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Context-aware system for proactive personalized service based on context history

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ABSTRACT

Predicting the preferences of users and providing the personalized services or products based on their preferences are the important issues. However, the research considering users' preferences on context-aware computing is a relatively insufficient research field. Hence, this paper aims to propose an agent-based framework for providing the personalized services using context history on context-aware computing. Based on the proposed framework, we implement a prototype system to show the feasibility of the framework. Previous researches require that the users input their preference manually, but this research provides the personalized services extracting the relationship between users' profile and services under the same context automatically.

1. Introduction

Many researchers have been interested in context-aware computing (Brown, 1996; Cao & Li, 2007; Chen & Kotz, 2000; Schilit et al., 1994). Context is any information that can be used to characterize the situation of an entity where an entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including location, time, activities, and the preferences of each entity (Abowd et al., 1999; Yau & Karim, 2004). Context awareness is about capturing a broad range of contextual attributes (such as the user's current positions, activities, and their surrounding environments) to better understand what the user is trying to accomplish, and what services the user might be interested Lee (2007). In recent, the context information of users has been captured and processed on context-aware computing. It is essential that a service must be offered based on a specific context because the kind of services is different according to the context (Lee, 2007). So, the services are provided to users efficiently by utilizing the context (Figge, 2004; Lee et al., 2005).

The services that users want to receive are different despite of the same context. Despite its fact, the previous researches about personalized services based on the users' preferences ignore it and provide each user with the same services under the same context. Users' preferences are different from each other according to environment around them or their characteristics such as sex and age. Specially, users want to receive personalized services or products based on their preferences in e-commerce, information retrieval, document classification and multimedia recommendation, etc. Therefore, predicting the preferences of users and providing the personalized services or products based on predicted users' preferences are the important issues in recent. E-commerce applications or recommendation systems for the personalized services applying the extracted users' preferences have been carried out by many researchers. However, the research concerning personalization considering users' preferences on context-aware computing is a relatively insufficient research field (Byun & Cheverst, 2004; Chalmers, 2004; Chen & Kotz, 2000; Dey & Abowd, 1999; Henricksen & Indulska, 2004; Kaenampornpan & O'Neill, 2004; Schmidt et al., 1999).

Most researches on context-aware computing have focused on inference of high-level context such as users' current activity from sensor data (Brunato & Battiti, 2005; Henricksen & Indulska, 2005; Krause, Smailagic, & Siewiorek, 2006; Ladd, Bekris, Rudys, Kavraki, & Wallach, 2005; Niemegeers & Heemstra De Groot, 2005; Ranganathan, Al-Muhtadi, & Campbell, 2004; Samaan & Karmouch, 2005; Satoh, 2003). But, predicting the users' activity based on only sensor data is so limited for providing the personalized services and the preferences of users are also not extracted automatically. There were some previous researches for the personalized services using the users' preferences on context-aware computing. However, there are some limitations like these: (1) first, the users have to input their preferences manually to receive the personalized services. (2) Second, the previous researches did not provide the personalized services extracting the users' preferences automatically. (3) Finally, it is difficult to provide new user with the personalized services due to the deficiency of their history or information.

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Hence, this paper aims to propose an agent-based framework for providing the personalized services based on users' preferences using the context history on context-aware computing. According to the proposed framework, we implement a prototype system to show the feasibility of the framework. There are some contributions like these: (1) first, our research proposes an agent-based framework for offering the personalized services considering users' preferences on context-aware computing. (2) Second, our research implements the system, Context-Aware System considering User Preference (CASUP), that can provide new user with the personalized services. (3) Finally, our research indicates the strategy about the utilization of context history.

This research is organized as follows: in Section 2, we review previous researches about the personalized services considering users' preferences on context-aware computing and explain context history. In Section 3, we propose an agent-based framework for providing the personalized services on context-aware computing. In Section 4, according to the proposed framework, we implement a prototype system, CASUP, to show the feasibility of the framework. The research finishes with concluding remarks in Section 5.

2. Literature review

2.1. Personalization services

The research about providing the personalized services based on users' preferences has been carried out by many researchers in recommendation systems. Tapestry (Goldberg et al., 1992) developed mail filtering system which is one of early recommendation systems. After this, the various automated recommendation system were developed (Zhang & Jiao, 2007). In e-commerce, Sarwar et al. (2000) suggested e-commerce application using users' feedback about product catalog for recommendation of product that users want on web for personalized web services and Cao and Li (2007) developed fuzzy-based system for recommendation of product optimized based on customers' needs extracted using interaction between system and user and Kim et al. (2004) suggested wallpaper-recommending system, "VISCORS", in mobile web combining collaborative filtering with content-based image retrieval.

