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普及家庭環境下之情境感知節能系統

Context-Aware Energy Saving System in a Pervasive Home Environment

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本論文係 **葉慧文** 君（學號R98922065）在國立臺灣大學資訊工程學系完成之碩士學位論文，於民國 100 年 7 月 27 日承下列考試委員審查通過及口試及格，特此證明

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中文摘要

近年來，由於能源過度使用所造成的能源危機及全球暖化問題，「節能」儼然已成為一個值得我們思考如何建立一個永續發展世界的重要議題。大多的節能研究著重於技術導向的解決方法，少數使用活動辨識技術來輔助節能系統，但他們仍然忽略了使用者的感受，因此提供的節能服務無法滿足使用者需求。

智慧家庭下的使用者活動辨識技術已逐漸成熟，其做法大多為在環境中佈建各類感測器以收集環境資訊以及使用者與環境之互動資料，例如：室內溫度、室內照度、使用者動靜及環境中感測器之觸發狀態，並建立活動辨識模型。現有的行為辨識節能系統多半只考慮當下與該活動相關性密切的感測資料，未考慮到背景已開啟之電器，這些被忽略的電器可能也與該活動相關且具大量能源消耗，而在多人活動辨識的情況下，辨識率往往較單人活動辨識低，此外，他們往往忽視環境中使用者的感受，可能導致節能效果不佳或更多不必要的能源消耗。

本研究的主要貢獻有以下三點：第一，將家電的能源消耗量納入推論考量，找出執行某活動所觸發的確切能源消耗，並透過推論技術得知該活動與某些家電耗電量的關係。第二，因為我們是過群體生活，為了能進行多人活動辨識，我們根據區域性來進行資訊匯集(data aggregation)以有效簡化多人辨識時所需資料關連(data association)的複雜度，如此亦能較準確推論該區域內的所有活動以及相對應的耗電量。第三，不只是單純的行為辨識，我們根據廣受接受的標準化舒適度評量指標來全面性地衡量環境中使用者的舒適程度，結合前述之能源相關行為辨識結果，在兼顧舒適度以及節能效應前提下提供適當的節能服務。

關鍵字: 普及家庭環境、行為辨識、節能、群體活動、動態貝氏網路、使用者舒適度、情境感知

Abstract

In the recent years, energy saving has become an important issue due to energy crisis and global warming caused by overused energy consumption. Therefore, it is worthy of concern for us to think about how to create a sustainable world. Most of the prior works on energy saving focused more on technology-oriented solutions whereas few works exploit activity recognition to assist energy saving system. Even taking human activity into consideration, most of them ignore user feeling. For this reason, the energy saving services these systems provided often cannot meet user need.

The techniques of activity recognition in a smart home have been more mature than ever. The researchers often deploy many kinds of sensors to collect environmental information and the interactions between users and their environment, *e.g.* indoor temperature, indoor illumination, users' motion and states, to build activity recognition models. Now the present home energy saving systems based on activity recognition merely take those appliances switched on due to the onset of an activity, yet often ignoring those appliances which are turned on and indirectly or implicitly related to the activity (referred to as background appliances). The usage of these implicit appliances might be one of the main factors that cause the power consumption. Moreover, the accuracy of multi-user activity recognition is often lower than the one with single-user, which makes energy saving in multi-user environment more difficult. And the most important issue about energy saving is that most of prior works or systems seldom evaluate user comfort in a more quantifiable way to determine a more favorable energy saving policy.

To sum up, there are three main contributions in this work: (1) We associate power consumption level with a context of interest so that we can provide users more thorough feedbacks. More specifically, we will identify the power usage of those implicit appliances when a context is recognized. As a result, such a correlation between a context and its power consumption can be utilized to facilitate more spontaneous power saving. (2) In order to make multi-user activity recognition far less intractable, we reformulate this problem and take a group of users in the same area/zone as a whole to greatly reduce the complexity of data association inherent in a multi-user activity problem. (3) Using a composite and standard-based index to comprehensively evaluate real user comfort and to make appropriate energy saving policies without compromising both user comforts.

Keyword: Pervasive Home Environment, Activity Recognition, Energy Saving, Group Activity, Dynamic Bayesian Network (DBN), User Comfort, Context-Aware

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Chapter 1

Introduction

1.1 Motivation

In the recent years, environmental issues regarding energy saving have become a significant problem that cannot be ignored. The phenomena of rapidly changing climates and draining of energy resources are believed to be caused by the overly consumed energy, especially from the non-renewable energy resources, known as the current main sources of electricity. Therefore, it is worthy for all of us to share great concern with the energy saving issue to maintain a sustainable world.

Although energy is consumed everywhere, the amount of power consumption in the households should not be underestimated because majority of people nowadays are living in the home most of the time, excluding the working hours. A variety of appliances (*e.g.* computer, dish drainer and air conditioner, etc.) are increasingly used in the household, and in the real life we often incline to abuse the electricity and forget to unplug or turn off the appliances when they are not being used, both of which can lead to unnecessary energy consumption. For this reason, having a good energy saving strategy in the household is an imperative need. Furthermore, to provide more accurate and fine-grained energy saving strategies, we utilize the technology of wireless sensor networks (WSNs) to collect sensing data about environment and user-related information. Next, we can make use of the collected information to infer users' on-going activities and to evaluate their feeling about the environment via a composite and quantifiable comfort index. With the context of the on-going activities and the comfort index, we can in turn make more desirable decisions to achieve the goal of energy saving in a real-life scenario.

1.2 Challenges

Several challenges need to be addressed to obtain the aforementioned energy saving. We roughly classify the challenges into two major categories including challenges in multi-user activity recognition and in evaluating user comfort for optimal energy control.

1.2.1 Challenges of Multi-user Activity Recognition

Compared with single-user activity recognition, multi-user activity recognition is more difficult and complicated due to the difficulty of correct data association. Such difficulty becomes even more formidable if we want to recognize what activity is performed by which user when the number of users increases. Moreover, another difficulty is that users in the same environment would interact with one another, which would cause concurrent activities. For the reasons mentioned, we have to cope with the problems of data association and interpersonal interactions to increase the accuracy of multi-user activity recognition.

Data association is to associate a sensor event, such as activity, with its corresponding user who triggers the event. Data association is often used to improve the performance of multi-user activity recognition [1]. There exists positive correlation between the accuracy of data association and that of activity recognition [2]. However, it is very laborious to annotate an event with its associated user ID if the annotation is done manually.

Interactions among humans are inherent in everyday life. That is, users might perform activities together, such as chatting, shaking hands, or playing cards. These types of activities are triggered by more than one human; therefore, we have to make sure that who are involved. Moreover, if the distance of any two users interacting with each other gets closer, it becomes harder to distinguish each individual's activity for multi-user activity recognition. Carrying wearable sensors is one method to solve the problem, but it often causes discomfort. Furthermore, human activity in a smart home is often related to the usage of a set of certain appliances in the energy saving system. With the challenges mentioned above, the services regarding energy saving will be unreliable if the accuracy of multi-user activity recognition is not high enough.

1.2.2 Challenges of Making Optimal Energy Saving Decision

In a pervasive home, the goal of energy saving system is to help users reduce the unnecessary consumption of energy by providing appropriate services or controls to change the state of appliances. Due to the fact that home is a space for human living and the preference of distinct residents about appliance settings may differ, unsuitable appliance control without considering the users' comfort will cause interference to them.

Most of traditional energy saving systems merely regards turning on or turning a set of appliances, *i.e.* binary control or coarse-grained control, as an energy saving service. However, this type of appliance control lacks of adjusting the appliances' state according to the users' real needs and the current parameters of the environment. Besides, some appliances cannot be turned off arbitrarily such as a refrigerator, a central HVAC or home servers. On the contrary, fine-grained control can flexibly adjust the levels or change the states of an appliance. For example, the energy saving system is able to adjust the temperature of an air conditioner from 28°C to 26°C in order to cool down the indoor temperature. Moreover, the information of human and environment, *e.g.* the physical activity level, temperature, humidity, and illumination, would change from time to time, leading to the difficulty of user comfort evaluation.

With these concerns, we need to have an automatic mechanism to adjust the appliances if necessary, and have a quantifiable index to evaluate the user comfort through standard-based indexes.

1.3 Related Work

In the literature survey on energy saving, we can roughly classify the energy saving system into two main categories: (1) **human intervention** based on the feedbacks of energy consumption from the system, and (2) **technology intervention** using appliances control to do energy saving automatically.

Energy saving systems of the first category does not provide any controls or decisions, whereas the second category provides automatic appliances control. Furthermore, the second category can be further divided into two subcategories which are non-context-aware technology intervention and context-aware technology intervention. The former purely control the energy usage by the power consumption while the latter takes the user's feeling (*e.g.* comfort or preference) into account. Most works with the context-aware technology intervention applied the technique of activity recognition to address the context-aware issue.

In the next sections, we will discuss the prior works about activity recognition and energy saving decision making of energy saving systems respectively.

1.3.1 Activity Recognition

The technique of activity recognition has evolved for several years. Many kinds of sensing devices are used to collect information for inference, including wearable sensors, ambient sensors, and cameras. There exist varieties of approaches used for activity inference, such as machine learning and vision-based approach. The most common methods of these approaches are Bayesian network, decision tree, support vector machine (SVM), conditional random field (CRF), and hidden Markov model (HMM), etc. Logan *et al.* [3] used a large amount of sensors, including RFID, ambient sensors, cameras and microphones, and implemented with Naïve Bayes and C4.5 decision tree classifiers to infer user activities. Kim *et al.* [4] compared four activity recognition methods, which are HMM, CRF, skip-chain CRF, and emerging patterns (EP). For improving the accuracy rate, Ye *et al.* [5] utilized the temporal feature, which is inherent human activities, to produce more accurate results of recognition at low infrastructural cost.

However, it is inevitable that there are multiple humans living in the home. Hsu *et al.* [6] used non-obtrusive sensors and CRF to solve the problem of data association. To cope with the challenge of interaction among multiple users, a few prior works had proposed approaches using coupled hidden Markov model (CHMM) [7, 8], dynamic Bayesian networks (DBN) [9], and emerging patterns (EP) [10] respectively.

There are many applications on activity recognition, such as systems for healthcare or energy saving. In this thesis we focus on the relationship between activities and the energy saving system. Based on the results of activity recognition, the system could get the information about what a user is doing, and the system is able to further calculate the physical activity level of the user. Integrated with the parameters of the environment, the system will provide corresponding services to the user.

However, too many uncertain factors (*e.g.* human interactions, etc.) in a dynamic home environment lead to unsteady activity recognition of multiple users. Thus the energy services provided by system may become annoying. To solve the problem, we use group-based instead of individual-based activity recognition in multi-user environment. In other words, we care more about the activities occurred in an area of interest rather than the activity of each user. There exists some works that use cameras to recognize the group activity [11, 12], and the definition of their group activity is the activities performed by the humans moving in the same direction.

1.3.2 Energy Saving Decision Making

As previously mentioned, we classify the energy saving system into two categories: human intervention and technology intervention.

For the first category, some works indicated that providing the information about the overall usage and cost of energy consumption as feedbacks to users promotes energy saving [13-15] due to constant energy-consumption awareness. They used real-time displays or smart energy monitors to show the graphical, numerical, or textual information about total energy consumption to users. According the information, the users would take actions to change their habits of using electricity or other energy resources to save the energy and their money as well.

The second category is divided into two subcategories: non-context-aware technology intervention and context-aware technology intervention. For the non-context-aware technology intervention, the researchers mainly used smart meters and control relays to achieve the goal of saving the excess power consumption. Most of works in this subcategory focus on reducing the standby power of home appliances which are not being used. Williams *et al.* [16] found that about 40% residential energy usage is apparently wasted in delivering "unused energy" services, which include overheating/overcooling to cause temperature variations or include heating/cooling a unoccupied space. They monitored the indoor temperature and power consumption, and utilized the thermostats to regulate the temperature. Hwang and Wu [17] proposed a predictive system-shutdown method for energy saving. They used event-driven control to decide when to initiate predefined sleep-mode operations for all associated appliances. Likewise, Heo *et al.* [18] implemented a similar control mechanism to do energy saving.

Nevertheless, these approaches in the non-context-aware technology intervention pay little attention to human comfort, which should be an important factor in a smart environment. For the context-aware technology intervention, several energy saving systems used various kinds of sensors to sense or infer the information of the human and environment, and then made decisions to control the appliances in home. In order to provide energy-aware services, the Adaptive House project [19] focuses more on the adaptive ability of the house to a user based on his/her occupancy patterns, preference, and schedules. The project developed an energy monitoring system named ACHE (adaptive control of home environments) based on reinforcement learning to estimate users' comfort, then to control air heating, lighting, ventilation, and water heating [20-22] via the actuators in the environment. The European project AIM [23-25] uses wireless sensor networks (WSNs) to monitor and optimize the power consumption in the home network according to users' previously observed behaviors. The behaviors are based on the monitoring data the sensors collected as the users' daily profiles, which include user presence and the real-time environment such as temperature, and lightness. Another example is the work from Davidsson and Boman [26]. They proposed a system consisting of Multi-Agent System (MAS) to monitor the user's location and utilize the user's preference to provide appropriate lighting and temperature related services.

But these works above did not consider the power consumption not caused by the activities, which may lead to waste a plenty of unnecessary energy. In addition, they just regarded user preference, which is learned by all collected data or routine schedule, as user comfort, without taking the real-time parameters (such as one's current physical activity level, indoor temperature at the moment, etc.) into account. Therefore, we propose a context-aware energy saving system but also consider four important factors to provide more human-centric and optimal energy saving services. The four factors and the comparison of our work with the aforementioned three categories of energy saving system are illustrated in TABLE 1.

TABLE 1 DIFFERENCE BETWEEN FORMER TREE CATEGORIES OF ENERGY SAVING SYSTEM AND OUR WORK

	Multi-user Support	Comprehensive User Comfort	Fine-grained Control
Human Intervention	Δ		
Technology Intervention	Δ		
Context-aware Intervention	Δ	Δ	
Our Approach	O	O	O

Δ: partial implementation

1.4 Objective

With the above mentioned challenges, the objective of this thesis is to propose a context-aware home energy saving system to optimize energy saving policies while maintaining the acceptable (or least) level of user comfort. Therefore, the system processes the following features:

- **Inferring "energy tagged contexts"**

  To identify the relationship of a context of interest and its actual power consumption level, we will try to "tag" a context of interest with its associated power consumption information, which all together is named an energy-tagged context (ETC). The context of interest can be a multi-user activity, which is often considered a very challenging or even intractable problem in a real-life setting. We will utilize group-based or zone-based approach to make the problem far less intractable. With the information, we can, on one hand, provide context-aware information to users. Furthermore, we will also identify the implicit relation, which is often ignored in the previous work, to achieve more energy saving.

- **Adopting a comprehensive user comfort index (CCI)**

In a traditional energy saving system, making an energy saving decision often rely on preference-based or non-standard based comfort index, which may not truly reflect the real user comfort. Therefore, we propose a comprehensive user comfort index to address this challenge.

- **Optimizing energy saving decisions**

Given the aforementioned ETCs and CCIs, our system can determine an optimal energy saving policy by solving a constraint satisfaction problem (CSP). This way, we can achieve the goal of implementing a context-aware home energy saving system to optimize energy saving policies while maintaining the best level of user comfort.

1.5 Thesis Organization

This thesis consists of seven chapters, and the chapters are organized as follows.

In Chapter 2, we introduce some background knowledge of the thesis, such as Dynamic Bayesian Network (DBN) which can be utilized to infer contexts, clustering which can be used to group individual activities, and wireless sensor network (WSN) which can non-obtrusively collect environment and human information. Both DBN and clustering are later used for inferring the Energy Tagged Contexts.

In Chapter 3, we describe the problem definition and give an overview of the system architecture and succinctly introduce each layer of the architecture.

After the system overview, we will mainly focus on the last two layers, *i.e.* the inference and evaluation layer and the decision layer. In Chapter 5, the Energy-prone Context Inference Engine is described in detail and the context-aware energy saving will be introduced. The energy saving decision is made based on maintaining a balance between the energy-prone context discussed in Chapter 5 and the user comfort evaluated by the User Comfort Evaluation Engine which will be discussed in this chapter. In addition, we will use some standards to measure the human feeling about the environment such as Predicted Mean Vote (PMV) or Lux.

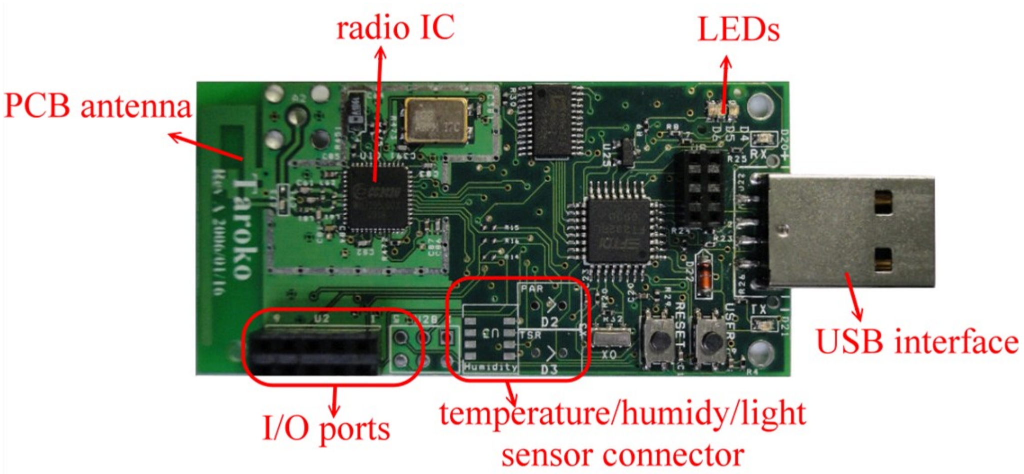
In Chapter 6, we detail the experiment settings and the evaluations of the proposed energy saving system. The experimental results are also discussed and analyzed in this chapter. Finally, Chapter 7 summarizes the whole thesis and lists the future work.

