An Incremental Statistical Method for Daily Activity Pattern Extraction and User Intention Inference

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Abstract

This paper presents a novel approach for extracting simultaneously human daily activity patterns and discovering the temporal relations of these activity patterns. It is necessary to resolve the services conflict and to satisfy a user who wants to use multiple services. To extract the simultaneous activity patterns, context has been collected from physical sensors and electronic devices. In addition, a context model is organized by the proposed incremental statistical method to determine conflicts and to infer user intentions through analyzing the daily human activity patterns. The context model is represented by the sets of the simultaneous activity patterns and the temporal relations between the sets. To evaluate the method, experiments are carried out on a test-bed called the Ubiquitous Smart Space. Furthermore, the user-intention simulator based on the simultaneous activity patterns and the temporal relations from the results of the inferred intention is demonstrated.

Keywords: Ubiquitous computing, context-awareness, conflict resolution, human activity pattern, statistical learning method

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1. Introduction

Ubiquitous computing aims to provide users with personalized services based on the analysis of information obtained from the distributed resources. With services utilizing contextual information, ubiquitous computing aims to provide users with personalized services based on the analysis of information obtained from distributed resources [1]. Context is the entire information about the circumstance, object, or condition that a user is bound and which is related to the interaction between the user and the ubiquitous system. In addition, context is defined as the characterized information of state of the existing entity, which is the interaction between a human and some service [2]. Context-aware computing for providing appropriate services should have four tasks involved in dealing with contexts: 1) acquiring the context; 2) interpreting the context; 3) disseminating the context to interested parties; and 4) service modeling.

Traditional context-aware systems accomplish complicated sensing tasks and employ some complicated context interpretations. Thus, various conflicts occur between applications that discover and those that provide services. These conflicts could occur in an application running on a particular device, and do arise among applications running on different devices. For instance, CARISMA [3] classifies the different types of conflicts that may arise in mobile computing. However, previous studies considered only sequential human activities for the context modeling [4][5][6]. Furthermore, in simultaneous situations, some conflicts may not be conflicts depending on the habits and the capabilities of the users.

Researchers at the University of Oregon [7] found that the human brain has a built-in limit on the number of discrete thoughts it can entertain at one time. According to the research, the limit for simultaneous activities is four. Previous context-aware systems disregard simultaneous activities. However, some people often do several activities at the same time. In order to determine whether a conflict occurs or not, a variety of situations should be considered, including simultaneous activities, and analyses of users' multi-behavioral patterns. In this paper, a novel incremental statistical method is proposed to determine conflicts and to infer user intention through analyzing human daily activity patterns.

Information of the existing interactions between the daily activity patterns and the durations is significant contexts to infer user intention of their service preferences. The proposed approach can construct temporal information using the daily activity patterns. When the system provides services, the temporal relation of simultaneous activity sets are used effectively in order to obtain the services, which are discovered form the activity patterns.

An outline of the remainder of the paper is as follows. Section 2 discusses preliminary technologies on context awareness and related works of static learning approaches. Section 3 introduces the extraction process of the simultaneous activities and Section 4 presents the discovery process of the relation between sets. Section 5 introduces our experimental environments and section 6 presents the experimental results. Finally, section 7 concludes the paper and discusses future work.

2. Related Work

Context acquisition is an essential part in extracting human activity patterns in ubiquitous computing environments [8][9]. Home is the best place for observing frequent daily activity patterns using physical sensors. In order to analyze these activities in the home, past researchers have focused on recognizing location information from floors, RF transmitters, cameras, and microphones [10][11][12]. In addition, many projects have proposed systems for monitoring the human activities. MARC (Medical Automation Research Center) has developed an in-home monitoring system that records a resident's movement and collects data by using various sensors and a PDA [13]. Researchers at Yale University have studied the human activity recognition using the data acquired from cameras and PIR sensors [14]. However, location context is not sufficient to extract human activity pattern. Thus, activity context also is acquired from various sensors and devices.

When the context-aware systems provide adequate services based on context-awareness, conflicts can occur among different applications. To resolve the conflicts, many approaches have proposed context modeling methods [4][5][6]. To interpret and disseminate context effectively, most researchers have presented context modeling methods with location, identity, and time context. Approaches for context modeling are classified into six key concepts: Key-value Model (KVM), Markup Scheme Model (MSM), Graphical Model (GM), Object-Oriented Models (OOM), Logic-Based Models (LBM), and Ontology-Based Models (OBM) [15]. CoBrA [4] is an architecture employing ontology-based context model to detect conflicts between applications. Bu [5] and Xu [6] proposed an ontology-based context model to resolve conflicts that occurred in dynamic contextual environments. It is necessary to consider human activity pattern that occurs repeatedly and simultaneously. However, previous context modeling did not handle these kinds of situations. In this paper, such repetitive human simultaneous activity patterns are extracted.

To extract human activity patterns, the collected contexts could be analyzed based on data mining methods. Data mining aims to find useful regularities and to efficiently extract the frequent patterns that occur in large data sets [16]. Numerous studies have shown analysis of the collected contexts over a certain period of time and have shown daily human activity pattern using the data mining methods [17][18][19]. Perkowitz [17] presented a toolkit (PROACT) for activity recognition by using automatic methods to examine text documents and the web for the activity structure. Lymberopoulos [18] presented an automated methodology based on an *apriori* algorithm for extracting the spatiotemporal activity of a person using a wireless sensor network deployed inside home. In particular, their works are similar to our work with respect to dealing with simultaneous activity patterns. In this paper, the probability relations between simultaneous activities are calculated for extracting simultaneous activity patterns incrementally.

North American and European governments have considered aging-in-place solutions as a viable alternative to more costly, and socially isolating, institutional care. However, necessarily concomitant approach with successful aging-in-place programs is the implementation of robust and reliable monitoring, evaluation mechanisms to measure technology efficacy and safety for older people choosing to live independently. In such context, Jakkula [19] describes temporal patterns in an older person's daily activities at home using Allen's temporal relation [20]. It can be used to predict normal events and identify anomalous ones. In this paper, Allen's algebra is applied to describe relations between the activity patterns sets. In addition, the probability of occurrence for each relation is extracted by the proposed method.