In information retrieval and documentation classification, Middleton et al. (2004) developed *k*-NN-based recommender system that recommends research documentation based on similar users' preferences and uses Ontology to analyze the profiles of users, Singh and Dey (2005) developed document ranking system based on users' preferences using filtering agent, "Sieve", after learning the users' evaluation for documentation and it uses rough-based reasoning. "Syskill & Webert" (Pazzani et al., 1996) is a software agent which learns page ratings (a three-point scale) for deciding interest of the user to web pages applying Bayesian classifier. Balabanovic's Fab system (Balabanovic, 2000) recommends the customized web sites based on users' profiles and users' ratings of pages. Keyhanipour et al. (2007) introduced meta-search engine, "WebFusion", based on data about users' URL click and Ves et al. (2006) suggested content-based retrieval system that retrieve the images that user want using Bayesian framework. "WebPlanner" (Jochem et al., 1999) is guided search application for providing users with personalized information applying domain-specific structured query schemes. Singh et al. (2003) developed a text-filtering system applying rough-set based analysis to capture the preferences of users.

In multimedia recommendation, Hill et al. (1995) suggested video recommender for recommending the movie and Konstan et al. (1997) developed news and movie recommendation system and Shardanand and Maes (1995) suggested "Ringo" for recommending the music. Like this, the research about personalization services has been carried out by many researchers in the various areas except for context-aware computing.

2.2. Personalization services on context-aware computing

Currently, the researches about context-aware computing have been studied by many researchers (Brown, 1996; Chen & Kotz, 2000; Schilit et al., 1994). The research concerning context-aware application and services can be divided into six parts (Lee et al., 2006): smart space providing users with smart environment, tour guide guiding the travelers, information system (Kang et al., in press; Kim et al., 2007), communication system providing social community, m-commerce, web service. There has been recognized that capturing and inferring the users' preferences is important to offer the personalized services (Byun & Cheverst, 2001; Jameson, 2001). However, there is little research utilizing the preferences of the users to recommend the personalized services on context-aware application and services. Most researches about context-aware computing have been focused on the acquisition, inference and management of context information (Krause et al., 2006; Brunato & Battiti, 2005; Henricksen & Indulska, 2005; Ladd et al., 2005; Niemegeers & Heemstra De Groot, 2005; Ranganathan et al., 2004; Samaan & Karmouch, 2005; Satoh, 2003).

There are some researches about context-aware computing application considering the users' preferences. NAMA (Kwon et al., 2005) is reminder system providing the personalized services on context-aware computing. For example, in shopping, if there are some products which the user resisters into to-do-list near him, the reminder system recommends them to him. Doulkeridis et al. (2006) required users to input the keywords for the information that he wants for providing the services to satisfy his context and preferences simultaneously like web search engine. In that, if the user requires some pictures that the user wants to see, the system provide the services based on the context such as current status of devices, time. GUIDE provides the personalized information with travelers based on user profiles or user's preference such as user's interest and language, inputted into interface (Cheverst et al., 2000).

Like this, some researches for providing the personalized services using users' preferences have been carried out. However, most researches require the users to input their preferences manually. So, the users must input their preferences according to each situation or circumstance around them manually. Because the preferences of all users should be stored according to each situation or circumstance around them, it is difficult to provide the new user who did not have any information about him with the personalized services.

There was little research to provide the automated personalized services learning the users' preferences. Byun and Cheverst (2004) used Decision tree based on context history to infer the preferences of the user. In that, the system provides the personalized service based on preference rules extracted from learning the user's actions (windows open/close, fan on/off, blind open/drawn) according to current context near the user (temperature, noise, etc.). However, it is difficult to predict new user's preferences because individual preferences were extracted and saved. There is also lack of specific method to infer user's preferences. Si et al. (2005) proposed the context-aware service platform, "Synapse". They applied Hidden Markov Model (Rabiner, 1989) which is one of Bayesian Networks. After the users' habits are learned, the most appropriate services are provided based on the users' habits in active mode or passive mode. However, it is also difficult to offer the personalized services predicting the preferences of new user like the above research. Lee (2007) suggested the framework utilizing agent-based methodology for providing the personalized mobile services. This research developed the system which predicts and recommends the program that the user wants. It predicts the user's preferences using Decision tree based on the preferences of users similar to the unique user and provides the personalized programs. However, the user has to evaluate the preferences for some programs manually and similarity between users is also determined based on the difference of preference for the programs simply. So, it also makes the users to input their preferences manually for providing the personalized services. It is difficult to provide the services with new user.

