Microsoft). Users provide their home profile, such as year built, square footage, etc. Then, the service can roughly predict the energy distribution of the house and suggest suitable energy saving tips to user. However, these two services only provide the energy information in a globle view. In our work, we aim to provide the energy information of individual appliance, such as operating states, accumulative electricity comsumption, and accumulative cost. We think that these work can complement each other to promote the service better.

Performing Automatic Control Some other reserache intend to automatically change the operating states of appliances according to the environmental context. These work detect the location of devices and users, and then prevent devices "idling" to save electricity. Context-Aware Power Management (CAPM) (Harris and Cahill 2005; 2007) detect user's location by bluetooth, microphones, etc., and then identify whether user is within range of a device to separate the status of the device into using, about to use, or idling. That is, when user is far away from the device, the system can turn off or suspend the device to save energy. In addition, Location-Aware Power Management (Harle and Hopper 2008) is similar to CAPM. However, it uses high accuracy location information and separates devices into three categories by their resume times from a reduced-power state. The work can provide suitable approaches for different types of devices. Both of the two projects proposed a solution to prevent device idling. The idea motivates us to develope a method to find the appliances which may be wasting energy. We will describe on the Section - Unattended Appliances Detection in detail.

From the above, these studies give us a nice demonstration to develope our system.

An Energy Conservation Framework

In this section, we will describe the detailed process flow of our energy conservation framework. Figure 1 shows the framework with four blocks of process. First of all, appli-

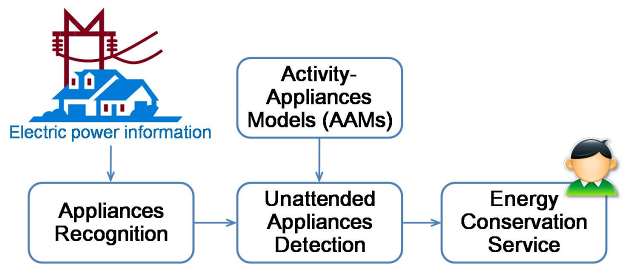

Figure 1: System framework

ances recognition could identify what appliances is in use. It monitors electric information from distribution boards, and then outputs the operating states of appliances in real time. Second, activity-appliances models construct the "used for" relationships between activities and appliances. It makes connections with weight when an activity used for an appliance. After that, we can combine the results of appliance recognition with the activity-appliances models to find unattended appliances. Such appliances may waste electrical energy because of not participating in the user's current activity but still working there. Finally, we can provide a various of energy conversation services, such as displaying how much energy be wasted, when detecting these unattended appliances. Therefore, users can acquire more meaningful information about the energy distribution in home from our system.

Appliance Recognition

To accomplish our system, we have to obtain the operating state of each appliance in the environment first. We take the electrical consumption from the distribution board to identify the states of appliances. In this section, we will describe the assumptions, input, and output of this problem and the approach we used.

There are two assumptions we make for the problem. First, the appliances in an environment have been informed. Second, the states of these appliances are pre-defined. In other words, we do not detect the appliance state which is not contained in trianing data.

The input data is the feature values which are extracted from the collected electric data. We compute feature values in following steps. First, we measure the electrical consumption (Wh) every 5 seconds from the circuit, then employ sliding window to process the data. The window size we select is 7 samples (a period of 35 seconds), and the window shifts 1 sample (5 seconds) per time slice. Therefore, the content of the window at time t is as the following

$$O'_t = \{Wh_t, Wh_{t-1}, \ldots, Wh_{t-6}\}$$

It keeps the recent 7 records of electrical consumption, where Wh_t means the total electrical consumption within 5 seconds from time $t-1$ to t. The feature values of each sliding window and corresponding notations are listed as following.

1. Raw records($Wh_t, Wh_{t-1}, \ldots, Wh_{t-(W-1)}$)
2. Average($Wh_{avg,t}$)
3. Peak value($Wh_{peak,t}$)
4. Root Mean Square($Wh_{rms,t}$)
5. Standard deviation($Wh_{sd,t}$)
6. Crest Factor(CF_t): $Wh_{peak,t}/Wh_{rms,t}$
7. Form Factor(FF_t): $Wh_{rms,t}/Wh_{avg,t}$
8. Peak to average ratio($F_{pta,t}$): $Wh_{peak,t}/Wh_{avg,t}$
9. Delay ratio of the peak value($F_{p,t}$): $\frac{1}{W} \times T_{Wh_{peak,t}}$

where W is the number of records in a sliding window and $T_{Wh_{peak,t}}$ is the index of peak value within the window.

