Exploring the Activity Fabric of an Intelligent Environment with Hierarchical Hidden Markov Theory

Chiung-Hui Chen

Abstract—The Internet of Things (IoT) was designed for widespread convenience. With the smart tag and the sensing network, a large quantity of dynamic information is immediately presented in the IoT. Through the internal communication and interaction, meaningful objects provide real-time services for users. Therefore, the service with appropriate decision-making has become an essential issue. Based on the science of human behavior, this study employed the environment model to record the time sequences and locations of different behaviors and adopted the probability module of the hierarchical Hidden Markov Model for the inference. The statistical analysis was conducted to achieve the following objectives: First, define user behaviors and predict the user behavior routes with the environment model to analyze user purposes. Second, construct the hierarchical Hidden Markov Model according to the logic framework, and establish the sequential intensity among behaviors to get acquainted with the use and activity fabric of the intelligent environment. Third, establish the intensity of the relation between the probability of objects’ being used and the objects. The indicator can describe the possible limitations of the mechanism. As the process is recorded in the information of the system created in this study, these data can be reused to adjust the procedure of intelligent design services.

Keywords—Behavior, big data, hierarchical Hidden Markov Model, intelligent object.

I. RESEARCH OBJECTIVES AND BACKGROUND

The ways in which an Intelligent Environment offers its service have varied from the traditional ones, which require users to request services in various ways. With advancement in network technologies, various convenient services are being rolled out. The traditional, passive intelligent environments have many devices of their own with particular ways of use; therefore, those who do not know how to use them cannot benefit from the services offered. An excellent intelligent environment can improve this situation by using context-aware devices and various inference systems to determine the service a user may need and provide it to him/her automatically. In the past, the user requested a service while the environment was in a passive mode; things have changed with an intelligent environment that turns itself from a passive environment to an active one. Services are provided anywhere automatically at proper times upon the decision, made by the system, of what a user may need. Therefore, the intelligent environment is the road map to the future. The system has controls over the information about the user and environment through context-aware devices. With this information, a user can benefit from the best services optimized for the environment.

An intelligent environment usually includes furniture, electrical appliance, materials and spaces provided for human activities, and deployed sensors that detect user behaviors and environmental changes, and activate specific services in response to corresponding events and things that are triggered. An intelligent environment requires sufficient user information to provide proper services; however, perceiving a user’s intention in a behavior from the user’s status information is the most important part of the job. In other words, as long as the intention of the user is confirmed, it will make it simpler for an inference system to search for the service that suits the user’s status. The better-known human behavior identification is mostly performed with image processing techniques, plus rule-based inference system: the system identifies according to user’s current behavior and then creates a semantic model based on logic model of the behavior. The solution offered by this type of research often contains few simple analyses for actions [13]. User behavior must be analyzed and his/her intent understood in order to provide optimum user information to an inference system. However, as the sensors deployed in an intelligent environment increase dramatically, various sorts of disorganized big data gather. Depending merely on specification logic built upon experts’ knowledge is not good enough to infer an event. Instead, Machine Learning and big data analysis should be adopted to explore the connection between data and event. Furthermore, IoT began mainly as an idea of providing the benefits of ubiquitousness and convenience. Massive dynamic messages are presented in the IoT environment in real time while the objects of content provide the real time service to the user through internal communication and interaction. Thus, providing services based on informed decision has become an important issue. Collection of user’s status information by the environment is mandatory for both rule-based and probabilistic inference systems; therefore, such a collection is the key to a successful inference of the system for a proper service.

In consideration of the above factors, this study employs Praxeology as the basis, combined with environment model in reference to the probability module of Hierarchical Hidden Markov Chain Model. It aims at making inference through the process of data analysis and documenting when and where various human behaviors occur, to achieve the following objectives: 1. Define user behavior, predict user behavior path
through an environment model, and further analyze the user’s intent. 2. Create a Hierarchical Hidden Markov Chain Model based on behavior logic framework to obtain procedural strength between behaviors, for understanding the use of intelligent environment and activity texture. 3. Finally, create an object’s probability of use and relationship strength, which describes the possible limit of this mechanism. Because the process is documented in the system data developed by this study, interior designer or relevant professionals may reuse these data to optimize the procedure of smart design service.