2.3. Context history

One of the limitations of the previous context-aware application is to consider the only current context (Salber & Abowd, 1998). Context history has been recognized simply as the collection of the past context and users' actions for the past context. It has many possibilities to improve the services offered by some applications (Mayrhofer, 2005). If the context history can be used, the personalized intelligent services can be provided to the users by extracting useful users' patterns from context history. For instance, if the information such that the user always watches TV news at 21:00 in smart home exists, the system sets the intelligent environment that allows the user to watch TV news referring the patterns of the user. Context history has been used for the prediction of future context, selection of devices and adaptation (Byun & Cheverst, 2004; Mayrhofer, 2005; Si et al., 2005). Despite these advantages of context history, it is lack of utilization of it except for some researches (Byun & Cheverst, 2004). Not only the research for context history (Chalmers, 2004; Chen & Kotz, 2000; Dey & Abowd, 1999; Kaenampornpan & O'Neill, 2004; Schmidt et al., 1999) is a relatively under-explored area but most researches for context history have also focused on the record or construction rather than utilization of it (Mayrhofer, 2005). Although the useful information can be extracted based on the demographic data on context, there is no research combining the users' profiles and context information among the researches about use of context history.

In sum, the proactive, automated, intelligent and personalized services can be offered by extracting the useful information such as users' preferences, patterns and habits, etc. from context history on context-aware computing environment.

3. System framework

Fig. 1 shows the agent-based framework for offering the personalized services utilizing the extracted users' preferences and association rules. It has four layers. There are data gathering layer that collecting sensor data (raw context), user data (profiles) and service data, context management layer that infers high-level context from low-level context, stores collected information into context history and classifies the user profiles and the selected services under the same high-level context, preference management layer that reasons users' preferences from context history and manages them and infers the association rules for recommending the next services, and application layer to provide the personalized services to PDA or cellular phone referring the extracted preference rules and association rules. It consists of server side that manages the context, user profile and selected services and infers the high-level context, preferences rules and association rules, PDA or mobile devices side that collects users profile and selected services and provides the personalized services to users and sensor side that collects the raw context or sensed data using the hardware sensors or software programs.

Agent-based computing has been a new paradigm in software applications development and there are some characteristics, such as autonomy, adaptation and cooperation, for intelligent agents (Lee, 2007; Wooldridge, 2001). Multiagent systems consist of the various agents that execute each goals and the overall application goal. The multi-agent approach research has been carried out by many researches (Lee, 2007) such as electronic commerce (He et al., 2003; Lee, 2004), information filtering, retrieval and management (Ardissono et al., 2004; Durfee et al., 1997; Moukas, 1997), resource planning and allocation (Haque et al., 2005; Sycara et al., 1996), and mobile services (Panatiotou & Samaras, 2004; Ratsimor et al., 2004).

Because the context-aware services are usually provided in an open environment, multi-agent approach is appropriate for development of them. The framework consists of eight agents (context wrapper, user agent, context aggregator, context inference agent, filtering agent, preference miner agent, association agent and adaptation agent). There are various multi-agent platforms which is publicly available (Lee, 2007) such as AgentTCL that was later renamed as D'Agent (Gray et al., 2002), Tracy (Braun & Rossak, 2005), Aglets (Lange & Oshima, 1998), and JADE (Bellifemine et al., 2001).

3.1. Data gathering layer

Data gathering layer collects and processes the users' profiles such as sex, age, job and hobby, the raw contexts (sensed data) such as time, location and temperature, and the selected services by the users such as destination.

Context wrappers [the location context wrapper, the environment context wrapper (collecting the information such as temperature, noise and light), the device context wrapper (managing the status of linked devices) and the weather context wrapper (collecting the weather information using a Weather Web Service)] that can be implemented by Universal Plug and Play (www.upnp.org) services collects the raw context information using the various sources like sensor and software programs and processes them into context markup (Wang et al., 2004). In that, context wrappers transform the received sensed signals into context markup automatically.

```
<User rdf:about="#Kim">
<locatedIn rdf:about="#downtown"/>
</User>
```

Meanwhile, the users' profiles and the services selected by the users based on the ontology are sent to context history in context management layer due to the user agent that manages the profiles of the user in the their mobile devices. The example of user profile markup that is managed in user agent is shown.

```
<User rdf:about="#Kim">
  <name>jykim</name>
  <mail address>posmisjy@postech.ac.kr</mail address>
  <sex>male</sex>
  <age>25</age>
<job>student</job>
<hobby>sports</hobby>
••••••
</User>
```

3.2. Context management layer

Context management layer infers the current high-level context processing the raw context and classifies the users' profile and ser-