Chapter 2

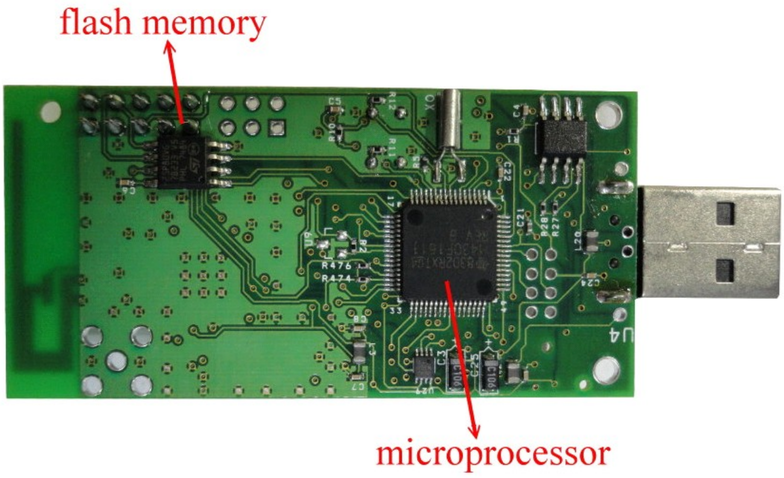
Preliminaries

2.1 Wireless Sensor Network (WSN)

Wireless sensor network (WSN) is composed of several nodes which can send massages to each other through IEEE 802.15.4. In the WSN, the autonomous sensor is connected to a wireless node, and a wireless node can contain more than one sensor. According to the function, the common sensor types are temperature, humidity, light, motion, and pressure, etc. For the wireless node, it consists of a microprocessor, a radio transmitter/receiver with an antenna, a flash memory, and an electronic circuit for connecting with sensors and power source. With the microprocessor and the small memory, the wireless node has the property of low power consumption, small volume and long transmission distance with multi-hop technique. An instance for sensor node is Taroko, shown as Fig. 2-1, it comprises several parts: a MSP430 microprocessor (including an analog-to-digital converter, ADC), a radio IC (CC2420), an 8MB flash memory, a USB interface for connecting to power source or computers, some I/O ports and extension connectors, etc.



(a)



(b)

Fig. 2-1 Taroko wireless sensor node, (a) the front and (b) the rear.

Due to the small size of sensor node, the WSN is often used to monitor the physical environment, for example, air pollution monitoring or residential safety/healthy monitoring. For the sake of recognizing the residents' activity at home, many kinds of sensors are deployed with objects used daily or directly in the environment, such as current-flow sensors with the appliances or thermometers in the rooms. With these daily data collected by WSN, we can build the activity models of the residents for extending more applications in the pervasive home environments.

In the following, we list and introduce the sensors deployed in the experimental environment of this thesis.

- **Light sensor (as shown in Fig. 2-2(a))**

  The light sensor can be used to measure the luminous intensity in order to detect the change of brightness. Through detecting the illumination of the indoor and outdoor environment, the system can automatically decide whether to turn on the light indoor or not, and it can further arrange the light combination to optimize the energy utilization. Moreover, the system can turn on the light indoor while there is no human motion detected in the room, which would achieve the goal of energy saving.

- **Humidity and Temperature sensor (as shown in Fig. 2-2 (a))**

  The inappropriate indoor humidity or temperature do has impact on many aspects, including the freshness of food, the quality of air, and, the most important, the health and comfort of human. For the purpose of providing a suitable and comfortable environment for residents, the information the humidity and temperature sensors sensed indoor can help the system control the air conditioner and the fans in the cause of maintaining the constant or more comfortable temperature and humidity.

- **Current-flow sensor (as shown in Fig. 2-2 (b))**

  The current-flow sensors can be used to measure the amperage of the appliances; thus, the on-off state can be detected. Hence, the system can calculate the total power consumption by the recorded electricity usage. Similarly, with information of the on-off state, the appliances will be turned off or switched into energy saving mode if the appliances are no more used.

- **Passive infrared, PIR (as shown in Fig. 2-2 (c))**

  The passive infrared is used as the motion sensor that can detect whether there are humans moving in a room. Therefore, the accuracy of activity recognition can be enhanced so that more accurate services will be provided for residents.

- **Accelerometer (as shown in Fig. 2-2 (d))**

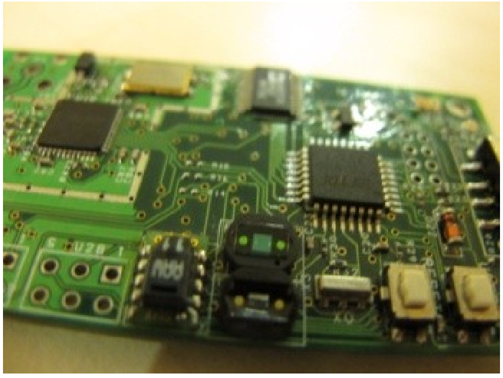
  Attaching the accelerometers on those objects which we are interested in can help us know the trajectory of the corresponding object. In addition, users can attach accelerometers to their body parts so that system can further recognize users' postures/gestures.

- **Microphone (as shown in Fig. 2-2 (e))**

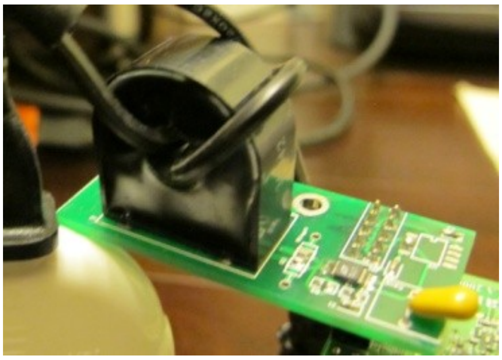
  It is inevitable that there exists a variety of sound in everyday life. In addition to other ambient sensors, the sound the microphone collects can be analyzed for providing more features to increase the human activity recognition rate.

- **Camera (as shown in Fig. 2-2 (f))**

  The number of humans in the home is an important clue for multi-user activity recognition. The video recorded by camera can be used to judge how many people in the room by the vision-based technique and the people can be tracked until they are out of the vision of camera.

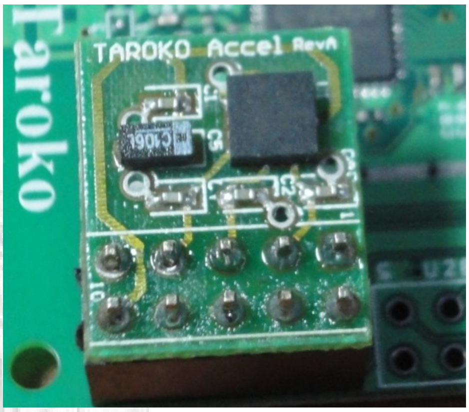


(a)



(b)

(c)



(d)

(e)

(f)

Fig. 2-2 The autonomous sensors.

(a) light, humidity, and temperature sensor (b) current-flow sensor (c) passive infrared (PIR) (d) accelerometer (e) microphone and (f) camera

2.2 Dynamic Bayesian Network (DBN)

A Dynamic Bayesian Network (DBN) [27] extends form Bayesian network [28], and it is used to model the temporal uncertainty we are interested in. It is represented as sequences of variables where the sequences are often referenced by time. In addition, DBNs assume that there are some underlying hidden states of the world that generate the observations, and these hidden states evolve in time. Therefore, DBNs have the ability to analyze sequential data such as audio signals, sensor measurements, sequential images, etc. The corresponding applications are speech recognition, location prediction of robots, and objects tracking. In this thesis, we apply DBNs to model human behaviors with various sensors deployed in the home environment according to the assumption that human behaviors are ordinarily composed of sequences of actions.

In the following subsections, we will introduce how to represent DBNs and how to learn the parameters. Finally, the inference method of the DBNs is shown.

A DBN is a directed graphical model in which nodes represent variables, and the arcs represent the causal relations among nodes. An arc from node A to node B can be informally interpreted as "*A* causes *B*", which hence disallow the directed cycles. For constructing a DBN, we should know the structure among all variables at first. Otherwise, the probability of node *A* given node *B* will be calculated by exhausting all of the possible structures. A technique, which is called structure learning, can score each possible structure, and then choose the most possible one which has the highest score. Therefore, we can find a possible structure among variables after applying structure learning.

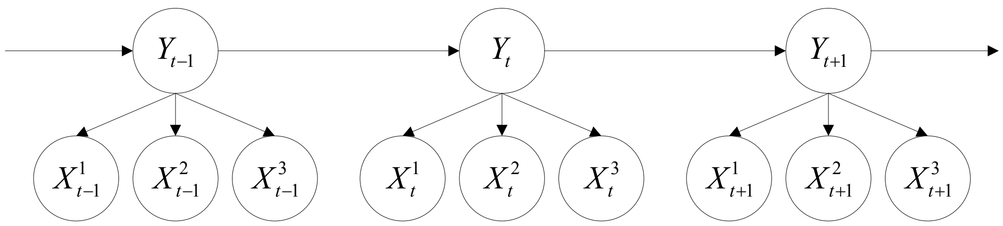


Fig. 2-3 An example of DBN with single state variable and three evidence states

In general, each slice of a DBN can have any number of state variables Y_t and evidence variables X_t. For simplicity, the variables and the corresponding links are assumed that they are exactly replicated from slice to slice. In Fig. 2-3, it is an example of a DBN which has single state variable and three evidence variables. The joint distribution with length T and with N random variables in each time slice can be formulated as the following equation:

$$P(V_{1:T}) = \prod_{t=1}^{T} \prod_{i=1}^{N} P(V_t^i \mid Pa(V_t^i)) \tag{2-1}$$

where V_t^i represents i-th random variable and a random variable is denoted as $V_t = (X_t, Y_t)$. $Pa(V_t^i)$ are the parents of V_t^i in the graph.

2.2.1 Inference

The inference of the DBN is to compute the posterior $P(Y_t|X_{1:\tau})$ based on the collection of observations: it is filtering if $\tau = t$; it is smoothing if $\tau > t$; it is prediction if $\tau < t$.

- **Filtering**

  Bayes Filter is the most general algorithm for estimating the belief state based on the observations which are collected so far, and it possesses two essential steps such as prediction and measurement update. The prediction step is done by calculating a belief over the state Y_t based on the prior belief over state Y_{t-1}. The equation of the prediction can be formulated as

$$\sum_{y' \in Y_{t-1}} P(Y_t = y_t \mid Y_{t-1} = y') P(Y_{t-1} = y' \mid X_{1:t-1}) \tag{2-2}$$

In the measurement update, the Bayes Filter algorithm multiplies the result computed at prediction step by the probability that the measurement X_t may have been observed. It does so for each hypothetical posterior state Y_t and then normalize the value such that the resulting product is a probability. The equation of the measurement update is formulated as

$$\gamma P(X_t \mid Y_t = y_t) \sum_{y' \in Y_{t-1}} P(Y_t = y_t \mid Y_{t-1} = y') P(Y_{t-1} = y' \mid X_{1:t-1}) \tag{2-3}$$

where γ is a constant which is for normalization. By recursively performing the above two steps, $P(Y_t|X_{1:t})$ can be calculated at each time slice.

- **Smoothing**

  Smoothing is the task to estimate the state of the past given the observation up to the current time, i.e., compute $P(Y_t \mid X_{1:T})$ for all $1 \le t \le T$.

- **Prediction**

  Prediction is the task to predict the future state, i.e., compute $P(Y_{t+h} \mid X_{1:t})$, where $h > 0$ is how far we want to look-ahead.

2.2.2 Learning

In a supervised learning which means that model is trained with labeled training data, learning the parameters of DBN is regarded as finding the maximum likelihood estimation (MLE) of the parameters of each conditional probability table. The parameters of DBN are denoted as θ which includes three types of parameters, such as initial probability $P(Y_t)$, observation probability $P(Y_t|X_t)$, and transition probability $P(Y_t|Y_{t-1})$. The optimization objective of MLE is to find parameters which maximize the likelihood based on the corresponding training data:

$$\theta^*_{MLE} = \arg\max_{\theta} P(D \mid \theta) = \arg\max_{\theta} \log P(D \mid \theta) \tag{2-4}$$

where $D = \{D^1, \ldots, D^K\}$ are the training data.

An alternative optimization objective is maximum a posteriori (MAP) which further takes a prior distribution into consideration:

$$\theta^*_{MAP} = \arg\max_{\theta} \log P(D \mid \theta) + \log P(\theta) \tag{2-5}$$

This can be useful when the size of the training data is out of proportion to the number of parameters because the prior acts like a normalizer which prevents over-fitting.

However, it costs time and money to obtain many labeled training data because the task of labeling data requires the expert knowledge in some specific domain, and it also is error-prone. Therefore, the techniques of semi-supervised learning or unsupervised learning can be applied to train a DBN where the training data of semi-supervised learning are composed of labeled and unlabeled data, and the training data of unsupervised learning are only composed of unlabeled data. Learning in these two cases is much harder than supervised learning; however, expectation-maximization (EM) [29] algorithm is a technique which can deal with missing data or hidden/latent variables when learning the parameters of DBN. The basic idea behind EM algorithm is to apply Jensen's inequality to get a lower bound on the log-likelihood of the training data, and then to iteratively maximize this lower bound:

$$
\begin{aligned}
L(D \mid \theta) &= \sum_{k=1}^{K} \log \sum_{h} P(H=h, D^k \mid \theta) \\
&= \sum_{k=1}^{K} \log \sum_{h} q(h \mid D^k) \frac{P(h, D^k \mid \theta)}{q(h \mid D^k)} \\
&\geq \sum_{k=1}^{K} \sum_{h} q(h \mid D^k) \log \frac{P(h, D^k \mid \theta)}{q(h \mid D^k)} \\
&= \sum_{k=1}^{K} \sum_{h} q(h \mid D^k) \log P(h, D^k \mid \theta) - \sum_{k=1}^{K} \sum_{h} q(h \mid D^k) \log q(h \mid D^k)
\end{aligned}
\tag{2-6}
$$

where q is a function such that $\sum_{h} q(h \mid D^k) = 1$ and $0 \leq q(h \mid D^k) \leq 1$, and H represents the latent variables. Maximizing the lower bound with respect to q gives:

$$
q(h \mid D^k) = P(h \mid D^k, \theta) \tag{2-7}
$$

This is called E (Expectation) step, which calculates the expectation with respect to the possible distribution of the latent data based on the current estimates of the desired parameters conditioned on the given observations; and this makes the bound tight. Maximizing the lower bound with respect to the parameters θ is equivalent to maximizing the expected complete-data log-likelihood:

$$
\sum_{k=1}^{K} \sum_{h} q(h \mid D^k) \log P(h, D^k \mid \theta) \tag{2-8}
$$

This is called M (Maximization) step which generates a new set of estimates of the desired parameters by maximizing the objective function.

The whole EM algorithm is an iterative method which recursively perform the E-step and M-step until convergence, and it is guaranteed to converge at the local maximum. Therefore, the different initial parameter θ is possible to result in different local maximum.

2.3 Home Appliance Categorization

Home appliances are the machines powered by electricity or natural gas/propane. Generally, according to their function, home appliances can be classified into two categories: white goods and brown goods [30], and they are also called major appliances and small appliances respectively. White goods are usually large and can assist residents in accomplishing some house chores, such as cooking or doing the laundry. The typical examples for white goods are refrigerator, washing machine, air conditioner, and microwave oven. And the brown goods are portable or semi-portable, which can help perform some job or provide residents with entertainment, for instances, DVD player, electric blender, and food mixer.

Recently, there is new definition of appliance categorization. They are classified into four categories: white goods, brown goods, beige goods, and green goods. Addition to white goods and brown goods, beige goods refers to the computer information products, and green goods refers to the appliance that can be recycled after using so that they will not do harm to the environment and humans.

However, in the energy saving systems, the appliances should be categorized according to their power consumption since the issue we aware of is how to efficiently utilize the energy. There is so far no unified standards of home appliances categorization for energy saving. Accordance with the U.S. EPA Energy Star's classification, the home appliances are categorized into seven types: heating, cooling, water heating, appliances, lighting, electronics, and others [31]. On the other hand, the Environmental Protection Administration of Taiwan [32] classifies them into six categories: HVAC (Heating, Ventilation, and Air Conditioning), lighting, kitchen appliances, hygiene-related appliances, entertainment appliances, and others. In this thesis, based on U.S. EPA Energy Star and EPA of Taiwan, taking the function of appliances as a classified factor, we categorize the home appliances into four types: (1) HVAC, (2) lighting, (3) high-power appliances, and (4) entertainment appliances.

For the energy consumption in Taiwan, about 30-40% is caused by HVAC, 20-30% is caused by lighting, and the remaining three categorizations account for 40-50% of total household energy consumption.

In the following sections the four types of appliances will be introduced individually.

2.3.1 HVAC

HVAC is the abbreviation for "Heating, Ventilation, and Air Conditioning", refers to the technology that regulates the indoor temperature in order to provide a comfortable environment for residents. The HVAC system consists of electric air heater, water heater, dehumidifier, and air conditioner, etc. Moreover, it always accounts for the largest part of household energy consumption due to its high-power property and being turned on for a long period frequently.

2.3.2 Lighting

Although there are a variety of lighting source, in this section we mainly focus on the artificial lighting that is commonly provided by electric lighting systems, *i.e.* from a light bulb, a lamp, or the light emitting diode (LED).

Illuminance is defined as the total luminous flux per unit area. The SI

(International System of Units) derived unit for illuminance is Lux (lx). It is undeniable that lighting is an essential part in our life, proper lighting can help human enhance task performance and stay healthy; further, it also has impact on human's emotion.

