Nonintrusive Appliance Load Monitoring for Smart Homes: Recent Advances and Future Issues

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In recent years, as Cloud Computing and Internet of Things (IoT) technologies develop rapidly, smart home technology has entered a new stage: smart electric power usage, which will break the traditional extensive management situation for electric power loads, particularly under the background of an energy crisis. People will gradually gravitate towards the demands for more energy-related and intelligent services in smart home systems such as energy saving, improved understanding of electrical consumption and electrical safety of appliances. When the power consumption is considered by a smart grid, detailed electrical information of power loads will be perceived for demand management and optimization. To address these issues, measuring and monitoring the power of residential individual appliances are highly demanded by many applications.

Appliance load monitoring (ALM) has become a key application in modern society for a better understanding of the usage and consumption of appliances, and it can be used to develop an energy-aware operation and detect abnormal operations of appliances for electrical safety. Moreover, ALM can also be applied to indoor personnel monitoring and positioning, since the operating states of appliances (such as what appliance is running or what kind of state the appliance is working in) can reflect users' lifestyles. Fig. 1 shows the basis of an ALM system that can be used for the complete control and management of the ALM in a smart home.

Two approaches exist for ALM: intrusive appliance load monitoring (IALM) and nonintrusive appliance load monitoring (NIALM). In IALM, traditional appliances are modified with necessary interaction and control methods in their internal electrical installation. In contrast, NIALM addresses the "sensor problem" for electrical load monitoring by extracting information about individual loads from a few measurements at an easy-to-access centralized location [1]. Compared with IALM, NIALM has advantages such as lower cost, easier installation and maintenance for residential systems. Accordingly, NIALM is more promising for future smart home applications.

In this paper, the recent advance of NIALM methods and techniques of appliance recognition are discussed and analyzed, some existing problems are summarized and feasible solutions are proposed. Finally, future developments and extensive applications of NIALM are suggested.

Nonintrusive Appliance Load Monitoring Systems

Nonintrusive appliance load monitoring (NIALM) focuses on how to monitor residential appliances, especially their operating states, by observing the whole load current and voltage at the power entry point of the household. Fig. 2 shows the concept of the NIALM system. The bottom layer indicates data measurement of appliances at the power entry point according to a smart meter or other instruments. Almost all of them use a microcontroller and/or DSP based hardware [2], which are incorporated with Wi-Fi, ZigBee or PLC (Power Line Communication) to transmit data to the gateway of the house. The gateway layer provides communication protocols that enable the communication between the smart device and the server. In the server layer, the data of appliances are processed and recognized. The top layer explores potential applications and adds new services for users. In this scheme, the main issue is

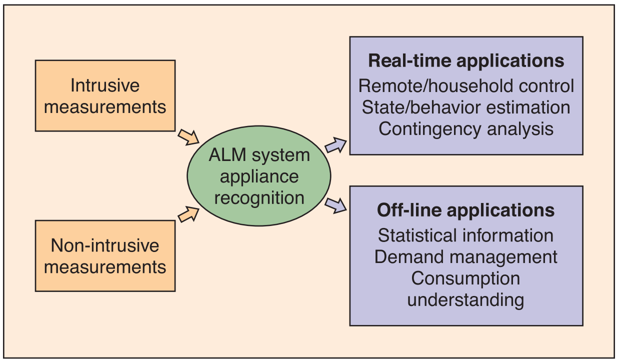

Fig. 1. Appliance recognition and possible associated applications in ALM system.

