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An Intercommunication Home Energy Management System with Appliance Recognition in Home Network

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Abstract In present days there are wide varieties of household electric appliances along with different power consumption habits of consumers, making identifying electric appliances without presetting difficulty. This paper introduces smart appliance management system to recognize electric appliances in home networks, which uses sensing devices that measure current to calculate the power consumption of the appliances. The system will set the characteristics and categories of each electric appliance, and then uses the classifications of the electronic energy features in order to recognize different appliances. The system searches the cluster data while eliminating noise for recognition functionality and error detection mechanism or the electric appliances using the current clustering algorithm. Afterwards the recognition are used to build a control list of appliances on the platform to provide appliance intercommunication. Simultaneously, the household appliance automatic control services are integrated by the system to control appliances based on userspower consumption plans to realize a bidirectional monitoring services. In actual experiments, the proposed system achieves a recognition rate or 95% as well as successfully controls general household electric appliances in home network.

Keywords smart appliance management system · appliance recognition · home energy management

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1 Introduction

A smart grid introduces Information and Communication Technology (ICT) into the two-way communication between a power company and customers in a power distribution system to optimize power generation, power distribution system, and power consumption [1]. However, in recent years, the concept of the smart grid has extended to general families, and is known as a home grid, where the power consumption of household appliances is measured by a smart meter. The smart meter is the bottommost component used in general home grid for smart grid services. The recently promoted smart meters, such as Google Power Meter or Microsoft Hohm, can show the total household power consumption at present, but cannot show the power consumption of each household appliance ,to say nothing of information about the household appliances that are consuming power [2–4]. As a result, users cannot further improve their power consumption habits or avoid the use of so-called high-power electric appliances. A system that can accurately detect and recognize electric appliances is a subject worthy of study. The paper is extended version of the paper A Smart Appliance Management System with Current Clustering Algorithm in Home Network [5] accepted for GreenNets 2011. This study proposed an intercommunication Home Energy Management System (HEMS) with current clustering algorithm in home network, which can measure the household power consumption through a current sensor, transmit the data back to the HEMS, recognize each electric appliance, and then determine whether it is working normally according to its staged power consumption and various electronic energy features caused by its power sine wave intervals, so as to avoid overloading problems arising from old or faulty electrical appliances. However, older or large numbers of household appliances and wireless transmission will cause power noise problems, which would result in the inaccurate recognition of electric appliances. Therefore, in this study, a set of current clustering algorithm was presented to determine the cluster value and cluster potential for measured current information. When an abnormal value arises from the system, it is identified as noise or an abnormal state according to the clustering characteristics. In Section 2, we introduce the smart meter and review related proposals in the area of appliance recognition on HEMS. In Section 3, we introduce the proposed system and describe system structure and module design. The implementation of the experimental platform and Experiments Analysis is given in Section 4. We conclude with Section 5.

2 Related Work

This section briefly provides an outline of a smart meter and relevant studies of electric appliance recognition, which can help readers outside the specialty of the article to understand the system structure.

2.1 Smart Meter

The smart meter is an advanced gauging instrument. According to its design concepts, besides measuring power consumption, some can identify electric appliances and communicate with other electronic equipments. Some smart meters are mounted with displays to show current power consumption and corresponding price. One type of smart meter has extended sockets [6–8], meaning that it has one or multiple sockets and contains voltage and current sensors. Cho et al. [6] designed a Smart Multi-Power Tap (SMTP) for extension-line smart sockets to obtain the position information of a smart socket, thus, preparing for subsequent situations of sensor systems. Park et al. [8] predicted and reduced the amount of data for a smart meter in order to reduce the load of data transmission, and verified the accuracy rate. Yingcong et al. [9] designed and analyzed measured information for a low-cost logic circuit with a microprocessor to read electronic energy information, and switch off standby electric appliances to save energy.

2.2 Appliance Recognition on HEMS

The HEMS is combined with a smart meter and related technologies for adjusting home power to save energy which can be integrated into a Smart Grid [10–13]. Jahn et al. [14] managed and controlled electric energy information of electrical appliances using Hydra Middleware, that allow users to identify electric appliances and obtain power utilization information directly from home through intelligent mobile phones with image recognition. Son [15] used PLC (Power Line Communication) to build HEMS, which used a smart meter to monitor the measured power consumption and notifies users through a network for remote monitoring, as well as enabling power utilization planning according to user demands and power rates. The present HEMS systems has a defect in household appliance control, since it is difficult to position every electric appliance being used and apply control to specified appliances. Ito et al. [16] designed special electric energy parameters to analyze voltage and current wave signals, indicated that, realize effective recognition and instance some simpler calculated parameters. Ruzzelli et al. [17] build a RECAP (RECognition of electrical Appliances and Profileing in real-time) system that identifies specific electric appliances by creating electronic energy feature parameters that were stored in the database and a neural algorithm was used for recognition and displaying on the user interface. Akbar et al. [18] used Fast Fouriere Transform to convert the time-domain current wave forms to frequency domain signals to obtain special electric parameters for ease of recognition.

