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Multi-appliance recognition system with hybrid SVM/GMM classifier in ubiquitous smart home

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ABSTRACT

Ubiquitous computing provides convenient and fast information distribution service by using sensor nodes and wireless network, and a good household appliance recognition system will allow users to effectively understand the household appliance usage and develop habits of power preservation. At present, smart meters convert the information of traditional electric meters to easily accessible digital information, based on which, the household appliance recognition service can be carried out. However, it is different from video or audio recognition service, when a variety of electrical appliances run, they will all have individual impact on power consumption, thereby resulting in the difficulties in recognition. Presently, the complex current information arising from many household appliances also increases the difficulty in extracting power features. For addressing the challenge, this study proposes a set of multi-appliance recognition system, which designs a single smart meter using a current sensor and a voltage sensor in combination with a microprocessor to meter multi-appliances. After fuzzy processing of the power information are read through the smart meter and extraction of the power features, electric appliances are classified using the hybrid Support Vector Machine/Gaussian Mixture Model (SVM/GMM) classification model. GMM is mainly used describe the wave distribution situation according to the current information, so as to find the power similarity; while SVM is used to classify the power features of different electric appliances, so as to summarize the classification properties of different electric appliances and establish a classification model. Finally, the household appliances that are in use can be recognized with the household power supply terminal, and their information can be reported to users through wired or wireless network to achieve ubiquitous recognition service. This study has developed and implemented this system prototype, and is used to prove its design theory.

1. Introduction

With the development of wireless communication, sensor design and micro-electronics allow microsensors to be integrated into everyday life and provide users ubiquitous services, which were first proposed in 1993 by Mark Weiser as ubiquitous computing in Computing [34]. In other words, anyone and anything can conveniently transmit messages anytime and anywhere, the people-oriented starting point can allow access to any message anytime and anywhere, including the ubiquitous smart space built within the scope of all existing internet researches. Using the ubiquitous smart house as example, energy management of household appliances, automation control and situational intelligence services, and its household

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appliance recognition services, are all important elements, therefore correct and effective recognition of the household appliances in use is a productive study for functionality [9,18]. At present, most studies meter the power information through smart meters, so as to achieve recognition service mainly in two ways: one is to install a smart meter for an individual electric appliance [10,28,12]. In this method, electric power consumption of each electric appliance may be clearly obtained, but there are many electric appliances in a family, and the installation cost and network topology add more difficulties. The other is to install a single meter at the total power panel [20,21]. In this way, it is easy to install the meter and inform the users of the total electric power consumption, but the recognition service of individual electric appliances will still have some challenging.

1. Hybrid power waveforms: Different electric appliances have different current waveforms and phase differences between voltage and current. However, when many electric appliances are activated, fuzzy current may be resulted from mutual influence on the current waveform, thereby resulting in the difficulties in separating power features, as shown in Fig. 1A.
2. Complex current information of intricate electric appliances: Electric appliances are mainly divided into two groups: linear loads and non-linear loads. The former has a spin wave with fixed cycle, and its current waveform does not have deformation, and only has phase difference between voltage and current. While structure of the latter is a complex circuit including resistors, capacitors and inductors, so that its current waveform is not a proper sine wave, and it is hard to extract a proper waveform of a cycle based on the zero point and slope of the waveform. Due to its complex circuit, the waveform of each cycle may also be different, as shown in Fig. 1B.

To solve the above problems, this study proposes a multi-appliance recognition system with a single meter and hybrid Support Vector Machine/Gaussian Mixture Model (SVM/GMM) classifier, describes the Gaussian similarity of complex waveforms using the good classification performance of SVM in combination with GMM, achieves the multi-appliance recognition by learning to establish a power feature model, and sends the recognition results through wireless network to usersmobile device or home information display, allowing users to understand the electric appliances in use in their families at any moment so that users can manage these electric appliances, and providing users with a ubiquitous appliance recognition service.

The research contributions of this paper can be summarized as follows:

a. Multi-appliances meter design: The study designs a smart meter which combined the current and voltage sensors used for metering multi-appliances waveform of each cycle.
b. Power feature extraction: Define the power features required by electric appliances, and compare the influence of each feature on the recognition results.
c. Recognition mechanism design: This study solves the difficulties in extracting the characteristics of non-linear load electric appliances using a hybrid learning module in combination with the classification advantages of SVM and GMM classifiers. Through the design of power separation, the system solves the complexity of power information caused by the mutual influence of multi-appliances.

This paper will introduce SVM and GMM-related background knowledge and present research and discussion of electric appliance recognition in Section 2, illustrate the overall system structure and classifier design concept in Section 3, shows the results achieved in this study and the analysis and discussion of the system in Section 4, and finally presents the research findings and future expectation and planning in Section 5.

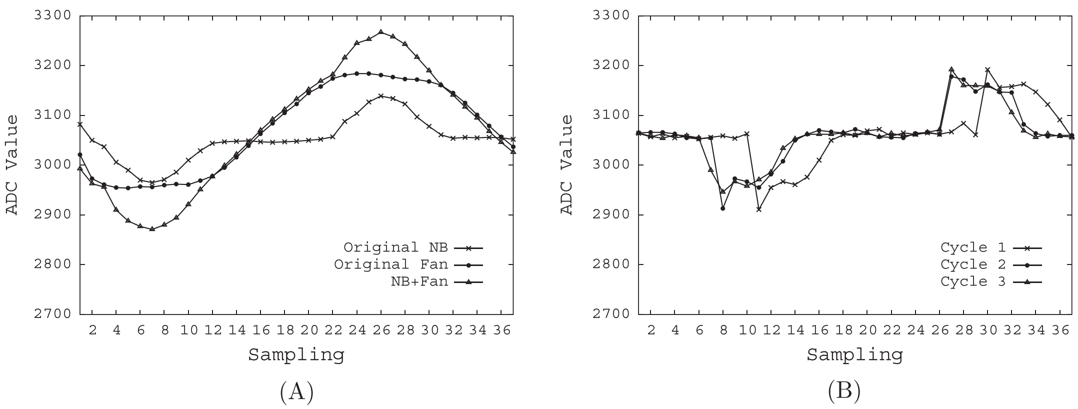

Fig. 1. The challenge with multi-appliance A. Hybrid Power Features. B. Non-linear current information.

2. Background and related work

This section will introduce the basic knowledge related to SVM and GMM classifiers, so as to facilitate the description of subsequent system design and basic introduction of the personnel with irrelevant background, as well as present researches related to electric appliance recognition.

2.1. Support Vector Machine, SVM

SVM is widely used in data mining classification models. It is a supervised machine learning method originated in statistical learning theory, and it is characterized by the ability to solve the problems of high-dimensional data, and to represent the decision-making boundary in the form of training subset, which is the general meaning of support vector[7,26,13]. The initial design concept of SVM is generated for binary classification, which of SVM is achieved by finding a hyperplane, and dividing the data into two groups, one group is located in one side of the hyperplane, and another group is located in another side of the hyperplane. But a lot of classifiers can achieve such classification, so SVM also hopes to find the best plane, so that two different types of groups can have the largest compartment, and the plane is called the maximum margin hyperplane. The larger the boundary of a hyperplane, the higher the correct determination rate of the subsequent incoming data, which is the Structural Risk Minimization (SRM) from the statistical point of view, so as to minimize the error rate [36,8,24].