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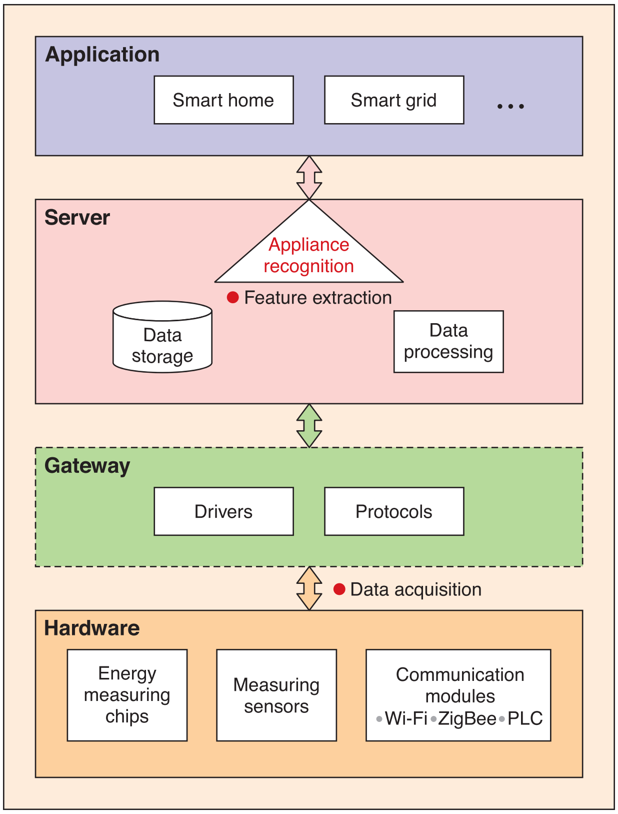

Fig. 2. NIALM system architecture.

how to distinguish individual appliances and recognize their operating states from a composite signal measured at the power entry point, so the appliance state recognition is very important for NIALM systems.

Recently, many NIALM methods have been proposed. Though different techniques are used in these methods, they have some common components: data acquisition, feature extraction and appliance recognition. The following sections review the methods in light of these three components.

Data Acquisition

Acquiring appliance data at the measurement point is the foundation of appliance recognition and it has an important impact on the final result. To the best of our knowledge, the main metrics include current, voltage and power. Among them, the current waveform in the time domain provides one of the most complete sets of information to describe load behavior, such as the instantaneous jump of the current amplitude when an appliance is turning on. Fig. 3 presents an example for the current data of three different appliances in the ON/OFF switching state. As shown in Fig. 3, the working status of appliances can easily be distinguished by the current data. For example, the humidifier has an instantaneous jump of the current amplitude when it is starting, and the LCD monitor has a sudden downward current change in the steady-working state.

Since harmonics higher than the 11^{th} harmonic are not usually used in appliances, the minimum sampling frequency of measurement sensors is about 1-2 KHZ (using Nyquist sampling for 50 Hz commercial power). The selection of sampling frequency should concern two issues: Low sampling frequency probably leads to omitting some important frequency components which may be the key functional characteristics of the appliances; and High sampling frequency results in a more detailed description of electrical changes of appliances at runtime that is beneficial to the classification and recognition. However, high sampling frequency increases the difficulties of data transmission and the cost of measurement sensors.

As the voltage remains nearly the same in any operation of an appliance, the power load can be reflected by the current data. In NIALM systems, the current data of all the appliances is measured as an overall metric. Thus, how to extract the features of an individual appliance is a critical issue for appliance recognition.

Feature Extraction

Power load is the intrinsic feature for each individual electrical appliance. Optimal features are representative for the appliance, which can be easily extracted from the composite signal at the measurement point. Moreover, good features can optimize the feature space, so as to reduce the complexity of storage and calculation in the process of appliance recognition.