3 Smart Appliance Management System

This section introduces the overall system and expatiates on the various function modules. Then the power clustering was described how to reduce the noise and error. Finally, the appliance recognition was presented.

3.1 System Overview

Figure 1 is the system scenario consisting of smart meters, control modules, and HEMS. The smart meter transfers the electric energy information to HEMS through the wireless transmission interface and measures power consumption of electric appliances. HEMS manages the energy within household appliances, integrates and transfers the power consumption information of all smart meters to Automatic Meter Reading (ARM) or Home Information Display (HID) in a home network for display purposes. HEMS also recognizes appliance using Electric Energy Feature Parameters (EEFP) captured from the power information. But large numbers of household appliances and wireless transmission causes power noise problems which will affect the EEFP. Abnormal error detection rates that are cause by rates can be reduced using current clustering.

3.2 Smart Meter Design

In this study, a smart meter measured the power consumption of the household appliances, which mainly composed of an energy metering integrated circuit (IC), voltage and current sampling circuits, and a microprocessor, to obtain voltage and current signals. This study uses the energy metering ID ADE7763 chip produced by Analog Devices which can be connect with a variety of power measurement circuits, including current converter circuit and low resistance voltage divider circuit. The metering system start to take 42 simples in a period when voltage value equal 0 and raise state. After using an energy metering IC to measure the power information, the microprocessor with communication interface for external transmission receives the results, allowing administrators to understand the measurement results remotely, monitor household power consumption systems, or carry out additional commands to the microprocessor. The interface communication structure is shown in Fig. 2. The micro-controller unit (MCU) controls the relays after powering-on, and sockets control whether to power on. Current values from a current sensor will be converted to digital signals through a Digital-to-Analog Converter (DAC) if needed. The digital signals are sent to the MCU and then to load side. The MCU can use ZigBee sensors to transmit data or commands to central control center [19–21], or record data in the electrically-erasable programmable read-only-memory (EEPROM).

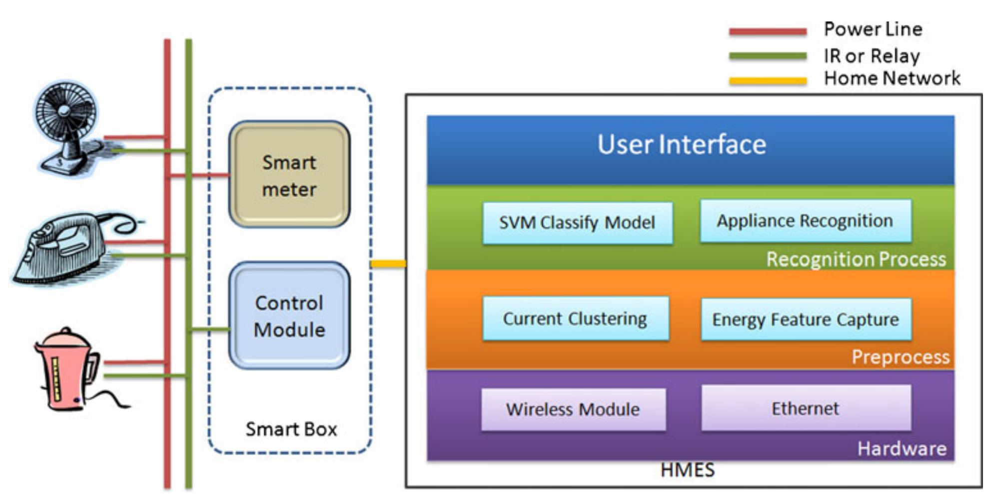
3.3 Definition of Electric Energy Feature Parameters

This electric appliance recognition method of this study bases its calculations on the unique EEFP, and multiple and special energy features tend to be obtained as reference for identification. Hence this study designs a data structure to store EEFP, and each parameter are described as below:

- **State**: Number corresponding to the name and state of the electric appliance.
- **Max**: Maximum current.
- **Min**: Minimum current.
- **RMS**: The root mean square current.
  The current signal is obtained through the root mean square (RMS) operation, and its expression is shown in Eq. 1.