Such data can be used for constructing the probabilistic models based on statistics. During the learning process, we use the collected data to build the model so that the parameters of the appliance recognition model will be determined. In addition, the output of the process is the operating states of appliances at time t. We use a string with length N to represent the states of all N appliances at every time slice, and each digit of the string is corresponding to certain appliance. For instance, if appliance No.1, 4, 9 are in use, the others are off, and there are 9 appliances. We present it as a nine digits string, 100100001. (If the appliance is in use, we encode the state as 1, otherwise, encode as 0.)

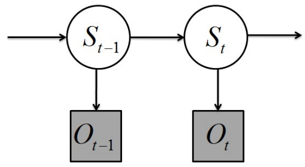

Figure 2: A dynamic Bayesian network describing tracking for the state S_t

After intruducing the assumptions, input data and output format of the appliance recognition problem, the following will depict the approach we used for solving this problem, including model design, inference method, and parameter estimation.

Model Design We think that there exists some patterns for using appliances in real environment. For example, when we use a computer, we may turn up the computer first, then turn on the monitor. The order of using appliances are relevant to user behaviors and the position of appliances in the house. If the user has a regular lifestyle, the pattern is likely to be regular. Based on above assumption, we take the temporal character into consideration. Therefore, we consider Dynamic Bayesian Network (DBN) for solving our problem. Fig. 2 shows the structure of our DBN model.

Inference We adopt the Bayes filter to infer the appliance states in real time. The Bayes filter efficiently compute the posterior distribution, $p(S_t|O_{1:t})$, over the current state given all observations to date, where $O_{1:t}$ is the set of observations up to time t. Here we want to estimate this conditional probability and assign the state with the maximal probability as the prediction at time t. By the Bayes' rule and the Markov property, the conditional probability can be written as

$$p(S_t|O_{1:t}) = \frac{p(O_t|S_t)p(S_t|O_{1:t-1})}{p(O_t|O_{1:t-1})} \tag{1a}$$

$$= \frac{p(O_t|S_t)\sum_{S_{t-1}} p(S_t|S_{t-1})p(S_{t-1}|O_{1:t-1})}{p(O_t|O_{1:t-1})} \tag{1b}$$

where $p(O_t|O_{1:t-1}) = \sum_{S_t} p(O_t|S_t)p(S_t|O_{1:t-1})$ is the normalized term of (1a). According to (1b), we could estimate the state transition probability $p(S_t|S_{t-1})$, and the observation probability $p(O_t|S_t)$. Hence, we regard the state with maximal posterior probability as the status at time t.

Parameters Estimation According (1b), the model parameters are the probability distributions $P(S^j|S^i)$ and $P(O|S^i)$ for all S^i, where S^i and S^j are the state combinations of all appliances. $P(S^j|S^i)$ is the transition probability from state S^i to S^j, which is called transition model. For the observation model, $P(O|S^i)$, because all feature values are real number, we apply two methods to handle the feature values, which are discretization and mixture of Gaussian distributions.

First, we discretize numeric attributes into nominal numbers using the discretization proposed by Fayyad and Irani's MDL method(Fayyad and Irani 1993). The method uses entropy minimization heuristic to discretize continuous-valued attributes into multiple intervals. After discretizing, we compute $P(O|S^i)$ by $P(O_d|S^i)$, where O_d is a discrete value calculates from O.

$$p(O_d|S^i) = \frac{\text{number of instances observe } O_d \text{ in } S^i}{\text{number of instances in } S^i} \quad (2)$$

Second, the mixture of Gaussian distributions is adopted to estimate $P(O|S^i)$(Gauvain and Lee 1994). For each state, we use 5 Gaussian distributions to approximate $p(O|S^i)$. That is,

$$p(O|S^i) = \sum_{k=1}^{5} c_{ik} N(O; \mu_{ik}, \Sigma_{ik}) \quad (3)$$

where c_{ik}, Σ_{ik} and μ_{ik} are the weight, covariance matrix and mean vector of the k-th Gaussian component respectively, and $\sum_{k=1}^{5} c_{ik} = 1$. Therefore, all we have to adjust are the weights c_{ik}, mean vectors μ_{ik}, and covariance matrix Σ_{ik} for all i, k. For calculating these parameters, we use k-means, where $k = 5$ to generate 5 clusters for each S^i. Then, we can compute μ_{ik} and Σ_{ik} from a corresponding cluster. Finally, we assign the ratio of instances in k-th cluster to all instances in S^i as weight c_{ik}.