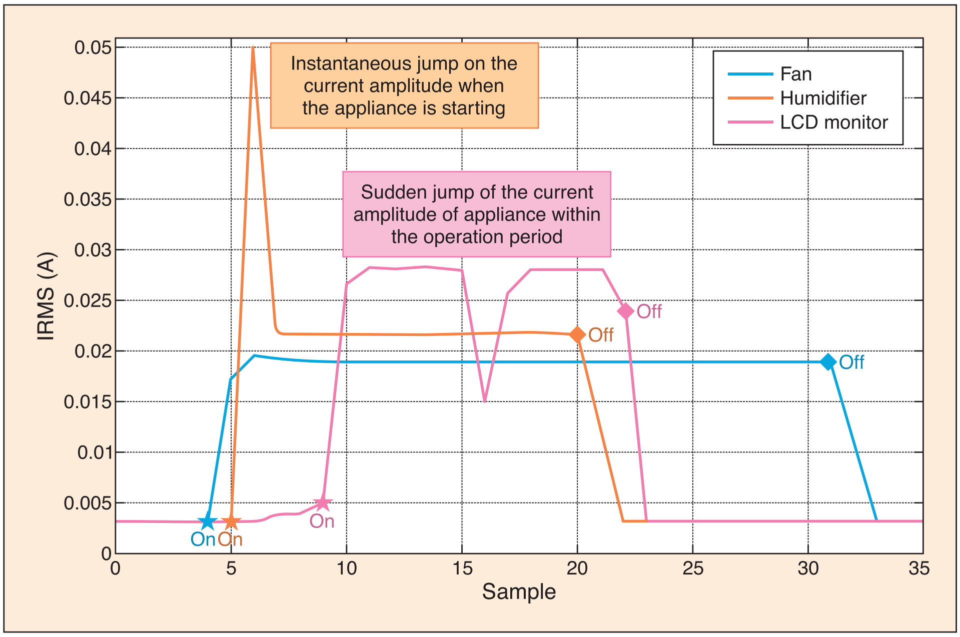

Fig. 3. The current data of three appliances in the ON/OFF switching state.

Therefore, extracting effective features is the most critical step for nonintrusive appliance loads recognition.

Feature extraction of appliance data is a problem of one-dimensional signal processing and analyzing, so there are two types of features to choose: time-based features and frequency-based features for appliance recognition.

Time-based features: In NIALM, common temporal features are extracted, such as the active power P, reactive power Q and current I, the waveforms of which are represented as measured time series, i.e., points of measured current values [3]. Among them, P and Q can be computed by:

$$P = \sum_{n=0}^{N} P_n = V_0 I_0 + \sum_{n=1}^{N} \frac{1}{2} V_n I_n \cos\theta_n \tag{1}$$

$$Q = \sum_{n=1}^{N} Q_n = \sum_{n=1}^{N} \frac{1}{2} V_n I_n \sin\theta_n . \tag{2}$$

Here, n is the harmonic order; V_0 and I_0 are average voltage and average current; V_n and I_n are the nth harmonic components of the voltage and current; and θ_n is the nth harmonic components of the phase difference between the voltage and current. Some appliances can be easily distinguished in the P-Q space depending on their resistive, capacitive and inductive characteristics [4]. However, they may not be recognized when they operate under the similar P and Q, since ambiguities on the changes in P and Q may exist. Generally, most research uses features of I and P to characterize the appliances, for instance, the root mean square, peak values, form factor, and crest factor of the current or power waveforms.

Other features like the components of electromagnetic interface (EMI) noises in a residential power line are analyzed in [5]. Some are based on counting the number of occurrences of events in a period of time, such as the number of transition between power intervals in [6] and the number of threshold crossing in [7]. Such features have been proved to be very effective in the recognition tasks.

Frequency-based features: Discrete Fourier Transformation plays a crucial role in analyzing frequency-based features for appliance recognition and can be described by:

$$X(k) = \sum_{n=0}^{N-1} x(n) \cdot W_N^{nk} \qquad (k = 0,1 \ldots N-1) \tag{3}$$

$$W_N = e^{-j\frac{2\pi}{N}} . \tag{4}$$

Here, $x(n)$ is the discrete digital signal sequence which derives from sampling with sampling frequency f_S; N is the number of frequency points, and it is generally equal to the length of the sequence; and W_N is the rotation factor.

