Applying Power Meters for Appliance Recognition on the Electric Panel

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***Abstract*—Recognition of appliances states is an import building block for making energy-efficiency schemes and providing energy-saving advice and performing automatic control. Several existing approachs use smart outlets or detectors to acquire the information of individual appliance and recognize the operating state. However, such approachs have to install numerous devices if they want to monitor the states of all appliances. This will increase the cost and complexity of installation and maintenance. Therefore, we develop an appliance recognition system which minimizing the scope of deployment. We install smart meters at single-point, distribution board, to measure the power consumption at circuit-level. In addition, to improve the recognition accuracy of our system and detect the state changes in real time, We use dynamic baysian network to take user behavior into account and Bayes filter to perform online inference. Finally, we design several experiments to compare our approach with some commonly used classifiers, such as Naive Bayes, k-Nearest Neighbor (kNN) and Support Vector Machine (SVM). Results shows that our model outperforms these classifiers and the accuracies of all appliances are greater than 92%. Furthermore, we also compare the results of Bayes filter with Viterbi algorithm, which is an offline inference method. The difference in accuracy of every appliance between Bayes filter and Viterbi algorithm is less than 1%.**

***Index Terms*—Appliance Recognition, Bayes Filter, Smart Meter, Electric System, Mixture of Gaussian, Discretization.**

I. INTRODUCTION

Energy-conservation has been a popular issue in recent years. Studies show that there are approaximately 5-15% savings if people can acquire the energy information directly[1]. However, most people lack for such information so that they are unable to manage power consumption efficiently. There are several ways to help users for saving power consumption. One is that showing the detailed energy information for users, such as the operating states of appliances and the accumulative power consumption of each circuit, they will be more clear about the energy usage. Another is that providing energy-saving tips or advice for users according to the current context[2]. The other is that employing automatic control system to control the states of appliances appropriately. Therefore, what we mentioned above motivates us to design a mechanism providing more detailed energy information for users and services providers. In order to reach this goal, it needs intelligent application to provide such abundant information.

Based on this idea, we propose a solution on how to recognize the states of appliances. We aim to devise a system which can provide more energy-related services in the future. To do this, there are two challenges of our system. First, we want to minimize the scope of sensor deployment, because numerous sensors would increase the difficulty in deployment, raise the cost of maintenance, and may frustrate the residents. Second, Chetty *et al.* stated that people desire for real time electrical information to alter their behaviors appropriately[3]. Therefore, the system must be able to detect the states of appliances in real time, or it cannot immediately provide services or tips for users.

For the first challenge, we only install smart meters on the distribution board to measure the total power consumption instead of using intelligent outlets to extract the energy information of individual appliance. Therefore, it is much easier to install and maintain. Besides, it also decreases the degree of frustrating the residents, because the system is only installed at single place. For the second challenge, we employ a Bayes filter approach for the problem. This method is exploited for tracking or monitoring the states which we interest in. For example, the position of the resident in a house[4]. It can infer the current state from all observations which have been extracted. Therefore, Bayes filter can compute the most likely states of appliances in real time.

In brief, our goal is that recognizing the states of appliances by monitoring the circuit-level electrical consumption from the distribution board.

This paper is organized as the following sections. In section II, we give a more detailed description about the appliances recognition. In section III, we describe relevant work about appliance recognition and activity recognition by simple and a small number of sensors. In section IV, we discuss how we design and train the model. In section V, we design two experiments and compare the model we used with other classifiers. In section VI, we describe conclusion and future work.

II. PROBLEM DESCRIPTION

In this section, we offer the detailed description of the problem we aim to solve, including pre-defined assumptions, the format of input data, and the expected output results.

There are two assumptions we make for this problem. First, we assume that we have known what appliances and the states of theses appliances will be used in the environment. Second, we believe that there are some regular behavior when residents use appliances. For example, when using computer, user may switch on the light in the room first, start up the power of the computer and, finally, turn on the monitor.

The input data is consisted of two parts, one is observation sequences, and the other is label sequences. The observation sequences are composed of several features values extracted from the collected energy data, which will be described in section IV for more details. Furthermore, the label sequence is the operating states of all appliances at each time slice, which are labeled by researchers when there is any states being changed. To do this, 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 state 1, 3, 4 respectively, the others are off, and there are 9 appliances. We use a 9 digits string, 100300004, as the label. (When the appliance is off, we encode the state as "0" uniformly.) As a result, the process of using appliances is annotated as a label sequence.

Such input data set can be used for constructing the probabilistic models based on statistics. During the learning process, we use the collected data set to build the model so that the parameters of the appliance recognition model will be determined. Therefore, the learned model can be applied to decode the operating states of appliances in real time when giving the observation sequence.