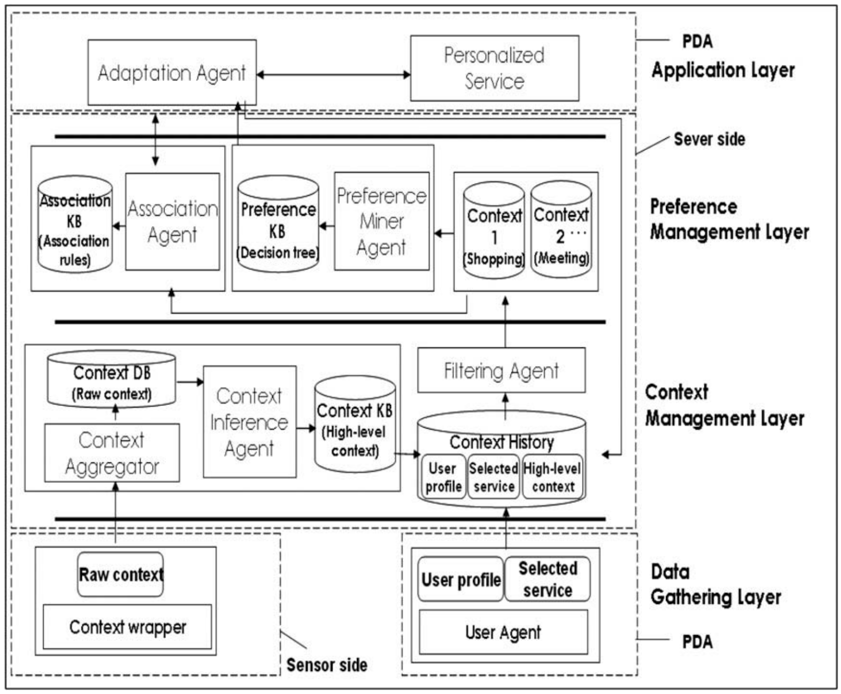

Fig. 1. System framework.

vices according to the reasoned high-level context using the filtering agent. Context aggregator that can be implemented using UPnP control point finds context wrappers and collects context markups from context wrappers (Wang et al., 2004). Context database stores the sensed raw context from users or context wrapper utilizing context markup and context ontology. Context inference agent infers the high-level context using the sensed context. The semantic web-based rule engines such as ontology reasoning and machine learning algorithms such as bayesian network, *K*-nearest neighborhood, case based reasoning and decision tree, etc, can be utilized to infer the high-level context. Meanwhile, the users can also define the rules directly. In this research, ontology reasoning and user-defined rule-based reasoning are used as rule-based approach.

(?user rdf:type Person)^(?user locatedIn ?livingroom)^(TV status On)→
(?user status WatchingTV)
(?user rdf:type Person)^(?user locatedIn ?Bed)^(light status Off) →
(?user status Sleeping)

Context history is used for reasoning the preference rules and recommending the personalized intelligent services in this research. And context history consists of users' profile, the current context of users and the services selected by the users. Context history is represented using ontology based on Semantic Web technology and OWL (Web Ontology Language; Smith et al., 2004), an ontology markup language. The OWL is applied for representation of context ontology because the expression of OWL is better than other ontology languages (Chen & Finin, 2003). There are OWL Lite, OWL Full and OWL DL as the OWL sublanguages. The ontology is considered for representation of context history with the following advantages.

- The formal description of the concepts (Gruber, 1993).
- The comprehension of real meaning about a particular item and the richer meanings using inheritance or attribute resources (Kwon et al., 2005).
- Context management and inference using semantic web tools (Wang et al., 2004).
- Reuse of domain ontology due to the hierarchical structure of ontology (Wang et al., 2004).

Because to manage and process lots of context information on context-aware computing is difficult and the amount of context information and the burden of processing the context information are reduced by using the hierarchical approach (Gu et al., 2004), the hierarchical approach that consists of common ontology and domain-specific ontology is used in this research Fig. 2. The common ontology manages general information such as basic concepts common across various environments.

The context history consists of the users' profiles (such as name, sex and age), high-level context and the service selected by the user as Table 1.

Meanwhile, in filtering agent, the users' profiles and selected services which are stored into temporary storage at preference management layer are filtered under the same high-level context Table 2 using context query language such as RDF Data Query Language (Miller et al., 2002).

```
SELECT ?sex, ?age, ?service
WHERE (?highlevelContext <eq> <dinner>)
```

3.3. Preference management layer

Preference management layer extracts the preferences of users for each service processing the filtered data set (users' profile and

