Power consuming activity recognition in home environment

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Abstract. This work proposed an activity recognition model which focus on the power consuming activity in home environment, to help residents modify their behavior. We set the IoT system with lower number of sensors. The key data for identifying activity comes from widely used smart sockets. It first took residents' acceptability into consideration to set the IoT system, then used a seamless indoor position system to get residents' position to help recognize the undergoing activities. Based on ontology, it made use of domain knowledge in daily activity and built an activity ontology. The system took real home situation into consideration and make full use of both electric and electronic appliances' data into the context awareness. The knowledge helps improve the performance of the data-driven method. The experiment shows the system can recognize the common activities with a high accuracy and have a good applicability to real home scenario.
Keywords: activity recognition, ontology, second-order HMM

1 Introduction

Electric energy is one of the most widely used energy sources in the world. It is mainly used in industrial production, residential life, buildings, transportation and service industries. People's abuse of electricity, resulting in a lot of waste. Almost every activity in home need consumption of electricity, it is useful to recognize them for the conservation. As the Internet of Things (IoT) stimulates the development of the Smart Home (SH), SH uses the IoT technology to connect domestic devices together into the Internet, gets the status data of the devices, and provides smart control along with some related services. Activity recognition in home is more and more necessary for SH to offer the personal service. Activity recognition now has become a hot topic and received increasing attention from many fields, such as image processing, pattern identification, wireless sensor network and data mining. First we should distinguish between action and activity, action is a basic human motion or repeat of a kind of basic motion, e.g. stand, walk or sit. But activity is a combination of the basic human motion, e.g. watching TV can be decomposed into opening TV, sitting and watching it. So an activity is more complicated than an action. In home, lots of daily activities need power consumption. With the help of the activity recognition, we could find what activity consume some unnecessary power, and power feedback will have a good effect on end user to save consumption [1]. So it can remind the residents to modify their behaviors and save the energy.

A lot of works have been done to this area, but to home environment, these works have encountered problems of one kind or another to real scenarios, such as privacy concern, installation complexity, residents' acceptance and so on. So our work focused on the real situation in home, took the residents and home environment's characteristic into consideration. Nearly every activity in home will have something to do with these appliances. So it makes sense that we use the domestic appliances to infer home activity. The proposed method used the intelligent sockets to collect the load data about the appliances, utilized smart phones to assist our indoor position system. We do not need too many additional sensors to construct the system. Depend on the load data of appliances, we can classify them for a fine-grain activities. The main contributions of this study are described below:

1. This study has made full use of existing equipment in home, we not only used the electric appliances but also the electronic appliances. Depend on residents' acceptance, users do not need to take any specific devices with them, and there is no risk of privacy concern. The system do not need too many additional sensors.
2. We proposed a domain knowledge based activity model, which can store necessary knowledge in our ontology model. The model is also helpful to the accuracy for the activity recognition.

2 Related work

A lot of researchers have done many studies on this topic, recognition methods have different ways of data extraction and different activity models. According to the architecture proposed by Chen et al. [2], most recognition models have the following steps: data collection, data label, feature extraction and activity recognition.

According to the pattern of data collection, methods can be divided into four categories, one is depend on the video frame ([3] is a review for it), the second one is based on the wireless sensor networks, the third one is based on wearable sensors, and the last one is based on the wireless technology. Image-based method has the problem of the privacy concern, intrusive mood and installation cost and complexity. Also, this kind of approach suffers from the variability of human activity, complex background and ambient illumination, so it is limited in some specific circumstances, such as medical care [4], [5], [6] or security, and it is not desirable in home environment. Wireless sensor networks based on ambient sensors is able to collect the context aware information in indoor situation. The works like [7], [8] and [9] utilized a large number of sensors to get the context, then used these data to infer the activity that the user is doing. It is inevitable that these methods need huge deployment and maintenance cost. Wearable sensors [10], [11], [12] have become a mature technology, more and more wearable products have been in mass production by the manufacturers. But these approaches require subjects to wear separated sensors on different parts of the body, so they need specific devices and these devices need charging and cannot be wore all the time. There are also lots of methods utilizing the accelerometer and gyroscope in smartphone [13], [14], [15] or RFID [16] to recognize activities. These methods all require users to take certain specific devices with them, the problem they brought is just like the wearable sensors. Recent years, the wireless technology have been a promising work, such as Wi-See [17] and Wi-Vi [18], but both of the works depend on specific platform, i.e. the USRP-N210 SDR system. The availability in home remains.