III. Related Work

There are two domains of researches which are related to our work, including appliance recognition and activity recognition which make use of home existing infrastructures.

For the first domain, researches aiming to solve appliance recognition problem can be classified into two categories among the difference of sensor devices. One is using smart outlets to measure the energy information of each appliance. The other is employing the power line interface to capture the pulse of electric events.

A common method for recognizing appliances is to distinguish the difference between a variety of appliances by using individual energy information. Ito *et al.* and Saitoh *et al.* proposed several feature parameters to characterize the power waveform[5], [6], such as average, peak, crest factor, form factor, etc. They applied nearest neighbors method to recognize what appliance was plugged in. Serra *et al.* taked clustering approach to divide the power values of 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[7]. Kato *et al.* designed a wireless intelligent outlet which is called Communication and Energy Care Unit (CECU). They used one-class SVM to classify appliances[8]. Kim *et al.* used magnetic, light, and acoustic sensors to estimate the power consumption and detect the states of each appliance[9].

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 at least one intelligent outlet or sensor for each appliance. This deployment will increase the cost of system and the difficulty of maintenance. Moreover, power supply of each sensing device is another issue. Therefore, there are some obstacles to popularize such systems in actual residences.

The other approach for detecting appliances is employing power line interface to acquire the noise of electric events[10]. Patel *et al.* performed Fast Fourier Transform 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 energy 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.

For the second domain, there were several researches on activity recognition which take advantage of existing infrastructures. Making use of infrastructures could reduce the number of sensors and the degree of invasion. For example, Fogarty *et al.* attached a few microphone-based sensors to water pipes in the basement. They attempted to recognize the activities involve with water usage[11]. Patel *et al.* did a series of researches which made use of existing home infrastructures. They employed the power lines to build a sub-room-level localization system[12], exploited power lines to detect and classify the states change of appliances[10]. In addition, they deployed air pressure sensors in HAVC's air handler unit to detect human movement by sensing the differential air pressure[13].

From the above, these studies give us a nice demonstration to deploy sensors on a home existing infrastructure. Such concepts conform with the first challenge, that is minimizing the cost and scope of sensor deployment.

IV. Approach

Our goal is to provide information, including the states of appliances and power consumption, in real time. In addition, we want to take user behavior into account. Hence, the filter methods are considered first, since such approaches were developed for tracking or monitoring problems. In the following, we introduce the feature extraction, model design, inference approach, and parameters estimation.

A. Feature Extraction

After collecting data, we compute features in following two steps. First of all, We extract electrical consumption (Wh) from sensors. It accumulates energy consumption within a period of time. We think the property could preserve information between two samples when the duration between them is long, i.e. we capture such information by low sample rate. Next, we take temporal factor into account and compute features. Since we have known that the states transition of an appliance is a sequential process, and recognizing it by only considering the power consumption within 5 second, single sample, is insufficient. The sliding window is employed to solve this problem. The window size we select is 7 samples (a period

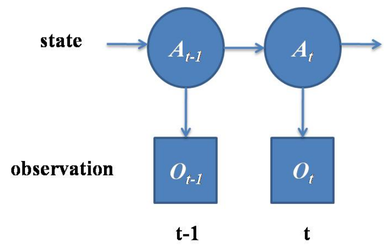

Figure 1. A dynamic bayesian network describing tracking for the state A_t

of 35 seconds), the window shift is 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 power consumption within 5 seconds from time $t-1$ to t. Besides, the features above, O'_t also be calculated in several forms for getting more meaningful information. Table I shows the detailed features.

B. Model Design

We think that there exists some patterns for using appliances. For example, when Rose is preparing a meal, she takes food from a refrigerator, and then heats the food by microwave. 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. 1 shows the structure of our DBN model.

C. Inference

We adopt the Bayes filter for solving this problem. Bayes filter can compute $p(A_t|O_{1:t})$, which is the posterior distribution 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

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

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

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

D. Parameters Estimation

From the above, the parameters that we have to learn are the probability distributions $P(A^j|A^i)$ and $P(O|A^i)$ for all A^i, where A^i and A^j are the combinations of appliance states. $p(A^j|A^i)$ is the probability of transition from state A^i to A^j, which is called transition model. It just need to calculate the ratio of all possible states transition from A^i. However, the observation model $P(O|A^i)$, which is the probability of observing O at state A^i, is more complicated than the transition model, because the observations O are continuous which cannot be calculated by simple counting. We use two methods to handle the observation model and discuss the result in section V.

In the first method, we discretize a range of numeric attributes into nominal attributes by Fayyad and Irani's MDL method[14]. The method uses entropy minimization heuristic to discretize continuous-valued attributes into multiple intervals. After that, we can easily compute $P(O|A^i)$ by $P(O_d|A^i)$, where O_d is a discrete value calculates from O.