SVM, also known as linear SVM, designs a linear classification method to calculate the maximum margin hyperplane. Suppose that there exists N sample points as the training data in the space R^d, for example, (x_1,c_1), (x_2,c_2), ..., (x_n,c_N), where $x_i \in R^d$, and $c_i \in [-1,1]$ is used to indicate which group they belong to, and the decision-making boundary is as follows:

$$f(x) = w \cdot x + b = 0 \tag{1}$$

where w and b are parameters of the model. If corresponding (x,b) can be found, so that all the data of $c_i = +1$ fall to the side of $f(x) > 0$, and all the data of $c_i = -1$ fall to the side of $f(x) < 0$, then it shows that the set can be linearly divided. In order to find the maximum margin hyperplane, it is necessary to calculate by the support hyperplane, which is the hyperplane H1 and H2 paralleling to the maximum hyperplane and closest to the edge points of the data on both sides, as expressed as follows:

$$\begin{cases} H1 : w \cdot x + b = 1 \\ H2 : w \cdot x + b = -1 \end{cases} \tag{2}$$

The distance from the maximum hyperplane to the origin is $-b/|w|$, that from H1 to the origin is $1 - b/\|w\|$, and that from H2 to the origin is $-1 - b/\|w\|$, so the distance from H1 to H2 is $2/\|w\|$, that is the margin distance. Based on the linear segmentation features, the boundary $2/\|w\|$ is the maximum value, so as to solve the maximum margin hyperplane, i.e. the smaller the w, the larger the margin. Based on the above description, the formula can be classified as shown as follows:

$$\min \|w\|/2 \tag{3}$$

$$y_i(w \cdot x_i + b) \geqslant 1, \quad i = 1, \ldots, N \tag{4}$$

This is a dual problem. The above two formulae can be converted to Eq. (5) by the Lagrange multiplier method.

$$\mathcal{L}(w,b,\alpha) = \frac{1}{2}\|w^2\| - \sum_{i=1}^{N} \alpha_i [y_i(w \cdot x_i + b) - 1], \quad \alpha_i \geqslant 0 \tag{5}$$

Extremum of the Lagrange function can be obtained through respective differential coefficient of w and b:

$$\frac{\partial \mathcal{L}}{\partial w} = w - \sum_{i=1}^{N} \alpha_i y_i x_i \tag{6}$$

$$\frac{\partial \mathcal{L}}{\partial b} = \sum_{i=1}^{N} y_i \alpha_i \tag{7}$$

Eqs. (8) and (9) can be obtained through substituting the results of Eqs. (6) and (7) into Eq. (5).

$$\max \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j x_i x_j \tag{8}$$

$$subject : \begin{cases} \sum_{i=1}^{N} y_i \alpha_i = 0 \\ \alpha_i \geqslant 0, i = 1, \ldots, N \end{cases} \tag{9}$$

Based on the above listed calculation results, it can then be rewritten to a form in compliance with the KKT (Karush–Kuhn–Tucker) conditions, so as to find the solution. The above-mentioned results can be organized into the KKT conditions as follows:

$$\partial_b \mathcal{L} = 0 \rightarrow \sum_{i=1}^{N} y_i \alpha_i = 0 \tag{10a}$$

$$\partial_w \mathcal{L} = 0 \rightarrow w - \sum_{i=1}^{N} x_i y_i \alpha_i = 0 \tag{10b}$$

$$y_i(wx_i + b) = 0 \tag{10c}$$

$$\text{Lagrange multiplier condition} : \alpha_i \geqslant 0 \tag{10d}$$

$$\text{complementary slackness} : \alpha_i[y_i(wx_i + b) - 1] = 0 \tag{10e}$$

Some points in line with the KKT conditions will be obtained by substituting the training data into the obtained KKT conditions. These points are called the support vectors, all of which fall within the support hyperplane ($\alpha_i \geqslant 0$). Finally, the Eq. (1) to be obtained in this study is converted like Eqs. (11) and (12), and w and b can be obtained.

$$c = f(x) = w \cdot x + b = \sum_{i=1}^{N} \alpha_i y_i x_i x - b \tag{11}$$

$$b = \sum_{j-1}^{N} \alpha_j y_j x_j x - y_i, \quad i \text{ is support vector} \tag{12}$$

2.2. Gaussian Mixture Model, GMM

GMM is the extension of a single Gaussian probability density function; it can smoothly approximate density distribution in any shape, and is the most frequently used classification method in voice recognition. Because the action signal characteristics are close to the voice signal characteristics, this paper takes GMM as the action signal classification model.

1. ***Single Gaussian probability density function***
   The bell curve is frequently seen in many applications related to the probability theory. All probability models used in these applications are actually related with the Gaussian random variables to a considerable degree, and can also be said as one link of the Gaussian random variables. Gaussian random variables are applied or referred to in many actual examples, and therefore, they are also known as normal random variables[11,17]. Gaussian model is a well-known model, and the whole model depends on two parameters: the average value and standard deviation. The figure shows the Gaussian Probability Density Function (PDF), where is the average value, and is the standard deviation[3,35]. Suppose that the distribution of a group of points in a high-dimensional space (the dimension is d) is approximately egg-shaped, the Gaussian density function $g(x; \mu, \sum)$ can be used to describe the probability density function producing these points:

   $$g\left(x; \mu, \sum\right) = \frac{1}{\sqrt{(2\pi)^d |\sum|}} \exp\left[-\frac{(x-\mu)^T (x-\mu)}{2\sigma^2}\right] \tag{13}$$

   where μ (average value) represents the center point of this PDF, and $\sum$ represents the covariance matrix of this PDF. These parameters can be used to determine some characteristics of this PDF, such as the center point location, width and direction of the Gaussian function shape distribution.
2. ***GMM***
   If distribution of the data $X = [x_1, x_2, \ldots, x_n]$ in the d-dimensional space is not a bell-shaped normal distribution curve, then it is not suitable to describe the PDF of these data points using a single Gaussian density function. Here, the alternative solution is to express it using the weighted average of several Gaussian functions. If three Gaussian functions are used, then it can be expressed as:

   $$p(x) = \alpha_1 g\left(x; \mu_1, \sum_1\right) + \alpha_2 g\left(x; \mu_2, \sum_2\right) + \alpha_3 g\left(x; \mu_3, \sum_3\right) \tag{14}$$

   Parameters of this PDF include $\left(\alpha_1, \alpha_2, \alpha_3, \mu_1, \mu_2, \mu_3, \sum_1, \sum_2, \sum_3\right)$ and α_1, α_2, α_3 shall satisfy the following conditions:

   $$\alpha_1 + \alpha_2 + \alpha_3 = 1 \tag{15}$$

   PDF expressed in this form is called the Gaussian mixture density function or Gaussian mixture model, abbreviated as GMM.