II. RELEVANT THEORIES AND MAJOR LITERATURE

In this section, the important literature for target needs is further explored and discussed, including three major dimensions: intelligent environment network, Praxeology, and Hidden Markov Chain Model for Machine Learning approach. The model of the theory of the study is therefore proposed and concludes as follows.

A. Intelligent Environment Network

In 2005, the International Telecommunication Union (ITU) published an article in the subject of IoT, defining IoT as the next phase of network in which people can connect with each other and exchange information with things through network anytime and anywhere. An information exchange platform can also be created among objects with computing power of network in the dimensions of Time, Place and Thing, adding a new dimension to the development of information and telecommunication technology [10]. Likewise, Kim [12] once mentioned that the objective of Machine to Machine (M2M) technology was to equip all devices with capabilities of interconnection and communication. Such a technology is a networking application and service that uses machine as the core of smart communication between terminals. With such a technology, a world of network, present everywhere, is thus created. Although M2M technology is consistent with the core concept of IoT, its technology and extensiveness of application are different from those of IoT. M2M focuses on the applications in wireless telecommunication network that has wider coverage, reducing the cost of using a satellite service. M2M not only stands for Machine to Machine communication, but also includes Machine to Man, Man to Machine, Machine to Mobile, and Mobile to Machine connections and communications, realizing smart and interactive communication among Man, Machine, and System [1].

The rapid development of recent intelligent environment network includes advancements in massive diversified devices and equipment. Through a family network, a Smart Home can connect smart things at home, which can communicate with the user and record his/her behavior. With simple controls and status setups, a user can allow smart things to function automatically; all of them are monitored by a family network and capable of receiving instructions. Family network can also communicate with external network through a central family channel. As such, a user can even connect to new, external services through network. In the concept of intelligence, there are three elements in an indoor environment: (1) device as thing, such as refrigerator; (2) control devices, such as sensors; (3) user interfaces, such as visualizations of sound and temperature, etc. In the outdoor environment, the communication between the family and service provider, and the service updates are provided by network carrier [16].

The smart perception living space, Inphase, was proposed jointly by Hitomi et al. [7]; it expands the connections between people and family environment object and emphasizes a more natural human interaction. The on-going event that the other family members are involved is communicated through prompts given indoors, allowing interlink of activities that happen in different spaces. Similar case studies include Spatial Context-aware Building Data Model proposed by Lertlakkhanakul et al. [14]. In such a study, the spatial context-aware data model consists of five major elements - User, Activity, Context, Space, and Object, which are an integral part in the design of the interaction among themselves. When a constructing element of a real space is embedded into each object of the sensing device, each object then contains the sensor module that is carried. When a user is engaged in his/her daily activity in real space, the user event is then recorded by the sensing device embedded in the objects used in daily life, such as floor, partition wall, furniture, and home appliance. The information will be recorded continually; the dynamic information, computed with the analysis method of the system, is compared against the rules defined in the behavior database for making a judgment; the dynamic information is then fed to the object that is capable of providing feedback. Such is a cycle of the dynamic information.

B. Praxeology

Mises [15] indicates that human decisions are made on the principle of sorting even though they can be sorted quickly. It is therefore concluded that human behavior follows a certain sequence while the objective of a behavior is “change” which implies the concept of time; therefore, a human behaves in the procedure of time. Since no two human behaviors occur simultaneously, they must be completed one by one in the order of time. Therefore, the factor of “sequence” must be considered in creating a behavior model. In the analysis of a behavior path, the sequence of such a path must be made reasonable.

A behavior may consist of various behaviors-human behavior is formed by many behaviors that intend to achieve some objective. The characteristics of a human behavior may be presented in the logic model shown in Fig. 1; through a certain path, human behavior attempts to achieve some objective that may serve as a path for achieving the next objective. The cycle therefore goes on and on until the final objective is achieved, an end of a behavior.

Objective: a result that a behavior seeks after, which is called the objective of such a behavior; the performer of such a behavior believes achievement of such an objective can ease his/her uncomfortable feeling.