2.3.3 High-power Appliances

Similar to HVAC, some appliances are also high-power appliances, for instance, hair dryer, microwave, and electric cooker, which often transform the electricity into heat. However, the main difference between HVAC and high-power appliances is that the latter would not be frequently turned on for a long duration.

2.3.4 Low-power Appliances

In order to the three types we have mentioned above, there are numerous home appliances that consume lower power, such as the appliances we use in everyday life (*e.g.* blender and fans), audiovisual appliances (*e.g.* TV, DVD player, and stereo), and the communication equipment (*e.g.* computer), etc.

2.4 Predicted Mean Vote

Predicted mean vote (abbreviated as PMV), proposed by Fanger, is one of the most common thermal comfort index for evaluating the thermal sensation of a large population of people exposed for a long period to constant conditions in an environment [33, 34]. PMV uses four environment parameters (air temperature, air velocity, mean radiant temperature, and air humidity) and two personal factors (clothing insulation and activity level) to predict the thermal comfort of humans.

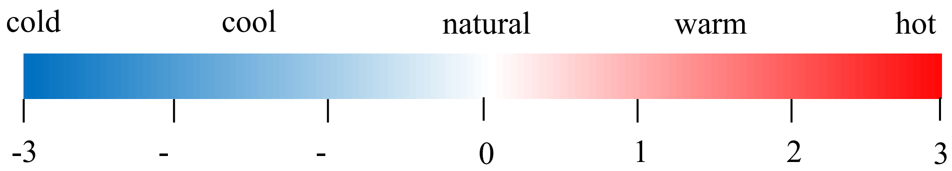


Fig. 2-4 The PMV thermal scale

According to the ASHRAE thermal sensation scale, the PMV index for thermal comfort predicts the average vote on a 7 point scale. More specifically, the scale from -3 to +3 refers to cold, cool, neutral, warm, and hot, respectively, as shown in Fig. 2-4. And the ISO (International Standards Organization) Standard 7730 (ISO 1984) recommends that the PMV between -0.5 and +0.5 is better for human.

The PMV equation is an empirical one for predicting the mean vote on an ordinal category rating scale of thermal comfort of a large population of people. The equation uses a steady-state heat balance for the human body and builds a link between the thermal comfort vote and the degree of stress or load on the body (*e.g.* sweating, vasoconstriction, vasodilation). The greater the load, the more the comfort vote deviates from zero. And it only applies to humans exposed for a long period to constant conditions at a constant metabolic rate.

The PMV referred to more than 1300 subjects' thermal sensation votes. The following is the equation:

$$
\begin{aligned}
PMV = {} & (0.303 \cdot e^{-0.036M} + 0.028)\{(M-W) - 3.05 \cdot 10^{-3} \cdot [5733 - 6.99(M - W) - p_a] \\
& - 0.42 \cdot [(M-W) - 58.15] - 1.7 \cdot 10^{-5} \cdot M(5867 - p_a) - 0.0014M(34 - t_a) \\
& - 3.96 \cdot 10^{-8} \cdot f_{cl} \cdot [(t_{cl} + 273)^4 - (\overline{t_\gamma} + 273)^4] - f_{cl} \cdot h_c \cdot (t_{cl} - t_a)\}
\end{aligned}
\qquad (2\text{-}9)
$$

where

$$t_{cl} = 35.7 - 0.028(M - W) - I_{cl}\{3.96 \cdot 10^{-8} f_{cl} \cdot \left[(t_{cl}+273)^4 - (\overline{t_\gamma}+273)^4\right] + f_{cl}\, h_c\,(t_{cl} - t_a)\} \tag{2-10}$$

$$h_c = \begin{cases} 2.38(t_{cl} - t_a)^{0.25} & \text{, for } 2.38(t_{cl} - t_a)^{0.25} \geq 12.1\sqrt{v_{a\gamma}} \\ 12.1\sqrt{v_{a\gamma}} & \text{, for } 2.38(t_{cl} - t_a)^{0.25} < 12.1\sqrt{v_{a\gamma}} \end{cases} \tag{2-11}$$

$$f_{cl} = \begin{cases} 1.00 + 1.290 I_{cl}, \text{ for } I_{cl} \leq 0.078 \text{m}^2 \cdot ℃/W \\ 1.05 + 0.645 I_{cl}, \text{ for } I_{cl} > 0.078 \text{m}^2 \cdot ℃/W \end{cases} \tag{2-12}$$

where

M is the metabolic rate, in W/m^2;

W is the external work, in W/m^2, equal to zero for most activites;

I_{cl} is the thermal resistance of clothing, in m^2 □C/W^3;

f_{cl} is the ratio of man's surface area while clothed, to man's surface area while nude;

t_a is the air temperature, in $^\circ C$;

$\overline{t_r}$ is the mean radiant temperature, in $^\circ C$;

v_{ar} is the relative air velocity (relative to he human body), in m/s;

p_a is the partial water vapour pressure, in Pa;

h_c is the convective heat transfer coefficient, in W/m^2 □C;

t_{cl} is the surface temperature of clothing, in $^\circ C$;

Chapter 3

Overview of the Context-aware Energy Saving System

3.1 Problem Definition

In a home energy saving system, it is important to find out the sources causing unnecessary power consumption because human often unconsciously overuse energy, such as overcooling/overheating a room or not turning off lights while leaving a room. For the improvement of energy saving in a non-occupied room, we usually use a motion detection device, *e.g.* a passive infrared (PIR), to detect existence of the user to automatically turn off the power. However, the problem of avoiding overcooling/overheating a room poses more challenges to be addressed. For example, users may adjust the indoor temperature to very low or very high degree (*e.g.* 15°C or 35°C). Besides, although the most related appliances triggered by the undergoing activity can be selected out by the inference technique of activity recognition, we hardly figure out those appliances that are not triggered by the activity but still under operation, which could bring out a certain amount of power consumption. In addition, multiple-user contexts and their associated energy consumption information is the major challenge we need to take care of.

After finding out the causes of the unnecessary power consumption, it is also important that how to make right energy saving decision the users will accept. In other words, we have to take the issue of human comfort into consideration and there could be more than one activity performed by a group of people in the home.

For the purpose of solving the problem described above, in this thesis we design an energy saving system and deploy sets of sensor module in the home to collect the daily living data for monitoring the usage of appliances and the environment status and inferring the activities of human to make an optimized energy saving decision. In the next section, we will illustrate the overview of our energy saving system and describe briefly each part of the system.

3.2 System Overview

As illustrated in Fig. 3-1, the energy saving system consists of four layers that are “Device Management Layer”, “Feature/Context Exchange Layer”, “Inference and Evaluation Layer”, and “Energy Saving Decision Layer”. Every components in the four layers (*e.g.* a sensor in the Device Management Layer or an energy saving model in the Inference and Evaluation Layer) can interconnect with one another via a publish-and-subscribe manner through an integration platform [35]. That is to say, this platform is in charge of message exchange among all interconnected components. With the integration platform, it is easy to add new components into the energy saving system

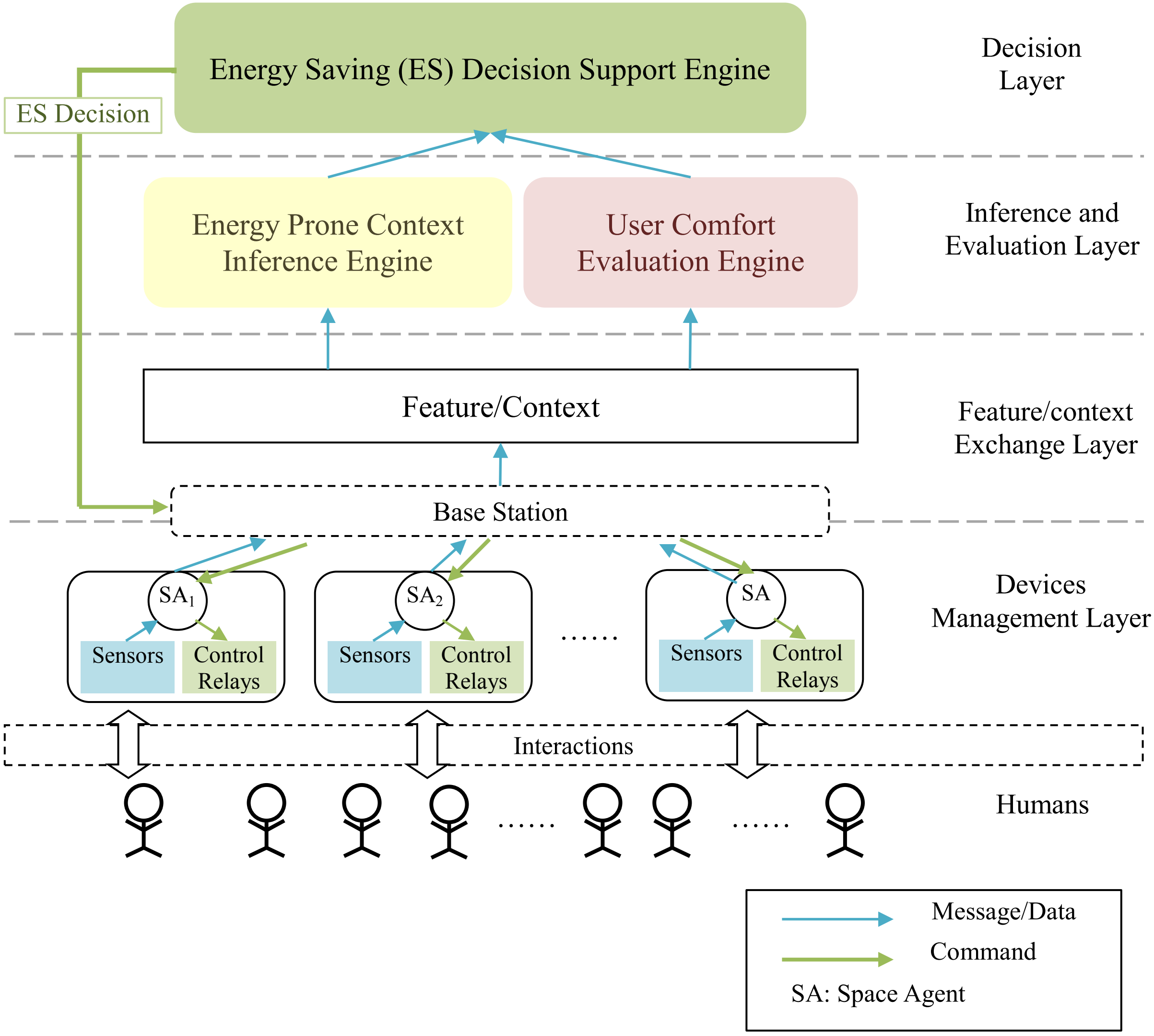


Fig. 3-1 The architecture of the energy saving system

as long as conforming to the publish-and-subscribe manner.

In the following, each layer of the energy saving system will be introduced in detail.

3.2.1 Device Management Layer

In order to sense the information of environment and control the appliances, we deploy many sensors and control relays in every rooms of the home. For the purpose of managing the sensors and control relays orderly, we design the space agent (SA) as a device manager to pass the sensing data to the Feature/context Exchange Layer and receive the energy saving decision from the Energy Saving Decision Layer to control the appliances. As shown in Fig. 3-2, the sensors $\{S_1, S_2, S_3...S_n\}$ in the $room_1$ send the sensing data representing the status of human or environment to the space agent, and then the space agent passes the data to the Feature/context Exchange Layer for later inferring. After the energy saving decision made by Energy Saving Decision Layer, the decision will be delivered back to the space agent that sends control commands to control the relays to regulate or turn on/off the appliances in the room.

The advantage of the structure in the Device Management Layer is that it increases

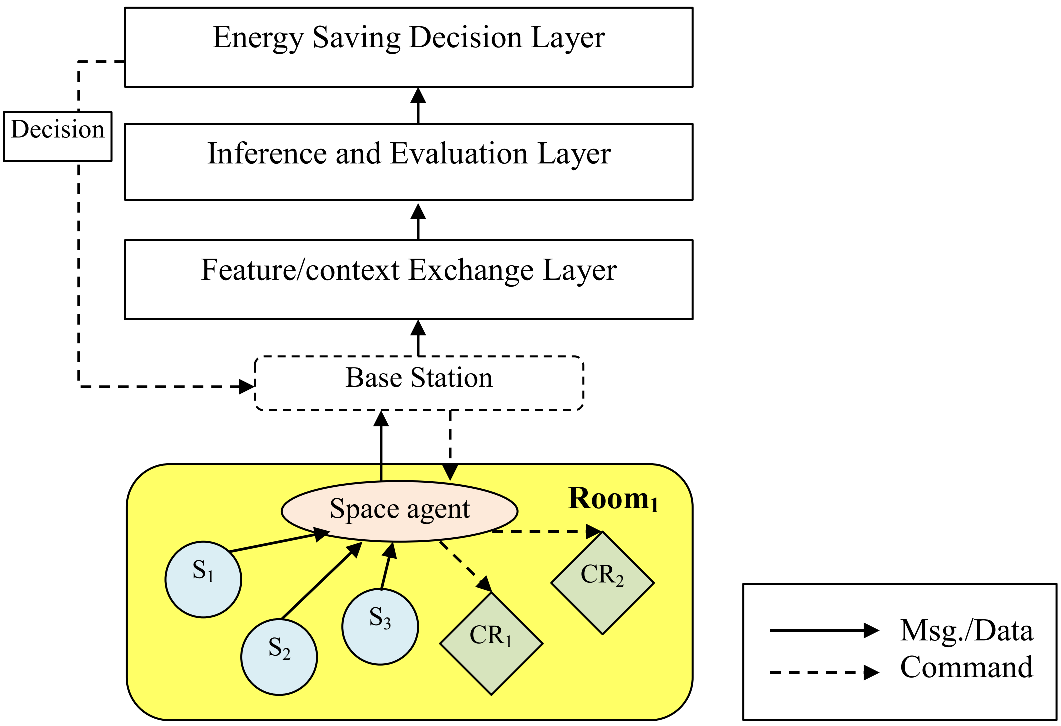


Fig. 3-2 An example of space agent in Device Management Layer

the convenience of adding/removing sensors and control relays to/from the space since the space agent keeps all the information of the devices.

3.2.2 Feature/context Exchange Layer

In the previous layer, the sensing data collected is the type of raw data; that is, the original data in the numerical format. In order to quantize the numerical data for acquiring the higher-level information, such as features and contexts, the data should be preprocessed at the gateway (*i.e.* the base station in Fig. 3-3) before being publishing to the Feature/context Exchange Layer. And the features/contexts in this layer could be subscribed for inference later. The common method of quantization is to divide the range of value into two or more parts by the predefined thresholds. For example, we define the feature that the level of temperature is high if the value of temperature exceeds 30ºC; therefore, we can get the information called "high temperature" while the value is 37 ºC.

In the energy saving system, we use several kinds of sensors for sensing the state and information of environment or humans, including temperature/humidity/light sensor, accelerometer, microphone, and current-flow sensor, etc. After data preprocessing, all the sensing data is transferred from raw data to features/contexts that are more comprehensible for representing the state, information or contexts. For the purpose of easily publishing and subscribing, different types of features/contexts are putted into different topic of queues. As shown in Fig. 3-3, there are several queues for saving the features/contexts published from the Device Management Layer.

3.2.3 Inference and Evaluation Layer

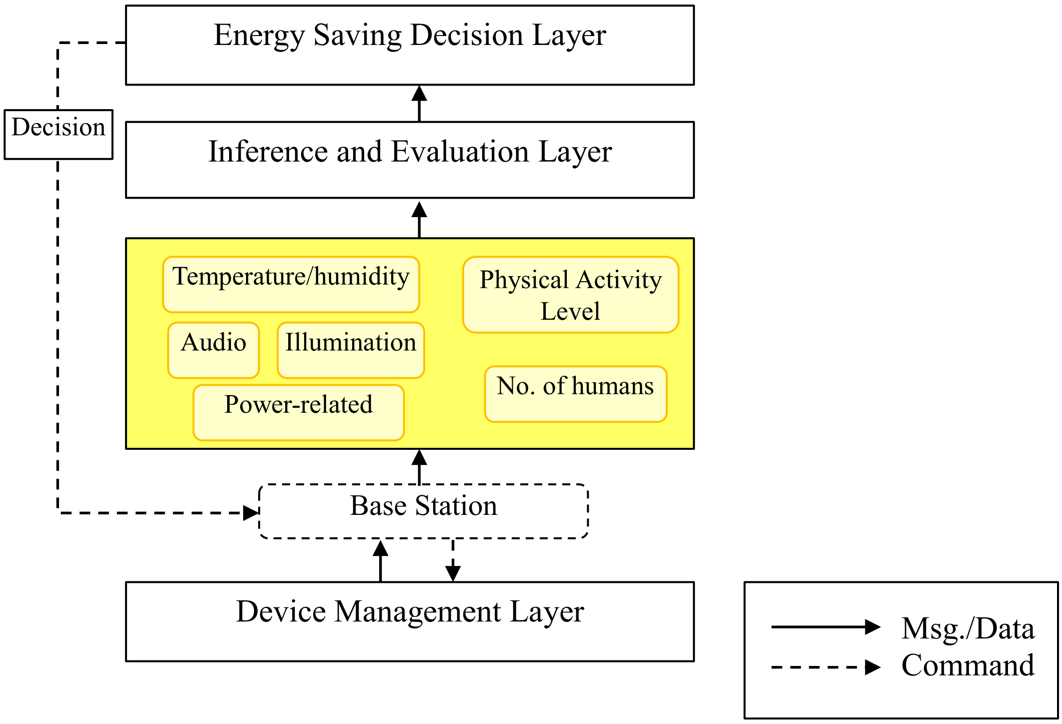


Fig. 3-3 Different topics of features/contexts in the Feature/context Exchange Layer

As the name implies, the Inference and Evaluation Layer contain two main components: Energy Prone Context Inference Engine (EPCIE) and User Comfort Evaluation Engine (UCEE), which will be introduced in Chapter 4 and Chapter 5 respectively. These engines subscribe the features or contexts in the Feature/Context Exchange Layer to infer the higher-level context, as shown in Fig. 3-4. Specifically mentioned, the EPCIE uses the features representing the state of human or the environment, the power consumption and the current on/off state of appliances to infer the contexts tagged information of power consumption, called energy tagged context that will be discussed in Section 4.2. On the other hand, the UCEE uses state of human (*e.g.* the physical activity level) and the real-time parameters of the environment (*e.g.* the temperature, illumination and humidity) to evaluate the user comfort that can reflect how the conditions in the environment influence on user.