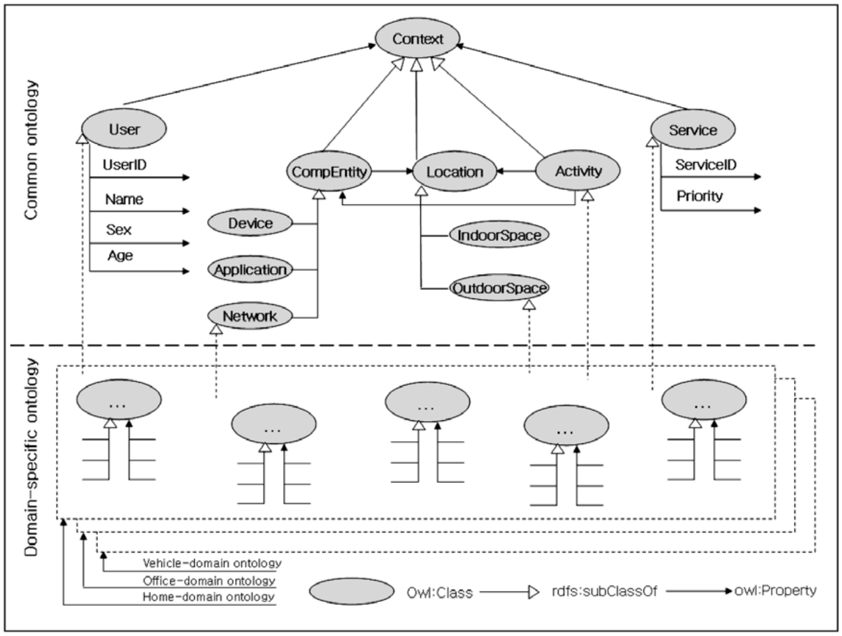

Fig. 2. Ontology-based context history.

Table 1
Context history

User ID	Sex	Age	•••	High-level Context	Selected services (Destination)	•••
Kimjy	M	25	•••	Dinner	Family restaurant	•••
Kange	F	20	•••	Shopping	Department store	•••
•••	•••	•••	•••	•••	•••	•••

Table 2
Filtered data set (Context: dinner)

User ID	Sex	Age	•••	High-level Context	Selected services (Destination)	•••
Kimjy	M	25	•••	Dinner	Family restaurant	•••
Kange	F	20	•••	Dinner	Chinese restaurant	•••
•••	•••	•••	•••	Dinner	•••	•••

services) stored temporally. Table 3 is the example of classified context history under the same high-level context for data mining.

The relationship between users' profiles and services under the same high-level context are analyzed to infer the users' preference rules using classification such as decision tree algorithm. To provide the real-time, proactive and personalized services, the training time is very important. In this research, decision tree algorithm which does not require a long training process and can reduce modeling time of users' preferences for SVM and Neural network (Zhao & Zhang, in press) is applied. The decision tree algorithm is considered for inference of users' preferences with the following advantages in addition to the above characteristic of decision tree algorithm.

Table 3
Classified context history for data mining (Context: dinner)

Sex	Age	•••	Selected services (Destination)
M	25	•••	Family restaurant
F	20	•••	Chinese restaurant
M	17	•••	Snack bar
F	43	•••	Food court
F	37	•••	Korean food restaurant
•••	•••	•••	•••

- It is easy to understand (Anand et al., 2006; Li et al., 2001; Zhao & Zhang, in press).
- Non-linear interactions among variables, multicollinearity, missing data can be processed (Dzeroski, 2001).
- It is not sensitive for outlier.
- It is not difficult to process extremely large datasets (Anand et al., 2006).
- Both categorical and numerical data can be processed (Zhao & Zhang, in press).

Furthermore, the association rule is used to extract the relationship among the services or service sequences for recommending the next service after offering the previous service. In this paper, we apply the Apriori algorithm (Agrawal & Srikant, 1994), one of the most prevalent techniques to locate association rules. For providing the personalized services under the same high-level context, the preferences of users are inferred in preference miner agent using decision tree algorithm based on the users' profile and services Table 3. The preferences of users are inferred in preference miner agent using decision tree algorithm based on the users' profile and services.

type(?user, User), age(?user, ?x), greaterThan(?x, 20), lessThan(?x, 25),sex(?user,male)
→preference(?user, familyRestarunat)
type(?user,User2),age(?user2, ?x), greaterThan(?x, 18), lessThan(?x, 20),sex(?user2,female)
→preference(?user2, chineseRestaurant)
type(?user, User3), age(?user3, ?x), lessThan(?x, 17), sex(?user3,male)
→preference(?user3, snackBar)
type(?user,User4),age(?user4, ?x), greaterThan(?x, 40), lessThan(?x, 60),sex(?user4,female)
→preference(?user4, foodCourt)
type(?user,User5),age(?user5, ?x), greaterThan(?x, 35), lessThan(?x, 40),sex(?user4,female)
→preference(?user4, koreanFood)

The preference model of users is formed based on the inferred preference rule. It is stored into preference KB Table 4 and sent to adaptation agent to offer the personalized services referring the inferred users' preferences.

Association agent infers the association rules based on the sequence of the selected services. The inferred association rules are used in adaptation agent of application layer to recommend the next services according to the service selected by the user.

```
type(?user, User2), locatedIn(?user2, ? chineseRestaurant)
→
association(?user2, beverageStore)
type(?user, User3), locatedIn(?user3, ? snackBar) →
association(?user3, iceCreamStore)
```

Association agent reasons the association rules related with the service selected by the user to provide the next service Table 5 and they are stored into association KB.