Path: the behavior that is generated or the thing that is used for achieving any objective.

End: an indication of the end of a behavior also of the achievement of an objective by such a behavior.
The Behavior Logic Model in Fig. 1 can be presented as shown in Fig. 2 as a Hierarchical Analysis of Behavior. Take coffee-making as an example, for such an objective, the actions for achieving it can be broken down into more paths, such as preparation of milk, coffee beans, etc. For achievement of such an objective, these paths can be further broken down into various paths: uses of water purifier, coffee machine, gas stove, etc.

Behavior analysis can be explored from the perspectives of Praxeology and Psychology. Current studies on behavior analysis in an intelligent environment are aimed mainly at the identification of a single action, rarely at user behavior from the perspective of Praxeology. This study attempts to create an analysis mechanism of the objective of a user’s behavior from the perspective of Praxeology. It also aims to create an alternative behavior analysis in an intelligent environment for the definition of a behavior from the perspective of Praxeology and for the logic framework inherent in a user’s behavior. Moreover, since there exists many uncertainties in the correlations among human behaviors, the result of the behavior analysis must be presented with the help of probability. This study introduces the Hierarchical Hidden Markov Chain Model through which a prediction of behavior is made. Since the Hierarchical Hidden Markov Chain Model can show the transitions between states, it can thus be used to explain a behavior model and transitions between paths. In a similar study, Shibuya et al. [17] define the correlations among behaviors with a probabilistic model under Bayesian Theory; they propose that the correlation between two behaviors does not behave as the mathematical logic indicates. In mathematics, if A contains B, and B contains C, then A must contain C in conclusion. However, such a correlation does not necessarily stand in human behavior.

C. Machine Learning: Markov process and Hidden Markov Chain Model

Popular Machine Learning methods employed in Ubiquitous Computing are Markov Chain Model, Bayesian Network, Neural Network, and Decision Tree, etc. The characteristic of the Markov Chain Model is that any process featuring a transition from one state to another and transition probability, may be deduced from its immediate preceding state. Such a process is called a Markov Chain Model; and the whole thing that consists of a series of such transition processes is called a Markov Chain. A model created with such a method is called Markov Transition Matrix. What makes analysis method of Markov Transition Matrix differ from traditional methods the most is the addition of a variable of time sequence. Such a method is more consistent with the perspective of humanity than older probability operation methods.

This study focuses on the perspective of human behavior that, together with human needs, varies with time. Machine Learning method must be employed to analyze an event to provide users a model that is stable enough and can correspond automatically to a dynamic environment. The difference between an event and an activity lies in the fact that an event is rich in timeliness and the semantics of other structures. For example, Point of time (certain time of the day at which an event happens), Duration (a period of time that an event lasts), Frequency (the number of times an event may happen within a week) and Sequence (various events may happen in a particular sequence of time), etc. An event may be referred to as an abstract state of a physical object (like a living room being occupied) or a behavior of a user in an environment (such as reading), but it may also be referred to as one event that consists
of multiple events. Both an event at a point of time and a pattern that is formed by gathering multiple continuous events in time can be used to describe a user behavior. The data acquired by the subjects are analyzed with probability distribution shown in Markov Transition Matrix to understand the behavior distribution of a user in an environment.

1) Markov Process

Markov process is a random one with states; P (S′|S) indicate the probability of transition from current state S to next one S′. Such a probability is not affected by any factor external to the state and is thus independent of time. Random Walk is an example of Markov Process. A point in the figure indicates the state of each step in Random Walk. Each step can move to any adjacent point and the probability for moving to any point is identical and independent of the previous random walk path. Continuous observance of a certain random phenomenon generates a series of observance values, x1, x2,..., xn, which form the space of the entire random phenomenon, X1, X2,...., Xn.

If there exists, any causal relations between these observance values, it is then possible to describe such causal relations with Markov Process. For example, if each event is affected by previous event only, P (Xn+1|Xn) can express the random phenomenon. Such a random process is called time-homogeneous Markov Chain, or Stationary Markov Chain. If the next observance value may be affected by previous observance values in the number of “m,” such a random process can be expressed by a probability distribution P (Xn+1|Xn,...,Xn−m+1), and is hence, called m th order Markov Process. However, for certain phenomenon of probability, not all random variables can be always observed. In such a case, only partial random variables can be observed, indicating that there are implicit variables that cannot be observed in the system. As such, implicit variables that cannot be observed must not be ignored.