Few researchers worked on the domestic appliances to activity recognition. Lai and [19] Cho et al. [20] worked on this, and they calculated a relevance between devices and activities, then used a Naïve Bayes to classify the activity.

There are mainly two kinds of recognition methods: data-driven methods and knowledge-driven methods. The two most commonly used data-driven methods are hidden Markov model (HMM) [21] and Conditional random field (CRF) [22]. There are some variations of the two methods used to deal with the activity recognition. The other is knowledge-driven approaches [23], it can solve the cold start problem that data-driven methods have, make the model reusable.

3 Proposed system architecture

Traditional activity recognition methods based on wireless sensor networks has several shortcomings. First, it need install a large number of sensors, which is difficult for user to accept. Second, to different home environments, it needs different sensors. Third, it assumes that the activity can only happen in a fixed room, but in fact, you can use your laptop in your bedroom or sitting room. Next we will introduce our system, it can solve the above problems.

3.1 Intelligent sockets

People's life cannot be without appliances today, a large number of the indoor activities are connected to the appliances. So using domestic appliances is possible to recognize human activity in home. Now the smart meter and intelligent sockets are used more and more broadly by the residents, the construction of smart grids has also become goals for many countries. We designed our own intelligent sockets to get the load data of appliances. The system adopts the power measurement chip HLW8012 produced by Shenzhen Heliwei Technology Company, and the ESP8266 WIFI module produced by Shanghai Lexin technology company. The intelligent socket is show in Fig.1. In our experiment, we detected 11 appliances and recognized 10 activities.

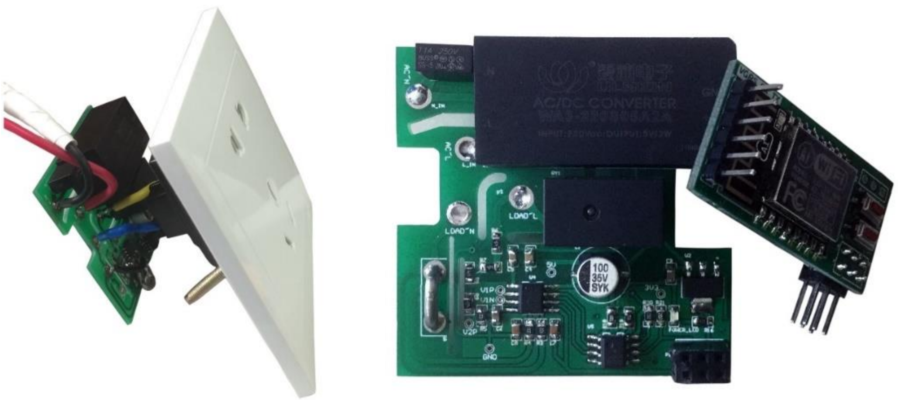

Fig. 1. Intelligent socket

3.2 Indoor seamless positioning module

Positioning based on the mobile phone Wi-Fi RSSI (Received Signal Strength Indication): With the increasing popularity of smart phones, smart phones increasingly become an indispensable device in people's lives, residents often carry mobile phones in home. In a modern home, a router is an indispensable device in many homes where the location is basically fixed and a router's signal cannot generally cover all parts of the home. So a home with more than one router is a normal phenomenon. In the system we do not need add more expensive equipment. Using the smartphone system SDK to access to the surrounding Wi-Fi hotspot (i.e. access point, AP) signal strength value, we can use the phone to detect the person's indoor location. At present, there are two main indoor positioning algorithms based on RSSI, one is the trigonometric positioning method and the other is the fingerprint localization algorithm.

Fingerprint algorithm needs to divide the indoor area into grids first. Because the temperature, humidity, multipath, occlusion of the object and the influence of shadow fading effect, RSSI values the receiver gets in the same position are also different at the same point, So a large number of samples are need (Usually 100 times) to represent the average RSSI value of the region, and then record the location and address of the AP. The experimental environment is a 60-square-meter single room, if using the fingerprint algorithm, it is necessary to sample 100 values in the range of $1*1m^2$ to $1.5*1.5m^2$, so the cost of sampling is very large and time consuming, so it is not recommended to be used in home environment.