In practice, Fast Fourier Transformation (FFT) based features are commonly used in appliance recognition, especially the harmonic features. Appliance harmonics as complementary features can alleviate the problem that appliances operate in similar P, Q or I. That is, features with harmonics analysis make the appliance load recognition more robust. Detailed analyses of harmonics using high sampling frequency are reported in [5].

Nevertheless, FFT is not suitable for non-periodic and non-stationary signals, since FFT is unable to provide the temporal or spatial characteristics of these signals. In these cases, the problem may be solved by STFT (Short-Time Fourier Transformation), which decomposes the time domain into countless small processes by way of adding a fixed window to make every small process approximately stationary. Thus, the moment when the frequency component appears can be confirmed. STFT can be expressed as:

$$STFT\{X(n)\}(m,w) = X(m,w) = \sum_{n=0}^{N-1} x(n) w(n-m) e^{-j\frac{2\pi kn}{N}} \tag{5}$$

where $w(m)$ is the window function. However, STFT is not suitable for time-varying non-stationary signals, because the width of the window in STFT cannot be changed; the time and frequency resolution cannot be ensured simultaneously for this kind of signal.

Since wavelet analysis allows the use of long time intervals for more precise low-frequency information and short regions for high-frequency information, the discrete wavelet transform (DWT), which allows simultaneous time and frequency localization, is quite suitable for NIALM systems where the signals are non-stationary [8].

Appliance Recognition

The real challenge, with respect to the appliance load monitoring for a smart home, is the appliance recognition according to the appliance features extracted from the composite loads at the power entry point. As shown in Table 1, appliance recognition is a classification issue since the operating state of different appliances or different states of one appliance can be deemed as disparate classes, and each class contains its own unique profile or features. However, the features are merged together at the power entry point when more than one appliance is running, so it is necessary to decompose the total features down to the individual appliance level. Most research adopts the solution of appliance event detection for load decomposition, because appliances are operated one by one (users will not manipulate multiple appliances at the same time).

Fig. 4 shows the structure of appliance event detection based load decomposition. The event detection module will detect the change of operating state when there is an actual appliance being operated, and the event recorder will record the time. Using the appliance-feature database after feature extraction, what appliance is being operated and what kind of state the appliance is in will be recognized according to recognition algorithms. Based on the tracking results, the operation pattern and energy consumption of each appliance can also be estimated.

Before recognition, a feature database should be established. Database creation is a very important part of the data mining process. An efficient database can greatly enhance the usability of a recognition system. At present, some public databases are available. Dedicated to appliance recognition, the Tracebase database contains more than a thousand electrical appliance features, recorded from 122 appliances spread into

Table 1 – Classification of the state of five appliances									
Class	**Fan**	**Class**	**Recirculation Fan**	**Class**	**Bulb**	**Class**	**Monitor**	**Class**	**Notebook**
1	OFF	4	OFF	8	OFF	10	OFF	12	OFF
2	Weak	5	Weak	9	ON	11	ON	13	FP
3	Strength	6	Medium					14	Power-Saving
		7	Strength						

31 categories; the ACS-F1 database in [9] contains 200 appliances consumption features recorded from 100 appliances of different brands and models spread into 10 categories.

Several methods may be applied to complete the recognition, including Euclidean distance, correlation analysis and machine earning.

Euclidean distance: Euclidean distance is a supervised based approach. When an unknown appliance is running, its features can be extracted and used to compute the Euclidean distance with each pre-stored feature vector in the feature database. Then it can be determined to which class it belongs, according to the nearest distance.

