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A Hierarchical GMM-based Method For Non-intrusive Load Monitoring (NILM)

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Abstract

By using non-intrusive load monitoring, energy consumption of individual appliances can be labeled through disaggregating the aggregated consumption of an electrical network by data analytical algorithms. Due to the advantage of low cost and easy installation, and the requirements of smart grid applications, NILM has been widely focused in recent years. However, the accuracy of the NILM can be greatly affected by the difference in power resolution of appliances. In this paper, a two hierarchical Gaussian mixture model-based method is proposed to solve this problem. At the 1st hierarchical level, the aggregated energy consumption signals are disaggregated into high-power appliances and low-power appliances. Consequently, at the 2nd hierarchical level, detailed appliances energy usage behaviors can be estimated with adapted power resolutions, respectively. The pubic dataset-- BLUED is used to verify the proposed method. The results show that the proposed method effectively improve the accuracy of NILM, particularly for low-power appliances, compared with conventional Gaussian mixture model method.

Keywords: Non-intrusive load monitoring (NILM), unsupervised learning, Gaussian mixture model (GMM), clustering, power resolution.

NONMENCLATURE

Acronyms	
NILM	Non-intrusive load monitoring
GMM	Gaussian mixture model
HMM	Hidden Markov models
HGMM	Hierarchical Gaussian mixture model
Symbols	
P	Active power
Q	Reactive power

1. INTRODUCTION

With the rapid increase of energy demand, energy conservation is becoming a highly concerned public issue nowadays. Studies show that the building energy consumption in commercial and residential sector is responsible for over one-third of all electricity use [1]; therefore, household energy usage is one of the key areas for energy conservation. In this area, energy usage feedback is the basis to motivate the customers to adopt energy conservation behaviors and participate in demand response, which highly depend on real-time appliance-level load monitoring. Due to the advantage of low cost and easy installation, non-intrusive load monitoring (NILM), which estimates the energy consumption of individual appliances through disaggregating the overall household energy usage by data analytical algorithms, is expected to be the most promising technique to realize large-scale household load monitoring.

Since NILM was first introduced by Hart, many NILM techniques have been proposed in [2]. Most of the methods can be classified into supervised or unsupervised methods. The former estimate disaggregated household loads based on the training of labeled appliances' loads data [3]. However, the lack of applicable training datasets is the main obstacle to the practical implementation of those methods. On the contrary, the latter do not require any prior knowledge for the disaggregation, therefore are more appropriate for real-world application. A review of unsupervised methods for load disaggregation can be found in [4]. A common unsupervised method is the factorial hidden Markov model (FHMM) discussed in [5] and [6]. However, HMM-based methods tend to be computing-expensive, and require a great deal of training data. Clustering is another widely used unsupervised learning method with less complexity and fewer training data requirements. Two clustering methods of unsupervised learning, K-means and GMM, have been compared in [7]. [7] indicates that GMM can classify the raw data more accurately. So GMM is selected in this paper. However,

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since the noise and variation of high-power appliances are much larger than low-power appliances, high-sensitivity cluster algorithms might over-classify high-power appliances while low-sensitivity algorithms might not be able to distinguish low-power appliances.

To solve this problem, a novel clustering method which is based on Hierarchical GMM is proposed in this paper. Different from conventional clustering methods, the detected events are clustered in the 1st hierarchical level based on their power ranges, i.e. clustered into high-power and low-power samples. Then, the samples are clustered again into appliances categories, respectively. In this way, the impact of the difference of resolution between high-power and low-power appliances on clustering results is effectively reduced. The proposed method is tested on a public dataset--BLUED, results show that the proposed method effectively improve the accuracy of NILM, particularly for low-power appliances, compared with conventional clustering method.

This paper is organized as follows. In Section II, the framework of the paper and the proposed method is described. In Section III, the proposed method is compared with conventional clustering method and some results is obtained. Finally, Section IV contains conclusions and future work.