2.3. Appliance recognition

Among existing ubiquitous smart house, it is difficult to achieve the ubiquitous household appliance control as it is difficult to exactly know which electric appliances are being used, so as to make corresponding control. According to existing methods, for example, John La Grou plugs smart power outlets [1], additionally installs a data label on the plug of electric appliances, and a sensor in the socket. When the plug is inserted into the socket, the data label will be sensed for electric appliance recognition, and whether there is current flow is detected through the socket, then the power consumption information is sent to the back-end. This socket can be designed for earth leakage protection, so as to automatically cut off power supply on occurrence of abnormal current. However, it is generally an inconvenient practice for families with a large number of electric appliances and sockets. In addition to the method of using sensors, some additional academic researches analyze and research power features of electric appliances, so as to achieve electric appliance recognition; Ito et al. [14] designed special electric energy parameters in studies, analyzed voltage and current waveforms, and considered in their studies that microprocessors had limited computing power to process these power information, so it is necessary to design some parameters that are easy to compute and can serve as features, and send them to database for storage, in order to achieve effective recognition and instantaneity, and allow the comparison with the data in the database in future electric appliance recognition, so as to achieve the recognition effect; Lam et al. [19] proposed to draw a *V–I* diagram after the voltage and current of electric appliances are normalized, so as to classify electric appliance characteristics and establish a classification list to facilitate subsequent inquiry; Ruzzelli et al. [27] built in their studies a RECAP (RECognition of electrical appliances and profiling in real-time) system for real-time identification of individual electric appliances, which is achieved by establishing power features parameters and storing them in database, identifying through the neural algorithm and finally displaying the results in users interface; Akbar et al. [5] converted in their studies the time domain current waveform to the frequency domain through fast Fourier transform, so as to obtain special electric energy parameters for recognition. However, recognition through electric appliance characteristics has a defect, that is, if the power information is not obtained from the socket of individual electric appliance but from that of the total power supply, then it is difficult to identify multi-appliances [30,16]; electric appliance characteristics obtained from the socket of individual electric appliances will also be more difficult to implement in general families due to difficult installation.

3. Proposed multi-appliance recognition system

This section will completely introduce the overall structure of the system, design principle of each internal component, and classifier training process.

3.1. Design of the recognition system architecture

This study designed the architecture of an electric appliance recognition system, as shown in Fig. 2.

The structure designed in this study is divided into three layers, namely the hardware layer, middleware layer and application layer, as shown below:

- ***Hardware layer***
  Hardware layer is responsible for converting current and voltage signals of the household power panel to processable signals through sensors, where the voltage part is to decline the voltage to a reference signal of synchronization, while the current part is to convert the current to a processable single.

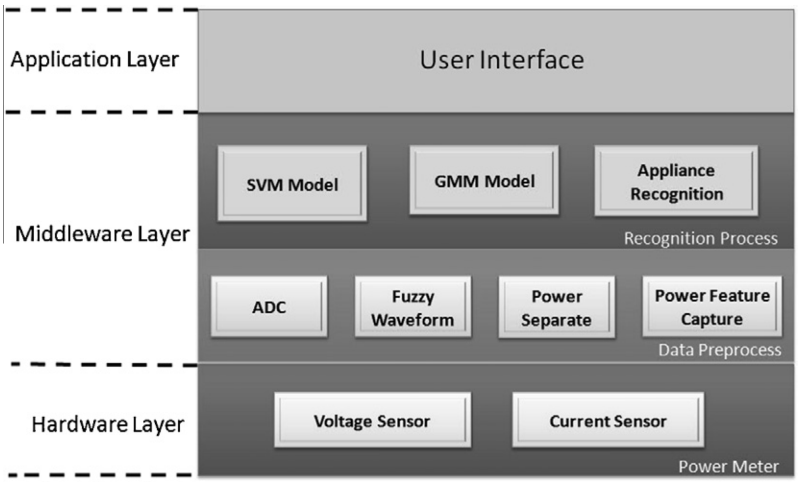

Fig. 2. Recognition system architecture.

- ***Middleware layer***
  Middleware layer is the most important part in this study. It is necessary to do a lot of processing of the signals transferred from the hardware layer, which can be divided into the data preprocess layer and recognition process layer. The former pre-processes the data transferred from the hardware layer, while the latter recognizes electric appliances according to the processed information.
- ***Application layer***
  A user interface is required to allow end users to easily understand the electric appliances being used at present according to the electric appliance recognition results. In addition, in the application layer, control or overload protection of electric appliances and other applications can still be implemented later in combination with the concept of Home Energy Management Systems (HEMSs).

3.2. Hardware layer

The power information to be obtained in this study was classified into the current part and voltage part. In terms of the current measurement, this study used current sensor chip called ACS714T, the measuring range of which was plus to minus 20 A, while the supply voltage was 5 V. When no current flowed through the chip, V_{OUT} was 2.5 V, and after electrification, V_{OUT} would start to vibrate with 2.5 V as the intermediate quasi-position. If this datum was directly sent to the microprocessor for ADC conversion, too small scale would be caused, so that recognition would be difficult. Therefore, it was necessary to design an amplifying circuit in this study, so as to amplify the V_{OUT} by two times the original to facilitate subsequent judgement. While in terms of the voltage, the study was required to observe the phase difference between voltage and current with voltage as the frequency, information of the electric appliance characteristics can be obtained through this phase difference, and taken as the basis to extract the current waveform. The voltage measurement circuit declined its voltage through general voltage drop components, but its positive and negative spin wave values were still required to stay within the ADC conversion range of voltage by using a simple voltage booster circuit, the overall circuit design was shown in Fig. 3.

3.3. Middleware layer-data preprocess

Middleware layer is the main function block of the system. The signal generated by the hardware layer will first go through this function so as to convert analog signals to digital signals through ADC, and make pre-processing of digital signals in accordance to address complex current information. The voltage can be converted as timer signals, so as to extract correct current waveform through voltage timer. Fuzzy waveform model obtains standard periodic waveforms through fuzzy