Activity-Appliances Model

The activity-appliances model (AAM) quantifies the intensity of relations between activities and appliances. In other words, AAM associates an activity A with a set of appliances D in different weights w. We formulate this model as the following representation,

$$AAM(A_i) \rightarrow \{(D_j, w_{i,j}) | 1 \leq i \leq N_A, 1 \leq j \leq N_D\}$$

where A_i and D_j represent activity i and appliance j respectively, $w_{i,j}$ is the weight between A_i and D_j, N_A is the number of activities, and N_D is the number of appliances. For example, when using a computer, we turn on the power, monitor, and sometimes use an electric fan when we feels hot. In such a situation, "using a computer" can be connected with "computer", "monitor", and "electric fan". However, these appliances may also be used in other activities. Accordingly, we use weights to quantify the connections between appliances and activities. If appliance j has a big chance to participate in activity i, the $w_{i,j}$ will be a large number. We follow the below three steps to build the activity-appliances models.

First of all, we narrow down the scope of human activites we have interest in. For providing energy conservation services, we only focus on the activities which must involve at least one appliance. Table 1 shows some of these activities.

Table 1: Examples of human activity we have interest in

	Activity
A1	using computer
A2	preparing meal
A3	studying
A4	watching TV
A5	sleeping
A6	bathing
A7	going to the toilet

Subsequently, we have to collect data to build AAMs. Instead of directly collecting actual user behavior, we gather the knowledge of people from commonsense. Hence, commonsense is introduced here. Commonsense tends to relate events to human experiment. The collected method could reduce the difficulty of data collection. Furthermore, it helps to construct general activity-appliances models. To do this, we design some questions to collect the relationships between activities and appliances. In particular, the question is in the form of sentences. Users just need to fill the blank of the questions. Table 2 lists examples of these questions. In a case, we can give "computer", "monitor", etc. as answers in Q1 in Table 2. After collecting data, we acquire numerous activity-appliance pairs. We calculate the number of each activity-appliance pair in database, which is called the match count $M_{i,j}$. A large $M_{i,j}$ indicates that appliance j is highly related to activity i.

Table 2: Examples of the questions

Question
Q1. When using computer, you may use what appliances
Q2. When preparing meal, you may use what appliances

Finally, the match count can be used to compute the weight $w_{i,j}$ in activity-appliances model. We adopt Term Frequency-Invert Document Frequency (TF-IDF), which is commonly used in information retrieval, to calculate $w_{i,j}$. We take an activity as a document and appliances can be viewed as terms in each document. Therefore, the weight can be computed as

$$\begin{aligned} w_{i,j} &= af_{i,j} \times iaf_j \\ af_{i,j} &= \frac{M_{i,j}}{\sum_k M_{k,j}} \\ iaf_j &= \log \frac{N_A}{|\{A : D_j \textit{ participates in } A\}|} \end{aligned}$$

where $af_{i,j}$ is the *appliance frequency* which indicates the importance of D_j in A_i, and iaf_j is the *inverse activity frequency* which is a measure of the general importance of D_j. Therefore, following above steps, we can construct the AAMs from a set of activity-appliance pairs.

Unattended Appliances Detection

In this process, we intent to find some electric equipments which may waste electrical energy. We first define the status of appliances in an activity's view, see Table 3. We define the appliances which operating state is on and does not participate in the user's current activity as the *unattended appli-*

Table 3: Status of appliances

Appliance	Operating state	
Participate in the current activity	ON	OFF
YES	attended	–
NO	unattended	not in use

ances. These appliances may waste energy because of operating without purpose. For instance, when a user is preparing meals and the table lamp at his study has been turned on. We think that the table lamp is wasting electrical energy, because it is not participating in the user's current activity but still working there. Hence, picking these appliances out should be useful to save electrical energy. The process is formulated as the following function.

$$F(AAMs, S_t) \rightarrow \{\text{unattended appliances}\}$$

That is, given activity-appliances models $AAMs$ and the operating states of appliances S_t at time t, we can get the unattended appliances from this function.