2. METHODOLOGY

2.1 Framework

To realize the purpose of hierarchical clustering, event detection is demanded at first, then the electrical features of events are selected to match different appliances. At last, a hierarchical GMM (HGMM) method is presented, which includes 2 hierarchical levels. The posterior probability of HGMM output is used to obtain the final classification results of samples. In order to show the novel method proposed in this paper more clearly, the working principle of the proposed method is shown as Fig.1

2.2 Event detection

The turning on or turning off of an electrical appliance in a circuit is called an event. The occurrence of events in the circuit is often accompanied by obvious changes of variables; therefore, the changes of selected variables can be used to detect events. Different methods for event detection have been proposed and compared in [8]. In this study, the most commonly used method has been adopted, which detects events by the step-changes of active power. The change rate of active power in a sample period can be formulated as

$$\Delta \mathbf{d}(t) = \frac{\boldsymbol{Y}(\boldsymbol{t}) - \boldsymbol{Y}(\boldsymbol{t} - \Delta \boldsymbol{t})}{\Delta \boldsymbol{t}} \tag{1}$$

By setting appropriate threshold of $\Delta \mathbf{d}(t)$,and using the median filter to remove the noise, whether there is an event at time t can be determined.

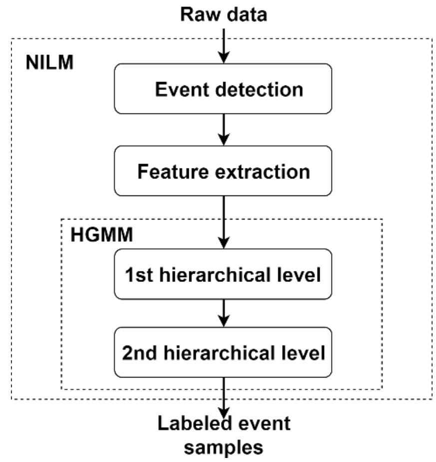

Fig 1The framework of HGMM-based NILM

2.3 Feature extraction

Features of data are the basis of load disaggregation algorithm, which are generally divided into steady state features, transient features. Reviews of features can be found in [9] [10]. Since complex features are not commonly used in unsupervised learning, the two commonly used features: the changes of active power (ΔP) and reactive power (ΔQ), are selected in this study.

2.4 Hierarchical GMM-based Method

To adopt the feature distances of appliances of low or high power differently, a hierarchical GMM (HGMM) is proposed as shown in Fig. 2.

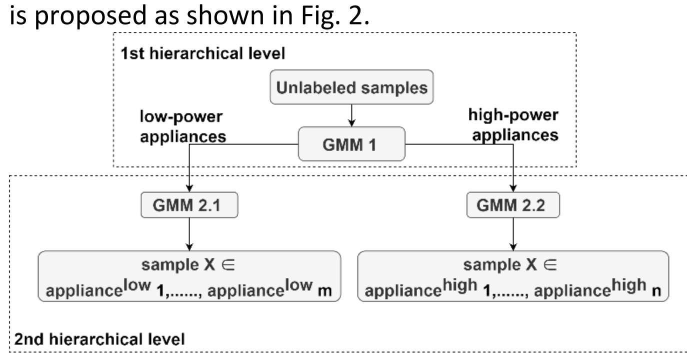

Fig 2 Structure of HGMM

GMM is a simple extension of Gaussian model. This method uses Gaussian distribution as the parameter model, and uses expectation maximization (EM) algorithm for model training. Usually fitted GMMs cluster by assigning query data points to the multivariate normal components that maximize the component posterior probability given the data. Its advantage is showing how to fit a GMM to data, cluster using the fitted model, and estimate component posterior probability. If we use x to represent the sample value $(\Delta P, \Delta Q)$, then the probability of sample X is defined as:

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k p\left(x \mid \mu_{\mathbf{k}}, \mathbf{\Sigma}_{\mathbf{k}}\right) \quad (2)$$

Where K is the number of components of GMM, π_k is the weight of the k th component, $g\left(x \mid \mu_k, \Sigma_k\right)$ is the Gaussian PDF, μ_k and Σ_k are mean vector and covariance matrix of the k th components respectively.