3. Extracting Patterns of Simultaneous Activities

People engage in multiple activities at the same time and have physical activity habits which only occurred for a specific period of time [7]. For instance, a person may enjoy reading a book, while watching TV while lying in bed while using a laptop from eight o'clock to nine o'clock. In this case, the simultaneous activities are reading, watching TV, lying in bed, using a laptop for a specific period of time. This section presents a proposed method for extracting activities and discovering patterns that occur simultaneously.

To better illustrate this concept, the daily activities of single business people are considered after working hours. According to the collected data, he/she arrives home from work around 8 p.m. and goes to sleep around 11 p.m. The regularity of the activities has been observed, and the simultaneous activity patterns are extracted.

3.1 Activity Pattern Extraction Process

The aim of extracting the activity patterns is to organize the simultaneous activities in order to resolve conflicts, and to discover habits. The simultaneous activities occur at a certain place for a certain time period. The process of extracting the activity pattern is described in **Fig. 1**. First, many contexts are acquired from environmental sensors and electronic devices. Then, the activity patterns and the simultaneous activity patterns are analyzed using the Incrementally Simultaneous Method (ISM) which organizes the activities context model. In addition, temporal relations between the simultaneous activity patterns are represented using Allen's temporal relation logic after constructing the simultaneous activities as sets. Finally, an activity context model can be constructed, which has both the probability and the temporal relations.

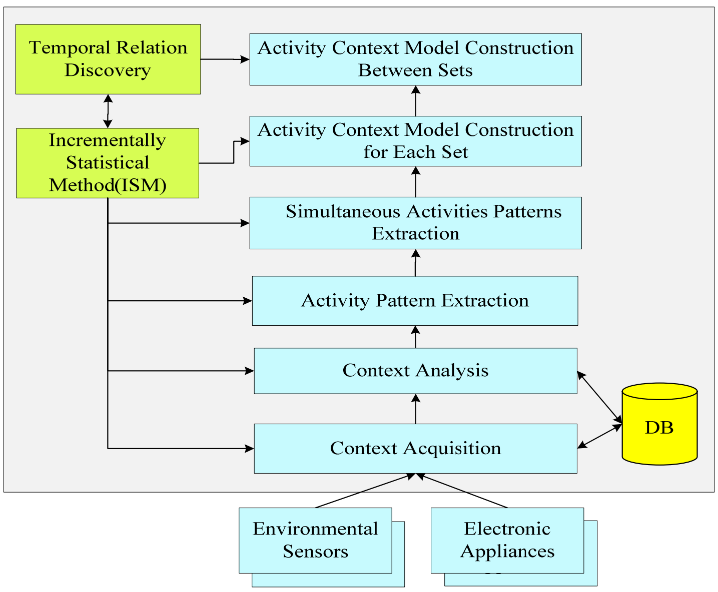


Fig. 1. Process of constructing the activity context model

3.2 Set of Simultaneous Activities

To extract the simultaneous activity patterns, the activity context model is constructed from the sets of simultaneous activities which determine the probability relations between the activities and determine a temporal relation within the sets. The simultaneous activity set is a set of activity contexts which have occurred at the same time. People can undertake a maximum of four activities at a time, because the limit of activities in each set is four [7].

To organize the set of simultaneous activities, activities are first divided into simultaneous activities and non-simultaneous activities. A non-simultaneous activity is a representative activity that does not occur simultaneously with other representative activities, but has sub-simultaneous activities.

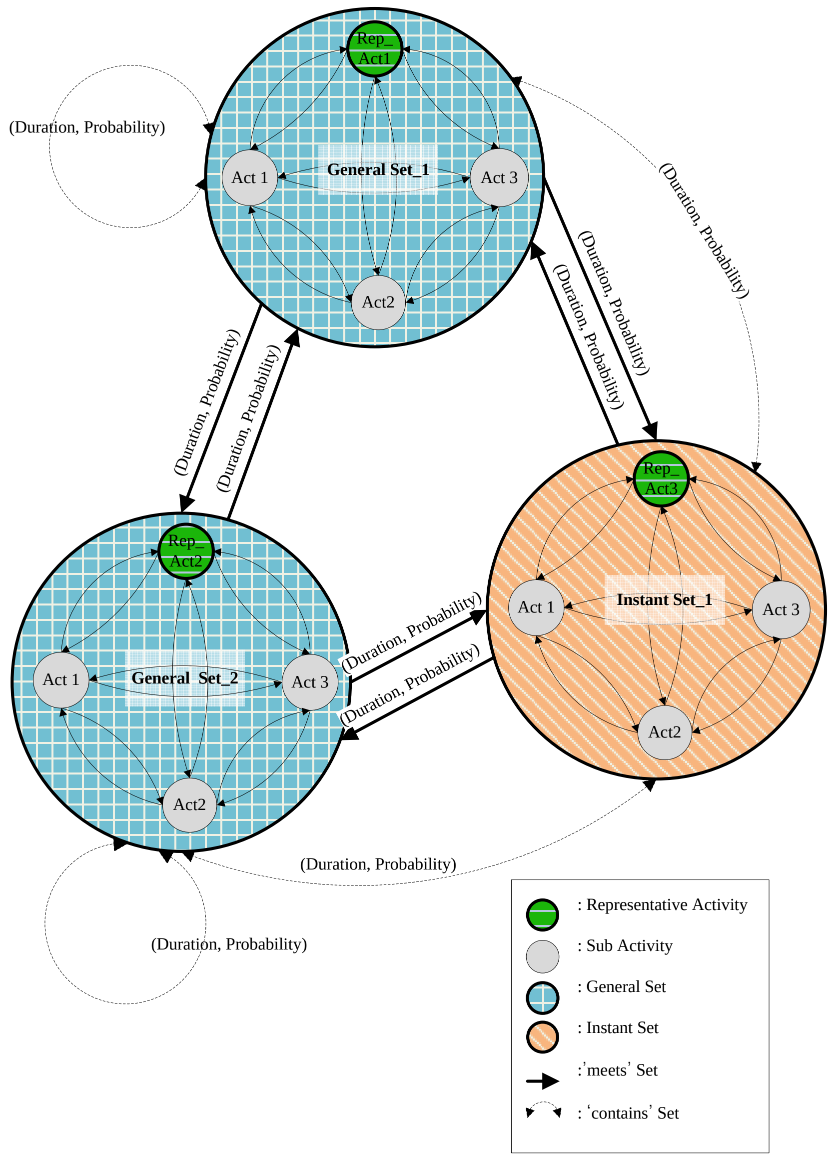


Fig. 2. An example of the activity context model with the simultaneous sctivities sets