$$I_{RMS} = \sqrt{\frac{\int_0^T I^2(t)dt}{T}} \quad (1)$$

Fig. 1 The system scenario of appliance management



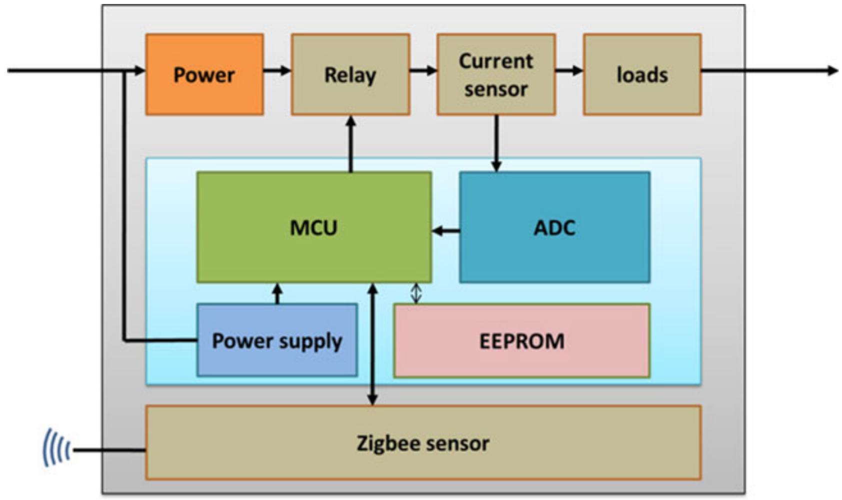


Fig. 2 The design of smart meter

Due to the time signal sampling, Eq. 1 must be converted to Eq. 2.

$$I_{RMS} = \sqrt{\frac{\sum_{j=1}^{N} I^2(j)}{N}} \tag{2}$$

The process of Eq. 2 in the hardware is as follows: after the integration of the digital signal, the multiplier obtains the square of the current signal, and accumulates the signal through a low pass filter. The RMS current value can then be obtained from the square root operation.

- **Avg**: Average current.
- **Power**: actual power consumption
  Here the instantaneous power consumption can be calculated as per Eq. 3.

$$p(t) = v(t) \times i(t) \tag{3}$$

The instantaneous voltage v(t) and instantaneous current i(t) in Eq. 3 can be expressed as Eq. 4.

$$v(t) = \sqrt{2} \times V \sin(\omega t) \tag{4}$$

$$i(t) = \sqrt{2} \times I \sin(\omega t) \tag{5}$$

V and I in Eqs. 4 and 5 are respectively the RMS values of the voltage and current, so Eq. 3 can be expressed as Eq. 6.

$$p(t) = VI - VIcos(2\omega t) \tag{6}$$

For the sinusoidal waveform, the actual power can be obtained through the instantaneous power, as shown in Eq. 7.

$$P = \frac{1}{nT} \times \int_0^{nT} p(t)dt = VI \tag{7}$$

- **Ptoa**: Self-determined parameter, ratio of peak value to average value.
- **Entropy**: Information entropy measures the expected value of the occurrence of a random variable, and expresses the disorder of information. The information entropy is calculated in the hope of knowing the disorder of distribution of current information. If the instant current value X is a random variable, its range is $\{X_1, \cdots, X_n\}$, the entropy value H is defined as:

$$H(X) = E(I(X)) \tag{8}$$

E is the expected value function, I(X) is the self-information of X, and I(X) is a random variable. If p represents the probability mass function of X, the equation of entropy can be expressed as:

$$H(X) = \sum_{i=1}^{n} p(x_i)I(x_i) = -\sum_{i=1}^{n} p(x_i) \log p(x_i) \tag{9}$$

- **Max-count and Min-count**: The power factor is difficult to calculate due to the complexity of current electric appliances, this study determines the difference between maximum and minimum current, as based on the signal triggered by the voltage square wave rising edge, as the basis of voltage and current offset.

3.4 Recognition Transmission Packet Unit

This section describes the recognition transmission packet unit format and corresponding function. The smart meter transfers information through PLC or wireless networks for HEMS for recognition of the transmission packet. The packet can be seen in Fig. 3, the start of the frame is represented by the start bit. The head block defines the signal sending device (Smart Meter) position and signal receiving device (HEMS) position, and contains the initiator local position of 4bits, the destination local position of 4bits, End of Message 1bit (EOM), and Acknowledge (ACK). The data block represents 8 bits of information data, EOM, and ACK, including explanatory information and the required electric energy feature parameters.