2) Hierarchical Hidden Markov Model

Hidden Markov Model (HMM) is a model employed to describe a random process with implicit variables. Such a model achieves great success in multiple sub-fields of Artificial Intelligence, including that of Yang et al. [18] who employ HMM for behavior learning. Hamid et al. [5] propose Unsupervised Learning Framework to explore time pattern of a behavior; their framework enables behavior learning in human daily activities with minimized supervision, achieving the purposes of knowledge expression and analysis. Fine et al. [4] analyzed the applications of Hierarchical Hidden Markov Chain Model that can describe not only the state transition within the same level, but also those between upper and lower levels. In a normal Markov Process, a state is visible to the observer, thus the transition probability of this kind of state is represented by all variables. However, in a HMM, a state is not visible directly while certain variables affected by the state are. Since each state has a probability distribution for the possible symbols that may be output, the sequence of output symbols can reveal some information of the state sequence [6]. Fig. 3 shows the concept of HMM, where x is an implicit variable; y, an observable variable; “a,” the Transition Probability; and “b,” the Output Probability. If the state transition and the output are further distinguished, the connecting lines, shown in Fig. 4, can be further broken down to output line and transition line. If the focus of observance switches to time sequence, the implicit variable x_n becomes the key in determination of the state, affecting output variable y_n and the next state x_{n+1}.

\begin{center}
\begin{tikzpicture}
\node (x1) at (0,0) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {X_1};
\node (y1) at (0,-1) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {y_1};
\node (x2) at (1,0) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {X_2};
\node (y2) at (1,-1) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {y_2};
\node (x3) at (2,0) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {X_3};
\node (y3) at (2,-1) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {y_3};
\draw (x1) -- node[midway,above]{a_{12}} (x2);
\draw (x2) -- node[midway,above]{a_{23}} (x3);
\draw (y1) -- node[midway,left]{} (x1);
\draw (y2) -- node[midway,left]{} (x2);
\draw (y3) -- node[midway,left]{} (x3);
\end{tikzpicture}
\end{center}

Fig. 3 Concept of HMM

\begin{center}
\begin{tikzpicture}
\node (x1) at (0,0) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {x_1};
\node (y1) at (0,-1) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {y_1};
\node (x2) at (1,0) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {x_2};
\node (y2) at (1,-1) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {y_2};
\node (x3) at (2,0) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {x_3};
\node (y3) at (2,-1) [shape=circle,draw,fill=black,inner sep=0pt,minimum size=2mm] {y_3};
\draw (x1) -- node[midway,left]{} (y1);
\draw (x1) -- node[midway,above]{a_{12}} (x2);
\draw (x2) -- node[midway,above]{a_{23}} (x3);
\draw (y1) -- node[midway,left]{} (x1);
\draw (y2) -- node[midway,left]{} (x2);
\draw (y3) -- node[midway,left]{} (x3);
\end{tikzpicture}
\end{center}

Fig. 4 Concept of HMM with implicit variable

D. Theoretic Model of the Study

As indicated in the above literary, although HMM is a popular probability model, its efficacy may be compromised as a behavior becomes more complicated and the index for the state probability of an event may decrease with time, leading to dramatic decline of computing efficacy for the behavior with long-term dependence correlation. Confined to the limitation of one-order Markov Model described above, this study intends to adopt hierarchical HMM to explore the hierarchical structure of human behavior. The drawback of the one-order method is addressed by increasing the efficacy in processing the major and composite behaviors, keeping the assumption unchanged before one state transitions to another.