Triangulation algorithm requires us to know the locations of the APs in advance. This is easy to do because the home AP (router) locations are fixed. Using the classic signal attenuation model, you can use less data points to get accurate distance. Finally, according to the calculated RSSI value, the distance of the smartphone to the AP access point is obtained, and the position is calculated according to the triangle centroid algorithm. RSSI signal strength and distance of the classical theoretical model:

$$\mathrm{RSSI} = \mathrm{A} - 10\mathrm{nlg(d)} \tag{3.1}$$

where A is the received signal strength value of the receiving end get per unit length. Equation (3.1) is a classical model for calculating the relationship between RSSI and distance d, where the parameters A and n are closely related to the AP access point hardware and the specific environment. Thus, in different home environments, parameters A and n are different. The parameter values of A and n in the current environment are calculated by the linear regression method through the actual measurement of multiple sets of test data. In our experiment, the relationship between distance d and RSSI is shown in Fig. 2, and A is -39.2 and n is 3.7.

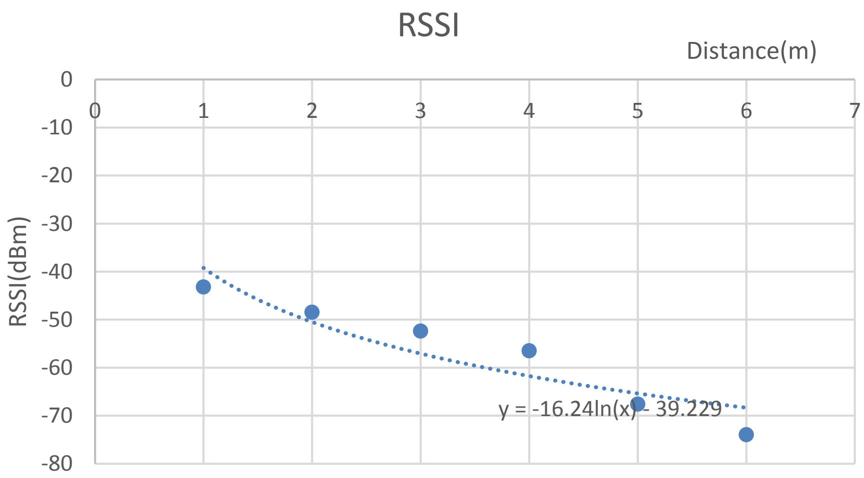

Fig. 2. RSSI Ranging

Triangular centroid algorithm: We need to know the coordinates of 3 AP access points in advance, $\mathrm{A}(x_a, y_a), \mathrm{B}(x_b, y_b), \mathrm{C}(x_c, y_c)$ and the measured distances d'_A, d'_B, d'_C, as fig. 3 shows, we get the centroid by the following formula:

$$\begin{cases} \sqrt{(x_e - x_A)^2 + (y_e - y_A)^2} \le d'_A \\ \sqrt{(x_e - x_B)^2 + (y_e - y_B)^2} = d'_B \\ \sqrt{(x_e - x_C)^2 + (y_e - y_C)^2} = d'_C \end{cases} \tag{3.2}$$

the coordinate of centroid D or D_1 is $(\frac{x_e+x_f+x_g}{3}, \frac{y_e+y_f+y_g}{3})$, we can get the room level of the person location. But in home, people do not always take a mobile phone with them. We only determine the location of a person based on the phone when the smartphone is moving (that is, when a user is carrying it). According to the built-in three-axis accelerator, if $|G_{t-1} - G_t| > \varphi$, G_t is the acceleration taken at time t, φ is the preset threshold of 0.1m/s^2.

Location of user with no device carried: Users can not always carry a smart phone at home, for example, when taking a bath. Two ultrasonic distance measuring sensors are installed on the door to detect the user's room level location when no device is being carried. The activation order of the two ultrasonic distance measuring sensors determines whether to enter the room or to exit the room. The whole seamless positioning system is shown in Fig. 4.