Euclidean distance is the most elementary part of distance measurement, as well as the basis of implementing multiple distance algorithms. If there are two finite data sets in a p-dimensional (p is the dimension of the features vector) Euclidean space, and

$$X = \{x\_1, x\_2, \ldots, x\_n\} \subset R^p \quad (6)$$

$$Y = \{y\_1, y\_2, \ldots, y\_n\} \subset R^p. \quad (7)$$

The equation of the Euclidean distance is defined as:

$$dist(X,Y) = | X - Y | = \sqrt{(x\_1 - y\_1)^2 + (x\_2 - y\_2)^2 + \ldots + (x\_n - y\_n)^2} \quad (8)$$

As the Euclidean distance does not involve the time axis, the displacement and noise will result in errors in system recognition, so it is inapplicable to accurate appliance recognition.

Correlation analysis: Correlation analysis is also supervised which is a waveform recognition approach. Here, the waveform is the unique identifier or feature of each appliance. When an unknown appliance is running, its waveform can be obtained at the measurement point and sent for correlation analysis. Then, the class with the largest correlation is selected. The correlation can be computed by:

$$R_{xy}(\tau) = \int_{-\infty}^{+\infty} x(t)y(t-\tau)dt \quad (9)$$

where τ is the time difference of x, y signal and the value of $R_{xy}(\tau)$ is the correlation coefficient.

Machine learning: Machine learning can generate classifiers automatically which can be directly used to classify the extracted features in the appliance recognition system. Thus, there is no need to do any comparison with the feature database. In the classifier training stage, the feature database is divided into training and testing sets for the classifier. The classifier will be trained by the training data via several machine learning algorithms, and the test data will be discriminated by the classifier in various target clusters. Since the choice of features has a major influence on the pattern separating in the feature space, the features have a significant impact on the performance of classifiers.

In this section, we provide more details on the structure of the NIALM system and conclude the methods to realize non-intrusive appliance load monitoring from three aspects. As aforementioned, appliance load monitoring can be ascribed to appliance state recognition. Therefore, the performance of an NIALM system depends on the accuracy of recognition, that is to say, the higher the accuracy rate, the better the performance.

Recent Advances and Future Issues

The first works on NIALM were reported by Hart in [8], who proposed a five-step load recognition method applied on a 2-D $\Delta P - \Delta Q$ feature plane. The method had been tested in different fields with excellent results in the early research.

In [10], an NIALM system that combines conventional Particle-swarm-optimization (PSO) with well-known back propagation ANNs (BP-ANNs) to identify load operation combinations of electric appliances was developed. Signatures P and Q are the input variables of the BP-ANNs, and it is assumed that P and Q of appliances are different. The study conducted electromagnetic transient program (EMTP) simulations and on-site load measurements to verify the performance regarding the training accuracy and generalization capability of the NILM system. In this proposal, the PSO works well to optimize the weight coefficients of the BP-ANNs, so that the performance of the BP-ANNs is improved.

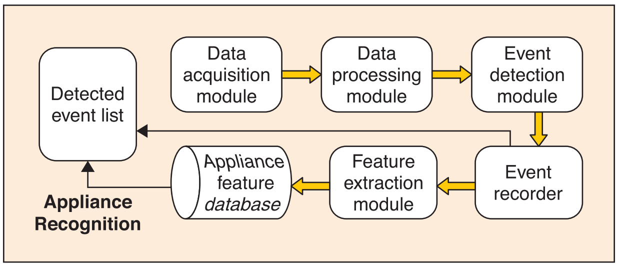

Fig. 4. Structure of load decomposition based on event detection.

Fan	Recirculation fan	Bulb	Monitor	Notebook
OFF	OFF	OFF	OFF	OFF
Weak	Weak	ON	ON	FP
Strength	Medium			Power-saving
	Strength			

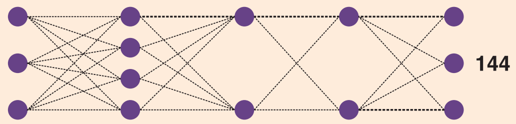

Fig. 5. The state combination of five appliances.