In equation (2), three parameters: π_k, μ_k, Σ_k can be obtained by EM (Expectation Maximization) algorithm shown as follows:

A latent variable $z = [z_1, \dots \quad z_k]$ is introduced to indicate which sub model the sample X is generated from. z_{nk} indicates the sample X_n is generated from model k. Then the responsibility of sub model k to x_n is shown as(3).

Step1, parameters (π_k, μ_k, Σ_k) needed to be initialized to calculate the GMM model.

Step2, calculate the posterior probability (responsibility) according to the initialized parameters (π_k, μ_k, Σ_k):

$$\gamma\left(z_{nk}\right) \leftarrow \frac{\pi_k p\left(\mathbf{x}_{\mathbf{n}} \mid \mu_{\mathbf{k}}, \mathbf{\Sigma}_{\mathbf{k}}\right)}{\sum_{j=1}^{K} \pi_j p\left(\mathbf{x}_{\mathbf{n}} \mid \mu_{\mathbf{j}}, \mathbf{\Sigma}_{\mathbf{j}}\right)} \quad (3)$$

Step3, the parameters are re-estimated using the current responsibility $\gamma(z_{nk})$:

$$\mu_{\mathbf{k}}^{\text{new}} \leftarrow \frac{1}{N_k} \sum_{n=1}^{N} \left[\gamma\left(z_{nk}\right) \mathbf{x}_{\mathbf{n}}\right] \mathbf{\Sigma}_{\mathbf{k}}^{\text{new}}$$

$$\mathbf{\Sigma}_{\mathbf{k}}^{\text{new}} \leftarrow \frac{1}{N_k} \sum_{n=1}^{N} \gamma\left(z_{nk}\right)\left(\mathbf{x}_{\mathbf{n}} - \mu_{\mathbf{k}}^{\text{new}}\right)\left(\mathbf{x}_{\mathbf{n}} - \mu_{\mathbf{k}}^{\text{new}}\right)^T \quad (4)$$

$$\pi_k^{new} \leftarrow \frac{N_k}{N} \qquad N_k = \sum_{n=1}^{N} \gamma\left(z_{nk}\right)$$

Step4, the new parameters π_k^{new}, μ_k^{new} and $\sum_k^{new}$ was used to calculate the log likelihood function:

$$\ln p(\mathbf{X} \mid \pi, \mu, \mathbf{\Sigma}) = \sum_{n=1}^{N} \ln\left[\sum_{k=1}^{K} \pi_k p\left(\mathbf{x}_{\mathbf{n}} \mid \mu_{\mathbf{k}}, \mathbf{\Sigma}_{\mathbf{k}}\right)\right] \quad (5)$$

Check whether the log likelihood function converges, if not, go back to the second and third step and repeat calculation until convergence is got.

Then the parameter values for GMM is obtained.

In this study, the NILM system collects a large amount of historical data of residential circuits, after event detection and feature extraction, HGMM model is trained with unlabeled event set. When training the model , the user needs to input the common power of each appliances as the initial cluster center. This ensures that the label order of the model output is consistent with the real label order. In addition, the number of components in the HGMM model is also set by the user, for example, the sample X is divided into 2 parts(low-power appliances and high-power appliances) at the 1st hierarchical level by, so the user need to set K to 2. At the 2st hierarchical level, the 2 parts are separated into m and n sorts of devices, respectively, which can be obtained by setting K to m and n.

3. RESULTS AND DISCUSSION

3.1 Dataset

In this section the proposed method is tested on the BLUED dataset. A whole week's aggregated power signal of 8 appliances, including refrigerator, air compressor, bathroom upstairs lights, backyard light, kitchen aid chopper, hair dryer and bedroom lights, of a family residence in Pittsburgh, Pennsylvania was selected. We can get 759 events from the selected residence according to the aggregated power signal.