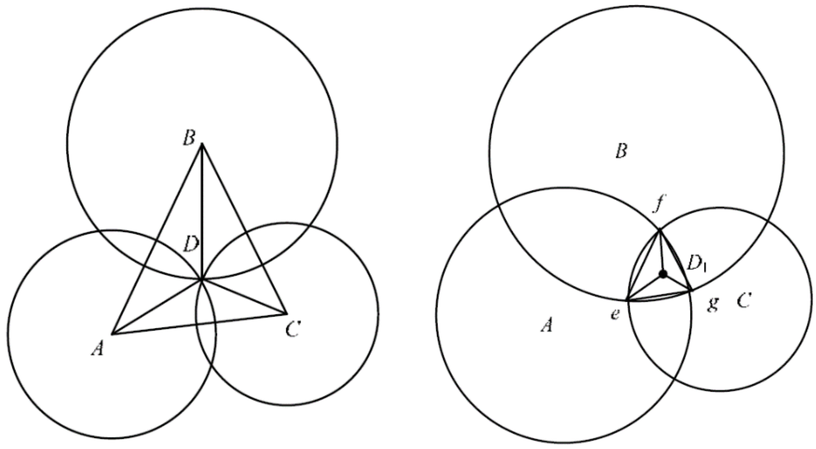

Fig. 3. RSSI location

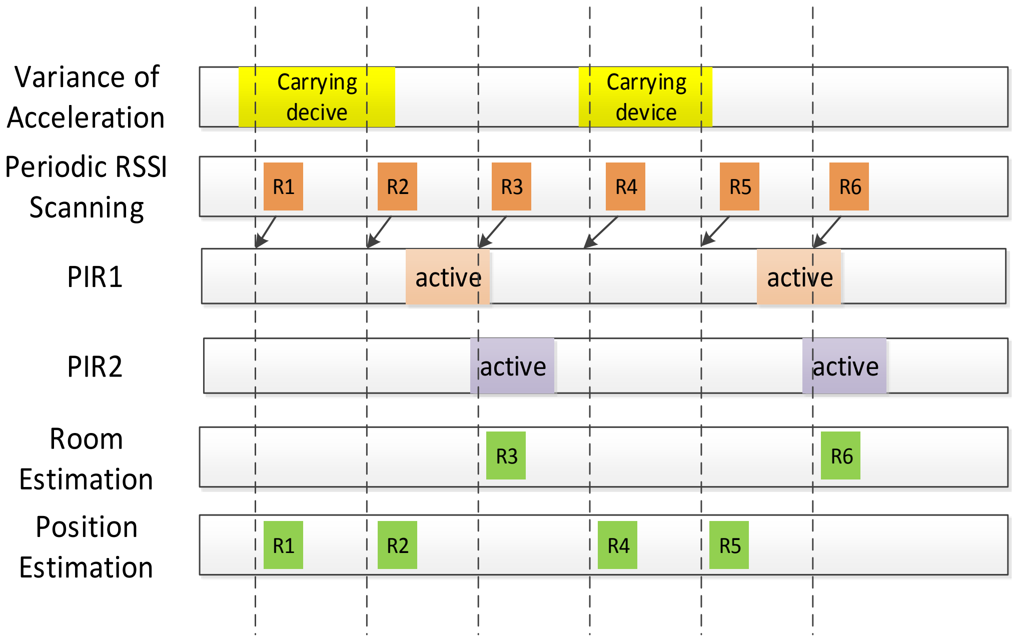

Fig. 4. Home seamless positioning

4 Acticity recognition

4.1 Activity ontology model

Ontology is a systematic explanation of objective reality, which is concerned with the abstract nature of objective reality. In 1993, Gruber gave one of the most popular definitions of Ontology:" Ontology is the clear specification of a conceptual model "[20].

Knowledge of domestic user activity. The activity model is based on the activity knowledge base in the family. With the knowledge of the user activity in the household, the model can judge the classification according to the current input context. Knowledge base is the storage location of semantic information in the domain. The concepts, attributes, rules and instances in the ontology model are stored in the knowledge base. The definition of the activity, person, appliances and locations are also stored in it.

Domestic users tend to conduct daily activities in a particular situation, that is, a specific time and a specific location to carry out an activity. For example, people usually brush teeth every morning and every night in the bathroom. It usually includes the use of toothpaste, toothbrushes, cups and faucets. This information is referred to as the contextual information for the corresponding activity. However, due to the particularity of the home environment, an activity can occur at any time of the day, or it can be repeated at any time. For example, brushing teeth can be done early in the morning, but if someone gets up in the afternoon, the brushing teeth behavior may be carried out in the afternoon, in view of this situation, we do not consider the time information dimension.