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

In the second method, mixture of Gaussian distributions is adopted to estimate $P(O|A^i)$[15]. For each state, we use 5 Gaussian distributions to approximate $p(O|A^i)$. That is,

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

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 learn 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 A^i. Then, we can compute μ_{ik} and Σ_{ik} from a corresponding cluster. Finally, weight c_{ik} can be computed from the ratio of the number of instances in k-th cluster to all instances in A^i.

V. Experiments

We deploy smart meters which are called PA-310 to monitor the total electrical consumption in a living laboratory. Fig. 2 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. Fig. 3 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.

We design two experiments to evaluate our approach, including binary states classification and multiple states classification. Then, we compare Bayes filter with three nontemporal

TABLE I
FEATURE PARAMETERS

Features	Equation[a]	Meaning
$Wh_t, \ldots, Wh_{t-6}$	Wh_i	7 original electrical consumption
$Wh_{avg,t}$	$\frac{1}{7}\sum Wh_i$	Mean value of the window
$Wh_{peak,t}$	$\max\{Wh_i\}$	Maximum value of the window
$Wh_{rms,t}$	$\sqrt{\frac{1}{7}\sum Wh_i^2}$	Root mean square of the window
$Wh_{sd,t}$	$\sqrt{\frac{1}{7}\sum (Wh_i - Wh_{avg,t})^2}$	Standard deviation of the window
CF_t	$Wh_{peak,t}/Wh_{rms,t}$	Crest Factor of the window
FF_t	$Wh_{rms,t}/Wh_{avg,t}$	Form Factor of the window
$F_{pta,t}$	$Wh_{peak,t}/Wh_{avg,t}$	Peak to average ratio of the window
$F_{p,t}$	$\frac{1}{7} \times T_{Wh_{peak,t}}$ [b]	Delay timing of the maximum value within the window

[a] The index i in Table I is from $t-6$ to t
[b] $T_{Wh_{peak,t}}$ represents the index of the maximum value of the window

Figure 2. Smart meter (PA-310)

Figure 3. PA-310, electric panel and server

models, which are KNN, Naive Bayes, and SVM. In addition, we also compare Bayes filter with Viterbi algorithm to verify the difference between online and offline inference approach.

To evaluate our approach, we use four criteria. First, the overall accuracy (OA) shows the accuracy of 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

TABLE II
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

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.

A. Binary States Classification

In this experiment, we assume that all appliances are binary states, on and off. We design two scripts to collect training and testing data. The appliances in the experiment are listed in Table II. These scripts both 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,

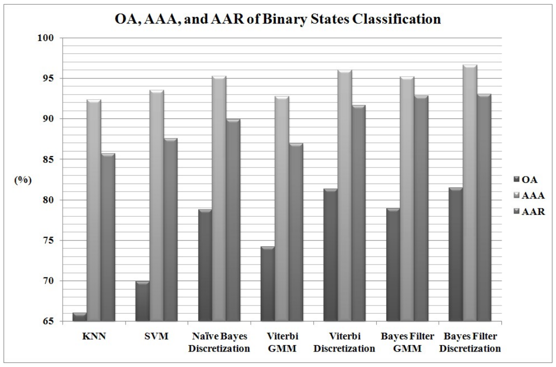

Figure 4. OA, AAA, and AAR of Binary States Classification

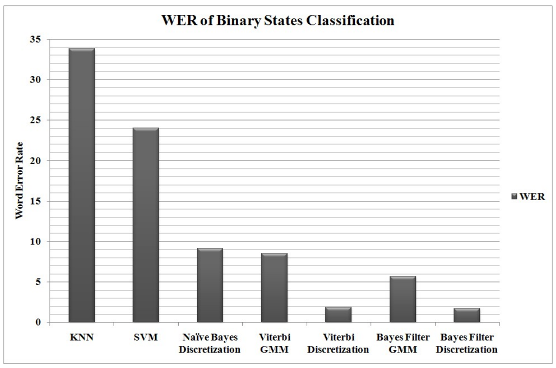

Figure 5. WER of Binary States Classification

TABLE III
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

TABLE IV
APPLIANCES ARE USED IN MULTIPLE STATES EXPERIMENT

Appliances	# of states	Power(W)
computer A	2	104
monitor A	2	58
table lamp A	2	21
electric pot	3	600
oven	3	600
hair dryer	4	1200
electric fan	4	30
microwave	5	1200

TABLE V
COMPARISON BETWEEN BINARY STATES AND MULTIPLE STATES USING BAYES FILTER + DISCRETIZATION

Experiment	OA(%)	AAA(%)	AAR(%)	WER
Binary states	81.42	96.63	93.01	1.72
Multiple states	81.41	95.62	87.16	2.78

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.