Fig. 2 shows sets of simultaneous activities consisting of the representative activity and the sub-activities. In this set, arrows indicate a sequential flow between the activities. All sequences have probabilities between the activities. The sets are classified into a general set and an instant set according to the user activity pattern. These organized sets have the temporal relations that are divided into ‘meets’ or ‘contains’. The bi-directional arrow indicates the ‘contains’ relation, and the uni-directional arrow represents the ‘meets’ relation. The ‘contains’ relation is when a set occurs for a short time while other set happens. The ‘meets’ relation is when a set occurs sequentially after another set finishes. These special sets are defined as instant sets that occur in the process of another set. Also, all relations contain duration averages and occurrence probabilities between the sets.

3.3 Incremental Statistical Process

Whenever simultaneous activities occur, the statistical value is measured and updated on the previously recorded. This value is the probability that a user does one action while doing another action simultaneously in the same set. These probabilities are calculated incrementally by updating the previous data as shown in **Fig. 3**.

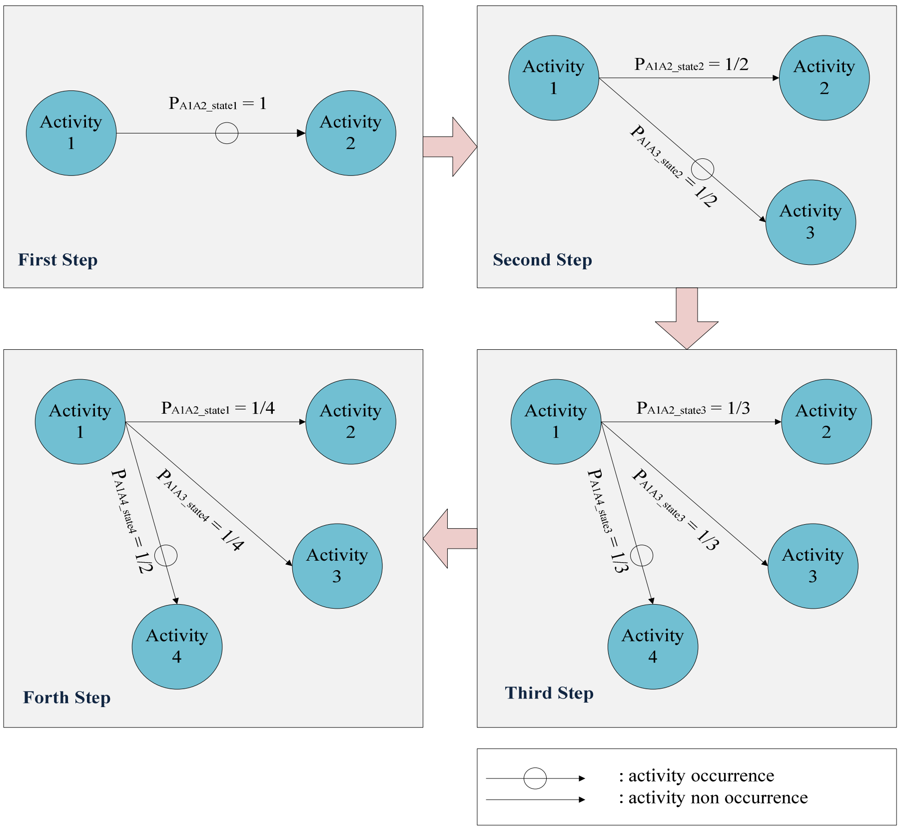


Fig. 3. Process of incremental statistical methods

In the first step, a user carries out activity 1 with activity 2, and the probability (P_{12}^{1}) between activities is 1. Then, activity 3 occurs anew in the next step. The probability (P_{12}^{2}) is changed to 0.5. In both the third and the fourth steps, another new activity 4 occurs. In the set, the probability between activity 1 and activity 2 is 1 at the first step. In both the second and the third step, the probability is changed to 0.5 and 0.33 respectively. Finally, the probability is 0.25 in the last step. The probability formula between the simultaneous activities is as follows.

$$P_{A_iA_j\_state}{}^{k} = \frac{1}{f_{A_i}{}^{k-1}+1}\{f_{A_i}{}^{k-1}P_{A_iA_j}{}^{k-1} + C_{A_j\_occur}{}^{k}\} \quad (1)$$

A_i : Previous occurred activity

A_j : Current occurring activity

$state$: Occurrence or non-occurrence

k : Order of step

$f_{A_i}{}^{k-1}$: Total frequency of occurred activities in a previous step

$C_{A_j\_occur}$: Occurrence frequency of the current activity

4. Discovering the Relations in Simultaneous Activity Sets

User intentions can be predicted by adding the temporal relations between the sets into the model that are composed of the probability relations. It is assumed that the temporal relations of each set occur based on the representative activities, because these decide the transference from the running set to another set. To determine the temporal relation between the simultaneous activity sets, first the duration times of the activity contexts are analyzed. Then, the temporal intervals, based on the time boundary between the sets in **Fig. 4**, are measured. Finally, the temporal relations between the sets are determined.