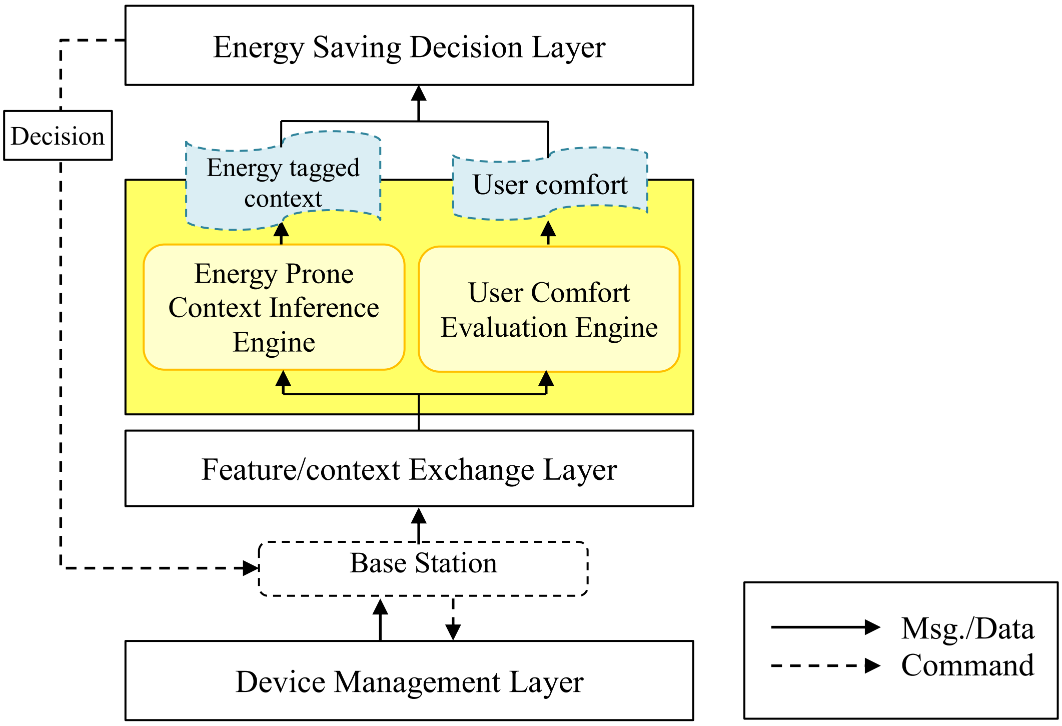


Fig. 3-4 The Inference and Evaluation Layer

3.2.4 Energy Saving Decision Layer

In this Energy Saving Decision Layer, the Energy Saving Decision Support Engine is charge of making the suitable decision of appliances control based on a certain degree of user comfort, as shown in Fig. 3-5. In order to achieve the goal of context-aware energy saving, the decision support engine takes the energy tagged context and user comfort as inputs at the same time. With the user comfort evaluated by standards, the system first tunes the appliances (the most part are HVAC and lighting) to adjust the indoor temperature, humidity and illumination to satisfy the user. And then it utilizes the information the energy tagged context provides to find out the major appliances that cause unnecessary power consumption so as to turn off or tune the appliances.

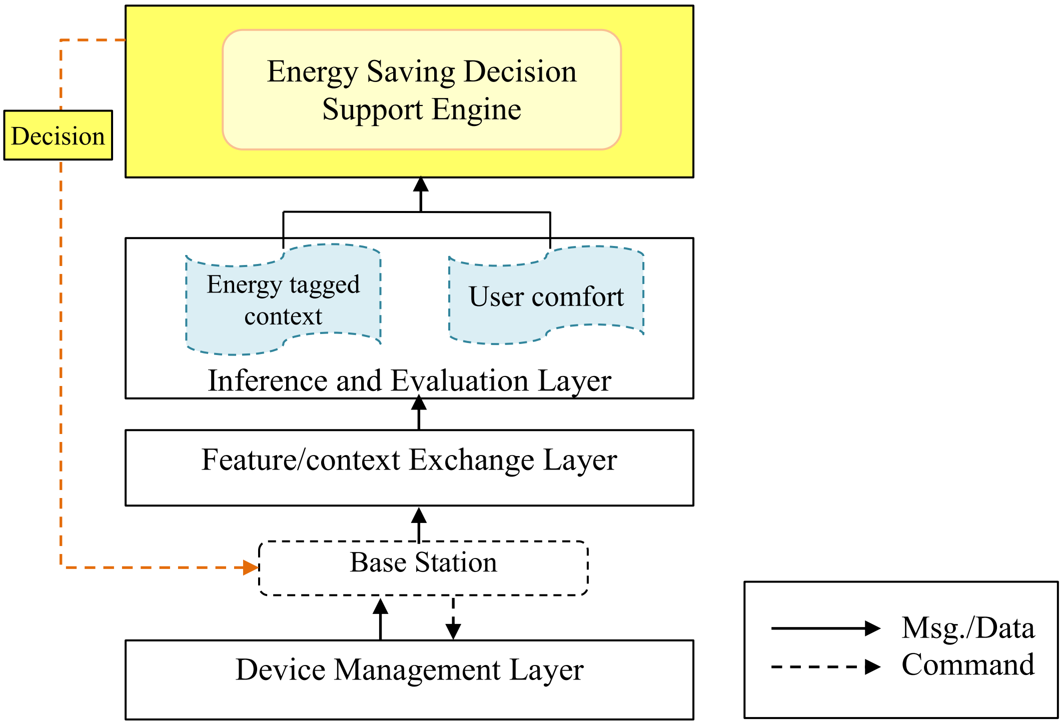


Fig. 3-5 The Energy Saving Decision Layer takes the energy tagged context and user comfort as input to make the energy saving decisions

Chapter 4

Energy Prone Context Inference Engine

Human activity is one of the main factors bringing about energy consumption, and it is also a critical factor for the improvement of energy saving since an energy saving system can proactively reduce energy waste by constantly paying attention to what activities are currently undertaken. In this chapter, we will elaborate how Energy Prone Context Inference Engine (EPCIE), one core component in the Inference and Evaluation Layer, infers the relationship between a context (especially users' current activities) and its power consumption. Furthermore, we also discuss how EPCIE infers a group-based context such as a social activity like watching TV together in the living.

4.1 Problem Definition

In this chapter, there are n individual activities $\{A^1, A^2, \ldots, A^N\}$ which can be detected by their corresponding activity inference engines given m observations

$\{O^1, O^2, \ldots, O^M\}$ in the environment, where O^M is an observation from a sensor. And we use a vector $\{\boldsymbol{O}_{set1}, \boldsymbol{O}_{set2}, \ldots, \boldsymbol{O}_{setT}\}$ to represent an observation sequence (*i.e.* features) which is composed of all sensor observations from the beginning to time *t* and $\boldsymbol{O}_{set}$ stands for the set of observations from O^1 to O^M. However, it is inevitable that there are multiple humans undertaking different activities in the same space. Almost prior works of multi-user activity recognition need to associate an observation to the user who generates the observation via an interaction with the environment, which leads to the difficulty in multi-user activity recognition. Such a problem becomes even more intractable when it comes to an environment involving more than three persons. Rather than knowing each individual' s power consumption, it is more important to figure out which appliances leading to the unnecessary power consumption when an activity is performed, we therefore ignore the data association between user IDs and their activities to makes multi-user activity recognition far less intractable.

For each activity we use EPCIE to infer an Energy Tagged Context (abbreviated as ETC and more details in Section 4.2) that comprises a context of interest (*i.e.* the activity being undertaken) and its associated energy consumption in a more readable format. The set **ETC** ($\{\mathrm{ETC}^1, \mathrm{ETC}^2, \ldots, \mathrm{ETC}^N\}$) is used for representing the energy tagged context of the *n* activities (*i.e.* $\{A^1, A^2, \ldots, A^N\}$), and each element in ETC is a vector that consists of many attributes, represented as $\{Att^1, Att^2, \ldots, Att^I\}$. In order to obtain the Energy Tagged Context of multi-user activities, we exploit the method of clustering to aggregate the activities with similar attributes (*e.g.* activities with similar physical activity levels or similar in the combination of power consumption) into a group activity.

The following sections are arranged as following: first, we define the Energy Prone

Context, including Energy Tagged Context, in Section 4.2, and the inference of individual activity and group activity will be discussed in the Section 4.3 and Section 4.4 respectively.

4.2 Definition of Energy Prone Context

An Energy Prone Context (EPC) is a context that is apt to leading to energy consumption, such as watching TV and studying at night. Humans usually perform activities associated with indoor appliances, which will cause energy consumption. For the purpose of expressing the energy information, we use Energy Tagged Contexts (ETCs) to represent the concept of EPC. And the Energy Tagged Context consists of likelihood of the occurrence of a context along with its states of power usage of appliances.

In the following, we introduce the appliance power usage signature and explain two types of power consumption. Finally, we use a graph to visualize the Energy Tagged Context of the Energy Prone Context.

4.2.1 Appliance Power Usage Signature

Every appliance powered by electricity will cause power consumption. The power consumption is decided by the power level and state of appliances, and can be measured by power meters. For example, we can measure that a fan with rated power of 0.035kW and its "low power consumption" state may cause 0.027kW of power consumption. Moreover, we can define the power consumption level to classify and quantize the power consumption of an appliance, an example of which is illustrated in TABLE 2.

TABLE 2 THE TABLE OF POWER CONSUMPTION LEVEL

Level	Power consumption (kW)
Level 0	X = 0 kW
Level 1	0.001 kW < X ≤ 0.015 kW
Level 2	0.015 < X ≤ 0.1 kW
Level 3	0.1 < X ≤ 0.3 kW
Level 4	0.3 < X ≤ 1kW
Level 5	1kW < X

Therefore, we propose power usage signature of an appliance and it includes two parameters, the power state and the power consumption level.

4.2.2 Explicit/Implicit Power Consumption

We divide the power usage signature into two categories: explicit power consumption and implicit one. The explicit power consumption refers to the power consumption of appliances that is directly triggered by or closely related to an activity, whereas the implicit power consumption is the power consumption caused by the appliances that are indirectly triggered by an activity and its operating period is longer than time period of the activity been performed. The detailed processes for inferring the two types of power consumption will be discussed in Section 4.3.1 and Section 4.3.3. In a few words, the explicit power consumption is generated as long as its corresponding activity occurred. The concepts of explicit and implicit power consumption are illustrated in Fig. 4-1.

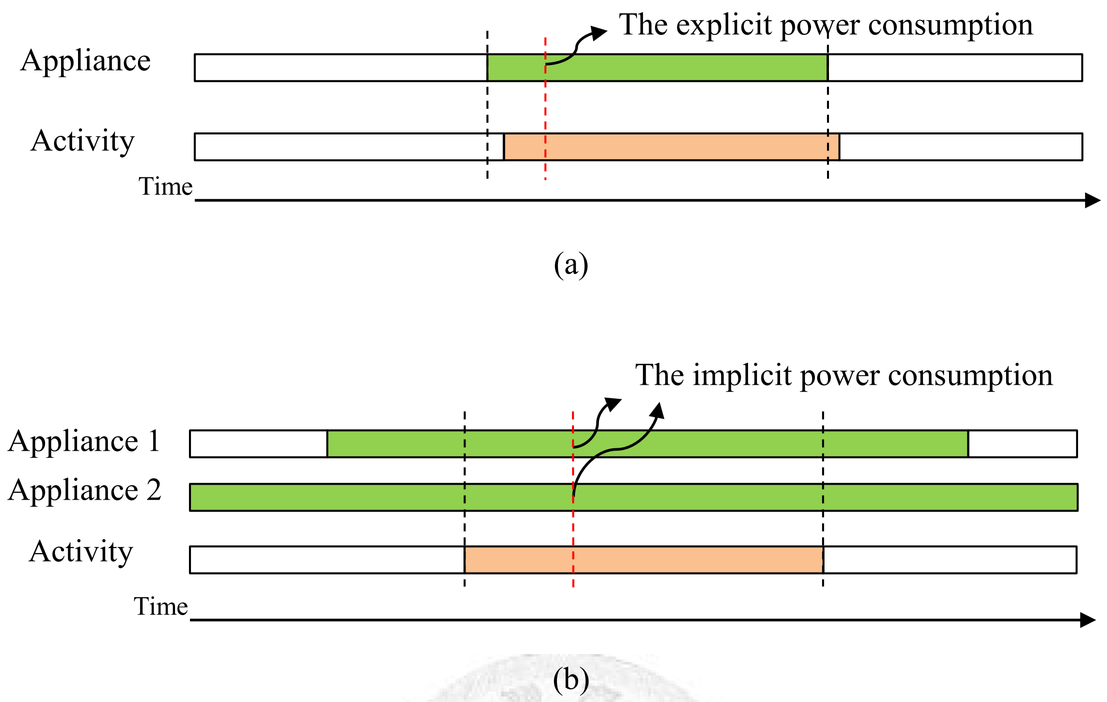


Fig. 4-1 The concepts of two kinds of power consumption.

(a) explicit power consumption and (b) implicit power consumption

4.2.3 Energy Tagged Context Graph

In this thesis, the Energy Tagged Context is represented as a feature vector that consists of two main parts: the context itself and the information of appliance power usage signature. The context contains the activity name, the number of humans in the room where the activity performed, and the corresponding physical activity level. The appliance power usage signature represents the level of power consumption of the appliance, the confidence of the correlation between the appliance and the activity, as well as the type and the area of power consumption of the appliance (*i.e.* explicit/implicit and global/local power consumption). For the sake of visualizing the relationship between the context and the energy tagged information, we use a graph to illustrate the concept, as shown in Fig. 4-2. In the graph, the node in the middle is the context we are interested in (*e.g.* the activity with the number of humans and the physical activity level or PAL). And the edges are the appliance power usage signature of different appliances correlated to the context. The length of the edge stands for the power consumption level of the appliance, and the width stands for the confidence of the correlation. The correlation of power consumption can be categorized into explicit or implicit power consumption, and they are represented by solid line and dotted line respectively. Moreover, power consumption can be further classified into local or global types according to the region the power consumption occurred with respect to the context. If an appliance is not in the current region and does have impact on every region, we call it a global appliance, such as the A/C or the water heater in Fig. 4-2. The solid point and hollow point are used for representing the local and global power consumption, as shown in Fig. 4-2.

4.3 Energy Prone Context Inference Model

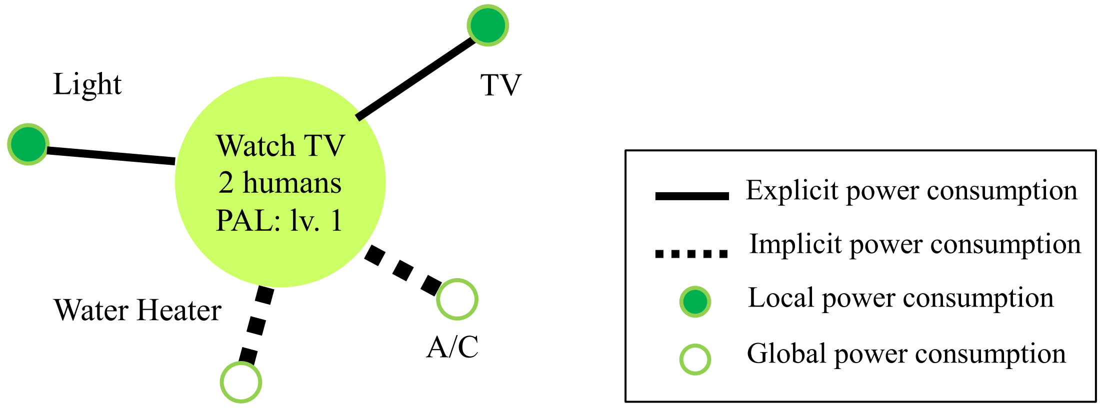


Fig. 4-2 The Energy Tagged Context

Distinguished from the traditional activity inference model, the energy prone context inference model additionally takes the power-related information of appliances into account, letting the energy saving system identify the main causes of energy waste, especially the implicit power consumption. In this regard, we can later control energy saving more accurately.

The flowchart of the learning phase of Energy Prone Context Inference Engine is shown in Fig. 4-3, which contains two main steps: DBN activity recognition model construction and power consumption relations identification, including explicit power consumption identification and implicit power consumption identification. The results of the two procedures, *i.e.* the DBN activity models and explicit/implicit power consumption, will be combined to build energy tagged contexts. In the following, we will delve into the process of generating energy tagged contexts.

After generating the energy tagged context (ETC) of each activity, we use a group activity aggregator to cluster activities into groups each of which we call it a group activity. This will be introduced in Section 4.4.