3.4. Application layer

Application layer provides the personalized services based on the inferred preferences of users and association rules and manages or processes the feedback of the user for the recommended services by the proposed system. The users' feedback has been tracked or updated continuously due to the changes of the users' preferences and to provide the personalized services referring the recent preferences of the users. In that, if the user requires the appropriate services using his PDA or mobile device, adaptation agent recommends the personalized services based on the users' preferences and association rules. For example, when there is the user who wants to have a dinner, the user asks the personalized services based on his preferences of PDA or mobile device. Then, the user agent in the user's PDA or mobile device sends the user's profiles to adaptation agent and it recommends the personalized service by matching the user's profiles and the stored preference rules in preference knowledge-base. If the login user is 27 and female, the PDA or mobile device recommends Chinese restaurant referring the preference rules. If the provided service does not satisfy the user, the service selected by the user in reality is sent to context history like feedback and users' preference is updated. In that, when the user who is recommended as Chinese restaurant does not want it, another service (such as family restaurant, Korean food restaurant and food court) selected by the user in reality is sent to context history. Finally, the next service is provided according to the user's choice based on the inferred association rules. If the login user located in Chinese restaurant, the PDA or mobile device recommends the beverage store as the next destination referring the association rules.

Table 4
Preference rule (Context: dinner)

Preference	Sex	Age	•••	Selected services (Destination)
P1	M	20–25	•••	Family restaurant
P2	F	25–30	•••	Chinese restaurant
P3	F	30–37	•••	Food court
P4	F	40–50	•••	Korean food restaurant
•••	•••	•••	•••	•••

Table 5
Association rule (Context: dinner)

Rule ID	Rule	Support	Confidence
R1	Chinese restaurant → Beverage store	11.0	41.0
R2	Snack bar → Ice-cream store	10.0	30.0
•••	•••	•••	•••

4. Prototype implementation (CASUP: context-aware system considering user preference)

4.1. Data gathering layer

It is difficult to capture raw context data or sensor data due to the constraints of tools and time. The researches for inference of high-level context such as users' current activity from raw context or sensor data also have been carried out by many researchers. So, we assume that the high-level context is already inferred in this research. And then, we extract the preferences of users using the survey about the preferred services when the high-level context is given. The scenarios of the survey consist of shopping and dinner and assume that the user is on the downtown, Daegu, Korea. The first scenario is the shopping at 15:00 and the second one is the dinner at 18:00. We surveyed the sensitivity for the trend, age, income and telecom fee, etc, as the users' profile. Finally, we had received the 140 data set and used the 119 data set except for the 21 data set that was not suitable. The users' profile and the selected services are stored into context history using ontology as Fig. 2.

4.2. Context management layer

The surveyed data are stored into context history. To reason the high-level context for filtering, the various algorithms such as case-based reasoning or rule-based reasoning, etc, are used. But, in this research, the focus is extracting user preference based on context history and it is difficult to obtain raw context data. Therefore, it is assumed high-level context is already inferred.

4.3. Preference management layer

To show the feasibility of the framework, this section presents two personalized services that consider users' preferences. First application is to recommend the shop for shopping and second application is to recommend the restaurant for dinner.

4.3.1. Shopping service considering users' preferences

The relationship between users' profile and services are analyzed to infer the users' preferences for the shops under the high-level context, shopping, using SAS Enterprise miner from context history Table 6.

The 12 preference rules, the relationship between users' profile and services, are extracted by Decision tree algorithm. The two shops that have high visiting probability among the shops are recommended. Fig. 3 shows the decision tree extracted from context history. As a result, the sum of visiting probability for the two shops is more than 80%. In this scenario, the users' profile is composed of age, PurPer, hobby, CostLiving and CloPurCost. In more detail, "PurPer" means the frequency of purchasing clothes during three months, "CostLiving" indicates the average cost of living per 1 month and "CloPurCost" means the average cost of buying clothes per 1 month.

If the age of the user is more than 29 and the average cost of living per 1 month is less than 450,000 won, the shop No. 2 or No. 3 is recommended using the inferred preference rule. The reasoned preference rules are stored into preference KB.

Table 6
Real data set for reasoning the users' preferences (Context: shopping)

Age	Average cost of living	•••	High-level Context	Selected service (Shop)	•••
34	350		Shopping	7	•••
25	30		Shopping	7	•••
30	80		Shopping	6	•••
27	30		Shopping	5	•••
20	40		Shopping	1	•••
31	50		Shopping	4	•••
•••	•••	•••	•••	•••	•••

type(?user, User1), age(?user, ?x), costOfLiving(?user, ?y), greaterThan(?x, 28), lessThan(?y, 45)
→preference(?user, shopNo2)
type(?user, User2), age(?user, ?x), costOfLiving(?user, ?y), greaterThan(?x, 28), greaterThan(?y, 46)
→preference(?user, shopNo2)
. . .