Because the user has a different way of life, habits and hobbies, the way of a person conduct a daily activity is different from the way that other people carry out the activity. For example, a person likes to use the computer every morning, while others like to use the computer every night. Even in the case of the same behavior, such as the use of computers, you can open the main chassis, then open the monitor, and then turn on the sound to start using the computer. Or open the sound first, then open the monitor, and then open the main chassis to start using the computer. Therefore, we do not consider occurrence order of the seed action.

And because of the particularity of the home environment, some activities can only occur in a fixed position, and some activities can occur in multiple locations, rather than a fixed location. For example, the user at home on the toilet, the bath can only be carried out in the toilet; and the use of the computer the event, the user can be carried out in the bedroom, you can also carry out in the living room, so we need to restrict the user to carry out certain activities, Define multiple locations where certain activities can be made. We call this knowledge rule 1, describe the rule in a standardized language:

Rule 1: Activity ∀ hasLocation (Balcony or Bathroom or Bedroom or Diningroom or Kitchen or Sittingroom or OutOfHome)

Activity ∃ hasLocation Locations

Rule 1 is to say that every activity must have a place to happen, and can be expressed as a The following matrix:

$$P_{ra}=\begin{bmatrix} 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \end{bmatrix}$$

P_{ra} is a 5 * 9 matrix, the horizontal axis represents that five indoor rooms, from top to bottom are: kitchen, restaurant, bedroom, bathroom, living room. The vertical axis indicates nine activities, from left to right, respectively, toileting, bathing, sleeping, cooking, eating, watching TV, using the computer, grooming, and doing nothing. The matrix represents the activities that may occur in each room.

Activity model. Based on the nature and characteristics of domestic users' activity in the family, we use "who", "where", "what", "how" to describe our activity, including people, location, sensors, electrical and activity information dimensions.

In this paper, we use the OWL language as a descriptive language that describes the concepts and correlations between different information dimensions of household user activity. As mentioned above, we divided five dimensions according to user activity. According to these five dimensions, we construct the corresponding ontology model, and each ontology model corresponds to the respective information dimension. The semantic links are established between the various dimensions through abstract attribute relations. These attributes relate to an ontology and some physical entities and conceptual entities. Each attribute has its domain and scope, the domain refers to the subject of the property, scope refers to the object of the property. An attribute uses a text or an instance of another class to describe a class, so you can interconnect two classes.

Figure 5 shows the five ontology models and the links between these models. The ontology models are as follows: Sensor, Person, Location, Appliance, and Activity. These ontologies are interconnected by attributes. The sensor ontology is used to abstract and describe the attributes and performance of different sensors; the human ontology standardizes the user identity in the home environment; the position ontology abstracts and normalizes the location of user, appliance and sensor; the Appliance ontology is used to abstract and describe the appliance attributes; activity ontology used to abstract and describe the property of the activity.

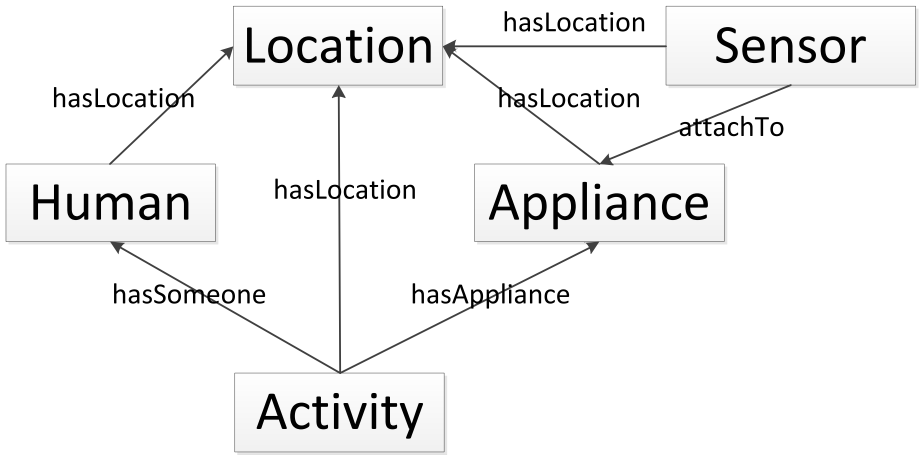

Fig. 5. Activity ontology model

4.2 HMM2

According to the actual situation, present activity is not only connected to the activity in previous state, the first-order assumptions are not very reasonable, so here we propose a second-order hidden Markov model, which also has two assumptions: a) The activity of time t is related not only to the activity of time t-1 but also to the activity of time t-2; b) The observed variable x_t at time t is related not only to the current state of the system but also to the previous state.