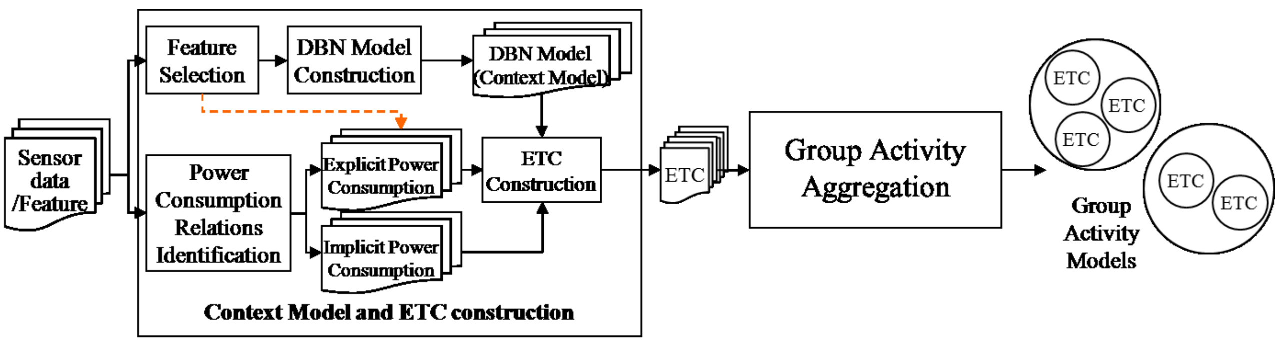


Fig. 4-3 The flow chart of the training phase of Energy Prone Context Inference Engine

4.3.1 Activity Recognition

Before identifying the correlation between power consumption of appliances and activities, we need to infer what the individual activity is performed at present in the first place. As the parameters defined in Section 4.1, the observations $\{O^1, O^2, \ldots, O^M\}$ will be preprocessed and compared with a threshold into context-level features, which can be represented as a vector $\mathbf{F} = \{f^1, f^2, \ldots, f^M\}$. In this thesis, we use Dynamic Bayesian Network (DBN), a supervised learning approach, to build the inference models for activity recognition and an example of an activity recognition model is shown in Fig. 4-4. In a DBN, an arrow between two nodes represents a causal relationship. The previous activity ($A_{T\text{-}1}$) will influence the current activity (A_T)which will in turn trigger or generate the features $\mathbf{F}_T$. Given the previous activity and all observations from the sensors (or their corresponding features), we can infer the probability of the current activity. And we judge whether the activity does occur by the probability inferred by the activity recognition model.

4.3.2 Explicit Power Consumption Inference

As mentioned in Section 4.2.2, the explicit power consumption is closely correlated to the occurrence of its corresponding activity. That is, while the activity is performed, the correlated appliances will be turned on to the operating mode, which causes the explicit power consumption. In our Bayesian activity recognition model, the process of feature selection that can choose the most important features; therefore, we exploit the advantage of feature selection to find out the key appliances that cause explicit power consumption.

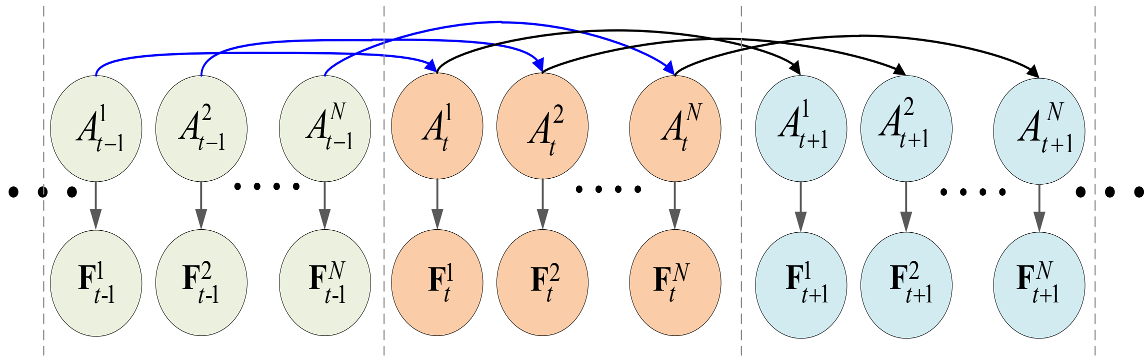


Fig. 4-4 The DBN of an activity recognition model

We use mutual information to measure the mutual dependence between a candidate feature (*i.e.* the correlated appliance) and its corresponding activity. Mutual information is calculated for each activity-feature pair of the training data for the purpose of choosing better ones from the set of sensor features to enhance the activity recognition model to be more discriminative. If we define all the activities and features as $\mathbf{A} = \{A^1, A^2, \ldots, A^N\}$ and $\mathbf{F} = \{f^1, f^2, \ldots, f^M\}$, the mutual information is calculated by the following equation:

$$\mathrm{I}(A_i\,; F_j) = \mathrm{H}(A_i) - \mathrm{H}(A_i \mid F_j) \tag{4-1}$$

$$\mathrm{H}(A_i) = -\sum_{a \in A_i} \mathrm{P}(A_i = a) \log\big(\mathrm{P}(A_i = a)\big) \tag{4-2}$$

$$\begin{aligned}
\mathrm{H}(A_i|F_j) &= \sum_{f \in F_j} \mathrm{P}(F_j = f)\, \mathrm{H}(A_i \mid F_j = f) \\
&= -\sum_{f \in F_j} \mathrm{P}(F_j = f) \sum_{a \in A_i} \mathrm{P}(A_i = a \mid F_j = f) \log\big(\mathrm{P}(A_i = a \mid F_j = f)\big) \\
&= -\sum_{f \in F_j, a \in A_i} \mathrm{P}(A_i = a, F_j = f) \log\big(\mathrm{P}(A_i = a \mid F_j = f)\big)
\end{aligned} \tag{4-3}$$

After estimating the mutual information between each activity-feature pair, we choose those features with higher value to construct the activity model. In other words, the selected features (or appliances) are more related to their corresponding activities, which cause the explicit power consumption. And the other features with lower mutual information are treated as noises which may influence the accuracy of the activity recognition.

In conclusion, each activity model will acquire its corresponding explicit feature set that causes the explicit power consumption. The explicit feature set can be represented as $\mathbf{F^{ex}}=\{F^{ex_1}, F^{ex_2}, \ldots, F^{ex_J}\}$, where the index set $\{ex_1, ex_2, \ldots, ex_J\}$ stands for the index of features causing explicit power consumption. The confidence of the explicit feature is assigned with the value calculated by mutual information. For the instance in Fig. 4-2, the explicit feature set of the activity "watch TV" is {*current_TV, current_light*}, implying that the appliances are the TV and the lighting.

4.3.3 Implicit Power Consumption Inference

In contrast to explicit power consumption, the appliances causing implicit power consumption are not triggered by the ongoing activity directly. They may be turned on all day long so that the process of feature selection will not regard the appliances as correlated features to the activity. However, these appliances actually consume power during the period the activity occurs, which may be major cause of energy waste, for example, the air conditioner or the water heater in Fig. 4-2.

In order to solve the problem of figuring out the appliances causing implicit power consumption, we again apply mutual information to select the implicit feature set ($\mathbf{F^{im}}$). In the training stage, if we want to find the implicit feature set of a target activity A, we first extract the data labeled activity A for correlation analysis because the implicit features can be detected during the training period. For the purpose of excluding the explicit feature set ($\mathbf{F}^{ex}$), we subtract the explicit feature set ($\mathbf{F}^{ex}$) from the total feature set (**F**) to obtain the remaining feature set (**F'**). With the remaining features, we estimate the mutual information between each activity-feature pair in the extracted data. Likewise, as with finding the explicit feature set in Section 4.3.2, we choose those features with higher value as the implicit feature set ($\mathbf{F}^{im}$), and the confidence of the implicit feature is assigned with the value calculated by mutual information. In Fig. 4-2, the implicit feature set is {*current_A/C, current_WaterHeater*}, implying that the appliances are the air conditioner (A/C) and the water heater.

4.4 Group Activity Recognition

In an energy saving system for a multi-user house or environment, it is less informative to associate the individual activity with its corresponding user information (e.g. user ID) or energy saving since we often need to know the major causes of energy waste or overall energy consumption. Besides, families or friends usually gather together to accomplish something, that is the reason why the energy saving decision should not be made without considering the feeling of the whole group. Therefore, we infer group activities based on the individual activities mentioned in Section 4.3.1 for figuring out the source of energy waste and evaluating the group user comfort in an area.

4.4.1 Definition of Group Activity

There have been different definitions about a group activity, most of the prior works define a group activity that the activities performed by the humans moving in the same direction or the activities many people intend to do [11, 12] (*e.g.* marching). In this thesis, we define group activity as following:

- One or more than one people doing the same thing in the same area
- More than one people doing different things in the same area

Doing different activities generates different level of thermal energy (or activity level) and the humans may turn on/off or tune up/down different combination of appliances to change the power consumption. For example, doing the activity "watching TV" may generate lower level of thermal energy (about 1~2 calories per minute) and the TV and the light will be turned on; whereas doing the activity "cleaning" may generate higher level of thermal energy (about 5~8 calories per minute) and the vacuum cleaner and the light will be turned on. Unfortunately, since real environment is complicated and often changes dynamically, there exists uncertainty that the same activity does not always cause the same level of thermal energy and the human may not turn on/off the same set of appliances. If we use the attributes (*i.e.* the level of thermal energy and the power consumption) for activity inference, it might bring about error recognition rate.

In order to address this issue, we assume that similar activities cause similar thermal energy on a human and require similar power consumption from appliances; thus, we can cluster the activities into a group with the similar attributes, and give each of the group activity a physical meaning as a representative label of this group. Later, if some activities with the similar attributes occur at the same time, the energy saving system can make decision on the appliance control according to the attributes of the group activities instead of on individual activities, which can improve the efficiency of energy saving.

We use Energy Tagged Context (ETC) to represent the related power consumption of a context we are interested in. In this work, the ETC has four attributes. The context in the node consists of activity and the physical activity level. And the power consumption can be divided into local and global power consumption according to the service scope that an appliance could provide in. In the next section, we will discuss which attributes will be chosen for group activity clustering.

4.4.2 Group Activity Clustering

The goal of the energy saving system is to reduce the unnecessary energy waste given the system needing to meet a certain level of user comfort. Therefore, we choose some attributes that can represent the user comfort, and then use them as the basis for clustering group activity, which are the physical activity level and the power consumption (including local and global power consumption) in the thesis. After group activity clustering, we can control the appliances according to the two types of power consumption and the physical activity level to do energy saving without violating the least level of user comfort.

We use the method of "k-means" clustering to cluster *n* individual activities into *k* group activities for each room in the home. In each room, we define that there are *n* individual activities, *i.e.* *n* ETCs ($\mathrm{ETC}^1, \mathrm{ETC}^2, \ldots, \mathrm{ETC}^N$), to be clustered, and *r* attributes for clustering (including the power consumption of local/global appliances and the physical activity level).

Given the *k* initial mean points for each cluster, the k-means decides which cluster every sample (in the thesis, the ETC is a sample point in form of a feature vector) should belong to by minimizing the within-cluster sum of squares, shown as below:

$$\underset{\mathbf{G}}{\mathbf{arg\,min}} \sum_{i=1}^{k} \sum_{ETC^N \in G^i} \left\| \mathrm{ETC}^N - \mu^i \right\|^2 \tag{4-4}$$

where $\mathbf{G} = \{G^1, G^2, \ldots, G^K\}$ is the set of group activity that contains k group activities, and $\{\mu^1, \mu^2, \ldots, \mu^K\}$ is the set of mean points of k group activities. In the equation, $\left\| \mathrm{ETC}^N - \mu^i \right\|^2$ is used to calculate the square distance between an ETC and the mean point, where the ETC^N to be clustered is an r-dimensional vector which contains the power consumption of x local appliances and y global appliances ($\{app_{local}{}^1, \ldots, app_{local}{}^x, app_{global}{}^1, \ldots, app_{global}{}^y\}$, and $x + y = r$), and the physical activity level (PAL^N). After this process, all the ETCs are clustered into k clusters, and the mean of each cluster will be recalculated until there is no apparent difference between the old mean and the new one.

Eventually, the ETCs with similar power consumption and physical activity level will be clustered into the same group activity, which can provide information of energy and user comfort for later energy saving decision making.

Chapter 5

Context-aware Energy Saving

In a home environment, it is an important issue that we should take the human feeling into consideration while doing energy saving. In this chapter, we introduce two measurements to evaluate the user comfort based on standards. Combined with the two user comfort indexes, we formulate an energy-saving into a constraint satisfaction problems (CSP) to make better or even optimal energy saving decisions to achieve the goal of context-aware energy saving.

5.1 Human-centric Consideration

In our daily living, many environmental parameters do have influence on the feeling of a human body, such as temperature, humidity, light, and wind velocity. Inappropriate environmental conditions may affect the physical or mental states of humans, such as living quality, the working performance and overall productivity, or even emotion. Thus, we cannot ignore human's feeling while doing energy saving.

In this thesis, we mainly focus on human sensation of thermal and illumination, since both factors cause more obvious effects on human comfort. And these two comfort indexes will be used for controlling indoor light and temperature respectively to achieve the goal of more desirable energy saving.

5.1.1 Thermal Comfort Index

The thermal comfort is used to evaluate the human's reaction about the temperature variation in the sensed environment. The range of temperature, 22~26°C, is considered to be the most comfortable thermal range for human's living or working environments, and the metabolic rate of human body will change with respect to the temperature and physical activity level. Therefore, human may feel uncomfortable while there is no thermal balance between environment and human body.

The thermal comfort is affected by heat conduction, convection, radiation, and evaporative heat loss. Here, we use the most common thermal comfort index called PMV (which has been introduced in Section 2.4) to evaluate the thermal sensation of the users in the home. It is reckoned when the activity (metabolic rate) and the clothing (thermal resistance) are estimated, and the following environmental parameters are measured including air temperature, mean radiant temperature, relative air velocity and partial water vapor pressure (ISO 7726).

For the purpose of simplifying the equation (2-9), we make some assumptions on the parameters, as shown below:

- M = 58, which is the metabolic rate (W/m^2)
- W = 0, which is the external work (W/m^2). The external work is the part of the metabolic rate that is used up in the activity being performed, rather than contributing to the heat balance of the individual concerned. It is usually taken

as zero, and should always be less than the metabolic rate. The default value is 0.0.

- I_{cl} = 0.7 (spring), 0.5 (summer), 1.0 (fall), and 1.5 (winter); each of which is the thermal resistance of clothing ($m^2 \cdot °C/W^3$) in a specific season.
- $t_a = \overline{t_\gamma}$, which are the air temperature and the mean radiant temperature (°C)
- $v_{a\gamma}$ = 0.5, which is the relative air velocity (relative to the human body) (m/s)
- h_c = 30, which is the convective heat transfer coefficient (W/ $m^2 \cdot °C$)
- t_{cl} = 30, which is the surface temperature of clothing (°C)
- Other parameters are sensed by the sensors

Different activity leads to different metabolic rate (M), which is shown in TABLE 3. With the thermal comfort index and PMV, the user's thermal sensation can be evaluated and then be quantized into seven scales, as shown in TABLE 4.

TABLE 3 THE METABOLIC RATE OF THE 17 ACTIVITIES

Activity	Metabolic Rate	Activity	Metabolic Rate
ComeBack	58	Cooking	170
GoOut	58	PlayingKinect	165
Sleeping	46	Chatting	58
WatchingTV	58	Studying	70
TakingBath	170	ListeningMusic	58
UsingPC	70	UsingRestroom	100
Laundering	93	BrushingTooth	100
ReadingBook	70	WashingDishes	145
Cleaning	145		

TABLE 4 THE 7-PIONT OF THERMAL SENSATION SCALE

PMV	**-3**	**-2**	**1**	**0**	**1**	**2**	**3**
Thermal Sensation	Cold	Cool	Slightly Cool	Neutral	Slightly Warm	Warm	Hot

5.1.2 Illumination Comfort Index

Light is also an indispensable element in our lives. Without the light, nothing will be visible and the environment will become lifeless since there is no light (or sunlight) for photosynthesis to maintain a balanced ecological environment. For an individual human, enough light resource can help improve working productivity and stabilize emotion.

The Chinese National Standards (CNS) defines a discrete illumination rank by giving each rank a specific lux of illumination, which is illustrated in the upper row in Fig. 5-1. Next, we further use the illumination rank to define the lux level. Each lux level is an interval of lux, which is shown in the lower row in Fig. 5-1.

Actually, it requires different intensity of light for different activity. For example, we need more illumination when reading newspapers, but may need less illumination

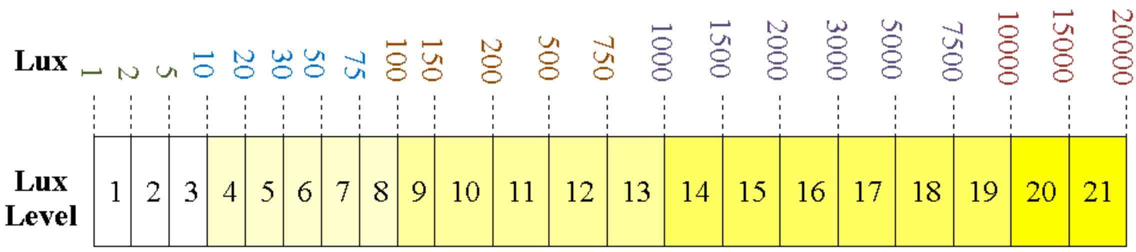


Fig. 5-1 The discrete illumination rank of CNS (upper) and our lux level (lower)

TABLE 5 THE APPROPRIATE LUX LEVEL OF THE 17 ACTIVITIES

Activity	Lux Level	Activity	Lux Level
ComeBack	30~75	Cooking	200~500
GoOut	30~75	PlayingKinect	150~300
Sleeping	1~2	Chatting	150~300
WatchingTV	150~300	Studying	500~1000
TakingBath	200~500	ListeningMusic	150~300
UsingPC	300~750	UsingRestroom	200~500
Laundering	150~300	BrushingTooth	200~500
ReadingBook	500~1000	WashingDishes	200~500
Cleaning	300~500		

while watching movies on a TV in the living room. The appropriate illumination for different activities is illustrated in TABLE 5. Similar to the thermal comfort index, in order to evaluate the satisfaction of illumination, we normalize the difference of lux level between the ideal level and real level into seven scales, *i.e.* it is from -3 to +3. We can formulate it as follows:

$$\frac{\text{real lux level} - \text{ideal lux level}}{\text{normalization factor}} \tag{5-1}$$

where the normalization factor could determine the level of energy saving, and we choose six as the normalization factor based on some pilot experiments. The concept of illumination comfort index is shown in TABLE 6.