The visiting sequences among the shops are analyzed using association rule for recommending the next shop. When the user selects the first shop, the next shop is recommended based on the extracted association rules. The extracted association rules among more than three shops are eliminated and the only inferred association rules between two shops are used. Two shops that have high Support and Confidence among the shops as the next service are recommended. Finally, the seven association rules are inferred.

type(?user, User1), locatedIn(?user1, ? shop1) →
association(?user1, shop6)
type(?user, User2), locatedIn(?user2, ? shop2) →
association(?user2, shop7)
. . .

4.3.2. Dinner service considering users' preferences

The relationship between users' profile and services are analyzed to infer the users' preferences for the shops under the high-level context, dinner, using SAS Enterprise miner from context history Table 7.

The six preference rules, the relationship between users' profile and services, are extracted by Decision tree algorithm. The two restaurants that have high visiting probability among the restaurants are recommended. Fig. 4 shows the decision tree extracted from context history. As a result, the sum of visiting probability for the two restaurants is more than 80%. In this scenario, the users' profile is composed of age, hobby, marriage and DinHab. In more detail, "DinHab" means the eating habit such as a meat-eater or a vegetarian, marriage indicates whether the user marry anyone or not.

The visiting sequences among the shops are analyzed using association rule for recommending the visiting destination after dinner. When the user selects the restaurant, the next visiting shop

Table 7
Real data set for reasoning the users' preferences (Context: dinner)

Age	Average cost of living	•••	High-level Context	Selected service (Restaurant)	•••
32	100		Dinner	10	•••
25	30		Dinner	4	•••
36	50		Dinner	2	•••
29	40		Dinner	7	•••
20	40		Dinner	6	•••
31	80		Dinner	4	•••
•••	•••	•••	•••	•••	•••

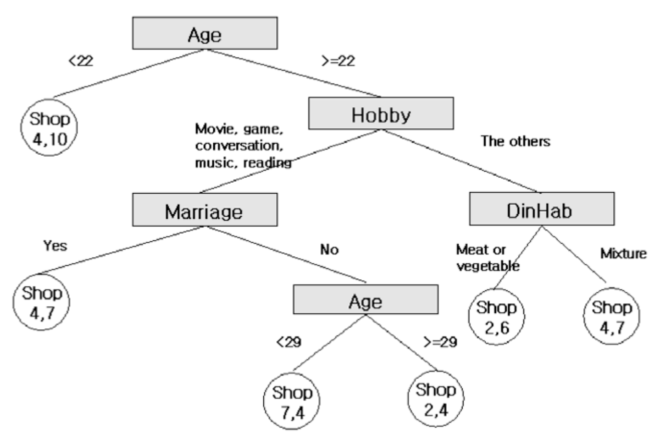

Fig. 4. Decision tree for dinner.

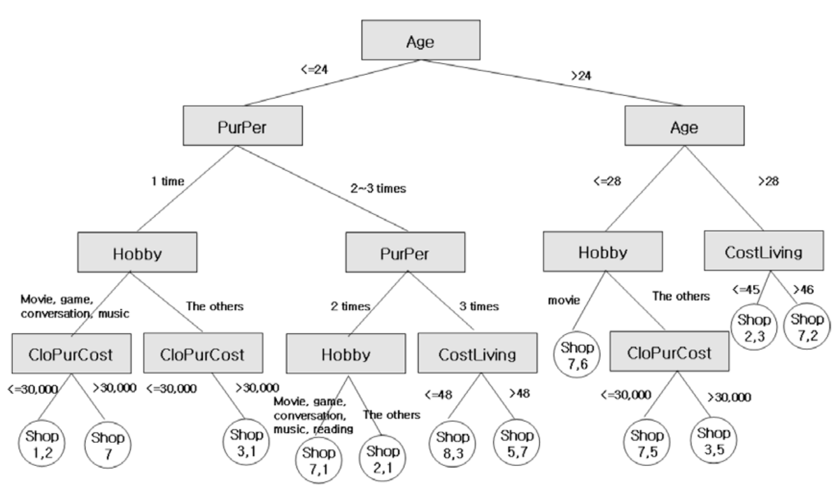

Fig. 3. Decision tree for shopping.

is recommended based on the extracted association rules. Two restaurants that have high support and confidence among the shops as the next visiting destination are recommended. Finally, the 5 association rules are inferred.