The behavior pattern of a user in space is the result yielded from the interaction between his/her internal behavior tendency and information received at his/her location. Therefore, the behavior pattern of a user in an intelligent environment can be considered as an information processing unit with whose internal state the pattern that responds to external information is determined, leading to the decision of corresponding service sequence. The Markov Process formed with a series of events by the system of the study is shown in Fig. 5. This model consists of finite hidden states and the content observed to which such a state corresponds. Such a HMM constructed in the study considers each state S (State) as one single behavior and describes the sensors’ data generated by each behavior in three
observance patterns. The prior probability trained by the model represents the probability for a user to begin a behavior; state transition probability represents the probability for a user to transition from one behavior to another, while the scattering probability of observance represents the probability for a set of sensors to be triggered when a user is performing a certain behavior.

The model is created based on three assumptions:

1. Each state \( S_t \) has dependence with the previous state \( S_{t-1} \) only; \( t \) represents time.
2. Each observance variable \( O_t \) has dependence with current state \( S_t \), and,
3. Each observance variable is independent of one another.

Moreover, there are three kinds of probability distributions:

1. Prior probability \( P(S_i) \), \( 1 \leq i \leq n \), where \( n \) is the code of the state;
2. State transition probability \( P(S_t \mid S_{t-1}) \), and
3. Observance scattering probability \( P(O_t \mid S_t) \).

All can be represented by the function of functions, (1):

\[
P(S, O) = \prod_{t=1}^{T} P(S_t \mid S_{t-1})P(O_t \mid S_t)
\]

(1)

The theoretic model of the study - Behavior prediction of Hierarchical Hidden Markov Chain Model in an intelligent environment - is proposed, based upon the principles as above. User’s behavior path is predicted with an environment model and a hierarchical HMM based on sensor technique. Take the sample space of the study for example, one user enters the room for digital drawing and then turns to use the plotter after a period of time, and finally leaves the room. There are also many factors of uncertainties involved in a user’s behavior. Simply using rules cannot present a complete user behavior path. Therefore, probability will come into play in the analysis of behavior; the probability of each behavior is independent, but there may be interaction among behaviors. The prediction made through the environment model may generate a series of behavior paths without standardized rules; however, such a prediction cannot describe the meaning of user behavior. Combined with Hierarchical HMM, the variability of path prediction is increased with the help of probability operation, and user behavior can be further approximated. For example, it is more probable for a user to use a computer after he/she enters a drawing room; it is more probable for one to drink a cup of coffee when one comes to a bar counter, and in such a case turning on the gas valve and then lighting the gas stove is more likely. In other words, the model of behavior analysis must be a continuous one as behaviors exist in a continuous sequence of time. The issue of continuity must be considered in the creation of a behavior model. Understanding the ambient environment is necessary to understanding a behavior; a user may behave in response to what the things in an environment may offer. In this study, user behavior is analyzed with environment information in cooperation with context-aware devices. Combinations that may appear frequently are categorized and the prediction of user behavior is then made with HMM.

III. CONTENT OF STUDY

Based on the theoretic basis and study objective the study is ordered in three major steps. 1. Create an environment information model based on interior design for the purposes of defining user behavior and further analyzing the user’s objective, by predicting a user behavior path with environment model; 2. Create an Hierarchical Hidden Markov Chain Model based on a behavior logic framework to obtain the procedural strength between behaviors, for understanding the use of the intelligent environment and activity texture; and finally; 3. Create a key list of the fundamental objects which define the order of objects being triggered, probability of use, and relationship strength between objects, which describes the possible limit of this mechanism (See below for details).

A. Create an Environment Information Model

The case study object in this study is a studio of interior design in a building located at 18th Datung Street, Taichung, Taiwan. In the sample space, there are two floors with a total area of 194 square meters. The first floor consist of a video conference room, a small meeting room, a study room, a bar counter and a kitchen; on the second floor are a supervisor’s office, a digital drawing area, and a file room for exhibition materials; all are shown in the floor plan in Fig. 6. There are four routine workers in the studio: Ms. Fan, the owner; Ms. Chung, the designer; Ms. Hu, the assistant to the designer; and Ms. Su.