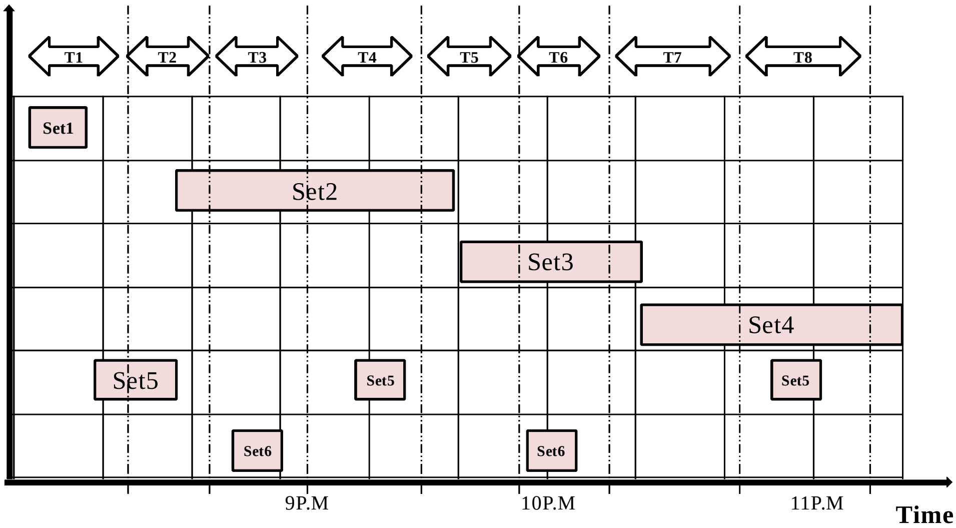


Fig. 4. A sample of the temporal intervals between the sets

The two relations of Allen's thirteen basic relations are employed to predict the next activities for user intention inference. In **Fig. 4**, the first relation is shown between set 1 and set 5 in the time interval T1. In this case, set 1 happened, and then set 5 occurred after 5 minutes. Therefore, set 1 and set 5 have the 'meets' relation in the T1. In the same way, the 'meets' relation is shown between set 5 and set 2, between set 2 and set 3, and between set 3 and set 4. In addition, the results obtained show that set 1, set 2, set 3, and set 4 cannot occur at one time as the 'meets' relation. According to the definition of the instant set, set 5 and set 6 have the ‘contains’ relation.

In order to calculate the probability and to extract the temporal relations from the collected activity contexts, the algorithm should be developed that can discover simultaneous activity relation and calculate the duration and the occurrence probability based on the frequency of input sets among the simultaneous activity sets. This algorithm can also calculate the daily temporal intervals and discover temporal relations of the simultaneous activities set. The probability and the temporal relations are reflected and reconstructed every day by being updated incrementally.

The process of the proposed algorithm is as follows. The first step in the process of the proposed algorithm is to wait until a set arrives. If there are sets, the relation is decided by comparing the start time with the end time about the selected sets. The next step is to calculate the occurrence probability. Finally, the average of the temporal difference between two simultaneous activities sets is calculated.

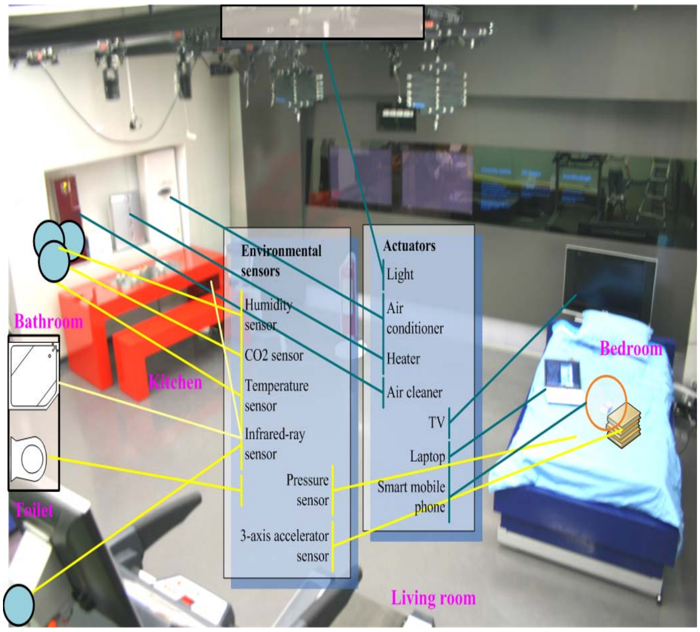
Simultaneous activities relation discovery algorithm

//Find the relation of sets, the occurrence probability, the occurrence time
while(S_{new} != 0)
{Input $_{s\_}$, T_{start}, T_{end} // S_{new} = new set, T_{start} = start time, T_{end} = end time
  while(S_{old} != 0)   // S_{old} = old set
    { if($T_{end\_s\_old} < T_{start\_s\_new}$)
      Relation = meets;   // Relation = temporal relations (meets or contains)
      $f_{s\_old\_After}$ ++; $f_{s\_new\_After}$ ++;   // Frequency of set having meets relation
      $P = \frac{f_{s\_old\_After}}{f_{s\_new\_After}};$ // P = occurrence probability
      $T = T_{start\_s\_old} - T_{start\_s\_new};$ // T = occurrence duration
      $S_{old} = S_{new};$
    else if ($T_{start\_s\_old} < T_{start\_s\_new}$ && $T_{end\_s\_new} < T_{end\_s\_old}$)
      Relation = contains;
      $f_{s\_new\_During\_s\_old}$ ++;   // Frequency of contains relation between sets
      $P = \frac{f_{s\_new\_During\_s\_old}}{f_{s\_old\_After}+1};$
      if ($f_{s\_new\_During\_s\_old}$ > 1)
        $f_{s\_new\_During\_s\_old}$ = 1;
      else
      $f_{s\_new\_During\_s\_old} = f_{s\_new\_During\_s\_old};$ $T = T_{start\_s\_old} - T_{start\_s\_new};$
      Return (S_{old}, S_{new}, Relation, P, T);
    }
    $S_{old} = S_{new};$
}