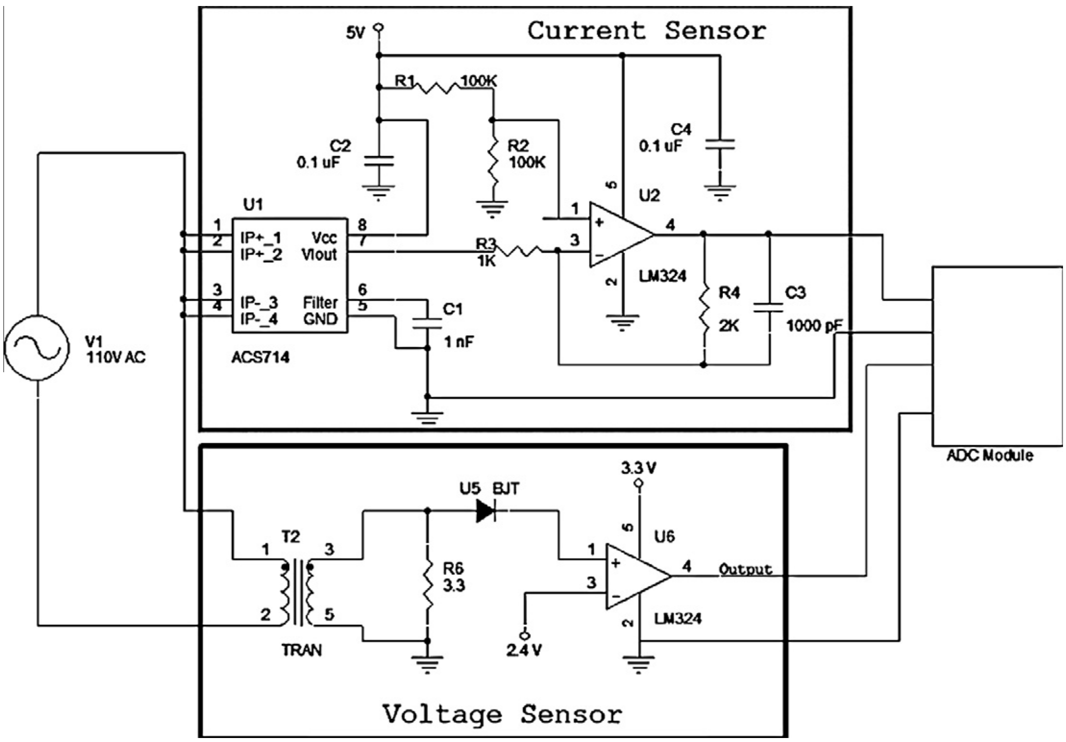

Fig. 3. The Hardware schematic of power meter.

processing of continuously fluctuating waveforms, so that the follow-up power feature capture model captures relevant power features and obtains relevant feature parameters through the SVM and GMM Model for recognition service. The power separate model monitors and recognizes functional components designed for multi-appliance recognition through their current fluctuations, and separates current during current fluctuations. Its detailed design concept will be introduced in later sections.

3.3.1. Fuzzy processing

At present, precise electric appliances are widely used in families, such as computers, TV, and VCR. These intricate instruments are often non-linear loads composed of very complex switching circuits. In addition to causing harmonic generation, different waveforms of each cycle will also be caused by its complex circuit, thereby resulting in different power feature parameters of the captured waveforms, and difficulties in judgement. As can be seen from Fig. 1B, the waveform is constantly changing in continuous cycles, including the left–right displacement and peak value changes. As a result, this study suggested determining its weight after capturing the cycle for some time, followed by weight fuzzy processing. Relevant formula is shown in Eq. (16) as follows, so a more stable waveform should be obtained.

$$A = \frac{p_x * A_x}{\sum p_x} \tag{16}$$

where A_x is the current value corresponding to weight, and p_x is the waveform weight coefficient set calculated by

$$p_x = \frac{u_x}{m_x} \tag{17}$$

u_x is a constant, and m_x is the difference value between average values.

3.3.2. Power separation

At present, most studies on electric appliance recognition can only recognize a single electrical appliance. In order to accommodate that generally many electric appliances operate simultaneously in a family, it is necessary to monitor current fluctuations, capture the variation since the current changes, and separate from the original waveform, so as to obtain correct waveform. This study will keep on monitoring the current, and adopt the Root Mean Square (RMS) current value as a basis for determination in order to reduce the difficulty of determination. The cause is that when an electric appliance is switched on/off or changes its state, power change, i.e. the current value changes, is the most apparent within the total power supply, so the RMS current value is taken as a basis for determination. In the beginning, a present steady RMS current and its current waveform will first be stored, and the difference between stable RMS and present RMS is constantly checked. Once the difference exceeds 0.1 A, that is, the power change reaches 22 W, then it is considered that an electric appliance changes its state or is switched on/off. Under these conditions, keep on monitoring for a short time to see whether the variation continues to maintain the same amplitude, so as to determine whether it is an error and ensure that power of the electric source enters a stable state, then subtract the previously stored stable waveform from this waveform to obtain a group of difference values, which are the waveforms of electric appliances with state changes. The results are shown in Fig. 4.

This study first separately measured the current waveform of a notebook computer and a fan, and then measured that of two electric appliances operating at the same time. Theoretically, sum of the current waveform of the notebook computer and fan minus the current waveform of either electric appliance will be equal to that of the other electric appliance, thereby verifying the Fig. 1A. A change waveform is obtained from Fig. 4 plus the total current waveform and minus the current waveform of the fan, as can be seen that its similarity is very high, so this study can load this method at the total power

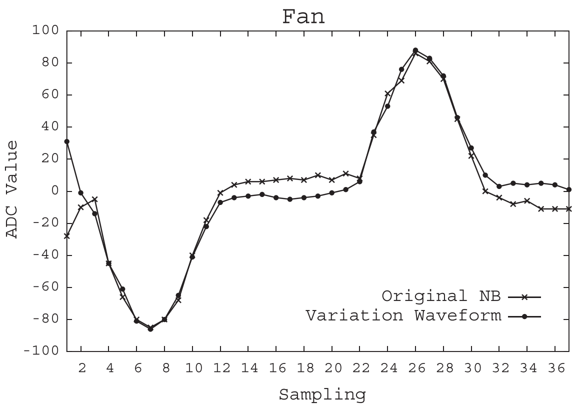

Fig. 4. Power separate between the original and variation.

Table 1
Data structure of feature parameters.

Data type	Function	Description
Rule int	Name	Name of the electric appliance
Float	Max	Maximum current value
Float	Min	Minimum current value
Float	Rms	RMS current value
Float	Avg	Average current value
Float	Std_dev	Standard deviation of dispersion degree of current information
Float	CF	Crest factor, the ratio of peak value to the RMS value
Float	FF	Form factor, the ratio of average value to the RMS value
Float	Entropy	Information entropy used to weigh a random variable
Int	Max_count	The time from the starting sampling point to the maximum current value
Int	Min_count	The time from the starting sampling point to the minimum current value

supply, so as to separate out the power feature information of a particular electric appliance, then capture the power features.

3.3.3. Power feature parameters

The power factor is a recognizable feature parameter, but present household appliance products are increasingly complex. There are a considerable number of non-linear loads, and it is difficult to calculate the power factor of non-linear loads. However, the electric appliance recognition method in this study took the unique power features of electric appliances as the basis for calculation, and was intended to get as diverse as possible unique power features as the reference for determination. This study designed a data structure to store power features, as shown in Table 1.

Entropy: Information entropy is used not only to weigh the expectation value of emergence of a random variable, but also to express the “scrambling degree” of information.

In this study, the scope where the converted current value would occur was stratified in proportion, and the probability of occurrence of current information distributed in each data layer was determined according to the statistical data. The operation of entropy was performed to find the scrambling degree of current information distribution. Let the instantaneous current value X be a random variable, and its value domain be $X1, \ldots, Xn$, then the entropy value H is defined as:

$$H(X) = E(I(X)) \tag{18}$$

where E is the expectation value function, $I(X)$ is the self-information of X, and $I(X)$ itself is a random variable. Let p represent the probability mass function of X, the entropy formula can be written as:

$$H(X) = \sum_{i=1}^{n} p(x_i) I(x_i) = -\sum_{i=1}^{n} p(x_i) \log p(x_i) \tag{19}$$

max_count and *min_count*: Due to the complex features of present electric appliances, it is more difficult to calculate the power factor. This study took the signal triggered by the rising edge of the voltage square wave as a benchmark, and the time difference between the maximum current value and minimum current value as a basis for the offset of voltage and current.