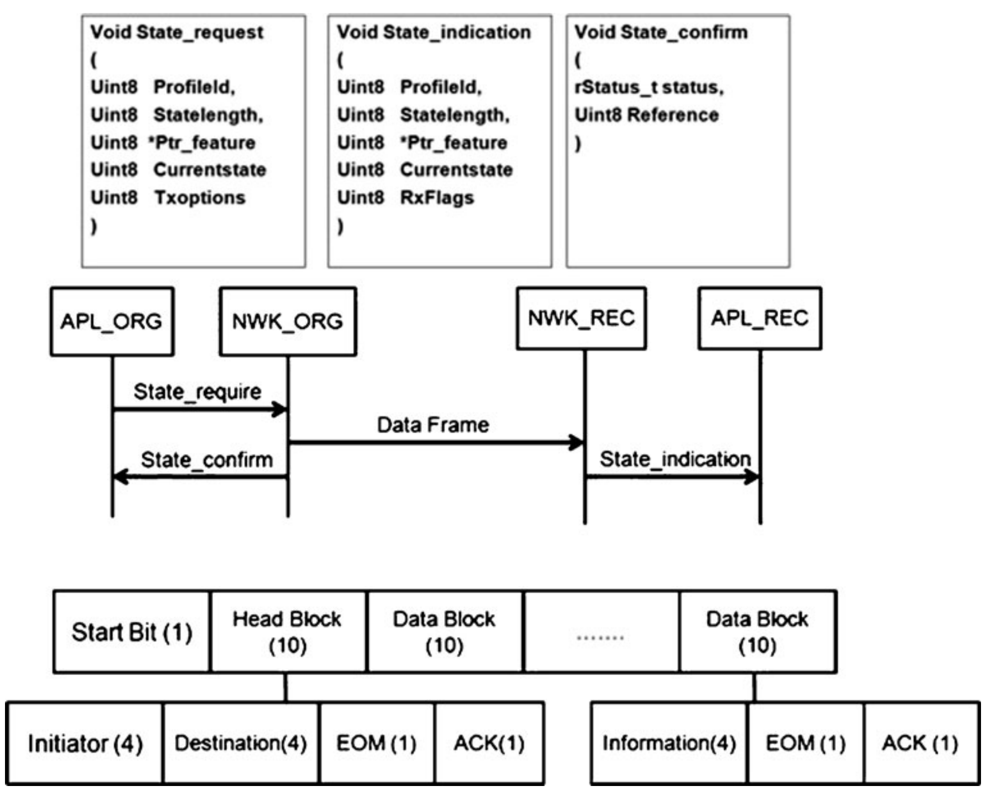
In the transmission function, the State_request function is an application layer function to transmit data by requesting from the network layer. State length is the length of data to be transferred; Ptr_feature is the structure pointer of the status data, (the detailed status data structure will be shown in the next section); Currentstate is current state number; Txoptions is option of the transmission mode, including whether to broadcast or not, transmission address, and security mechanism. State_indication is the network layer function that transfers to the target application layer, other than transmitted parameters; there are transmission quality parameters and transmission flags to identify the accuracy of the transmission. State_confirm is the network layer signal sent back to the application layer, indicating whether if the transfer of status data is successful.

3.5 Power Clustering

When the voltage and current information is received, the voltage information must be normalized to 110 V first. During wireless transmission, the incorrect values can be caused by transmission interferences and noise effect like those shown in Fig. 4a, affecting identification accuracy of electric appliances. For electric appliances under different operating states, conversions between its current and phase angle will be shown as a clustering distribution, and the final clustering distribution will be within a fixed number of regions. Hence according to the traits mentioned, whether if the current stays within the same state can be determined by whether if the subsequent trace falls within the clustering range through clustering operations. If the value appears out of the clustering range, it must be differentiated as abnormal clustering values or instantaneous noise distribution. Using the current clustering algorithm, the identification rates of electric appliances can be effectively increased while reducing abnormal error rates caused by noise.

In this study, the subtractive clustering method [22] in the neural algorithm processes the power clustering characteristics. This method regards all data points as potential center points and select clustering standards according to the density of surrounding data points.