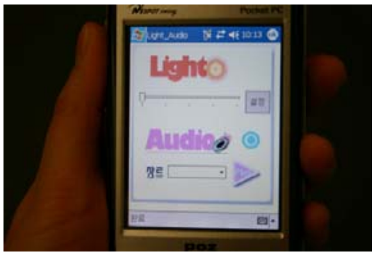
5. Experimental Setup

5.1 Ubiquitous Smart Space (USS)

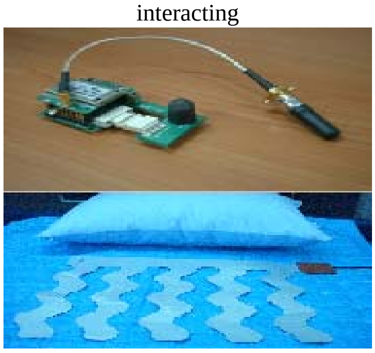
The USS has been designed and implemented as shown in **Fig. 5**. To evaluate the methods, experiments have been carried out on the test-bed over seven days over which the daily activity patterns, after returning home from work, have been monitored. It is assumed that the persons usually return home at around 8 p.m. and went to sleep at around 11 p.m., and so this daily three hour period is the focus of the observations. **Table 1** presents the data structure for acquiring the context information. The collected contextual information is; environmental context, activity context, and time context. The environmental context includes environmental data such as temperature, humidity, CO_2. The activity context contains action data such as watching TV, listening to music, turning on the lights, heaters, air cleaners, and air conditioners all collected using the PDA. The user can also choose up to three devices on the PDA screen. The time context is essential to extract the user's specific activity pattern for the specific periods of time. These three contexts are inserted into a database when the server collects data for the user model from the PDA, which includes user interaction observations and direct user inputs.



(a) View of the test-bed (USS)



(b) The PDA screen shot for interacting



(c) sensors

Fig. 5. Test bed, PDA and Sensors

5.2 User Intention Simulator

User intention has been applied using the temporal relation results and the simulator is linked with the context database as well as having the simultaneous activity pattern set and the temporal relation algorithms. In the simulator, services which can be provided to the users are arranged and provided based on the user activity and the time from the inferred intention results. **Fig. 6** shows the user intention simulator using the simultaneous activity patterns and the temporal relations. The previous system provided services that were inferred in the lump from the collected activities for a certain period. However, the proposed system provides services that are updated from the incremental intention results per day.

Table 1. Data structure

		Data type	State
Environmental context	Space	ction /:Indoor	Indoor: User enters in home.
		action /:awake	awake: User goes out from the bed.
		action / :sleep	sleep: User is on the bed.
		Space:Sofa	User is on the sofa.
		Space:LivingRoom	User is in the living room.
	temperature	Integer	Ex) temperature / :22
	humidity	Integer	Ex) humidity / :32
	CO2	Integer	Ex) co2 / :401
Activity context	Watching TV	On	User turns on TV.
		Off	User turns off TV.
	listening Music	On	User turns on the audio.
		Off	User turns off the audio.
	Light	Off	User turns off the light.
		Dark	Dark: user turns on the light darkly.
		Medium	User turns on the light little bit brightly.
		Bright	User turns on the light brightly.
	Reading	action / :Reading_Start	Start: user is reading a book.
		action / :Reading_End	End: user finishes reading.
	Laptop	action / :Laptop_Start	Start: user starts using a laptop.
		action / :Laptop_End	End: user finishes using a laptop.
	Mobile	action / :Call_Start	Start: user starts call with someone.
		action / :Call_End	End: user finishes using a mobile.
Time context	Time	Year/month/hour/minute/second	Ex)20081031215118

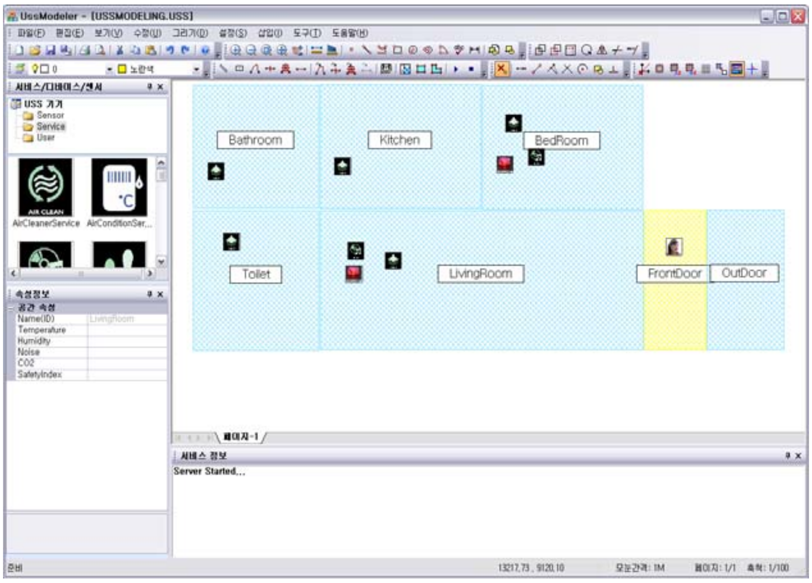


Fig. 6. User intention simulator using the simultaneous activities patterns and the temporal relations

6. Experimental Results

6.1 Simultaneous Sets

The analyzed data for organizing the simultaneous activity sets is shown in **Table 2**. The simultaneous activity pattern set consisting of sub-activities is shown in **Table 3**. The W_TV1 set is composed of four contexts: watching TV in the living room, reading, using a laptop, and using a mobile phone. Generally, this set is independent and sequential. However, the D_Toilet set and the D_Coffeepot set are instant sets because these sets occur for only a short time while another set occurs.

Table 2. Dataset of activity context

Seq	Activity Context	Duration	Set	Set type
1	In Entrance door	1m27s	LM_Audio1	General set
2	Listening music in the living room	1h47s		
3	Using Toilet	2m	Shower	General set
4	Shower	9m57s		
5	Watching TV1	2m35s	W_TV1	General set
6	Watching TV1, Using a Coffeepot	2m26s	D_Coffee1	Exceptional set
7	Watching TV1	14m45s		
8	Watching TV1, Reading	21m28s		
9	Watching TV1, Reading, Using a Toilet	2m8s	D_Toilet1	Exceptional set
10	Watching TV1, Reading	27m29s		
11	Listening music in the bedroom, Using a Laptop	2m12s	LM_Audio2	General set
12	Listening music in the bedroom, Using a Laptop, Using a Toilet	4m45s	D_Toilet2	Exceptional set
13	Using a Laptop, Watching TV2	5m25s	W_TV2	General set
14	Using a Laptop, Watching TV2, Using a Mobile	7m33s		
15	Using a Laptop, Watching TV2, Using a Coffeepot	2m56s	D_Toilet3	Exceptional set
16	Using a Laptop, Watching TV2, Reading	16m13s		
17	Using a Laptop, Watching TV2, Reading, Using a Mobile	58s		
18	Using a Laptop, Watching TV2, Reading	4m28s		
19	Using a Laptop, Watching TV2, Using a Mobile	4m4s		
20	Using a Laptop, Using a Mobile, Listening music in the bedroom	8m6s	LM_Audio2	General set
21	Using a Laptop, Using a Mobile, Listening music in the bedroom, Using a Toilet	1m54s	D_Toilet2	Exceptional set
22	Using a Laptop, Using a Toilet	1m9s		