3.4. Middleware layer-recognition process

After the above power features are available, they are transferred into the Recognition Process layer for recognition services. However, complex waveforms generated by non-linear load electric appliances are still unable to reach a higher recognition rate after the above-mentioned features are captured, so this study classified them using SVM/GMM hybrid classifier, its process was shown in Fig. 5. The system established a SVM classification model of their power parameters, and simultaneously classified their current waveforms for GMM training and found out the probability of their Gaussian waveform combination, followed by the recognition service through two types of training data and SVM classifier.

3.4.1. GMM model

This study carried out GMM training of one cycle of the current waveform after fuzzy processing. In order to simplify the discussion, it is assumed that the covariance matrix of each Gaussian density function could be expressed as follows:

$$\sum_{f} = \sigma_j^2 I = \sigma_j^2 \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 1 \end{bmatrix}, \quad j = 1, 2, \ldots, N \tag{20}$$

Here, the Gaussian density function could be expressed as follows:

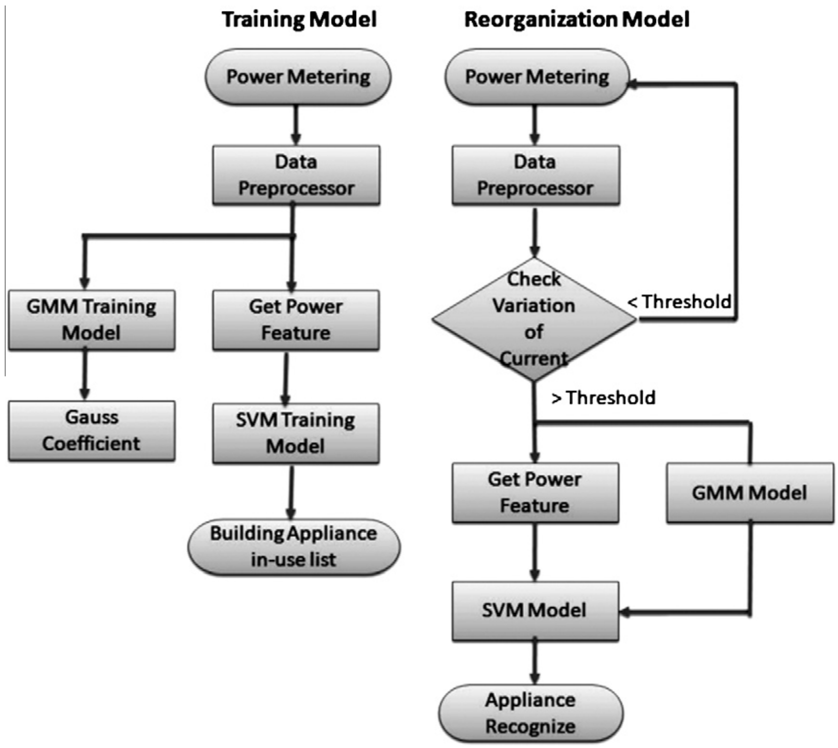

Fig. 5. Flowchart of electric appliance recognition.

$$g(x;\mu,\sigma) = (2\pi)^{-d/2}\sigma^{-d}exp\left[-\frac{(x-\mu)^T(x-\mu)}{2\sigma^2}\right] \tag{21}$$

where the parameters of $g(x)$ are $\theta = [\alpha_1, \alpha_2, \alpha_n, \mu_1, \mu_2, \mu_n, \sigma_1^2, \sigma_2^2, \sigma_n^2]$. In order to solve the best θ value, this study searched through Maximum Likelihood Estimation (MLE) and respective differential coefficient of μ_j and σ_j to obtain:

$$\mu_j = \frac{\sum_{i=1}^N \beta_j(x_i)x_i}{\sum_{i=1}^N \beta_j(x_i)} \tag{22}$$

$$\sigma_j^2 = \frac{1}{d}\frac{\sum_{i=1}^N \beta_j(x_i)(x_i-\mu_j)^T(x_i-\mu_j)}{\sum_{i=1}^N \beta_j(x_i)} \tag{23}$$

In addition, differential coefficient of α_j are required, and α_j as required to satisfy the conditions that the sum of Eq. (15) is 1. The following formula can be obtained through calculation after introducing Lagrange multiplier:

$$\alpha_j = \frac{1}{n}\sum_{i=1}^n \beta_j(x_i) \tag{24}$$

where $\beta_j(x)$ is called the post probability [23,6].

$$\beta_j(x) = \frac{\alpha_j g\left(x;\mu_j,\sigma_j^2\right)}{\alpha_1 g\left(x;\mu_1,\sigma_1^2\right) + \alpha_2 g\left(x;\mu_2,\sigma_2^2\right) + \alpha_3 g\left(x;\mu_3,\sigma_3^2\right)} \tag{25}$$

The solution cannot be found by general method based on the above four formulae. EM algorithm process is used for iteration, and EM algorithm is a process to estimate incomplete data, including the E-step and M-step iteration. E-step is used to solve the expectation value, while M-step is used to solve MLE [31,29]:

$J(\theta) - J(\hat{\theta}) > Q(\theta)$ can be obtained by applying Jensen's inequality [25]. $Q(\theta) > 0$, then $J(\theta)$ is larger than $\hat{\theta}$. The more the number of iterations through confirmation, the more the lognormal probability tends to climb all the way or remain the same, thereby proving that the EM algorithm allows the GMM parameters to be gradually approach to the original data.

Initialization

(1) Initial parameter value θ
$\theta = [\alpha_1, \alpha_2, \alpha_3, \mu_1, \mu_2, \mu_3, \sigma_1^2, \sigma_2^2, \sigma_3^2]$

(2) Usually let $\alpha_1 = \alpha_2 = \alpha_3 = \frac{1}{3}$, and use K–means to calculate the cluster center point as the initial parameter values of μ_1, μ_2 and μ_3.

E–Step:
(1) Use θ to calculate $\beta_1(x_i), \beta_2(x_i)$ and $\beta_3(x_i)$, i=1~n.

(2) Calculate new $\widetilde{\mu_j} = \frac{\sum_{i=1}^{N} \beta_j(x_i) x_i}{\sum_{i=1}^{N} \beta_j(x_i)}$

(3) Calculate new $\widetilde{\sigma_j^2} = \frac{1}{d} \frac{\sum_{i=1}^{N} \beta_j(x_i)(x_i-\mu_j)^T(x_i-\mu_j)}{\sum_{i=1}^{N} \beta_j(x_i)}$

(4) Calculate new $\widetilde{\alpha_j} = \frac{1}{n} \sum_{i=1}^{n} \beta_j(x_i)$

M–Step:
(1) Let $\widetilde{\theta} = [\widetilde{\alpha_1}, \widetilde{\alpha_2}, \widetilde{\alpha_3}, \widetilde{\mu_1}, \widetilde{\mu_2}, \widetilde{\mu_3}, \widetilde{\sigma_1^2}, \widetilde{\sigma_2^2}, \widetilde{\sigma_3^2}]$, if $\left\| \theta - \widetilde{\theta} \right\|$ is less than the target tolerance value, then stop.