Fig. 3 The recognition packet format



The subtractive clustering method is independent of system dimension complexity, however is proportional to amount of data. Here, M_i is supposed to be the power group, and r_a is the influence distance of the clustering group center point and is a positive constant. The potential value P_i (Eq. 10) of the sampling point group Mi can be calculated, that represents the potential of this point becoming the clustering center point.

$$P_i = \sum_{j=1}^{n} \exp\left(-\frac{\left\| M_i - M_j \right\|^2}{\frac{r_a^2}{4}}\right) \tag{10}$$

After the calculation of all potential values P of the sampling points, the $M_{c1}$with the highest potential value is selected as the first clustering center point. The potential values of the other points then need to be modified, as per the following Eq. 11:

$$P_i = P_i - P_{C1} \exp\left(-\frac{\left\| M_i - M_j \right\|^2}{\frac{r_a^2}{4}}\right) \tag{11}$$

Where in, r_b is a value to be set to avoid getting too close to the last clustering center point M_{c1}. It needs to be greater than r_a, and its recommended value is 1.5 times that of r_a. After this process is repeated, the sampling point group M can be divided into subgroups, wherein, $\overline{\varepsilon}$ and $\underline{\varepsilon}$ are the upper and lower limit ratios of the potential value, which are defined in this study as 0.5 and 0.15, respectively. The clustering current value shows as Fig. 4b.

3.6 Appliance Recognition

The system set up a factor queue of the various eigenvalues in sequence. When data from new electric appliances are generated and a factor queue of ten values is prepared, they are input into the search system and results are obtained [23, 24]. Then the results are saved in the form of a database. Each element within the queue has the same structure which includes data for device model, device importance, device description, and power characteristics. The power characteristics has a structure comprised of above parameters. After, the retriever carries out corresponding database operations from the factor queue based on different factor properties. Different cases of factor operations are shown below:

EEEP operation: The same power characteristics in the data base are compared to eliminate elements with overly different power characteristics in the database. In this operation, a set of appliance-recognition algorithm is implemented, which is a modified algorithm based on the hierarchical match classify model. The assumption here is that the system regularly captures clustering EEEP of the electric appliance as the recognition standard, and the system will save the currently average current of the measured power clustering in the D1 time used as EEEP for the first recognition. The system compares EEEP of the power clustering with a organized list obtained through the learning as a comparison target. Electric quantity clustering data are identified with the M1 appliances if M1 appliances are successfully classified as being related, for the next parameter step by step, until a complete power model can be identified and the recognition algorithm is completed, as shown in Fig. 5.

Presume that there are M electric appliance models, therefore it would take $M * T_1(D_1)$ to find the electric power models with first parameters, respectively, and $T_2(D_1)$ to identify and compare the next classified

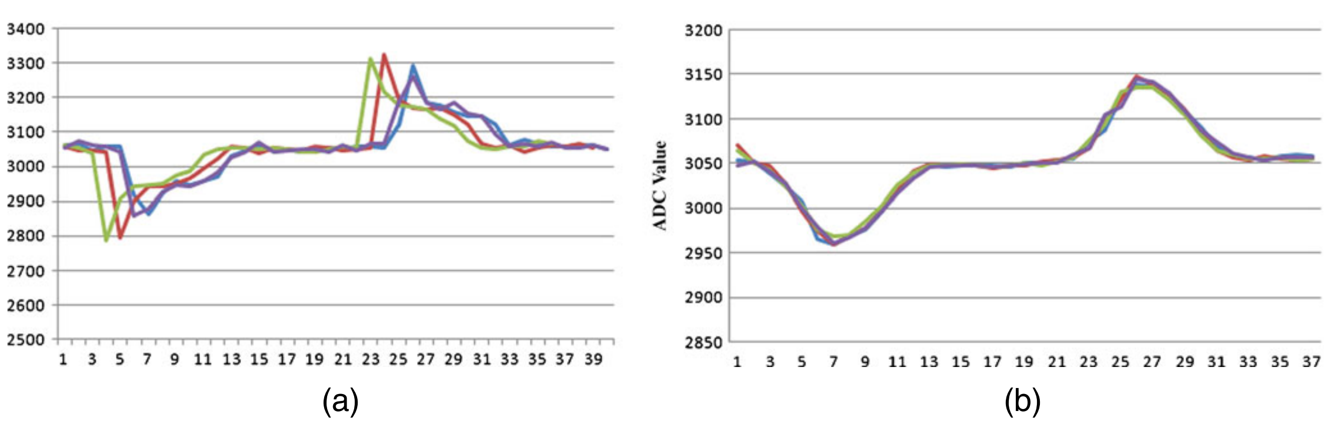


Fig. 4 The current waveform (**a**) in normal (**b**) with the power clustering algorithm

group. The total time consumption is as shown in Eq. 12:

$$T(M) = M * T_1(D_1) + M_1 * T_2(D_1) + M_1 M_2 * T_3(D_1) + M_1 M_2 * T_3(D_1) + \cdots + M_1 M_2 \cdots M_{N-1} * T_N(D_1) \quad (12)$$