3.2 Cross validation

Performance is evaluated on 20% of the data, whereas the remaining 80% is used for training. The data is randomly classified into 5 parts in this paper. For the first time, the first part is used as a testing set, the rest as a training set. Then, the second part as a testing set, the rest as a training set, and so on. Therefore, a fold cross validation is completed. Each time the training set is used in conventional GMM and HGMM for model-training, and the testing set is used to test the performance of these two models. In order to better compare the experimental results, some unreasonable classification results were eliminated, and the reasonable experimental results were retained and the average value of evaluation metrics was calculated.

3.3 Evaluation metrics

In order to evaluate the experimental results, the Accuracy (Acc), Precision(P), Recall(R) and F-measure metrics have been chosen.

3.4 Results

The results of the experiment are shown as Fig.3. Different color dots represent different sorts of appliances. The clustering result of the conventional GMM is shown as Fig. 3(b), the classification results of

category1,3,4 are clear enough to match detailed appliances. While the rest of categories are too concentrated and dense to identify detailed devices. In contrast to this, the clustering results of HGMM is shown as Fig.3(c)(d)(e). At the 1st hierarchical level, all appliances related are classified into low-power appliances and high-power ones, which represented by

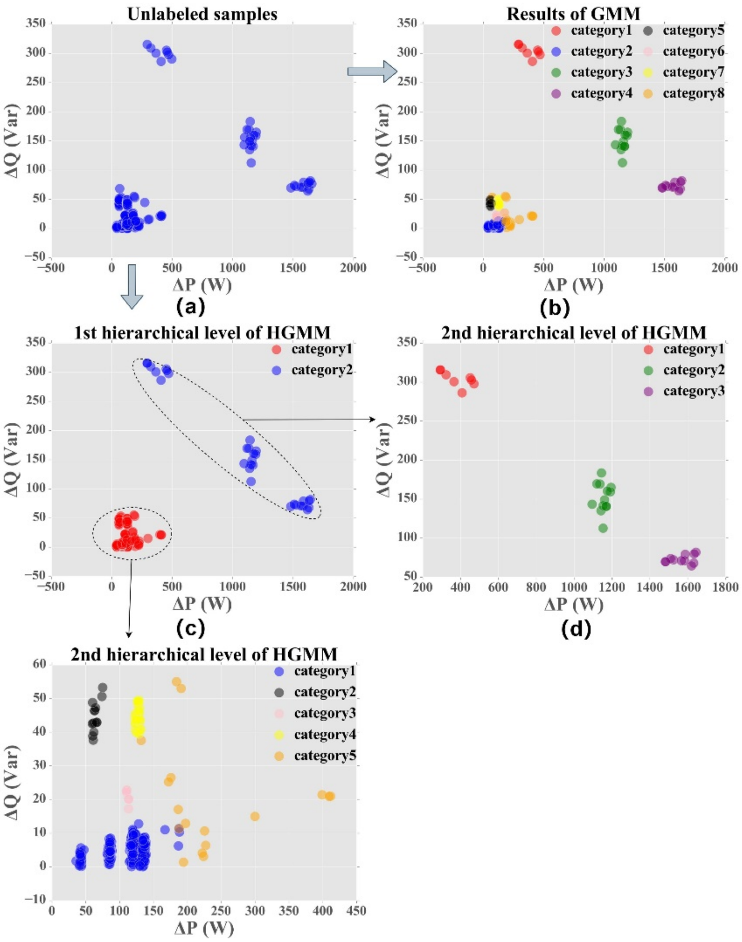

Fig 3 Results of GMM and HGMM

blue dots /and red dots. At the 2nd hierarchical level, the low-power appliances are divided into 5 different kinds of appliances. In the same way, the high-power appliances are divided into 3 kinds of appliances. In this way, the original difficult to distinguish the electrical appliances were successfully separated.

The comparison results of the two methods are shown in the Table1 and Fig.4. It is not difficult to find that for high-power appliances (Kitchen Aid Chopper, Air Compressor, Hair Dryer), the performance of the two method is almost the same. But for low-power appliances, the performance of HGMM is highly elevated. The performance of Bathroom upstairs lights and Bedroom lights have improved by 13.2%,20.8% (calculated in F-score). For Backyard Lights, the performance has improved 27.3%. The most significant performance improvement is Washroom Light, with improvement of 161%.