The second-order transition probability can be expressed as following:

$$a_{ijk} = P\left(y_t = s_k \middle| y_{t-1} = s_i, y_{t-2} = s_j\right)$$

The second-order emission probability can be expressed as following:

$$b_{jk} = P(x_t | y_t = s_k, y_{t-1} = s_i)$$

Considering the initial condition, the HMM2's parameters are $\lambda = (\pi, A_1, A_2, B_1, B_2)$, where $\pi = \{\pi_i\}; A_1 = \{a_{ij}\}; A_2 = \{a_{ijk}\}; B_1 = \{b_k\}; B_2 = \{b_{jk}\}$, they represents the initial probability of the model, the first-order transition probability, the second-order transition probability, the first-order transmission probability and the second-order transmission probability respectively.

Second-order Viterbi algorithm with ontology knowledge. During each iteration of the Viterbi, we add our position information and the position-activity state matrix P_{ra}. According to the user location, there are only some activities can happen, so we do not need to search the whole activity space but to search some possible activities. It can be formally described as:

Loc={kit,din,bed,toi,sit}, assume that kit=1, din=2, bed=3, toi=4, sit=5, the search space is S'=S.*P_{ra}(Loc(n),:).

5 Experiment

Our experiment is carried in a single room, the configuration is shown in table 1.

Table 1. Details of the experiment environment

Number of people	1
Number of rooms	5
Duration	7 days
Activity detected	leave house, use toilet, take shower, go to bed, prepare food, eat food, watch TV, use computer, dressing, Idle

The volunteer said she has bought the Xiao MI intelligent socket before to control the water heaters on the way home. So she do not refuse to use more intelligent sockets. The annotation of the data is recorded by self-reporting.

We first compared our method with the Naïve Bayes (NB) and HMM1, used "leave one day out" method to test the accuracy. The evaluation parameters we used are Precision, Recall, F-measure, Accuracy and Time. These can be calculated as following:

$$\text{Precision} = \frac{1}{C}\sum_{i=1}^{C}\frac{TP_{ii}}{NI_i}$$

$$Recall = \frac{1}{C}\sum_{i=1}^{C}\frac{TP_{ii}}{NT_i}$$

$$\text{F1} = \frac{2 * precision * recall}{precision + recall}$$

$$\text{Accuracy} = \frac{\sum_{i=1}^{Q} TP_{ii}}{Total}$$

The performance comparison is shown in table 2.

Table 2. Performance comparison

	Precision	Recall	F-measure	Accuracy	Time
NB	55.1	59.2	57.7	76.4	0.11
HMM	69.3	70.3	69.7	85.3	0.39
HMM2	70.4	71.8	71.1	88.0	0.51
HMM2+Knowledge	79.9	84.2	82.0	95.8	0.27

As we can see, Hmm2's performance is slightly higher than HMM1's. It shows that higher order HMM may lead to better performance, but we cannot say that higher order can definitely lead to better performance, because in real situation, closer activity should have a bigger impact on the following activity. The domain knowledge help reduce the time cost, and improve the recognition accuracy. The fusion method has the best performance.

6 Conclusion and future work

In this work, we proposed a novel activity recognition system, it collected the load data to recognize the power consuming activity, and it also contained a seamless positioning and appliance recognition. With the improved system architecture, we can solve the problem that traditional wireless sensor network brings. First, the system can be used to any other home environment. Second, the acceptance of the user is good, because if no user admit the activity recognition system, it is useless. Last, our knowledge and data driven hybrid method could increase the accuracy of the activity recognition.

However, the method is only used for single resident and sequence activities, which should be expanded to multi-user situation. Next, we should consider the feedback about the behavior to help residents save the energy and we also want to find out the performance of n-order HMM.

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