(2) Otherwise, let $\theta = \widetilde{\theta}$ and return to E–Step.

3.4.2. SVM model

The process of building the SVM classification model [15,4,37,32]can also be interpreted as the process in which the system first needs to learn the electric appliance. In this study, the household appliances were identified based on learning the power feature of electric appliance in families, so before operation and recognition of the whole system, it was necessary to first build a SVM classification model to be used in the follow-up recognition system. In the learning process, first the electric appliance to be tested was plugged in socket and switched on, and the state of electric appliance to be learned was selected and then metered using a smart meter. After the back end received the power information, pre-processing of raw power data was made, including the aforementioned extraction of a single-cycle waveform and fuzzy processing of the current waveform. On completion of the pre-processing, power feature in the waveform can be extracted, finally the learning file of electric appliances to be tested at present was established using the name, state and power features of that electric appliance, and a SVM classification model was established after handover to libsvm [2] for learning. All electric appliances to be learned in this study had completed this operation, so as to establish the SVM classification model for various electric appliances. But as a matter of fact, it is not enough to establish the SVM classification model of various electric appliances only, because many electric appliances have a variety of states. If these states are no longer sub-classified and are classified into the same category of the electric appliance, then electric appliances are unable to be recognized due to different waveforms caused by state changes. Hence, many categories must be additionally established for electric appliances with a number of different states, which have two categories:

- Different states of the same electric appliance are deemed as different categories.
- Variations of state switching of the same electric appliance are deemed as different categories.

If a fan with three speeds is taken as an example, then it is necessary to establish three state categories respectively as fast speed, intermediate speed and slow speed, plus switching from fast speed to low speed, from low speed to intermediate speed and from intermediate speed to fast speed in a total of six categories. The cause that different states must establish different categories is that the fan may be turned on in one of the three states, and only all the three SVM modules are set up, can the fan be identified. The cause that the variation of state switching must establish different categories is that the fan may be directly converted from one state to another state when in use. As can be seen from the above description, this study was designed for recognition through capturing the variation of current waveforms, so the variation was also required to establish a SVM classification module in order to facilitate identification. On completion of learning and establishing the SVM classification model and GMM model, the electric appliances are identified. First of all, the recognition system needs to establish a list of household appliances, shows whether they are in use at present, simultaneously receives the electric energy data of a smart meter for data processing, first takes out the RMS current value according to the processed data, and then constantly monitors whether the current changes. When the current changes and maintains a steady state, power features can be extracted and then identified through libsvm. Electric appliances with relatively higher probability of recognition are taken as the recognition results, finally recognized electric appliances are checked whether they are in the list. If there is a conflict, they will be handed over to the exception process for processing, otherwise, recognition will be continued.

4. System implementation and result analysis

This section shows the implemented system for multi-appliance recognition shown as Fig. 6. This study integrates a power meter and embedded platform, where the power meter can measure the current and voltage data of electric appliances, and convert the data into the required power features parameters, then transmit the data to computer for recognition. The multi-appliance was connected with extension cords for convenience.

The user interface, as shown in Fig. 7, displays the electric appliances in use, as well as their current values.

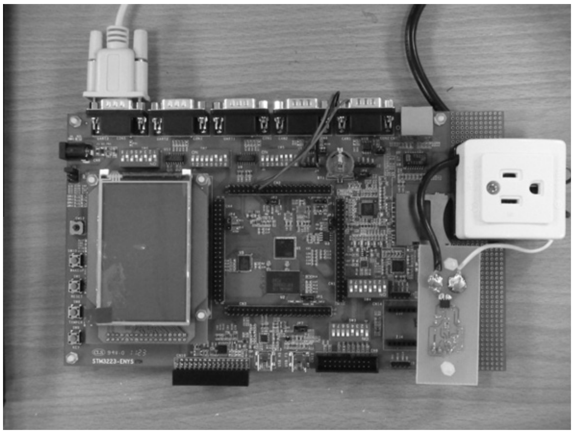

Fig. 6. The multi-appliance metering platform.

Fig. 7. The user interface.

4.1. Experimental hypothesis

In this study, the system implementation was established based on two hypotheses:

Hypothesis 1. This study hypothesized that two or more household appliances were not likely to simultaneously change (turn on, turn off, state change).

Hypothesis 2. This study hypothesized that each family had a clean environmental building conditions.

The cause for Hypothesis 1 is that if two electric appliances change at the same time, then the variation waveform obtained during the test in this study is an combined waveform comprising two electric appliances, which has never been previously established, hence cannot be identified as a consequence. While the cause for Hypothesis 2 is that a clean environment is required to establish the features of each electric appliance, so as to build a SVM model to avoid the impact of noise on recognition services.

4.2. Experimental environment

Due to the hardware limitation in this study, the microprocessor could not receive the induced voltage produced by high-wattage electric appliances, so the following four major categories of electric appliances were taken as the subject for determination.

- Resistive electric appliances
- Capacitive electric appliances
- Inductive electric appliances
- Non-linear load electric appliances

Among the four major categories in this study, five kinds of electric appliances of each category were used to test the recognition services. For example, notebook computers are representatives of non-linear load equipment, and hot melt guns belong to purely resistive electric appliances; fans belong to purely inductive electric appliances, Plug in – Light bulb (PL) lamps were representatives of capacitive electric appliances because its fluorescent lamp characteristics need constant charge and discharge through ballasts. Fuzzy waveform diagrams of these electric appliances are shown in Fig. 8.

4.3. Experimental procedures

The classifier used in this study was libsvm, which is an open source package, and is easy to start usage and modify, so it is used in this study. This study mainly used a PC-based Linux operating system, so the executable file names introduced below were all libsvm Linux version based. After libsvm was compiled under the Linux operating system, there were mainly two executable files, which were respectively svm-train and svm-predict. Due to the use of SVM in this study, each electric appliance and their states were classified and numbered, as shown in Table 2, in order to facilitate later comparison using libsvm.

On completion of numbering, it is necessary to first establish file formats supported by libsvm before handover to libsvm for learning. In this study, each electric appliance was sampled 30 times. First learn using the svm-train feature log files and output SVM classification model files, and the command is as follows:

```
$svm-train apmodel apmodel.model
```

where apmodel is a record document, and apmodel.model is the classification model after learning the electric appliance characteristics by libsvm through svm-train. After SVM classification model files are established, the main program designed in the system can be turned on, so as to begin analyzing and predicting current using svm-predict.