5.1.3 User Comfort Indexes in Energy Saving

TABLE 6 THE 7-PIONT OF THERMAL SENSATION SCALE

Illumination Level	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**
Illumination Sensation	Dark	Gloomy	Slightly Gloomy	Neutral	Slightly Blight	Blight	Glared

The thermal comfort index and the illumination comfort index are evaluated via User Comfort Evaluation Engine (UCEE) mentioned in Section 3.2.3. The engine takes the physical activity level and the environmental parameters, such as indoor temperature, illumination and humidity, as inputs to calculate the two comfort indexes. As shown in Fig. 5-2, there are two sub engines in UCEE: Thermal Comfort Evaluation sub Engine and Illumination Comfort Evaluation sub Engine. The Thermal Comfort Evaluation sub Engine uses the intensity (*i.e.* the physical activity level) of the corresponding activity and the value of indoor temperature and humidity to calculate a thermal comfort index

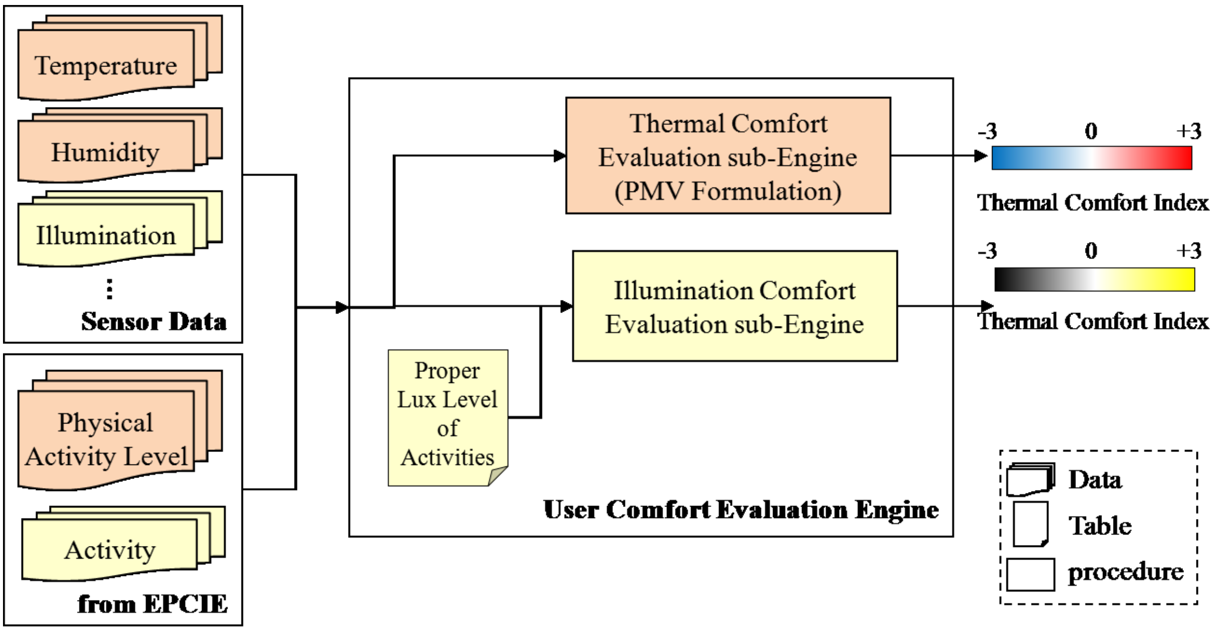


Fig. 5-2 The flowchart of User Comfort Evaluation Engine

called PMV, which ranges from -3 to +3. With the value of PMV, the system would be aware of the thermal sensation of a resident any time. For instance, users may feel cold when PMV is close to -3 and may feel hot when PMV is close to +3. Hence, the system can adjust the indoor temperature to be a more appropriate degree in accordance with the calculated PMV. Similarly, the Illumination Comfort Evaluation sub Engine uses the current illumination and the most appropriate lux level to calculate the degree of user comfort. As mentioned in Section 5.1.2, we normalize the illumination comfort into seven scales (*i.e.* from -3 to +3). When the light is too glared (the illumination index is +3) or too dark (the illumination index is -3), the system can decrease or increase the intensity of light in order to provide a more desirable environment for users. Therefore, with the two comfort indexes, the energy-saving system will achieve the goal of more satisfactory context-awareness.

5.2 A Pilot Evaluation of Context-Aware Energy Saving Realization based on the Thermal Comfort Index

In this section, we design a simple experiment regarding energy saving using the PMV index, and this experiment mainly focuses on the temperature adjustment of the air conditioner independently.

5.2.1 Experiment Setting

In this experiment, we simulate the user's activities in the home with some assumption on the environmental parameters to evaluate the PMV index, and exploit the user comfort to adjust the temperature of air conditioner for three scenarios. The assumption on the environmental are:

- The initial temperature: 30°C
- The energy consumption: additional 6% energy consumption on average while tuning up 1°C of the air conditioner
- The energy consumption: 100 virtual units at 30°C
- The A/C simulator: tune down 1°C per minute while adjusting the temperature of A/C
- The fixed experimental routine: come back → cleaning → watch TV (The metabolic rate of each activity is shown in TABLE 7.)

The aforementioned three scenarios are:

(1) Continuously adjust the temperature of air conditioner to fit the user comfort based on the PMV index

(2) The temperature is set at 28°C

(3) The temperature is set at 25°C

With the assumptions and the three scenarios, the system will calculate the integral absolute value of PMV every 10 seconds by the equation:

$$\int |\mathrm{PMV}| \cdot dt \tag{5-2}$$

TABLE 7 THE METABOLIC RATE OF 3 ACTIVITIES

Activity	Come back	Cleaning	Watch TV
Metabolic Rate	58 W/m^2	145 W/m^2	58 W/m^2

the users will feel more comfort while the integral absolute value is more closer to 0. The experimental results of temperature adjustment are shown in the next section.

5.2.2 Preliminary Experimental Results

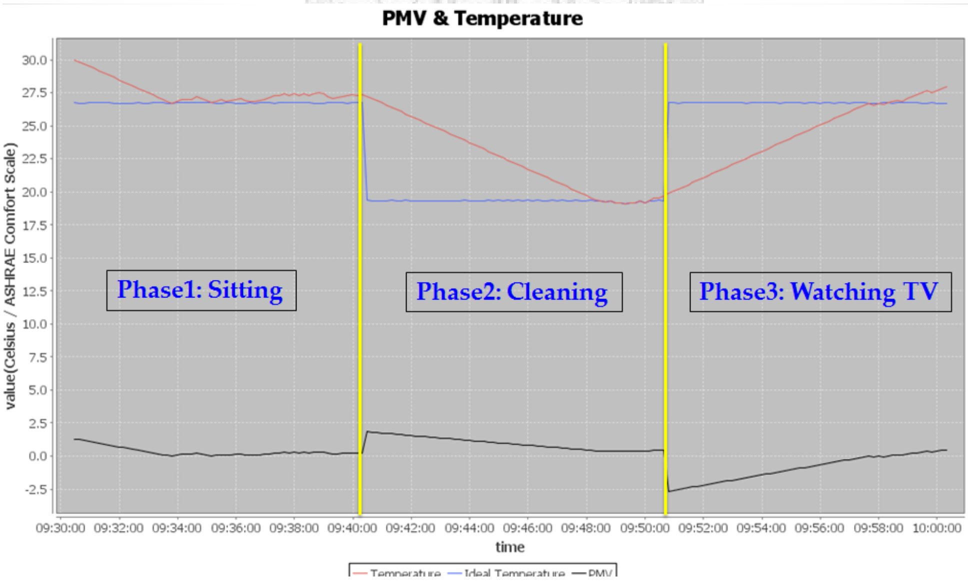
The preliminary experimental results about the three scenarios are shown in Fig. 5-3 and TABLE 8.

In Fig. 5-3, the red line stands for the real temperature, the blue line stands for the ideal temperature, and the black line is the PMV curve. In scenario 1, it shows that the real indoor temperature is adjusted in order to maintain the PMV near as much as value 0 as possible (*i.e.* putting higher priority on user thermal comfort). In scenario 2 and scenario 3, the system tries to keep the real indoor temperature as near 28°C and 25°C respectively as possible, and the PMVs of the two scenarios increase when the user is cleaning. In these two scenarios, the system posed a lower priority on user thermal comfort and adjusts the indoor temperature to let the value of PMVs closer to 0, which would cost less energy consumption than scenario 1, as shown in TABLE 8.

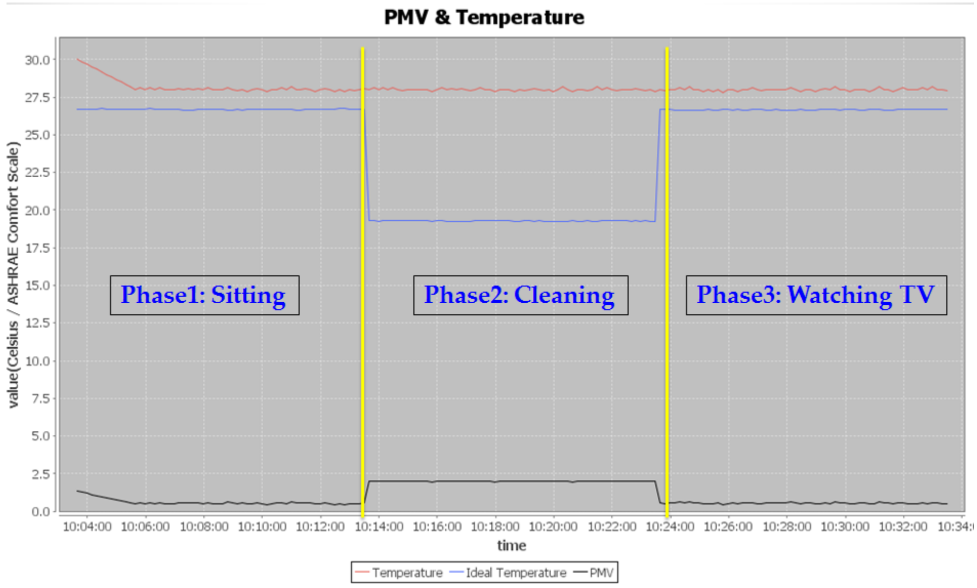
Within the testing period (30 minutes in total), the total energy consumption of the air conditioner in Fig. 5-3 and the integral absolute value of the PMVs of the three scenarios are illustrated in TABLE 8. Since the system tries to maintain the PMV at value 0 in the scenario 1 (*i.e.* putting more priority on user thermal comfort), the air conditioner is adjusted continuously by the system. This causes the highest total energy consumption on the air conditioner and the lowest integral absolute value of PMVs among the three scenarios. In contrast, in the scenario 2 and scenario 3, where the indoor temperature is set to a specific degree, the integral absolute values of PMV are higher than that in scenario 1 due to the lower priority on user thermal comfort.

However, some energy consumption caused by a user changing his/her on-going activities can be saved since the system needs not adjust the temperature of the air conditioner frequently, which originally would leads to more energy consumption.

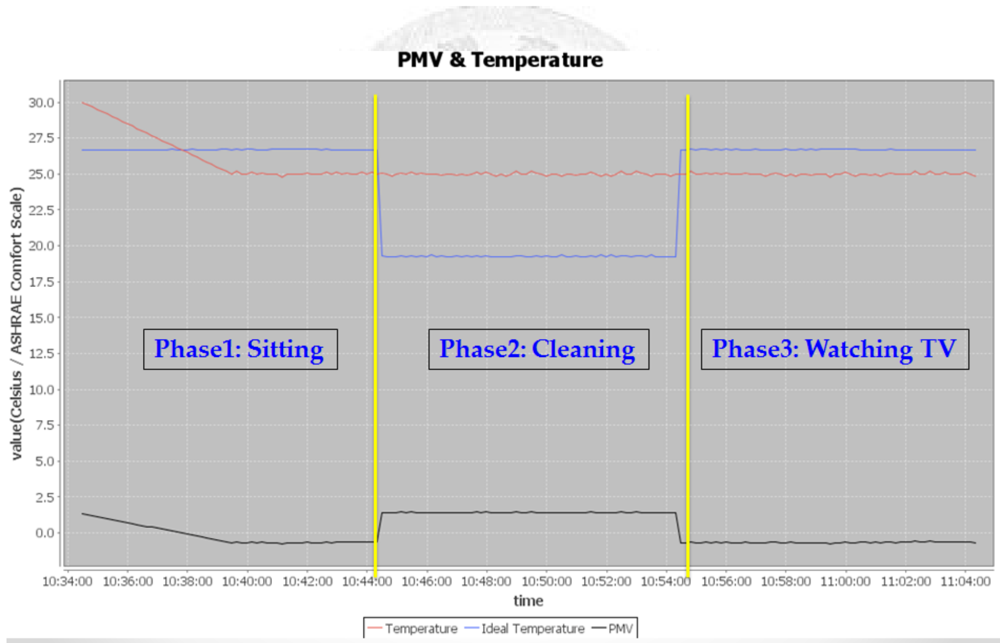
From the pilot experiment of context-aware energy saving, we find that there exists a trade-off between fulfilling the maximum user comfort and achieving maximum effect of energy saving. That is, fulfilling the maximum user comfort often leads to more energy consumption, whereas achieving maximum effect of energy saving may cause more user discomfort. Thus, we formulate this issue into a constraint satisfaction problem into energy saving decision making where the system will try to maintain a certain level of user comfort the user can accept, which will be introduced in the next section.



(a)



(b)



(c)

Fig. 5-3 The preliminary experimental results about the three scenarios. The horizontal axis and vertical axis are represented as time and the value (°C / PMV) (a) Based on the PMV index (b) 28°C and (c) 25°C

TABLE 8 THE EXPERIMENT RESULTS OF THE FIRST STAGE EVALUATION OF ENERGY SAVING REALIZATION BASED ON THERMAL COMFORT INDEX (PMV)

Scenario	Based on PMV	The temperature is set at 28°C	The temperature is set at 25°C
Total energy consumption of the A/C (with virtual unit)	23668.67 virtual units	20078.56 virtual units	22933.24 virtual units
The integrated absolute value of PMV	1382.39	1885.39	1621.60

5.3 Optimization for Context-aware Energy Saving

In the energy saving system developed in this thesis, energy saving is done under the constraint that the system should maintain at least a certain level of user comfort. Therefore, the system adjusts the appliances that do have influences on user comfort (*i.e.* evaluated by the PMV and the illumination level) and reduces energy waste by turning off those standby or unused appliances based on the user comfort indices (CIs) and the energy tagged contexts (ETCs) inferred by the Energy Prone Context Inference Engine. We can formulate the energy saving decision as shown below:

$$TPC_{\min} \mid_{\text{ETCs+CIs}} = \underset{s_i \in S,\, d_i \in D}{\textbf{arg min}} \sum_{i=1}^{N} (L(s_i) + d_i) \mid_{\text{ETCs+CIs}},\ |\text{CIs}| \leq T \tag{5-3}$$

where $D = \{d_1, d_2, \ldots, d_N\}$ is the adjustment of each appliance, $S = \{s_1, s_2, \ldots, s_N\}$ is the status of each appliance, L is the function to evaluate the power consumption level,

TPC is the total power consumption, and T is the threshold of comfort indices so that we can maintain as much comfort for users while doing energy saving.

For the comfort-related appliance control, we can divide it into two parts: temperature adjustment and light control. With the sensors deployed in the home, the User Comfort Evaluation Engine can exploit the sensor data to evaluate the thermal comfort index (PMV) and the illumination comfort index (illumination level) as mentioned in Section 5.1.3. For the thermal comfort adjustment, the engine calculates the PMV using the temperature, humidity, and physical activity level (metabolic rate). Next, under a certain level of thermal comfort (T in equation (5-2)), the system uses the equation (5-2) to find a best combination of appliance (*e.g.* the fan or the air conditioner) adjustments that cost the minimum power consumption. Similarly, the lighting adjustment with the minimum power consumption can be calculated by exploring the appropriate illumination level based on the activity information.

Chapter 6

System Evaluation

In Section 5.2, we have shown some preliminary experiment results of doing energy saving while considering the user comfort at the same time. In this chapter, we simulate a home environment on a PC program and it generates all sensor data which contains uncertainty to make it close to a real life scenario. Next, we can train the activity models and test accuracy of inferring the group activities and the effectiveness of our proposed context-aware energy saving.