Tree structure is considered as a more reasonable and complete approach, as indicated by several studies on the subject of the environment model of an intelligent environment [11], [3], [2], [8], [9]. The environment models mentioned in these studies are all tree structure-based. Following the basic principles of above researches, the study divides the environment model into three levels: the first level, “level of building,” being the beginning of the environment model; the second level, “level of interior space,” indicating spatial distribution of an intelligent environment for spaces like digital drawing room, video conference room, and bar counter; and the third level, also the most important one, “level of objects.” After the spatial distribution of an intelligent environment is created, the system must know which object(s) in each space can provide the service(s) or user information. The level of things documents the information of things contained in each space. The main objective of the level of things is to distinguish various things by using the second level of interior space, and to link all elements within the same level in terms of the hierarchical relationship; therefore, things in space may have relationships of communication with one another. With this method, the complexity in the analysis of the probability of use for the things triggered may be reduced.
In the study, Hierarchical HMM is mainly used in combination with an environment model. Not only the state transition within the same level, but also the transition between the upper and lower levels is indicated. In addition to the provision of detailed environment information to the system, the user behavior path in an intelligent environment may also be predicted with the help of probability model. Fig. 7 shows all the three levels in a combined probability model and environment model, with all three represented by $l$, $l+1$, and $l+2$. The relationship between things represents the probability of a state transition, while the relationship between the levels represents the probability of the user’s state transition to the next level, expressing what the initial entry state may be. Function expression is defined as follows:

1) Basic transition probability of each state: $(x^I)$, where $I$ stands for the number of this state underneath this level, $l$ stands for the level on which this state is. $P^I_{l,j}$ stands for the transition probability for state $(x^I)$ to transition to state $(x^j)$ while state $(x^I)$ and $(x^j)$ on the same level $l$, can be defined as the function expression (2):

$$P^I_{l,j} = P(x^j|x^I)$$  (2)

2) Transition probability between levels: $P^I_{l,l+1}$ stands for the transition probability for the state on level $l \times x^I$ to transition
to the state on level $l+1$ $x_{l+1}^j$. $P(x_{l+1}^j|x_l^j)$ stands for transition probability between levels; $P(x_l^j)$ stands for individual probability for each state to occur; $P(x_{l+1}^j|x_l^j)P(x_l^j)$ stands for the probability for the state that occurs on the upper level to transition to the state on the lower level. In the study, the probabilities for a user to use a certain space upon entering an intelligent environment and for a certain thing to be triggered for use when the space is used, and can be defined as function expression (3):

$$P_{l+1}^{i,j} = P(x_{l+1}^j|x_l^j)P(x_l^j)$$  \hspace{1cm} (3)

3) The probability for each state to occur individually: $P(x_l^j)$ stands for the probability for each state to occur individually; the probability of each occurrence will be considered and the probability for each state to occur during level transition is considered.

$$P(x_l^j) = \sum P_{l+1}^{i,j}P_{l}^{i,j}$$  \hspace{1cm} (4)

**B. Create a Hierarchical Hidden Markov Chain Model**

As far as the Cloud computing environment of IoT is concerned, the drawback of a tree structure is its focus on vertical context and its lack of horizontal relation in the network communication. Using a general tree structure cannot reveal the significance of it in time horizon; therefore, the sequence that defines the relative relation of the elements within the same level must be established horizontally in the order of time. Such a sequence thus defines the relationship among behaviors. The study links behaviors with relational strength; once the relation among behaviors are defined, it will be provided to the environment model and become important information for path prediction in the environment model. Used with Hierarchical HMM, the environment model make predictions for user behavior while the relationships among things may be defined by the relationships among behaviors that are on the lowest level in the behavior model. Since each behavior is the direct interaction between users and things in the environment, the relationship among behaviors that are at the lowest level can form the probability factor between things in the environment model. The function expression is defined as below.