4.4. Application layer

In this research, the implemented system recommends the appropriate service to the user considering his or her preferences and navigates. If the user logins, the adaptation agent utilizes the preference rules based on the user's profile and recommends the first service that is appropriate to the user's profile. After selecting the first service, the adaptation agent recommends the next services referring the association rules. For example, when the user shopping (age: 40, the average cost of living per 1 month: 230,000 won and the number of purchasing clothes during three months: 2) logins, the shop No. 2 or No. 3 is recommended using the inferred preference rule in Fig. 5. And then, if the user chooses the shop No. 2 as the personalized service, the PDA navigates the users for the shop No. 2. After the user visits the shop No. 2, the PDA recommends the shop No. 7 as the next destination utilizing the stored association rules Fig. 5. When the user having a dinner (age: 20, marriage: yes, hobby: game and a vegetarian) logins, the prototype recommends the shop No. 4 or No. 10 considering the learned preference rules Fig. 6. And then, if the user selects the shop No. 4 as the personalized service, the PDA navigates the users for the shop No. 4. After the user has a dinner in the shop No. 4, the PDA recommends the shop No. 5 as the next destination utilizing the stored association rules Fig. 6.

4.5. Validation

To provide a mobile application that is practical, effective, and easy to use is important to improve the satisfaction of users (Lee, 2007). Three main challenges, mobile context, network connectivity and mobile devices, are needed to be considered to offer successful mobile applications (Zhang & Adipat, 2005). To address these challenges, service personalization plays an important role to achieve a high-level satisfaction of users (Ozen et al., 2004; Panatiotou & Samaras, 2004; Pashtan et al., 2004). Goren-Bar has also indicated that service personalization is really important for mobile devices (Goren-Bar, 2004). The prototype on PDA recommends the personalization service utilizing the extracted preference rules and association rules to users. So, the proposed system, CASUP, will increase the satisfaction of users more than the previous context-aware applications or services.

The comparison between the prototypes of the previous researches for providing personalized service and CASUP is presented in Table 8. In more detail, "Context history" indicates whether it is utilized to infer users' preferences or not, "User profile" means whether it is used to provide the personalized services or not, "User preference" indicates the need of manual input of their preferences, "Personalized service" means the ability for providing the personalized services based on the learned preference rules auto-

Fig. 5. CASUP interface (Context: shopping).

Fig. 6. CASUP interface (Context: dinner).

Table 8
Comparison between the previous prototypes and CASUP

Research	Input			Output	
	Context history	User profile	Users' preference	Personalized service	Service for new user
Kwon et al. (2005)	X	O	O	O	X
Doulkeridis et al. (2006)	X	X	O	O	X
Cheverst et al. (2000)	X	X	O	O	X
Byun and Cheverst (2004)	O	X	X	O	X
Si et al. (2005)	O	X	X	O	X
Lee (2007)	X	X	O	O	X
CASUP	O	O	X	O	O

matically and "Service for new user" indicates the ability for offering the personalized service to new user without additional learning.

The previous researches for the personalized services using the users' preferences on context-aware computing require that the users input their preferences manually to receive the personalized services. So, it is inconvenient for users. But the users who use CASUP do not need to input manually their preferences due to the inferred preferences from context history. When the users run the CASUP in reality, they just input their ID and password without manual input for their preferences.

And the previous researches do not provide the personalized services extracting the users' preferences automatically. However, CASUP infers the users' preferences using Decision tree algorithm based on context history automatically. Meanwhile, it is difficult for the previous researches to provide new user with the personalized services due to the deficiency of their history or information. So, the new user's history and learning time for preferences is needed to offer new user with the personalized services when the new user want to receive the service. But the CASUP offers the personalized services to new users analyzing between the new user's profiles and the stored preference rules.

Specially, the next service or shop is recommended after providing the previous service utilizing the extracted association rules in CASUP. For instance, when the user is shopping visits the shop No. 2, the CASUP recommends the shop No. 7 or No. 6 as the next visiting shop considering the user's preference that is extracted automatically from context history. So the users who use CASUP can reduce their effort to find the next services or shops which are appropriate to their preferences.

5. Conclusion

Predicting the preferences of users and providing the personalized services or products based on users' preferences are the important issues. However, the research for offering the personalized services considering the users' preferences on context-aware computing is a relatively insufficient research field. Most researches on context-aware computing have focused on inference of high-level context such as users' current activity from sensor data (Henricksen & Indulska, 2005). Although some previous researchers focus on user preferences, they have reasoned the preferences of the user considering only the user's data or requiring the manual input by the user. Therefore, this research provides the personalized services extracting the users' preferences automatically. We proposed an agent-based framework for providing the personalized services based on context history on context-aware computing. Based on the proposed framework, we implemented a prototype system to show the feasibility of the framework.

The proposed framework consists of data gathering layer, context management layer, preference management layer and application layer for providing the personalized services based on the users' preferences. The prototype was implemented according to each layer. The system that offers each user with the personalized services under the same context was displayed using PDA.

This research suggests the basic direction for provision of the personalized services on context-aware computing and utilization of context history. In that, it indicated the need or usability of context history that was not considered in the previous researches. Additionally, this research can be the basic direction of design and the guidelines of development for context-aware computing system. However, the prototype was not completely implemented according to the proposed framework because the surveyed data is used instead of real sensor data due to the constraints of tools and time. Also, the protection of personal information or privacy needs to be considered.

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