Wang, et al. created a database mechanism, an appliance recognition classification, and a waveform recognition method to solve the large data volume problem in a current appliance recognition system [11]. The experiment in the research is different from the research environment of other appliance recognition systems because it considered parallel multi-appliances recognition and the general user's habit of using power. For the appliance recognition process, as shown in Fig. 5, Wang, et al. proposed a current information combination mechanism. By implementing this mechanism, and providing that one type of electric appliance is learned in the learning process, the mechanism can automatically determine all combinations. Therefore, the appliance features of all states can be rapidly obtained in a short time. However, the NIALM system proposed in [11] needs to learn all of the possible on/off operation combinations among the appliances. When the number of appliances increases, the combinations of on/off states increase exponentially. As a result, the training patterns also increase exponentially.

Lin, et al. proposed an improved time-frequency analysis-based NIALM method [12]. The method incorporated a multi-resolution S-transform-based feature extraction scheme with a modified 0-1 multidimensional knapsack algorithm-based load recognition approach to recognize individual household appliances that may either be energized simultaneously or be recognized under similar real power consumption. For the appliance load recognition process, an ant colony optimization algorithm was employed to perform combinatorial searches that are formulated as a modified 0-1 multidimensional knapsack problem. As a result, the improved NIALM strategy was confirmed to be feasible.

In [8], an automatic monitoring system for home appliances using infrastructure-mediated sensing technology was presented, and a practical solution for recognizing the operating states of electrical appliances and determining the consumption of each appliance in a household was proposed. Components of electromagnetic interference (EMI) noises in a residential power line were analyzed, and then the basic theory of switched mode power supplies (SMPS) was discussed. Finally, a set of practical approaches were proposed to detect and classify the electrical events, including a time-frequency transformation algorithm, power spectrum vector chasing, Gaussian function fitting and supervised pattern recognition. The monitoring system was implemented in real houses and it successfully classified SMPS appliances with accuracy from 92.6% to 99.2% for individual appliances and 88.0% to 95.0% for multiple appliances.

Challenges and Possible Solutions

The research on NIALM has made great progress in recent years with the maturity of each technology of this area. However, NIALM still faces numerous challenges, including appliance sets, feature availability, malfunction recognition, real-time processing, and computational complexity.

Appliance sets: The proposed methods are not applicable to the cases in which some appliances belong to the same type. For example, there is one lamp in the bedroom and another in the adjoining washroom. If a lamp-turning on event is detected at the power entry, it will be difficult to recognize which lamp is turning on. Furthermore, this kind of problem will affect the application of indoor personnel behavior recognition and indoor personnel positioning.

Feature availability: Until now, a complete set of robust and widely accepted appliance features has not been established. The available features do not provide unambiguous appliance detection and classification. It is not known whether there exist such features that the variability of these features is small whereas the interclass difference is large. If the target features do not exist, the recognition algorithms will require excessive training for each particular appliance of interest, which decreases the efficiency of an NIALM system.

Malfunction recognition: The present algorithms can achieve type recognition and state recognition of appliances in an NILAM, but the malfunction state recognition and diagnosis have not been proposed. The primary reason is that it lacks all kinds of faulted appliances; thus, there is no way to perceive the features of appliances under malfunction states.

Real-time processing: Higher sampling frequency of appliances data leads to better classification results as mentioned previously. Nevertheless, it is associated with high costs of sampling equipment and great pressure on the data transmission and storage for an NIALM system. This problem can be solved by local computation; hence, the present study is limited to offline experiments on the algorithm validation, which basically ignore the real-time requirements of appliance state monitoring.

Computation complexity: For the appliances with multi-modes, all of the appliance operation scenarios need to be considered and trained by an NIALM system in advance. Learning all of the appliance operation scenarios burdens the NIALM system with heavy commutating load when the number of appliances is very large. Additionally, with the improvement of system function, the program of the NIALM will become complicated, which will also aggravate the computation burden of the NIALM system.