1. The relationship strength generated from the level difference between the two states: Computation of level difference is derived from the root state, common to both current and target state; the level difference between root state and current state is the value of $n_{l,k}$, indicating the difference between orders of state $x_k^l$ and state $x_k^l$;

$$n_{l,k}level_{i,j}$$ shows the relationship strength between levels of state $x_i^j$ and state $x_j^i$. For example, turning on a plotter and using a computer are two behaviors on the lowest levels; the root behavior, common to both, is the event in the digital drawing room in the level of interior space. Therefore, the level difference between the two states is 3 with a level value of 0.125, as defined in function expression (5):

$$level_{i,k} = \frac{1}{2^{n_{l,k}}}$$  \hspace{1cm} (5)

2. Description of the procedural strength between behaviors: Procedural operation is also based on step difference, the number of steps required to reach the target state, indicated as the value of $O_{l,j}$; $order_{i,j}$ indicates the procedural relationship strength between state $x_i^j$ and state $x_j^i$; $O_{l,j}$ shows the number of the procedural levels between state $x_k^l$ and state $x_k^l$. For example, under the state of turning on computer for drawing, between the behaviors of sitting on the chair and turning on the table lamp are two steps of $x_i^j$; therefore, the value of $O_{l,j}$ between two states is 2 and its value of $order$ is 0.25. The procedural value is a tropic one; the transitions from one state to state $x_i^j$ and from state $x_i^j$ to state $x_i^j$ may represent different behaviors. As procedural value is a tropic one, take turning on a gas valve and gas stove for example, where the procedural value of...
turning on gas valve to turning on gas stove is 1, with a strength of order as 0.5. However, the procedural value from turning on gas stove to turning on gas valve does not exist, the strength of order is thus 0, as indicated in function expression (6):

\[ order_{ij} = \frac{1}{2^{\|ij\|}} \]  

(6)

(3). Obtaining relationship strength between behaviors: As a continuation from (2), once the hierarchical and procedural correlations are defined, the basic procedural and hierarchical relationship strengths are added together to obtain the relationship strength between behaviors. When the root state, common to two states, is on the same level as that of the two, it means these two states, in essence, do not belong to the same event; therefore, the value of \( ER_{ij} \) must be multiplied, where the value of \( ER_{ij} \) represents the relationship between final states, indicating the relationship value between the Final Event state \( x^1_j \) and state \( x^1_i \). If the root state, common to both states, is not on the same level, then the value of \( ER_{ij} \) is 1, as defined in function expression (7) \( r(x^i_j, x^j_j) \), indicating the relation function between state \( x^i_j \) and state \( x^j_j \).

\[ \prod_{m=1}^{k-1} r \left( x^{state_{i-m}}, x^{state_{j-m-1}} \right) \]

(7)

C. Create a Key List of the Key Objects

As a continuation from the above, the relationship strength obtained between behaviors can be provided to the environment model that can add this correlation as one of the factors that affect the probability for prediction. Take coffee-making for example, Fig. 8 shows the behavior path of a user on the first floor of the studio, indicating the user walks from the video conference room to the bar counter in the kitchen and is about to make a cup of coffee. Such a behavior requires the most basic sequence of actions in a finite cycle, such as preparation and grinding of coffee beans, turning on the water purifier, walking to the refrigerator to fetch milk, and turning on the gas valve and lighting the gas stove. Following the order of time, the objects used by the user can thus be documented and the behavior of using things then forms a path.

![Fig. 8 Path of user behavior](image)

A finite cycle of sequence defines a particular interaction among several key things during a period of time, while key things exist in the function environment that can provide the ability to execute a behavior. Take the sample space of the study as example, the sequence of using key things in this behavior is assumed as follows: coffee maker, water purifier, refrigerator, water purifier, refrigerator, water purifier, and gas stove. As a result, the sequence of using key things is shown in the function of Activity = \{1, 2, 3, 2, 3, 2, 4\}. Then the environment model will compute the probability of each key thing to be triggered for use with the help of the list that documents the correlations between things. Take the probability for things to be triggered for use as example, as shown in Table I, the probability of moving from the coffee maker to the refrigerator is 20%, with which the probability of using the coffee machine can thus be computed. Summing up, all probabilities of using coffee maker produces the probable occurrence of the coffee maker is 40%, while the refrigerator is 20%, and the water purifier is 25%. These values represent the probabilities of a user to use various things in an intelligent environment.