By analogy, suppose each time the same amount of models is successfully identified, and that $M_1 = M2 = \cdots = n$, and $T_2 = T_3 = .. = T_N$ it is simplified as Eq. 13:

$$T(M) = M * T_1(D_1) + nT_2(D_1) * (n^m - 1)/n - 1 \quad (13)$$

An index array will be obtained when the operation that corresponds to each factor has been completed. The array records the element index in the database and continuously inputs the structural sequence of this device into the operating queue in sequence. The operating queue is shown in the system while electric appliance is being used, and device models may also be collected by continuous control commands from this operating queue.

4 System Implementation and Analysis

This section introduced the implemented system for the two-way recognition and control service, where the system can identify the electric appliances and their power consumptions, and various home appliances can be controlled through a user interface.

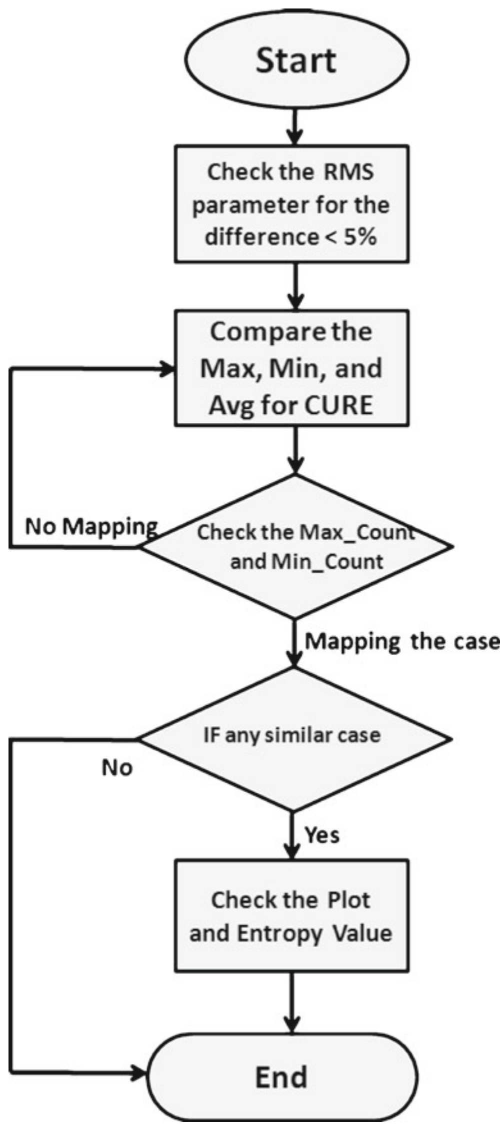


Fig. 5 Comparison programs of electric characteristics

4.1 The Smart box and User Interface

This study combines a smart meter that measures the current and voltage data of electric appliances and converts that data into required electric energy parameters, as shown in Fig. 6a, with a universal control module in order to form a smart box. Then it transfers through a wireless transmission interface to HEMS. The control services of current electric appliances are managed by the control module with IR and relay set control interface, which has a wireless transmission module for user control using wireless transmission mode. Figure 6b shows the result interface created in this study. The main goal of this study was to measure the power consumption of everyday household appliances and to be able to recognize electric appliances while permitting users to inquire related information remotely through Internet. The household temperature and humidity comprises the measure information received by sensors within surrounding environment that can display power, voltage, and current information at the same time. While content-awareness was defined as control automation within electric appliances due to environmental and historical user information. The definition of user-control was that all electric appliances which are self-controlled by users.

4.2 Experiments and Analysis

A total of 40 different household appliances were used in this study for experimental analysis. In the experiment, at most six electric appliances are started randomly in identification analysis, and there were 30 experiments in each stage.

4.2.1 Relation between recognition accuracy and recognition time

The training and recognition time was used to base the recognition accuracy study in this experiment, in which the rate was defined as:

$$S = \frac{N_S}{N_T} * 100\% \tag{14}$$

which N_S is number of successes for recognition and N_T is number of total test. When the training time was lacking (15 S), as can be seen from the experimental results, the sample establishment would not be complete, creating recognition difficulties. The recognition rate was still difficult to improve when the recognition time was lengthened, and if the time span was too short recognition difficulties would still occur. The best training time was seen from experimental results to be 60 s. The recognition accuracy was 92% when recognition time is 120 s, and the accuracy can reach as high as 95% (Fig. 7).