Table 3. Simultaneous activities context

Set		Activity context
General Set	LM_Audio1	In Entrance door, Listening music in the living room (Turning on a living room light)
	W_TV1	Watching TV in the living room, Reading, Using a laptop, Using a mobile phone (Turning on a living room light)
	LM_Audio2	Listening music in the bedroom, Using a laptop, Using a mobile phone (Turning on a bedroom light)
	W_TV2	Watching TV in the bedroom, Reading, Using a laptop, Using a mobile phone (Turning on a bedroom light)
	Shower	Using the toilet, Shower (Turning on a bathroom light)
Exceptional Set	D_Toilet	Using the toilet (Turning on a bathroom light)
	D_Coffeepot	Using a coffeepot (Turning on a kitchen light)

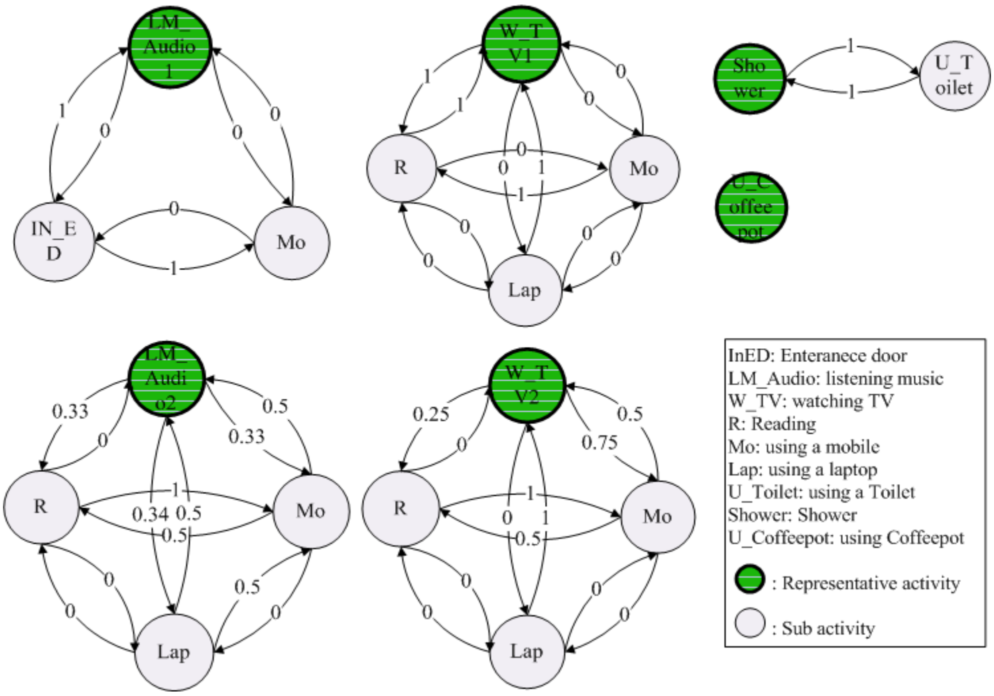


Fig. 7. The probability relations of the simultaneous activities

The activity context model has been constructed using the ISM. This model is organized on the simultaneous activities. **Fig. 7** shows six simultaneous activity pattern sets. According to the definition in section 3, the representative activities are LM_Audio1, W_TV1, LM_Audio2, W_TV2, Shower, and U_Coffeepot. The LM_Audio1 set contains listening to music in the living room, using a laptop, reading and using a mobile phone. The W_TV1 set contains watching TV, using a laptop, reading and using a mobile phone. The LM_Audio2 set and the W_TV2 set contains reading, using a mobile phone, and using a laptop. The Shower set contains U_Toilet as a sub-activity. The weight between the activities is indicated as a statistical value. In an example shown in **Fig. 7**, a laptop and a mobile phone have been used after listening to music in the bedroom. The probabilities of these activities are 0.5 and 0.25 respectively. **Fig. 8** shows the process of extracting the simultaneous activities set using the Incremental Statistical Method.

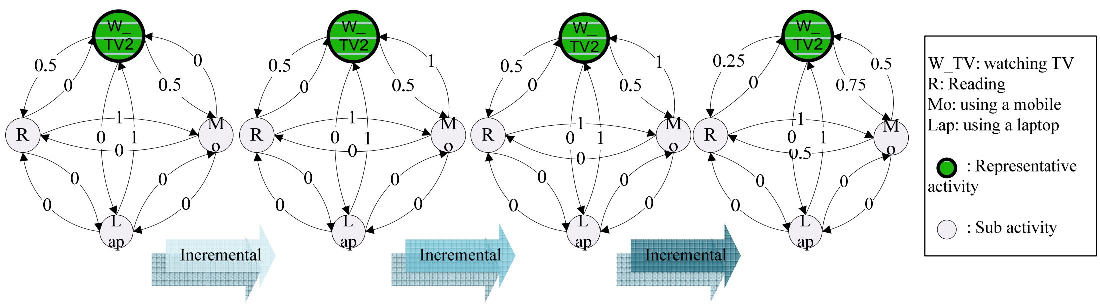


Fig. 8. Process of extracting the simultaneous activities set using Incremental Statistical Method.

6.2 Temporal Relation of Sets

More specific activity patterns have been extracted using the discovered temporal relations. To analyze the duration of the temporal intervals of each simultaneous activities set, the activity contexts' states, which are collected over the three hours, are represented. **Fig. 9** shows each activity state as 'on' or 'off'. For example, the user was listening to music in the living room for 10 minutes after 8 o'clock.