6.1 The Simulated Home

For the sake of generating sensor data close what could occur in a real home environment, we design a program of a simulated home where the layout is similar to a general home and there are four people living in it, as shown in Fig. 6-1. In the figure, the simulated home consists of 6 rooms: a hallway, a living room, a kitchen, a bedroom, a bathroom and a balcony. There are several virtual appliances and sensors (such as TV and current-flow sensors) populated in each room. In order to show the information of

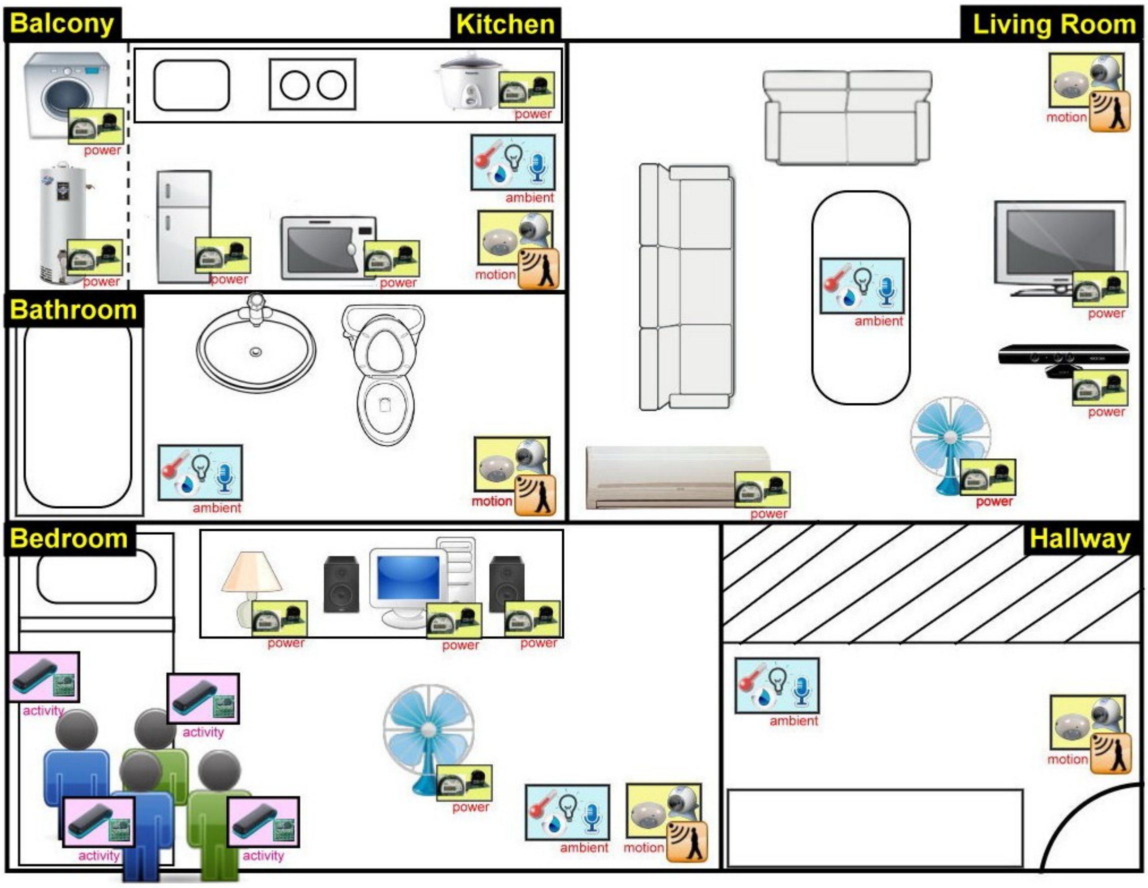


Fig. 6-1 The layout of the simulated home

sensors clearly, the sensors are classified into four sensor modules for detecting the human activities and the changes in the environment, including ambient sensor module, motion detection module, power monitoring module, and mobile activity-monitoring module. In the following, we introduce the components and the functions of these sensor modules in detail:

- Ambient sensor module

    An ambient sensor module is composed of a temperature sensor, a humidity sensor, a light sensor, and a microphone, all of which are used to collect the ambient sensing data representing the conditions of the environment, *i.e.* the temperature, the humidity, the illumination, and the sound.

- Motion detection module

  In this module, a PIR (passive infrared) and a camera sensor are used for detecting the human motion, tracking the humans, and counting the number of humans in the home.

- Power monitoring module

  A power monitoring module consists of a current-flow sensor and a power meter. It is equipped with an appliance to monitor the current-flow, power states and the power consumption of the appliance.

- Mobile activity-monitoring module

  The metabolic rate of a human body varies with the intensity of an activity, and the intensity can be detected by the mobile activity-monitoring module. The module is made of accelerometers or other commercial devices (*e.g.* fitbit) that can detect the physical activity level of a person.

Furthermore, the living styles of the four people are set based on an average adult in Taiwan. For instance, the common living style is that waking up at 8:00 in the morning and going to bed about 22:00-23:30 at night, and three meals are taken at 8:30, 12:30 and 18:00 respectively. There are 17 activities simulated in the experiment, and the noise of the sensors is also taken into account, which will be discussed in the next section.

6.2 The Activities in the Simulated Home

For the purpose of achieving a more realistic scenario, we simulate 17 daily living activities whose patterns are commonly occurred in a real-life setting, as illustrated in TABLE 9. Moreover, in order to make these simulated activities more realistic, we add some device-level noises generated by a Gaussian distribution to these 17 activities since there are non-predictable noises in a dynamic home environment, such as sensor failure or unexpected triggers from the residents.

However, in order to simplify the complexity of the simulated home environment, the living style and the 17 activities are created based on the assumptions and experiment settings as follows:

- The activities are simulated based on a pre-defined simulated scenario of a twenty-some person (*i.e.* pure program simulation), as shown in TABLE 10.

TABLE 9 THE LIST OF ACTIVITIES WITH THE METABOLIC EQUIVALENT OF TASK IN EACH ROOM

Location	**Activity**	**Metabolic Equivalent of Task (MET)**	**Location**	**Activity**	**Metabolic Equivalent of Task (MET)**
Hallway	GoOut	3~4	Bedroom	Studying	1.5~2
	ComeBack	2~2.5		Sleeping	0.9~1.2
Living Room	WachingTV	1~1.5		ListeningMusic	1~1.2
	PlayingKinect	8~12		UsingPC	1.5~2
	Chatting	1.2~2	Bathroom	TakingBath	3.5~5
	ReadingBook	1.5~2		UsingRestroom	2~2.8
	Cleaning	4~5.5		BrushingTooh	1.5~2
Kitchen	Cooking	3.5~5.5	Balcony	Laundering	2~2.5
	WashingDishes	2~2.5			

TABLE 10 THE SCENARIO OF ONE DAY IN THE SIMULATED HOME

Duration	Activity	Duration	Activity
07:00-08:00	Sleeping	14:00-17:00	Listening Music
08:10-08:25	Using Restroom	14:20-15:00	Using PC
08:15-08:30	Brushing Tooth	15:00-16:00	Studying
08:35-09:00	Cooking	15:30-17:00	Using PC
09:00-10:00	Watching TV	17:05-18:10	Cooking
09:10-09:30	Chatting	18:00-18:20	Washing Dishes
09:25-09:55	Reading Book	18:30-19:20	Chatting
09:50-10:40	Playing Kinect	19:00-21:50	Playing Kinect
10:35-11:00	Cleaning	21:55-22:20	Taking Bath
11:00-11:02	Go Out	22:20-23:00	Laundering
11:38-11:40	Come Back	23:00-23:10	Using Restroom
11:45-13:30	Cooking	23:10-23:20	Brushing Tooth
13:00-13:30	Washing Dishes	23:20-24:00	Sleeping
13:35-14:30	Studying		

- All devices (*e.g.* sensors) share the same device-level uncertainty parameters, and we use Gaussian noise in this thesis.
- The probability of a device failing to generate readings is at most 10%.
- Only Infra-red and camera sensors apply the device-level uncertainties since both of them are the most error-prone ones in our pilot study.

For each physical activity level, we use metabolic equivalent of task (MET) [36] to evaluate the intensity of each activity. MET is the ratio of the work metabolic rate to the resting metabolic rate, which can be defined as below:

$$1\ \text{MET} = 1\ \frac{\text{kcal}}{\text{kg}\cdot\text{hour}} \tag{6-1}$$

(which is roughly equivalent to the energy cost of sitting quietly). And the metabolic rate (mentioned in Section 5.1.1) of a relaxed seated person is one MET, thus we can represent it as below:

$$1 \text{ MET} = 58 \ \frac{W}{M^2} \tag{6-2}$$

Furthermore, the intensity of an activity represented by MET can be divided into three level, *i.e.* light (MET < 3), moderate ($3 \leq$ MET ≤ 6) and vigorous (MET > 6), and some examples are listed in TABLE 11. In the table, the published MET values for specific activities are experimentally and statistically derived from the average of a sample set of humans. With the value of MET, the calories the users consumed at different activity intensity can be calculated via the following equation:

$$\begin{aligned}&\text{The calories consumed (kcal)}\\&\quad = \text{MET} \cdot \text{Body Weight (kg)} \cdot \text{time (hours)}\end{aligned} \tag{6-3}$$

And the activity intensity, that is, the physical activity levels (abbreviated as PAL) of the 17 simulated activities are listed on the right side of their corresponding activities in TABLE 9.

6.3 The Flowchart of System Evaluation

In the experiment of this thesis, there are three main steps (as shown in Fig. 6-2):

(1) **ETC and group activity models construction (EPCIE)**:

Generate sensor data and preprocess them into features which are able to represent the higher-level meaning of the environment, such as the feature “TV_On” standing for that the TV is turned on. And the features are taken as the training data to construct the activity models and their ETC models.

Furthermore, we aggregate the ETC models into group activity models with

TABLE 11 THE THREE LEVEL OF PHYSICAL ACTIVITY INTENSITY

Physical Activities with Different Activity-Intensity Levels	MET
Light Intensity Activities	**< 3**
Sleeping	0.9
Watching TV	1.0
Writing, Desk Work, Typing	1.8
Walking (1.7 ~ 4 km/hr.)	2.3 ~ 2.9
Moderate Intensity Activities	**3 to 6**
Bicycling	3.0 ~ 5.5
Walking (4.8 ~ 5.5 km/hr.)	3.3 ~ 3.6
Calisthenics, Home Exercises	3.5
Vigorous Intensity Activities	**> 6**
Jogging	7.0
Calisthenics (*e.g.* pushups and sit-ups), Running Jogging	8.0
Rope Jumping	10.0

some key attributes (*e.g.* the physical activity level or the intensity of activity, and the combination of power consumption of appliances) since an appliance in the house are often shared among more than one resident. After the aggregation, the activities in each group activity model have similar attributes (*i.e.* physical activity level and combination of power consumption of appliances) and the group-activity models will be used later for inferring group activities.

(2) **ETCs and group activities inference and user comfort indexes evaluation (via EPCIE and UCEE)**:

This step can be divided into two sub-parts: (1) the testing phase of EPCIE to infer the ETCs and group activities and (2) the evaluation of user comfort indexes by User Comfort Evaluation Engine (UCEE).

EPCIE takes the features (preprocessed from the sensor data) as inputs to infer the current activities and find the corresponding ETCs from the constructed database of the ETC models. The group activities the inferred activities belong to are inferred based on the ETCs.

Simultaneously, the sensor data including temperature, humidity, illumination, power-related information, and the physical activity level of humans, are used to evaluate the user's thermal and illumination comfort indexes by UCEE.

(3) **Energy saving decision making (Energy Saving Support Decision Engine, ESSDE)**:

Exploit the results in the second step (*i.e.* the ETC of group activities and the user comfort indexes) and formulate into a constraint satisfaction problem (CSP) to make the more appreciate energy saving decisions for appliances adjustment given a certain degree of user comfort should be met (*e.g.* $-0.5 < PMV < +0.5$ and $-0.9 <$ illumination comfort < 1).

6.4 Experimental Result

In this thesis, the experiment results are divided into two parts: (1) the accuracy of group activity inference and (2) the degree of energy saving of the context-aware system.

After the group activity inference, each group activity has their corresponding activities, and there are different group activities in each room. Therefore, we use two types of performance evaluation in the experiment of the simulated home. That is, one is

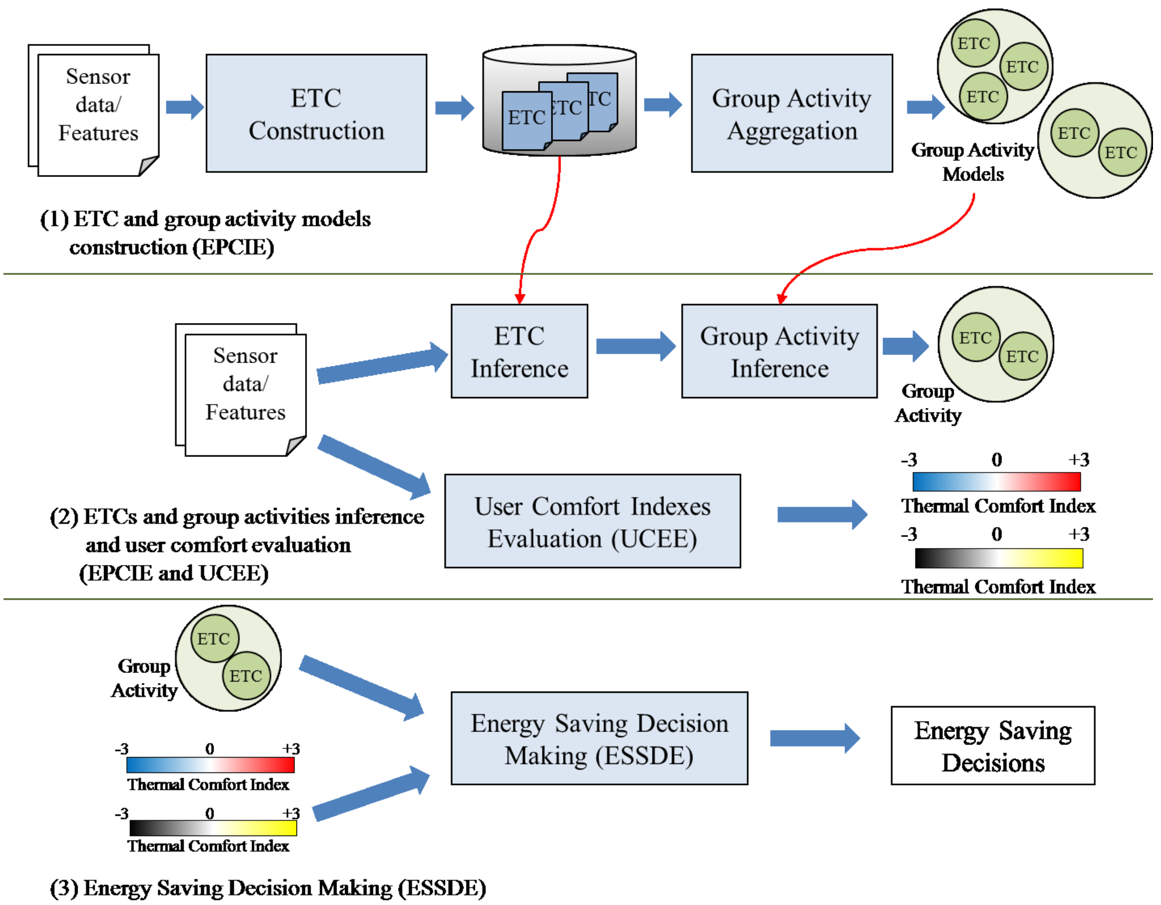


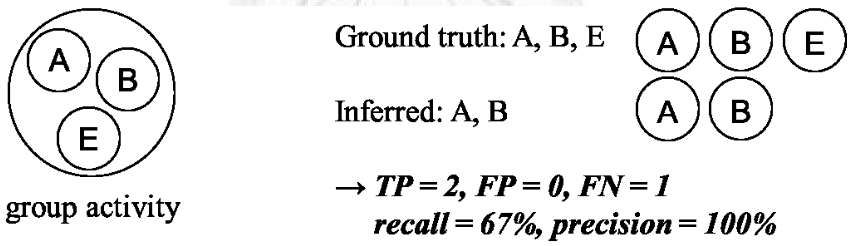
Fig. 6-2 Three steps of the experiment

the accuracy for each group activity, and another for each room (*i.e.* zone-based granularity). We give an example here for illustrating the idea of our performance evaluation. As shown in Fig. 6-3 (a), there are three activities (A, B and E) in the group activity. The ground truth is that activity A, B and E occurred, and the inferred result is that merely activity A and B occurred. Thus, the recall is 67% and the precision is 100% in this example, where the equations evaluating recall and precision are shown as below:

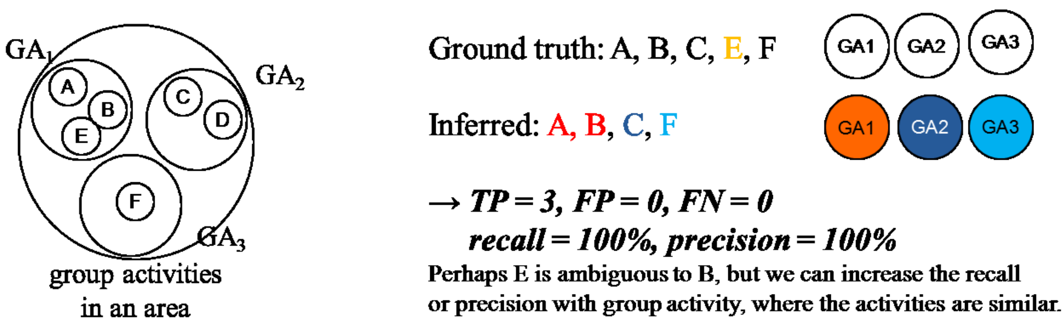
$$\text{recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{6-4}$$

$$\text{precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{6-5}$$

And the performance evaluation of group activities in each room is shown in Fig. 6-3 (b). There are three group activities GA_1, GA_2 and GA_3, and the individual activities of each group activities are shown in the figure. In GA_1, activity B (or activity A) is similar to activity E due to their similarity in the combination of power consumption of appliances; therefore, even though one of them cannot be recognized as "true," its corresponding group activity can still be successfully recognized. In the simple example of Fig. 6-3 (b), the ground truth is that activity A, B, C, E, F occurred, and the inferred result is that activity A, B, C, F occurred. With the concept of group activity, the inferred result of activity E, which is assumed not inferred as "true" but actually occurred, is



(a)



(b)

Fig. 6-3 The recall and precision

(a) within a group activity and (b) in each room corrected by the group activity GA_1 where activity A or B occurred. As the result, both the recall and precision are 100%.