4.2.2 Relation between Recognition Accuracy and the Current Clustering Algorithm

The effect of the clustering algorithm on the system recognition rate analysis is done in experiment, 0. An experiment is tested with a training time of 60 s with a recognition time of 90, 120, 150, and 180 s respectively.

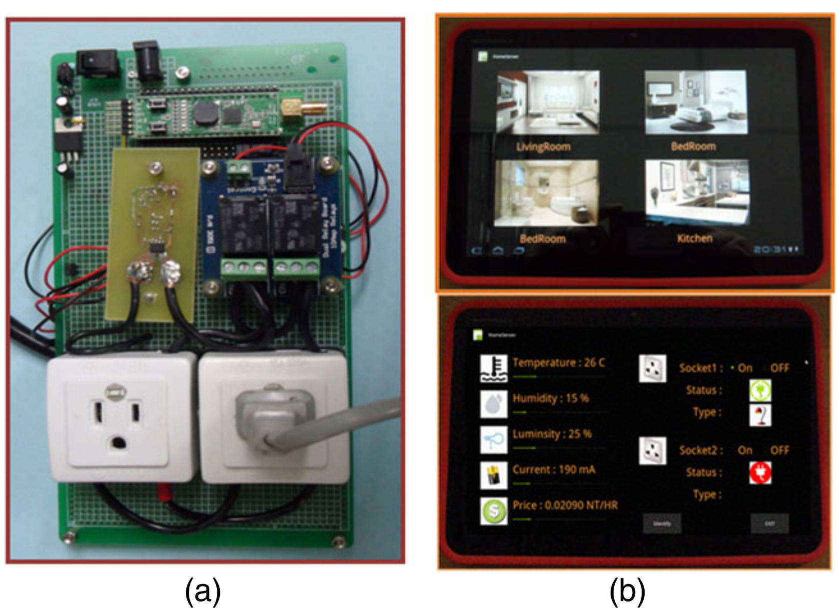


Fig. 6 The implement of (**a**) smart box included smart meter and universal control module and (**b**) the user interface

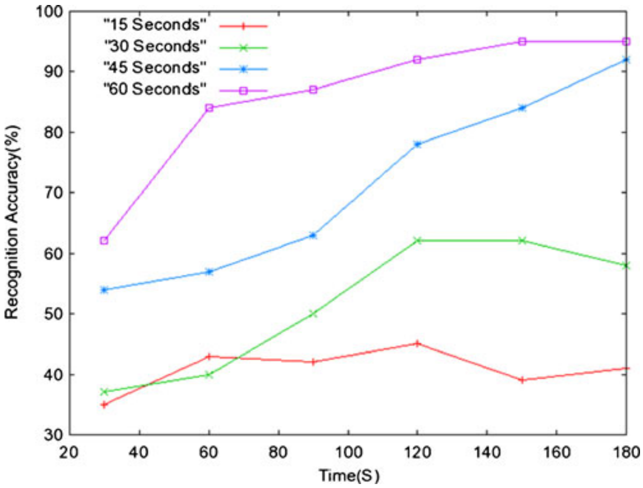


Fig. 7 Relation between recognition accuracy and recognition time

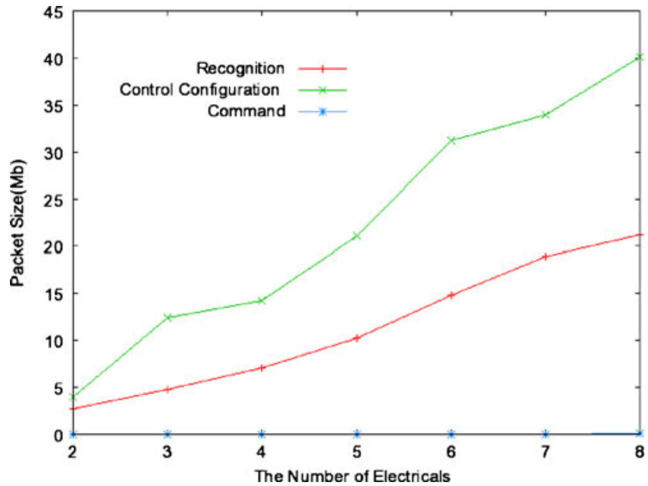


Fig. 9 The Packet Size for interconnecting service with different electrical

The following figure displays the experimental results, where it can be seen that the recognition accuracy was around 91.5% on average when the current clustering algorithm was used, and 79% on average without using the algorithm, due to noise effect on data collection, sampling and identification (Fig. 8).