There are two steps in this process. First of all, before detecting unattended appliances, the system should recognize the current activity first. We use the AAMs learned before to be an activities set. The operating states of appliances are query appliances. Hence, the current activity could be determined by searching the activities set.

$$\arg\max_{A_i} Similarity(AAM(A_i), S_t)$$

In other words, we calculate the similarity between AAM and the operating states of applinaces S_t at time t, and then selecting the most similar one as the current activity.

Next, we can pick unattended appliances out. After knowing the current activity, we only need to select appliances which has weak relationship to the current activity.

Energy Conservation Service

After detecting unattended appliances, the system can provide energy conservation services. Unlike other monitors display annoying energy statistic to user. We can provide information intelligently. The following shows two services we could provide.

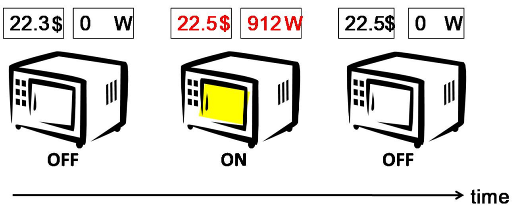

Figure 3: Display energy information on appliances level

First of all, the system not only provides the total electrical consumption, but also offers detailed information at appliance level. Figure 3 illustrates a scenario when we operate an appliance. When using microwave, the system could display the electric information and cost right away, since the

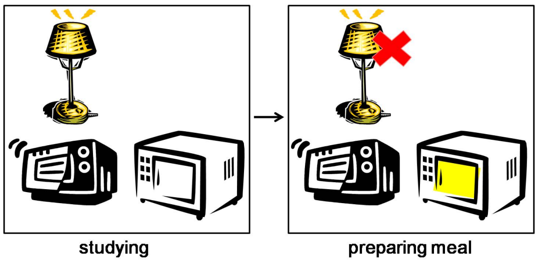

Figure 4: Display unattended appliances

appliance recognition process can infer the operating states of appliances in real time.

Second, the system could tell user where you waste electrical energy. Figure 4 demonstrates a situation about unattended appliances detection. To begin with, a user turns on a lamp and studies at the study. Then, he walks to the kitchen and start to prepare meals but forgets to turn off the lamp. At this time, the lamp would be detected as an unattended appliance, and then our system will trigger an alert to remind the user.

Experiments

In the section, we first describe the hardware deployment, and then introduce two experiments about appliance recognition and activity-appliances model analysis respectively.

Sensor Deployment

Before performing experiments, we deploy smart meters, which are called PA-310, to monitor the total electrical consumption in a living laboratory. Figure 5 presents the appearance of the PA-310 power meter. Such devices are installed on the distribution board. In other words, there is no need to install them everywhere. We measure the total electrical consumption from the distribution boards every 5 seconds in our experiments. Figure 6 shows the actual installation of our system. There are 3 PA-310 power meters, 4 distribution boards, and a server at the electrical room. First, we install current transformers on circuits which supply electricity for the experiment environment. Besides, each meter contains 3 current transformers. Every PA-310 power meter could monitor up to 3 circuits simultaneously. Then, we can extract electrical consumption to the server via serial port.

Figure 5: Smart meter (PA-310)

Experiment of Appliance Recognition

To evaluate our system, We design a script let user to manipulate appliances, see Table 4, in an experiment room. The

Figure 6: PA-310, electric panel and server

Table 4: Appliances are used in binary states experiment

Appliances	Power (W)
computer A	104
computer B	57
monitor A	58
monitor B	34
table lamp A	21
table lamp B	24
electric fan	30
electric pot	600
oven	600

scripts contain 26 events of states change and 17 combinations of operating states. When collecting training data, we change state of an appliance per 5 minutes regularly and spend 2 hours and 15 minutes. Also, when collecting testing data, we simulate the real situation, the duration of each state do not restrict to 5 minutes, but depend on the use of each appliance. For example, we set up 30 minutes to heat food by oven and switch off monitor immediately after shutdown a computer. The phase takes 4 hours.