4.4. Experimental results and analysis

4.4.1. Analytical studies of libsvm factors

For the use of libsvm, the parameters when establishing the classification module will decide the later recognition rate, so they need adjustment during classification. In addition to understanding the meaning of various parameters, the remaining is constantly trying to find a best parameter. When libsvm is learning data, *t*, *g* and *c* among the parameters used in svm-train have the greatest impact on the results. The options where t is the kernel function are as follows:

- 0–linear: uv
- 1–polynomial: $(\gamma * u\ \mathrm{v} + coef0^{d})$
- 2–radial basis function: $exp(-\gamma * |u - v|^{2})$
- 3–sigmoid: $\tanh\ (\gamma * u\mathrm{v} + coef0)$

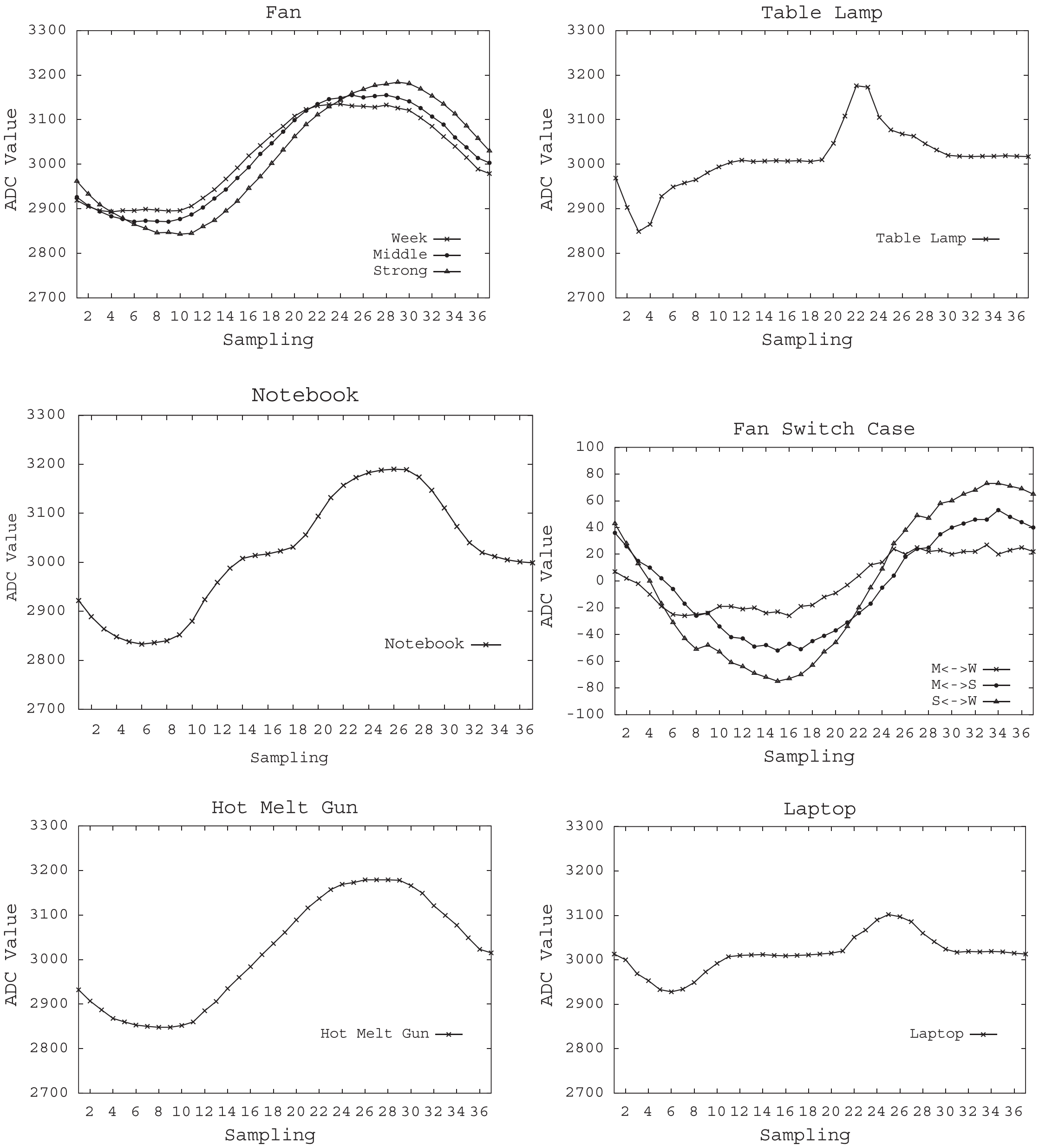

Fig. 8. The waveform of different categories.

In addition, *g* is the parameter gamma of the kernel function 1–3, *d* is degree in kernel function, and *c* is the penalty parameter. A higher value indicates that the determination is more accurate, but the operation will also be long and the problems will be overfit. In order to determine the kernel function most suitable for this study, this study only took half of the training data to be used as the training data, the other half as test data for testing. The best kernel function was determined, and the results were shown in Table 3.

As can be seen from Table 3, among the data of the electric appliance characteristics, the polynomial kernel function is the most accurate. After the best kernel function is known, it is necessary to find the best values of *c* and *g*. libsvm provides a set of optimized program grid.py, which can find the best *s* and *g* for learning. The command is as follows:

```
$grid.py t 1 apmodel
```

The accuracy rate can be obtained when $c = 32.0$ and $g = 0.0001220703125$, it reaches as high as 97.2% and is higher than the preset accuracy rate of 90.72% when $c = 1$, $g = 1$.

Table 2
The testing appliances list.

N	Appliance	Number	Class
1	Fan	1	Inductance
2	Fan switch	1	Inductance
3	Motor	1	Inductance
4	Motor state	1	Inductance
5	Adapter	2	Inductance
6	LCD	1	Capacitance
7	Charger	1	Capacitance
8	Fluorescent lamp	2	Capacitance
9	Lamp switch	1	Capacitance
10	Touch pad	1	Capacitance
11	Heating rods	1	Resistance
12	Hot melt gun	2	Resistance
13	Heater	1	Resistance
14	Oven	1	Resistance
15	Electric spoon	1	Resistance
16	DVD player	1	Non-linear load
17	Power supply	1	Non-linear load
18	Compressor	1	Non-linear load
19	Rectifier	1	Non-linear load
20	Computer	1	Non-linear load

Table 3
The accuracy of kernel function.

Kernal function	Linear	Polynomial	Radial basis function	Sigmoid
Accuracy	89.43%	90.72%	89.69%	11.34%

4.4.2. Recognition rate

In the previous section, the best classification model parameters are selected. In actual test, this study tested two to five categories using a random method, and the testing process was as follows:

1. Random selection of *N* categories. If the classification conflicts, for example, select the intermediate speed of a fan and switching from low speed to fast speed, then it will be reselected.
2. Random arrangement of N categories, set as the switching order, then switch on the electric appliances from the first one to the *N*th one in sequence, and then switch off them from the Nth one to the first one.
3. If there is a situation of misjudgment, then the recognition judgment of electric appliances fails. Otherwise, return to step 1 and repeated 20 times.

In order to compare with the recognition rate model, this study compared the recognition rate based on two classification models, one was Vector Quantization (VQ) [33,22], and the other was simply using SVM training modules for classification and comparison. The case success rate was defined as *S* and recognition rate was defined as *R*.

$$S = \frac{C_S}{\sum C} \tag{26}$$

$$R = \frac{N_S}{\sum N} \tag{27}$$

where C is testing case, C_S is successful recognition for one testing case, N is the number of testing appliances, and N_S is successful recognition number of appliances.