For the first two challenges, much more effort should be made on massive experiments of appliance and data analysis. For malfunction recognition, a public malfunction database of appliances like the Tracebase and ACS-F1 database is expected for the research of malfunction recognition. For other challenges, the emergence of cloud computing brings opportunities to solve these problems.

Cloud computing can provide a virtual infrastructure to process and integrate the monitoring equipment, storage equipment, analysis tools, and visualization platform within a smart home. As a kind of Internet based calculation mode with public participation, it is a new IT service architecture developing with the rapid growth of the needs for low cost data storage and parallel computing over the Internet. Cloud computing and Big Data principles are beginning to be used in instrumentation and measurement systems [13], in which a program does not run on a local computing device but on one or more remote servers. The servers process the data obtained from several measurement devices through wireless communication in parallel and provide relevant services to the client. So, applying cloud computing to the electrical appliance state monitoring, and establishing a cloud-computing-based monitoring system will provide a platform which has the ability for great capacity data storage and high-speed data processing. It will also provide an efficient storage method for a large amount of time-domain dynamic data. Besides, the construction of public data on the cloud platform lays a good foundation for the research of evaluating the platform for NIALM methods. In the future, data mining on the cloud platform will enhance the level of intelligent analysis and decision support. A good appliance state monitoring system not only needs an efficient recognition algorithm and a strong data support platform, but also needs reasonable data analysis methods to meet the required applications.

Future Developments and Applications of NIALM

Until now, techniques using nonintrusive appliance load monitoring still do not result in meaningful practical implementation. In the future, the research aiming at appliance load monitoring will be more specifically observed in the interest of customers of the utilities. With the development of smart home systems, users will expect more energy-related, safety-related and more intelligent services. Combining the current popular techniques with daily life, the future applications in NIALM can benefit smart home users in significant ways.

Home energy consumption understanding: An important application will allow a better understanding of the monthly electricity bill for users to develop habits of power saving. The principle is to compute the relative contribution of each appliance to the global consumption measured at the entry point by algorithms of the NIALM.

Malfunction prediction and diagnosis: With the augmentation of the function for household appliances and the complexity of the electrical system, the incidence of malfunction increases. Traditional breakdown maintenance and regular maintenance are costly and waste a great deal of manpower and material resources. In malfunction prediction and diagnosis, state monitoring is the core of this technology, which can be realized via the corresponding malfunction features extracted at the power entry and malfunction recognition.

Cloud monitoring platform of appliance states: The setup of a cloud monitoring platform makes the appliance enterprise know more about the usage of the appliances, and it also can provide data support for product improvement and active marketing for the appliance enterprise. In addition, the cloud monitoring platform brings possibilities of remote malfunction prediction, diagnosis and maintenance. Maintenance will be developed from traditional posterior maintenance services to on-state maintenance services. Maintenance specialists can analyze the state data of appliances on the cloud monitoring platform, and then they can estimate the cause of malfunction and provide door-to-door service.

Human activity recognition and positioning: The activity recognition is currently an area of growing research, particularly within a smart home, because we seek to provide a form of autonomy for individuals who require increased daily monitoring. Data and elements of daily living of the inhabitant can be collected to establish a daily activity database. In some cases, when the activity recognition is considered with the time and space, it can be used to locate the position of the inhabitant and even detect an abnormal situation according to the database of the NIALM system. Additionally, the appliance load monitoring system can also be applied to the health care of the elderly, which can provide reference information for the social endowment service.

Final Considerations of NIALM

Nonintrusive appliance load monitoring has a great significance for developing smart homes. We expect a novel home network system which integrates information and power networks, and the systems will induce various artificial intelligence that ensures the appliances monitoring. The smart grid and accompanying home automation networks have the potential to become main energy management tools to reduce residential energy consumption. Further, Cloud computing and a smart grid may be integrated to manage the electronic distribution and make an energy consumption schedule for any given areas.

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