After that, we compare the performance of inference approach Bayes filter with three nontemporal models, KNN, Naive Bayes, and SVM. In addition, we also compare to Viterbi algorithm to verify the difference between online and offline inference approach. There are four criteria use to evaluate the process. First, the overall accuracy (OA) shows the accuracy of the entire state combinations. It is defined as

$$OA = \frac{1}{T}\sum_{t=1}^{T} \delta(g_t = p_t) \tag{4}$$

where g_t and p_t are the states combination of ground truth and the prediction result at time t, respectively. Next, because we actually care about the states of individual appliance, we compute the average appliance accuracy (AAA), which represents the mean accuracy of each appliance. In addition, average appliance recall (AAR) can exhibit the correctness of each appliance that is in use. In other words, it shows the accuracy of rarely operating appliances, such as microwave or oven. They are defined as following,

$$AAA = \frac{1}{N}\sum_{n=1}^{N} \text{accuracy of appliance } n \tag{5}$$

$$AAR = \frac{1}{N}\sum_{n=1}^{N} \text{recall of appliance } n \tag{6}$$

where N is the number of appliances. Finally, word error rate (WER) displays the error rate of state transition sequences between ground truth and prediction results. It can be computed as,

$$WER = \frac{\sum_{n=1}^{N} MED(G_s^n, P_s^n)}{\sum_{n=1}^{N} \text{length of } G_s^n} \tag{7}$$

G_s^n and P_s^n are the "segment sequences" of ground truth and prediction, respectively. The definition of the segment sequence is that we treat sequential and identical states as one segment, for example, if the ground truth of the monitor is 001111100, G_s^n will be 010. Similarly, if the prediction result is 001010100, P_s^n will be 0101010. The $MED(G_s^n, P_s^n)$ in (7) is the minimum edit distance between G_s^n and P_s^n.

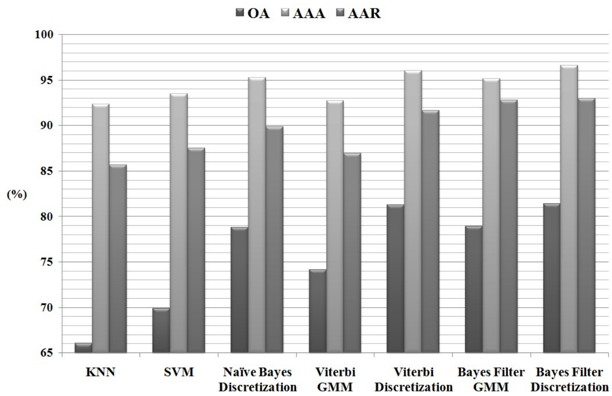

Figure 7: OA, AAA, and AAR of Binary States Classification

Figure 7 and Figure 8 show the results of several classifiers. It reveals that Bayes filter is more accurate than nontemporal models, especially on WER. In addition, the results show that constructing the observation model with discretized features contributes the best performance. The results of each appliance recognized by Bayes filter and discretization methods are displayed in Table 5. It reveals that we can recognize most appliances accurately. In brief, using discretization to build the observation model and employing Bayes filter to infer the current state is a better approach for recognizing the binary states of appliances.

Analysis of Acitivty-Appliances Model

We select seven actvities, see Table 1, to build their models. In the following, we introduce a platform where to collect data, and then show the analyzed results.

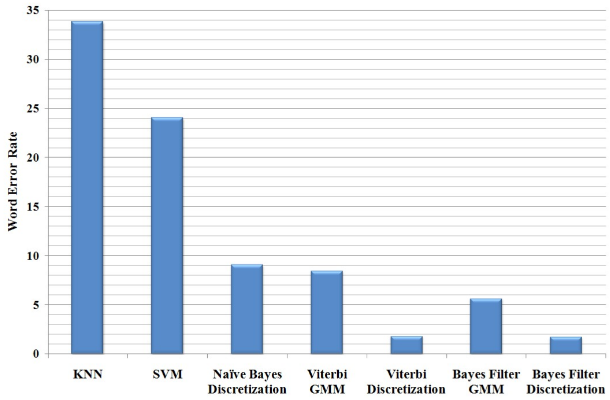

Figure 8: WER of Binary States Classification

Table 5: Results of each appliances using Filtering + Discretization

Appliance	Accuracy(%)	Precision(%)	Recall(%)
electric fan	92.47	97.87	92.52
Oven	98.12	98.40	78.72
electric pot	98.12	83.01	100
table lamp A	93.71	93.08	76.17
table lamp B	97.55	97.07	99.02
monitor A	99.43	99.53	99.64
monitor B	93.68	93.60	98.06
computer A	99.93	99.96	99.96
computer B	100	100	100

By mentioning above, we intend to collect people's knowledge, commonsense, to build the model. Hence, the Virtual Pet Game in PTT, a famous bulletin board system in Taiwan, is a good choise (Kuo et al. 2009). In that game, each player feeds a virtual pet. They can teach or ask questions to the pet for gaining knowledge points. That is, when a player ask a question, that question would be answered by another player. By the property, we put questions listed in Table 2 into the game. A week later, we have collected over 4,000 data.