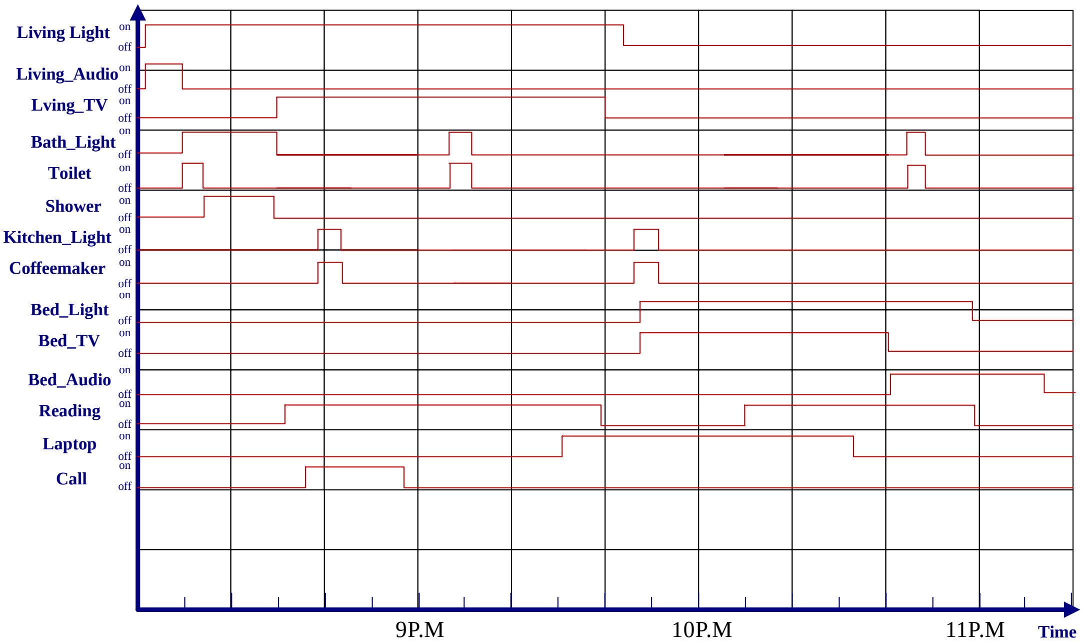


Fig. 9. A sample of temporal activities for about 3 hours

The result of the relations between the sets is then shown as a state diagram, which is converged by the probability and the temporal relations in **Fig. 10** The LM_Audio1 set, the Shower set, the W_TV1, the W_TV2 set and the LM_Audio2 set are general sets, and only occur sequentially. For example, the W_TV2 set occurs for 70 minutes after the Shower set has occurred for 20 minutes. However, the Toilet set and the U_Coffeepot set occur instantly in the process of another set. Therefore, the Toilet set and the U_Coffeepot set are general sets as well as instant sets, and can be labeled as a 'contains' relation. For example, the U_Coffeepot set occurs after 3 minutes in the running time of the W_TV1 set.

Fig. 11 shows the accuracy of user intention inference using ISM, Naïve, and non-incremental method. The accuracy is calculated by comparing with the results for five days using three methods as shown in the following equation.

$$\text{Accuracy} = \frac{\text{relevant services activated by a user in the present activity set}}{\text{services predicted by a method in the previous activity set}} \tag{2}$$

As shown in **Fig. 11**, the overall accuracy of ISM is 68.2%. The non-incremental method has lower accuracy than the incremental method because it does not reflect the new activity patterns. The overall accuracy of Naïve method is 53.5%. When activities occur at irregular intervals, Naïve method achieves low accuracy on the average. As a result, the accuracy of ISM is approximately 24% and 27% times better than that of non-incremental method and Naïve method, respectively.

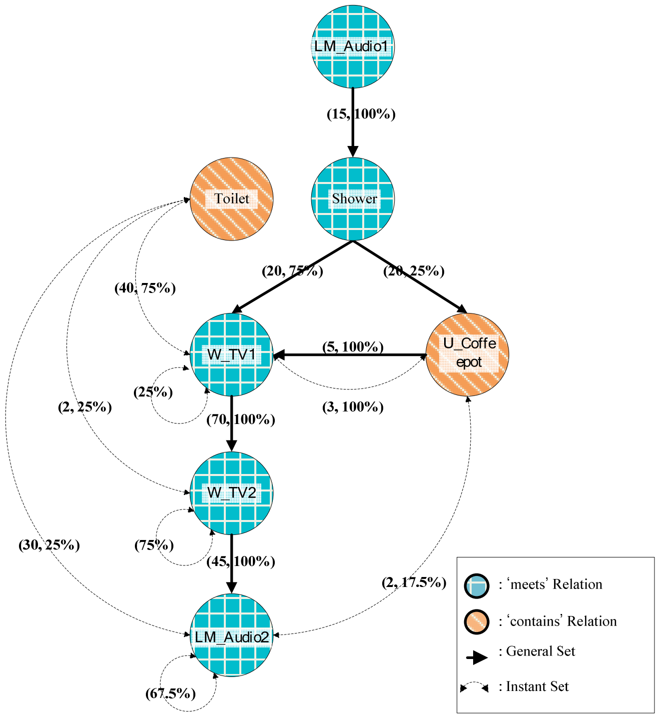


Fig. 10. The temporal relation and probability relation of activity sets

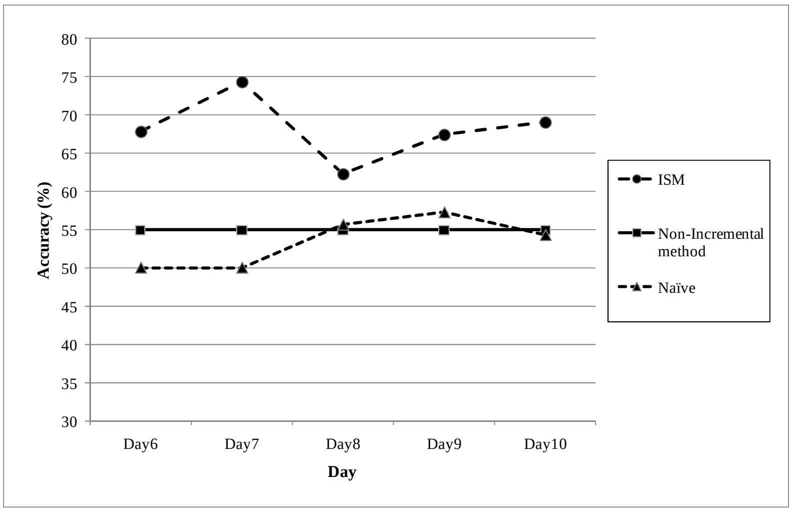


Fig. 11. Accuracy of user intention inference using ISM, Naïve, and non-incremental method