The recall and precision of each group activity in each room is shown in TABLE 12, and the recall and precision in each room (in zone-based granularity) is shown in TABLE 13.

In order to avoid the cases where recall or precision dominates the performance of inference, we use F-measure, which is a harmonic combination of precision and recall, to acquire the mean of precision and recall. The equation of F-measure is shown as below:

$$F = (1+\beta^2) \cdot \frac{\text{precision} \cdot \text{recall}}{\beta^2 \cdot (\text{precision} + \text{recall})} \tag{6-6}$$

where we assume $\beta^2 = 1$, thus the equation can be rewritten as below:

$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \tag{6-7}$$

and the results of F-measure of the two levels of experiment verification are shown in TABLE 14 and TABLE 15 respectively. From the results, we can find that applying group activity does increase the accuracy of multi-activity recognition while doing energy saving.

TABLE 12 THE RECALL AND PRECISION OF EACH GROUP ACTIVITY IN EACH ROOM

<table>
<tr><th>Location</th><th>Group Activity</th><th>Recall</th><th>Precision</th><th>Location</th><th>Group Activity</th><th>Recall</th><th>Precision</th></tr>
<tr><td rowspan="2">Hallway</td><td>Go Out</td><td>92%</td><td>94%</td><td rowspan="4">Bedroom</td><td>Studying</td><td>96%</td><td>97%</td></tr>
<tr><td>Come Back</td><td>95%</td><td>95%</td><td rowspan="2">Sleeping,
Listening Music</td><td rowspan="2">95%</td><td rowspan="2">94%</td></tr>
<tr><td rowspan="3">Living Room</td><td>Playing Kinect</td><td>95%</td><td>97%</td></tr>
<tr><td>Watching TV</td><td>94%</td><td>96%</td><td>Using PC</td><td>96%</td><td>98%</td></tr>
<tr><td rowspan="3">Chatting
Reading Book
Cleaning</td><td rowspan="3">71%</td><td rowspan="3">75%</td><td rowspan="3">Bathroom</td><td>Taking Bath</td><td>93%</td><td>95%</td></tr>
<tr><td>Using Restroom</td><td>94%</td><td>97%</td></tr>
<tr><td>Brushing Tooth</td><td>85%</td><td>90%</td></tr>
<tr><td rowspan="2">Kitchen</td><td>Cooking</td><td>94%</td><td>95%</td><td>Balcony</td><td>Laundering</td><td>96%</td><td>99%</td></tr>
<tr><td>Washing Dishes</td><td>95%</td><td>95%</td><td></td><td></td><td></td><td></td></tr>
</table>

TABLE 13 THE RECALL AND PRECISION IN EACH ROOM

<table>
<tr><th>Location</th><th>Group Activity</th><th>Recall</th><th>Precision</th><th>Location</th><th>Group Activity</th><th>Recall</th><th>Precision</th></tr>
<tr><td rowspan="2">Hallway</td><td>Go Out</td><td rowspan="2">99%</td><td rowspan="2">99%</td><td rowspan="4">Bedroom</td><td>Studying</td><td rowspan="4">99%</td><td rowspan="4">98%</td></tr>
<tr><td>Come Back</td><td rowspan="2">Sleeping
Listening Music</td></tr>
<tr><td rowspan="3">Living Room</td><td>Playing Kinect</td><td rowspan="3">97%</td><td rowspan="3">97%</td></tr>
<tr><td>Watching TV</td><td>Using PC</td></tr>
<tr><td>Chatting
Reading Book
Cleaning</td><td rowspan="3">Bathroom</td><td>Taking Bath
Using Restroom
Brushing Tooth</td><td>99%</td><td>99%</td></tr>
<tr><td rowspan="2">Kitchen</td><td>Cooking</td><td rowspan="2">99%</td><td rowspan="2">99%</td><td>Balcony</td><td>Laundering</td><td>99%</td><td>99%</td></tr>
<tr><td>Washing Dishes</td><td></td><td></td><td></td><td></td></tr>
</table>

TABLE 14 THE F-MEASURE OF EACH GROUP ACTIVITY IN EACH ROOM

Location	Group Activity	F-Measure	Location	Group Activity	F-Measure
Hallway	Go Out	93%	**Bedroom**	Studying	96%
	Come Back	95%		Sleeping, Listening Music	94%
Living Room	Playing Kinect	96%			
	Watching TV	95%		Using PC	97%
	Chatting Reading Book Cleaning	73%	**Bathroom**	Taking Bath	94%
				Using Restroom	95%
				Brushing Tooth	87%
Kitchen	Cooking	94%	**Balcony**	Laundering	97%
	Washing Dishes	95%			

TABLE 15 THE F-MEASURE IN EACH ROOM

Location	Group Activity	F-Measure	Location	Group Activity	F-Measure
Hallway	Go Out	99%	**Bedroom**	Studying	98%
	Come Back			Sleeping Listening Music	
Living Room	Playing Kinect	97%			
	Watching TV			Using PC	
	Chatting Reading Book Cleaning		**Bathroom**	Taking Bath	99%
				Using Restroom	
				Brushing Tooth	
Kitchen	Cooking	99%	**Balcony**	Laundering	99%
	Washing Dishes				

Another experiment result is the degree of energy saving using the context-aware energy-saving system. In the pre-defined scenario illustrated in TABLE 10, we have the control group (as the baseline and without the energy-saving system) and the experimental group (with the energy-saving system) to evaluate the degree of energy saving. For quantitative comparison, the power consumption for each state of an appliances is predefined in TABLE 16. By applying the equation of energy-saving decision mentioned in Section 5.3, we can save about 25% energy consumption on average without compromising user comfort, as shown in TABLE 17. From the experiment results, we can find that except for the appliances that have real impact on user comfort, the redundant energy consumption caused by those un-used or un-related appliances can be reduced via the assistance of context-awareness. This will save extra energy by more than 25%, but it is also important that we also keep user comfort in mind. That is, with our proposed energy saving system, both energy saving and user comfort are taken into account and the degree of energy saving is promising.

TABLE 16 THE POWER CONSUMPTION OF APPLIANCES

App. Name	**Power Consumption (W)**			**App. Name**	**Power Consumption (W)**		
	off	stby	on		off	stby	on
TV	0	3	60	Speaker	0	1	20
Vacuum	0	5	1000	Exhaust Fan	0	2	100
Kinect	0	2	165	Fridge	0	200	1000
A/C	0	700	3000	Rice Cooker	0	100	1605
Fan	0	2	35	Microwave	0	10	1285
Fan Heater	0	5	480	Dish Washer	0	10	1200
Lamp	0	2	20	Wash Machine	0	5	500
PC	0	2	100	Water Heater	0	1000	4000
Monitor	0	2	35	Light	0	0	60

stby: standby power consumption

TABLE 17 THE DEGREE OF ENERGY SAVING WITH THE SYSTEM

Situation	**Energy Consumption**
The control group (the baseline)	100%
The experimental group (with the context-aware energy saving system)	75%

Chapter 7

Conclusion

7.1 Summary

In the thesis, we propose a context-aware energy saving system that takes both the power consumption, including explicit and implicit power consumption, of appliances and user comfort into consideration to make optimal energy-saving decisions. There are three characteristics in the system:

- **Be more aware of the relation between activities and power consumption**

  We take the explicit/implicit power consumption of activities into consideration, which help us figure out the actual power usage of the appliances that is the most related with the activities and is the most easily ignored. More energy consumption will be saved via turning off or adjusting the power usage level of each appliance.

- **The quantifiable indexes for more fine-grained user comfort evaluation**

  A quantifiable index is available for evaluating more fine-grained and specific user comfort through the perception of the temperature and the illumination. Therefore, the energy-saving system can provide fine-grained appliances control to promote more degree of comfort (*i.e.* -0.5 ≤ comfort index ≤ +0.5 for average people).

- **The human-centric energy saving decisions without sacrificing user comfort**

  With more information of power consumption and of the user comfort needed to be maintained, the suitable decisions for users can be made. In our system, about 25% energy consumption on average can be saved.

7.2 Future Work

We propose a prototype of a promising context-aware energy saving system in the thesis. However, there are some points that can be improved:

- **A model for learning user comfort**

  The user comfort indexes in this thesis are used for evaluating user comfort based on the feeling of a large population of people. The indexes can be utilized in the multi-user environment regarding everyone has similar sensation of the temperature and illumination. However, the system should be more adaptive and flexible to learn the comfort model of a specific user, and it can be used for comfort evaluation when there is the specific user in the space.

- **An optimal energy saving decision making engine available for more situations**

  In this work, we have given an orientation of energy saving decision making engine for the simple scenario (*i.e.* there is conflict between energy saving and user comfort). Nevertheless, there are many possible situations in the dynamic environment. Therefore, we want to design a more powerful decision engine for more situations.

- **A scenario with more realistic living styles or activities**

The experiment results shown in Chapter 6 are very promising for the reason that there are at most 2-3 activities in a room, leading to the less complicated scenario. Thus, in the future work, we will design more activities and more complex real-life scenario for the system evaluation.

- **An evaluation in a real home environment**

We do the simulated home for the experiment; however, the problem of context-aware energy saving system is more difficult and there are more uncertainties in a real environment. In the future, we will deploy the four sensor modules into a simulated smart home in real life to verify our approach and make some improvement if necessary.

REFERENCE

[1] D. H. Wilson and C. G. Atkeson, "Simultaneous Tracking and Activity Recognition (STAR) Using Many Anonymous, Binary Sensors," presented at the the 3rd International Conference on Pervasive Computing, Munich, Germany, 2005.

[2] D. J. Cook and S. K. Das, "How Smart Are our Environments? An Updated Look at the State of the Art," *Pervasive Mobile Computing,* vol. 3, pp. 53-73, 2007.

[3] B. Logan, J. Healey, M. Philipose, E. M. Tapia, and S. Intille, "A long-term evaluation of sensing modalities for activity recognition," in *Proceedings of the 9th international conference on Ubiquitous computing*, Innsbruck, Austria, pp. 483-500, 2007.

[4] E. Kim, S. Helal, and D. Cook, "Human Activity Recognition and Pattern Discovery," *IEEE Pervasive Computing,* vol. 9, pp. 48-53, 2010.

[5] J. Ye, A. K. Clear, L. Coyle, and S. Dobson, "On using temporal features to create more accurate human-activity classifiers," presented at the Proceedings of the 20th Irish conference on Artificial intelligence and cognitive science, Dublin, Ireland, 2010.

[6] K.-C. Hsu, Y.-T. Chiang, G.-Y. Lin, C.-H. Lu, J. Y.-J. Hsu, and L.-C. Fu, "Strategies for inference mechanism of conditional random fields for multiple-resident activity recognition in a smart home," presented at the Proceedings of the 23rd international conference on Industrial engineering and other applications of applied intelligent systems, Cordoba, Spain, 2010.

[7] M. Brand, N. Oliver, and A. Pentland, "Coupled Hidden Markov Models for

Complex Action Recognition," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, San Juan, Puerto Rico, pp. 994-999, 1997.

[8] L. McCowan, D. Gatica-Perez, S. Bengio, G. Lathoud, M. Barnard, and D. Zhang, "Automatic Analysis of Multimodal Group Actions in Meetings," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 27, pp. 305-317, 2005.

[9] D. Youtian, C. Feng, X. Wenli, and L. Yongbin, "Recognizing Interaction Activities using Dynamic Bayesian Network," in *18th International Conference on Pattern Recognition*, Hong Kong, pp. 618-621, 2006.

[10] T. Gu, Z. Wu, L. Wang, X. Tao, and J. Lu, "Mining Emerging Patterns for Recognizing Activities of Multiple Users in Pervasive Computing," presented at the International ICST Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, Toronto, ON, Canada, 2009.

[11] C. Zhongwei, Q. Lei, H. Qingming, J. Shuqiang, and T. Qi, "Group Activity Recognition by Gaussian Processes Estimation," in *20th International Conference on Pattern Recognition (ICPR)*, pp. 3228-3231, 2010.

[12] M. S. Ryoo and J. K. Aggarwal, "Recognition of High-level Group Activities Based on Activities of Individual Members," presented at the Proceedings of the 2008 IEEE Workshop on Motion and video Computing, 2008.

[13] S. Karjalainen, "Consumer preferences for feedback on household electricity consumption," *Energy and Buildings,* vol. 43, pp. 458-467.

[14] T. Hargreaves, M. Nye, and J. Burgess, "Making energy visible: A qualitative field study of how householders interact with feedback from smart energy

monitors," *Energy Policy,* vol. 38, pp. 6111-6119, 2010.

[15] T.-S. Choi, K.-R. Ko, S.-C. Park, Y.-S. Jang, Y.-T. Yoon, and S.-K. Im, "Analysis of energy savings using smart metering system and IHD (in-home display)," in *Transmission & Distribution Conference & Exposition: Asia and Pacific*, pp. 1-4, 2009.

[16] E. D. Williams and H. S. Matthews, "Scoping the potential of monitoring and control technologies to reduce energy use in homes," in *Proceedings of the 2007 IEEE International Symposium on Electronics & the Environment*, pp. 239-244, 2007.

[17] C.-H. Hwang and A. C.-H. Wu, "A predictive system shutdown method for energy saving of event-driven computation," *ACM Transactions on Design Automation of Electronic Systems (TODAES),* vol. 5, pp. 226-241, 2000.

[18] J. Heo, C. S. Hong, S. B. Kang, and S. S. Jeon, "Design and Implementation of Control Mechanism for Standby Power Reduction," *IEEE Transactions on Consumer Electronics,* vol. 54, pp. 179-185, 2008.

[19] *The Adaptive House*. Available: http://www.cs.colorado.edu/~mozer/index.php?dir=/Research/Projects/Adaptive%20house/

[20] M. C. Mozer, R. H. Dodier, M. Anderson, L. Vidmar, R. F. C. III, and a. D. Miller, "The neural network house: An overview," presented at the L. Niklasson & M. Boden (Eds.), Current trends in connectionism, 1995.

[21] M. C. Mozer, "The Neural Network House: An Environment hat Adapts to its Inhabitants," in *Proceedings of the American Association for Artificial Intelligence Spring Symposium on Intelligent Environments*, pp. 110-114, 1998.

[22] M. Mozer, "Lessons from an Adaptive Home," *Smart Environments,* pp. 271-294, 2005.

[23] *European project AIM*. Available: http://www.ict-aim.eu/

[24] A. Barbato, L. Borsani, A. Capone, and S. Melzi, "Home energy saving through a user profiling system based on wireless sensors," presented at the Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Berkeley, California, 2009.

[25] A. Barbato, L. Borsani, and A. Capone, "A Wireless Sensor Network Based System for Reducing Home Energy Consumption," in *7th Annual IEEE Communications Society Conference on Sensor Mesh and Ad Hoc Communications and Networks*, pp. 1-3, 2010.

[26] P. Davidsson and M. Boman, "Saving Energy and Providing Value Added Services in Intelligent Buildings: A MAS Approach," presented at the Proceedings of the Second International Symposium on Agent Systems and Applications and Fourth International Symposium on Mobile Agents, 2000.

[27] K. Murphy, "Dynamic Bayesian Networks: Representation, Inference and Learning," Ph.D. Dissertation, Computer Science Division, UC Berkeley, 2002.

[28] D. Heckerman, "A Tutorial on Learning with Bayesian Networks," *Technical Report,* 1995.

[29] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum Likelihood from Incomplete Data via the EM Algorithm," *Journal of the Royal Statistical Society. Series B (Methodological),* vol. 39, pp. 1-38, 1977.

[30] *UK Government definition of Brown goods*. Available: http://www.defra.gov.uk/evidence/statistics/environment/waste/wrferrous.htm

[31] *U.S. EPA Energy Star Program*. Available: http://www.energystar.gov/

[32] *Environmental Protection Administration of Executive Yuan, R.O.C. (Taiwan)*. Available: http://www.epa.gov.tw/

[33] P. Fanger, "Thermal environment - Human requirements," *The Environmentalist,* vol. 6, pp. 275-278, 1986.

[34] K. E. Charles, *Fanger's Thermal Comfort and Draught Models*, 2003.

[35] C.-F. Liao, Y.-W. Jong, and L.-C. Fu, "Toward a Message-Oriented Application Model and its Middleware Support in Ubiquitous Environments," in *International Conference on Multimedia and Ubiquitous Engineering*, pp. 298-303, 2008.

[36] B. E. Ainsworth, W. L. Haskell, M. C. Whitt, M. L. Irwin, A. M. Swartz, S. J. Strath, W. L. O'Brien, D. R. Bassett, K. H. Schmitz, P. O. Emplaincourt, D. R. Jacobs, and A. S. Leon, "Compendium of physical activities: an update of activity codes and MET intensities," *Medicine and science in sports and exercise,* vol. 32, pp. S498-504, 2000.

PUBLICATION LIST

[1] **Hui-Wen Yeh**, Ching-Hu Lu, Yu-Chiao Huang, Tsung-Han Yang, and Li-Chen Fu, “Cloud-Enabled Adaptive Activity-Aware Energy-Saving System in a Dynamic Environment,” submitted to *International Conference on Pervasive and Intelligent Computing*, Sydney, Australia, 2011.

[2] Yuan-Ling Chiao, Ching-Hu Lu, **Hui-Wen Yeh**, Yuan-Yun Chou and Pei-Ling Liu, "Can I Help You?: Towards the Improvement of Occupational Experience for Convenience Store Employees in Taiwan," in *14th International Conference on Human-Computer Interaction*, pp. 361-368, Orlando, Florida, 2011.