After collecting data, we organize and analyze the collected data. Figure 9 shows a part of activity-appliances models. The center gray bubble in the figure is an activity. Other white bubbles connected to the center one are appliances used in that activity. Furthermorer, the size of the bubbles indicates the intensity between the activity and appliances. A larger bubble with a larger weight; otherwise, the bubble is small. In the figure, we can see that "monitor" bubble and "computer" bubble are larger, and "electric fan" bubble is smaller. It reflects that when using computer, we always use monitor and computer and sometimes use electric fan. The finding matches the behavior we do. Therefore, we think that the model could reflect the relation between activities and appliances.

Then, we look into the model by appliance count and activity count. The two terms are similar to term frequency

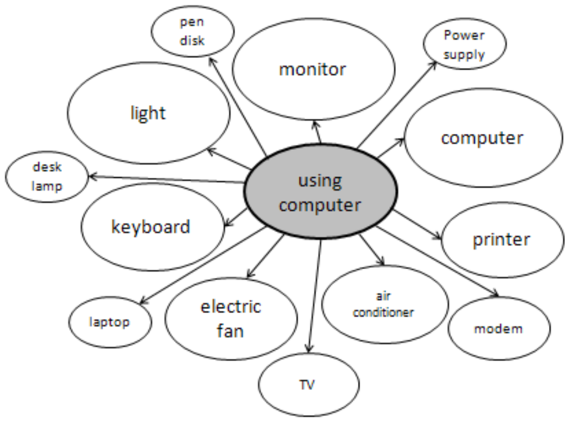

Figure 9: Part of activity-appliances model - using computer

and document frequency in the area of information retrival. In particular, appliance count is the times of appliances appears in an activity within the data we collected. Activity count is the number of activities containing the same appliance. Figure 10 demonstrates the number of appliances -

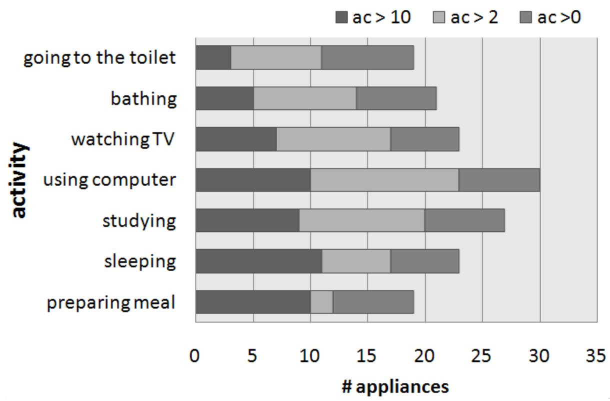

Figure 10: The number of appliances - appliance count (ac) stacked bar chart

appliance count stacked bar chart. It shows the usage frequency of appliances used in an activity. Each activity average involves twenty-three appliances. This is an interesting finding. Even a simple activity still relates to many appliances. However, there are half of appliances with a lower appliance count. We can classify the usage frequency of appliances by adjusting the value of appliance count. When appliance count greater than 10, 66% appliances can be filtered out.

Table 6 shows the activity count of appliances. It computes each appliance participates in how many activities within the seven activities, and then counts them by activity count. We find out that only a few of appliances appear in multi-activities. In the table, there are one appliance, light, be used in all seven activities, and 103 appliances participate in only one of the seven activities. The observation is make sense that most appliances are activity-related. Therefore, we can easily identify the current activity by knowing what appliances are in used. It is also a good information when detecting unattended appliances since we know what appliances should appear to the current activity.

Table 6: The number of appliances classified by activity count

activity count	7	6	5	4	3	2	1	total
# appliances	1	0	2	3	4	19	103	132

In conclusion, we think that activity-appliances models could actually express the relationships between activities and appliances. Furthermore, it could help to detect unattended appliances in the next stage of the system.