Table II shows the relationship strength between key things. When a user is using the gas oven, the environment model will predict based on the relationship table and the past probability
that was frequently associated with such a user. If the relationship table is not available, the environment model will only select the maximum occurrence probability. Such a problem can be improved with the help of relationship table that uses the values in it as weights for computation. In this case, turning on gas stove after turning on the gas valve out-weights all other things. The relationship strength between the refrigerator and water purifier is 10%, while that between the refrigerator and gas stove is 20%. The probabilities for using the refrigerator, the water purifier, and the gas stove under this environment are assumed to be 30%, 20%, and 50%, respectively, when a user enters this environment and uses the refrigerator first. According to the user’s original probability, the next behavior should be turning on the gas valve. However, the relationship strength between the refrigerator and the gas stove is only 20%, so the prediction path will lead to the water purifier instead of turning on the gas valve. Therefore, the relationship strength determined can be an influential factor for the prediction path; further with the help of Hierarchical HMM the prediction can thus be made for behaviors of single or multiple users, reducing occurrences of conflicting states and improving the accuracy of the service provision.

### TABLE I

<table>
<thead>
<tr>
<th>Name of a thing</th>
<th>Probability (Total=100%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water purifier</td>
<td>25%</td>
</tr>
<tr>
<td>Coffee maker</td>
<td>40%</td>
</tr>
<tr>
<td>Refrigerator</td>
<td>20%</td>
</tr>
<tr>
<td>Gas stove</td>
<td>15%</td>
</tr>
</tbody>
</table>

### TABLE II

<table>
<thead>
<tr>
<th>Name of a thing</th>
<th>Water purifier</th>
<th>Coffee maker</th>
<th>Refrigerator</th>
<th>Gas stove</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water purifier</td>
<td>10%</td>
<td>40%</td>
<td>10%</td>
<td>10%</td>
</tr>
<tr>
<td>Coffee maker</td>
<td>30%</td>
<td>10%</td>
<td>20%</td>
<td>10%</td>
</tr>
<tr>
<td>Refrigerator</td>
<td>10%</td>
<td>20%</td>
<td>10%</td>
<td>20%</td>
</tr>
<tr>
<td>Gas stove</td>
<td>10%</td>
<td>10%</td>
<td>10%</td>
<td>5%</td>
</tr>
</tbody>
</table>

### IV. CONCLUSION AND FOLLOW-UP STUDIES

The major contribution of the current study is a Praxeology-based Hierarchical HMM that integrates an intelligent environment model and expresses the behavior with hierarchical structure, using time for the determination of the sequence of occurrence. Reaching a state of “End” means the end of a behavior. The continuous behaviors prior to the End can be collected to form a behavior that is semantic. With this kind of framework, together with Hierarchical HMM for the prediction and determination of user behavior, the probability of occurrence for each state may be computed and the most probable state can be selected as the next probable state. Historical data can also be analyzed against the user behavior that has occurred. With this method, the most likely combination may be deduced from multiple-path data, and a new pattern may be further discovered and added to the model. Alternatively, such a behavior can also be analyzed to reveal the kind of behavior in which it is contained, for the solution that addresses the problem with massive behavior information.

Overall speaking, analyzing and predicting user behaviors can serve the purpose of behavior inference in real time. After the inference system understands the intent behind a user’s behavior, it can decide and provide a better service. The theoretic model of the study can be further expanded. With hierarchical framework, the environment can be added to a larger scope and the analysis of user behavior may be provided in real time in combination with the environment model to allow more diversified changes. Take a school campus for example, where services become the detections of student’s behaviors if an environment model is changed to school campus model. Such a change can be applied to the development and application of an intelligent campus environment. The expanded study, developed on the basis of the result from the current study, can continue the assessments of two important issues. The first one is the technical aspect in designing an effective visualized documentation interface for reducing the burden of a user’s operation. The second one is the application aspect in integrating and sharing database documented to and with an intelligent network platform to provide services common to multiple users, and communication and coordination necessary for the provision of more accurate service in an intelligent environment.

### ACKNOWLEDGMENT

This study is supported by the Taiwan Ministry of Science and Technology, grant- MOST-105-2221-E-468-003.

### REFERENCES


Chiung-Hui Chen is currently an Associate Professor of Department of Visual Communication Design, at the ASIA University, Taiwan, R.O.C.. Her research interests include the Future Architecture Design, Data Communications, Information Visualization, and Design Computing.