7. Conclusion

This paper has presented the incremental statistical method for extracting simultaneous activity patterns and for discovering user intentions. This method helps to understand human activity patterns and to infer the intentions of users. In addition, it can also provide the user with personalized services depending on the user's activities. In order to infer user intention, an activity context model has been constructed that reflects the temporal relations between the activities. Allen's temporal relation logic is applied to represent a sequential flow between simultaneous activity sets. Complimentary approaches can only handle single activities, and extract the human activity patterns by analyzing a large data set at once in a batch format. However, the proposed method could be extracted user activity patterns by real-time analysis of simultaneous activities as they occur. Some future directions of this work also include the expansion of the application domain to include more complex environments, including accommodating the needs of multiple users and elderly life care applications.

References

[1] M. Satyanarayanan, "Pervasive Computing Vision and Challenges," *IEEE Personal Communications*. vol. 8, no. 48, pp. 10-17, 2001.

[2] A.K. Dey, et al., "A Context-Based Infrastructure for Smart Environments," in *Proc. of 1st International Workshop on Managing Interactions in Smart Environments*, pp. 114-128, 1999.

[3] L. Capra, et al., "CARISMA: Context-Aware Reflective Middleware System for Mobile Applications," *IEEE Transactions on Software Engineering*, vol. 29, no. 10, pp. 929–945, 2003.

[4] H. Chen, et al., "Intelligent Agents Meet the Semantic Web in Smart Spaces," *IEEE Internet Computing*, vol. 8, no. 6, pp. 69-79, 2004.

[5] Y. Bu et al., "Context Consistency Management Using Ontology Based Model," in *Proc. of 10th International Conference on Extending Database Technology*, pp. 21-32, 2006.

[6] C. Xu, S.C. Cheung, "Inconsistency Detection and Resolution for Context-Aware Middleware Support," in *Proc. of Joint 10th European Software Engineering Conference and 13th ACM SIGSOFT Symposium on the Foundations of Software Engineering*, pp. 336-345, 2005.

[7] E. Vogel, E. Awh, "How to exploit diversity for scientific gain: Using individual differences to constrain cognitive theory," *Current Directions in Psychological Science*, vol. 17, no. 2, pp. 171-176, 2008

[8] D. Salber, et al., "The context toolkit: Aiding the development of context-enabled applications," in *Proc. of ACM Conference on Human Factors in Computing Systems*, pp. 434-441, 1999.

[9] A.K. Dey, "Understanding and Using Context," *Personal and Ubiquitous Computing*, vol. 5, no. 1, pp. 4-7, 2001.

[10] M. Mozer, "Lessons from an adaptive house," *Smart environments: Technologies, protocols, and applications*, pp. 273-294, 2005.

[11] C. D. Kidd, et al., "The Aware Home: A Living Laboratory for Ubiquitous Computing Experience," in *Proc. of International Workshop on Cooperative Buildings*, pp. 191-198, 2006.

[12] S. Shafer, B. Brumitt, and B. Meyers, "The Easy Living Intelligent Environment System," in *Proc. of CHI Workshop on Research Directions in Situated Computing*, 2000.

[13] G. Virone, M. Alwan, S. Dalal, S. Kell, Steven W. Kell, John A. Stankovic, and R. Feldel, "Behavioral Patterns of Older Adults in Assisted Living," *IEEE transactions on information technology in biomedicine*, vol. 12, no. 3, pp. 387-398, 2008.

[14] D. Lymberopoulos, T. Teixeira, A. Savvides, "Macroscopic Human Behavior Interpretation Using Distributed Imager and Other Sensors", in *Proc. of the IEEE*, vol.96, No.10, pp. 1657-1677, 2008.

[15] T. Strang and C. Linnhoff-Popien, "A context modeling survey," in *Proc. of 1st International Workshop on Advanced Context Modeling, Reasoning and Management*, pp. 34-41, 2004

[16] V. N Vapnik, "Statistical Learning Theory," *John Wiley*, New York, 1998.

[17] M. Perkowitz, M. Philipose, K. Fishkin, D.J. Patterson, "Mining Models of Human Activities from the Web," in *Proc. of 13th International Conference on World Wide Web*, pp. 573-582, 2004.

[18] D. Lymberopoulos, A. Bamis, and A. Savvides, "Extracting spatiotemporal human activity patterns in assisted living using a home sensor network," in *Proc. of 1st international conference on PErvasive Technologies Related to Assistive Environments*, 2008.

[19] V. Jakkula, A. Crandall, and D. Cook, "Knowledge Discovery in Entity Based Smart Environment Resident Data Using Temporal Relation Based Data Mining," in *Proc. of the ICDM Workshop on*

Spatial and Spatio-Temporal Data Mining, pp. 625-630, 2007.
[20] J. F. Allen, and G. Ferguson, "Actions and Events in Interval Temporal Logic," *Journal of Logic and Computation*, pp.1-59, 1994.
[21] E. Choi, B. Kim, Y. Nam, and D. Cho, "An Incrementally Statistical Activity Model using Extracting Human Simultaneous Activity Patterns in a Smart Home," in *Proc. of International Conference on Applications and Principles of Information Science*, pp. 159-162, 2009.

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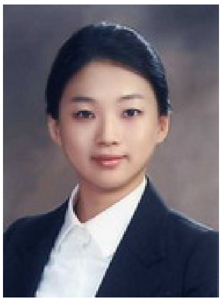

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