4.2.3 The Traffic Packet Size of Communication Service

Figure 9 shows the results of traffic pack size between electrics and services. It mainly transmits to HEMS the current value for recognition service. Hence, between the packet size and number of electrical, the relationship is near-linear. Downside being, 15 s are needed to complete electrical information on recognition service, taking 3.1 Mb packet transmission capacities for every kind of electrical. For control configuration, the number of packets required to be transmitted is determined by the control commands and the states. Such as, the packet size for simple switching of the electrical is about 1.2 Mb, while TV has larger states and control commands but on control configuration requires 14 Mb in packet size. Commands are usually set at 10 bytes.

For example, a simple switching of the electrical packet size is about 1.2 Mb, but TV which has a large states and control commands required packet size requires 14 Mb on control configuration. Commands are fixed size at 10 bytes.

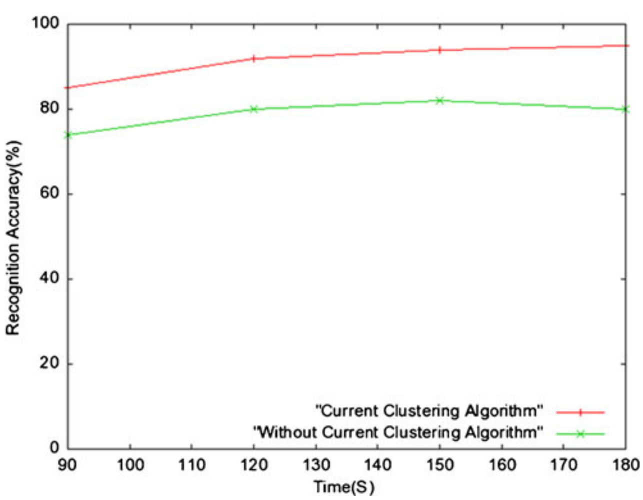


Fig. 8 Relation between recognition accuracy and the current clustering algorithm

4.2.4 The Effect of Feature Parameters

In order to provide appliance recognition service, this study proposes ten kinds of Electric Energy Feature Parameter, and in this section the efficiency of recognition will be analyzed. Within the scope of this research, 20 different appliances are chosen to be recognized which are classified into four categories: capacitance, inductance, resistance, and hybrid. Each category has influences towards appliances, and to explore the main influences some parameters are chosen in EEFP analysis. Figure 10 shows the results, max_count and min_count are mainly used to find the offsets of voltage and current of appliance that belongs to inductance, capacitance, or resistance categories that has the same power. The degree of data is commonly quantified using entropy. Hybrid type appliances can easily bring their currents to unstable states; hence the entropy

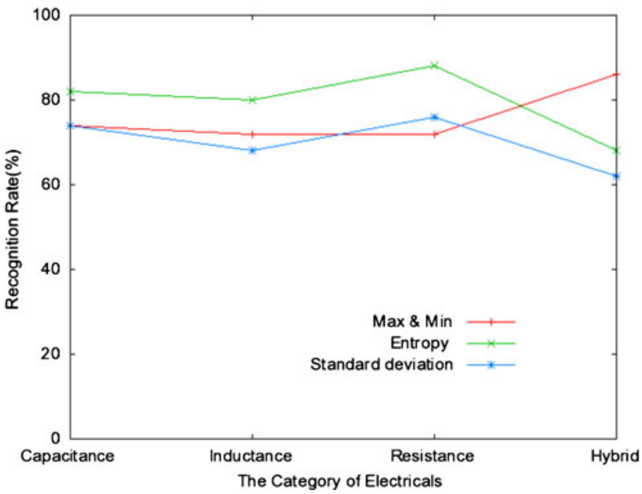


Fig. 10 The effect of feature parameters for recognition

is applied to the system to the identification between hybrid and other appliances. An important parameter for feature recognition is standard deviation, but if lacking the standard deviation the recognition accuracy decreases to 72%.

5 Conclusion

In this study, a smart appliance management system using current clustering algorithm in home network was presented. It uses a smart meter to measure power information and transmits data through wireless transmission back to the management platform. This enables users to know electric appliances currently being used and the power they consume by identifying the devices, and users can use the control interface to remotely control household appliances. With the aid of context information sensors and user habits it establishes content-aware service functions and can reach a recognition rate as high as 95% with the current clustering algorithm and the establishment of identification samples. In the future, research will be focused on creating planning control models matching with cloud services in order to expand the range of recognition and retrieving identification samples.

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