Fig. 4 and Fig. 5 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 III. 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.

B. Multiple States Classification

In the Fig. 4, we can see the AAA and AAR of Bayes filter approach are greater than 93%, which inspires us to recognize the more detailed states of appliances. Hence, we define multiple operating states for each appliance. For instances, there are three operating states of electric pot: not in use, keeping warm, and heating. Table IV lists the number of states of each appliance used in this experiment.

In this experiment, there is only one subject. Therefore, we remove computer B, monitor B, and lamp B. Furthermore, we add a microwave and a hair dryer. We ask the subject to use these appliances with his own habit and collect two data sets. Therefore, we can verify whether user behavior is helpful. Moreover, we do not restrict the duration of using each appliance when collecting data. The two data sets consist of 18 combinations of states and 48 state changes, both of which are about 3 hours. We perform 2-fold cross-validation to compare the performance of our approach with those nontempral models and Viterbi algorithm.

The results in Fig. 6 and Fig. 7 exhibit that Bayes filter has the best performance. However, taking GMM to approximate the observation model gets worse results than discretization. GMM cannot distinguish between the state combinations with similar power consumption well. In our experimental setting, there are several states with similar consumption, for example, the power consumption of the 3 wind settings of electric fan and the keeping warm state of electric pot are very close to 28W. For distinguishing such states, discretization is much better than GMM. Besides, Bayes filter with discretization method still outperforms those nontemporal models.

Table V shows the comparison between the results of binary states and multiple states classification using Bayes filter with discretization method. Although there are several states with similar consumption in multiple states classification, the results of multiple states experiment are slightly bad than binary states. This fact shows that our approach can still recognize detailed operating states of several appliances.

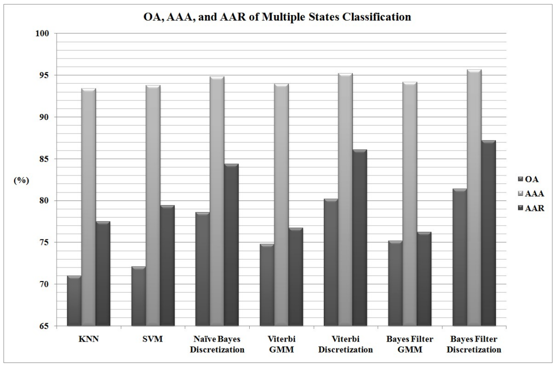

Figure 6. OA, AAA, and AAR of Multiple States Classification

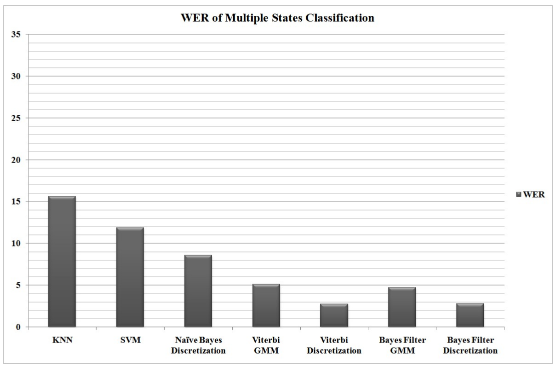

Figure 7. WER of Multiple States Classification

VI. Conclusion

In this paper, we propose a solution for recognizing the states of appliances by measuring the power consumption of circuits. There are two advantages of our system. First, we only install a small number of power meters to the distribution board. Therefore, the system will be easy to install and maintain, and the residents will not be frustrated by the deployment. Second, our approach can inference the states of appliances in real time. Hence, our system can immediately provide states information to residents or service providers. Finally, we compare our approach with nontemporal models and Viterbi algorithm. The results show that taking user behaviors into account can improve the performance. Therefore, the system can provide more accurate states for showing energy information, offering energy-saving advice, and applying automatic control.

In the future, we will keep on collecting the electrical consumption in a long term, and try to capture real relations between user behaviors and the usage of appliances. Moreover, We think that the states information of appliances would be very useful in other domains. In activity recognition, if we known what appliances are operating or the locations of these appliances, we could infer the most likely activity based on the outcomes of our system. In the domain of energy-management, it could provide a real time service, which is about the energy usage of each appliance, to motivate people saving their power consumption.

Acknowledgment

This research is supported in part by the Industrial Technology Research Institute of Taiwan, and in part by the Institute for Information Industry, under the ”Environment and behavior Perception of intelligent living Project” funded by the Ministry of Economic Affairs of Taiwan.

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