Conclusion

This research proposes a solution for developing a framework to provide energy conservation services. We conclude four characteristics of our work. First, we only install a small number of power meters in distribution boards instead of using individual power meter for every appliance. Therefore, it is easy to install and maintain our system. Second, our approach can inference the operating states of appliances, so that the system can immediately provide states information to residents. Third, we collect commonsense from the web to build activity-appliances model. Users on the web share their experiences on activities and contribute the information about appliances involve in an activity. Such approach utilizes features of web 2.0 and could reduce the complexity of collecting data from actual behaviors. Finally, the system provides energy-saving services. People can know the energy distribution at home on appliance level and how much electrical energy has been wasted. In the future, we will complete the experiment of unattended appliances detection, and provide more energy conservation services. In short, we think that such a system could provide useful information to help people save electrical energy.

Acknowledgment

This research is partially conducted under the Environment and Behavior Perception for Intelligent Living, a joint project by the Institute for Information Industry, NTHU, NCTU, and Academia Sinica, funded by the Ministry of Economy Affairs of Taiwan. This work was also partially supported by grants from the National Science Council, Taiwan (NSC 96-2628-E-002-173-MY3 and NSC 099-2811-E-002-020).

References

Darby, S. 2006. The effectiveness of feedback on energy consumption. *A Review for DEFRA of the Literature on Metering, Billing and direct Displays*.

Fayyad, U. M., and Irani, K. B. 1993. Multi-interval discretization of continuousvalued attributes for classification learning. In *Thirteenth International Joint Conference on Articial Intelligence*, volume 2, 1022–1027. Morgan Kaufmann Publishers.

Gauvain, J., and Lee, C. 1994. Maximum a posteriori estimation for multivariate Gaussian mixtureobservations of Markov chains. *IEEE transactions on speech and audio processing* 2(2):291–298.

Google. Google powermeter.

Harle, R., and Hopper, A. 2008. The potential for location-aware power management. In *Proceedings of the 10th international conference on Ubiquitous computing*, 302–311. ACM.

Harris, C., and Cahill, V. 2005. Exploiting user behaviour for context-aware power management. In *Proceedings of the Interntaional Conference On Wireless and Mobile Computing, Networking, and Communications*, 122–130.

Harris, C., and Cahill, V. 2007. An empirical study of the potential for context-aware power management. In *UbiComp 2007: Ubiquitous Computing*, 235–252. Springer.

Ito, M.; Uda, R.; Ichimura, S.; Tago, K.; Hoshi, T.; and Matsushita, Y. 2004. A method of appliance detection based on features of power waveform. In *Applications and the Internet, 2004. Proceedings. 2004 International Symposium on*, 291–294.

Kato, T.; Cho, H.; Lee, D.; Toyomura, T.; and Yamazaki, T. 2009. Appliance Recognition from Electric Current Signals for Information-Energy Integrated Network in Home Environments. *Ambient Assistive Health and Wellness Management in the Heart of the City* 5597:150–157.

Kim, Y.; Schmid, T.; Charbiwala, Z.; and Srivastava, M. 2009. ViridiScope: design and implementation of a fine grained power monitoring system for homes. In *Proceedings of the 11th international conference on Ubiquitous computing*, 245–254. ACM.

Kuo, Y.-l.; Chiang, K.-y.; Chan, C.-w.; Lee, J.-C.; Wang, R.; Shen, E.; and Hsu, J. Y.-j. 2009. Community-based game design: Experiments on social games for commonsense data collection. In *KDD-09 Workshop on Human Computation (HCOMP2009)*.

Microsoft. Microsoft hohm.

Patel, S.; Robertson, T.; Kientz, J.; Reynolds, M.; and Abowd, G. 2007. At the flick of a switch: Detecting and classifying unique electrical events on the residential power line (nominated for the best paper award). In *9th International Conference, UbiComp 2007, Innsbruck, Austria, September 16-19, 2007. Proceedings*, volume 4717 of *Lecture Notes in Computer Science*, 271–288. Springer Berlin / Heidelberg.

Pérez-Lombard, L.; Ortiz, J.; and Pout, C. 2008. A review on buildings energy consumption information. *Energy and Buildings* 40(3):394 – 398.

Saitoh, T.; Aota, Y.; Osaki, T.; Konishi, R.; and Sugahara, K. 2008. Current Sensor based Non-intrusive Appliance Recognition for Intelligent Outlet. In *ITC-CSCC 2008*.

Serra, H.; Correia, J.; Gano, A.; de Campos, A.; and Teixeira, I. 2005. Domestic power consumption measurement and automatic home appliance detection. In *Intelligent Signal Processing, 2007 IEEE International Workshop on*, 128–132.