As can be seen from the results as Fig. 9, the classification model proposed in this study does have a higher recognition rate compared to other two models. During analysis of multi-appliances, due to the error caused by current separation, more categories are more likely to be misjudged. Two causes of the misjudgement are summarized: one is the electric appliance with similar waveforms. In this experiment, the hot melt guns and fans in intermediate speed are most significant, the misjudgement is caused by similar waveforms plus the separation error; the other is the fan state change. The difference between fan state changes is too small, but if the separation current threshold is lowered, noise can also be caused, or slight changes of other electric appliances lead to misjudgement. It can be noted that if a single SVM classifier is used, rapidly declining recognition rate of more electric appliances will be caused by their complex waveforms, thereby proving that the SVM/GMM classifier does have better recognition performance for multi-appliances and non-linear loads. Vector quantization model records several important positions of the samples in the vector space using discrete values (vectors), but does not show the distribution shapes and sizes of these samples in the space, so it is still not ideal.

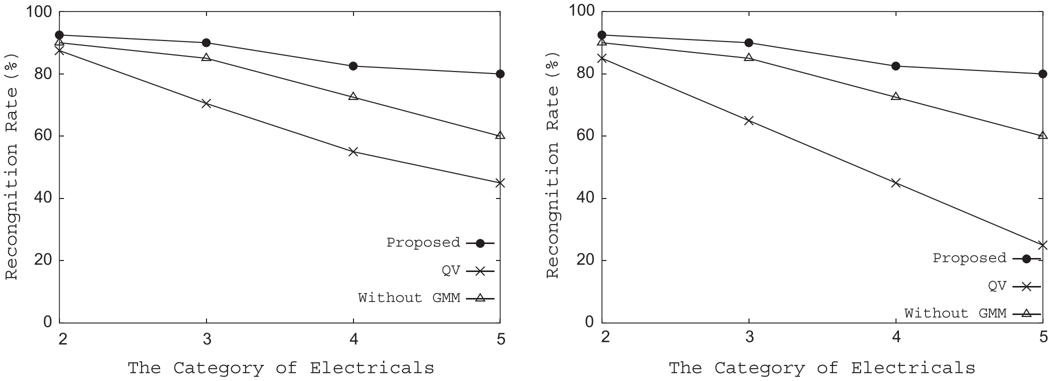

Fig. 9. (A) Recognition rate and (B) case success rate for different mechanism.

4.4.3. The impact of fuzzy degree on the recognition rate and time

In this paragraph, the impact of different fuzzy degrees on the recognition rate and recognition time will be tested. The fuzzy degree is defined as the number of cycles to be averaged. The more the cycles are taken, the higher the fuzzy degree is, and vice versa. The higher the fuzzy degree is, the more stable the waveform of intricate electric appliances obtained from fuzzy processing is, but the relatively longer the time of extracting the waveform obtained through one fuzzy process will be lengthened; on the contrary, the lower the fuzzy degree, the less stable the waveform obtained through fuzzy processing, but the shorter the time of extracting the waveform obtained through one fuzzy process. The unstable waveform will cause

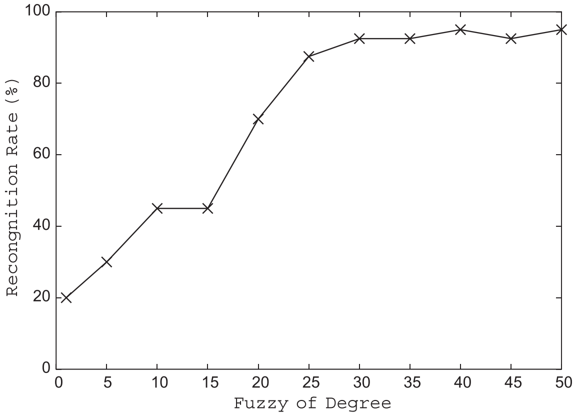

Fig. 10. Relationship between the fuzzy degree and recognition rate of the electric appliances.

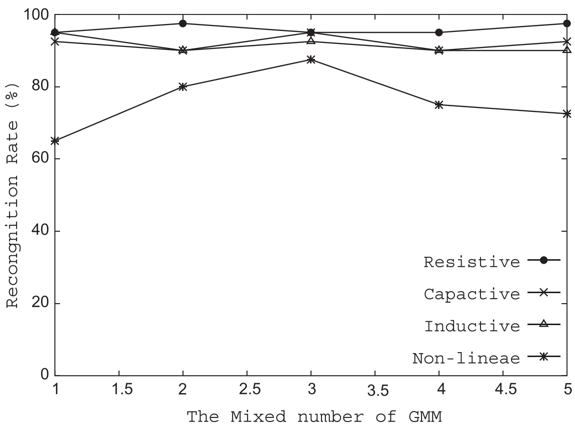

Fig. 11. Relationship between the GMM-based mixed number and recognition rate.

declining recognition rate. This study obtained the best value of time and recognition accuracy rate by randomly selecting three electric appliances and using different fuzzy degrees, and the results were shown in Fig. 10.

The fuzzy degree indicates the number of waveforms to be averaged. As can be seen from the results, when the fuzzy degree reaches 30, it has no effect on the recognition accuracy rate, so it can be concluded that the best fuzzy degree is 30.

4.4.4. The impact of GMM-based mixed number on the recognition rate

The GMM represents the probability-based description of current waveform, and is intended to discuss whether the model-based mixed number will affect the recognition rate in this section. The experiment in this study attempted 1, 2, 3, 4, 5 kinds of mixed numbers, as shown in the Fig. 11. Mix represents the mixed number.

There is an increase of the GMM-based mixed number that, on the contrary, makes the recognition rate decline. This is because the falling point distribution in the characteristic space is very concentrated, so only three Gaussian density functions can describe the distribution very well. Increase of the mixed number obtains counter productive results. Capacitive, resistive and inductive electric appliances have regular waveforms, and a single Gaussian module can obtain good recognition performance; non-linear load electric appliances have irregular waveforms, so more mixed numbers are required to obtain a better recognition rate.

5. Conclusions

A ubiquitous smart home must be capable of precisely understanding and manage every household appliance service, and multi-appliance recognition service becomes an indispensable basic work. This study designed a low-cost model capable of reading the original power information as well as simple data pre-processing, and transferring the power information to the back-end PC for processing using a development version of a microprocessor in combination with the voltage and current sensors. In addition to the basic meter design and in view of the difficulties that multi-appliances cannot be identified through a single smart meter, this study can separate power information of electric appliances from the total power by establishing a SVM/GMM classification model for electric appliances and combining with current analysis techniques, and then recognize electric appliances. The results showed that this hybrid classification model does have a higher recognition rate of multi-appliances and non-linear loads. In addition, present implementation done in this study was still limited by hardware, later the multiple frequency ADC for voltage frequency can be developed in compliance with the rate-related transport protocols and relevant processors enough to receive large voltage signals. Thus power-related information can be more precisely calculated, and the determination results must be more precise and accurate. In the future, the IoT, HEMS and other related application services will be designed and studied as a whole.

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