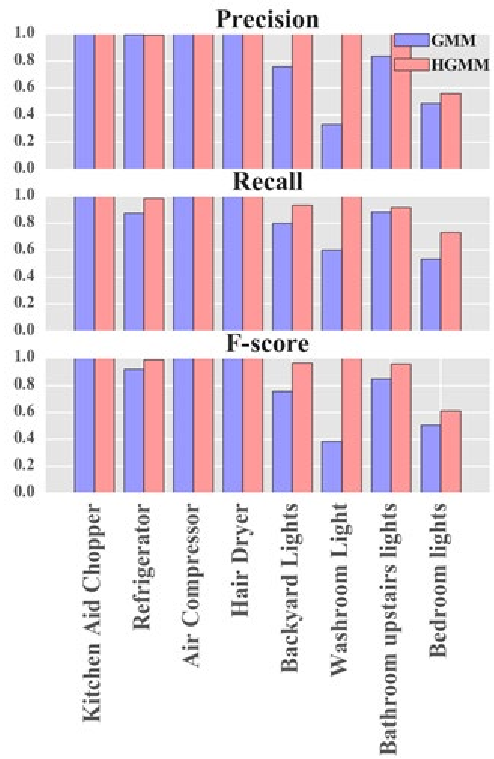

Fig 4 Comparison of GMM and HGMM

Table 1 Comparison of GMM and HGMM

Appliance	Event number	Accuracy		Precision		Recall		F-score	
		GMM	HGMM	GMM	HGMM	GMM	HGMM	GMM	HGMM
Kitchen Aid Chopper	1			1.0	1.0	1.0	1.0	1.0	1.0
Refrigerator	118			0.995	0.990	0.875	0.985	0.916	0.987
Air Compressor	3			1.0	1.0	1.0	1.0	1.0	1.0
Hair Dryer	2	0.803	0.968	1.0	1.0	1.0	1.0	1.0	1.0
Backyard Lights	3			0.757	1.0	0.800	0.933	0.754	0.960
Washroom Light	1			0.329	1.0	0.600	1.0	0.383	1.0
Bathroom upstairs lights	7			0.836	1.0	0.886	0.914	0.843	0.954
Bedroom lights	3			0.483	0.557	0.533	0.733	0.505	0.610

3.5 Discussion

From the results above, it is not difficult to find that the newly presented method together with the conventional GMM shares the same performance in classification of high-power appliances. While for low-power appliances, HGMM-based method is clearly superior to the conventional GMM method. This is because GMM clustering method is based on Euclidean distance between sample points, When the GMM method is used to cluster event samples directly, The fluctuation range of high-power samples is large, while that of low-power samples is small, Therefore, the distance between the same high-power samples may be greater than that between different low-power samples, which leads to the wrong classification: GMM divides the same high-power appliances into different categories, and divides different kinds of low-power appliances into the same class. While HGMM effectively avoids this kind of misclassification. Through the 2- hierarchy HGMM structure, high-power samples and low-power samples can have their own adaptive resolution.

However, like all unsupervised learning algorithms, HGMM method also has random results, and the accuracy of the results will be affected by sample conditions, initialization settings, and the distribution of power values in real scenes.

4. CONCLUSION AND FUTURE WORK

In this study, we presented a HGMM-based method, for NILM. which aims at improving the accuracy of the identification. HGMM classifies the aggregated power signals into high-power appliances and low-power ones before the detailed appliances are identified. By doing so, the impact of the difference of resolution between high-power and low-power appliances is highly reduced. The proposed method is tested on a public dataset—BIUED. The reliability of the novel method is verified by comparing with the conventional GMM. Experimental results demonstrate the accuracy of identification has been effectively improved compared with the conventional GMM, especially for the low-power appliances. The results presented here indicate that further studies are required, particularly for scenarios with large numbers of appliances. Because samples of intermediate-power appliances might be divided into two groups in the 1st hierarchical level, and an adaptive clustering criteria is expected to solve this problem. We would like to explore this in future work.

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