An Attribute-based Scheme for Service Recommendation using Association Rules and Ant Colony Algorithm

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***Abstract*—With the rapid development of m-commerce, predicting user's navigation and making the service recommendation become more and more important. Most researches focus on predicting user's navigation using context history and user preferences. But, the influence of the attributes of a service has been ignored. Simultaneously, some attributes are variable, so the recommendations are changeable. Therefore, the paper proposes an attribute-based scheme for service recommendation based on CASUP (context-aware system considering user preference). In proposed approach, the services are classified into several service clusters, and the service recommendations are carried out using Apriori algorithm and ant colony algorithm. Finally, the proposed model is validated by several simulation experiments, which demonstrate the effects of the service attributes in m-commerce.**

***Index Terms*—m-commerce; service recommendation; Apriori; Ant Colony algorithm**

I. Introduction

Due to the rapid development of wireless communication and hardware techniques, the mobile commerce (m-commerce) [1] has become more and more popular. M-commerce has shown immense potential in the electronic market through the encouragement of the wide promotion of mobile communication technologies and rapid adoption of mobile devices with Internet capabilities. In the future, there is no doubt that the mobile devices (e.g. hand-held PC, PDA and mobile phone) will enable to facilitate users' transactions over wireless networks. To make the transactions more convenient, providing proactive service recommendations to users becomes more important than ever before. The proactive service recommendation is based on the information that characterizes the situation of a user, also called as context awareness, including the user's current positions, activities, and their surrounding environments. At present, the context information of users has been captured and processed on context-aware computing [2]. Consequently, the wireless communication system plays an important role in m-commerce technologies.

In recent years, wireless communication systems focus on seamlessly integrating the existing wireless technologies and providing fast and pervasive access and service for mobile users. In this evolving environment, Wireless Sensor Networks (WSNs) [3] are expected to form an integral part of the foreseen ubiquity intelligent, future mobile network, and are envisaged to play a key role in the vision of offering mobile, personalized services, whenever and wherever needed, while supporting applications with broadband, wireless connectivity anytime and anywhere. The contextual information from sensor nodes is computed for the proactive service recommendation. Recent research has focused on the development of such services and scenarios. Providing the personalized service is the main objective of an agent-based framework (CASUP) in [4], aiming to contribute to the evolution and definition of proactive service recommendation based on the users' context histories using context-aware computing. The CASUP provides the personalized services extracting the relationship between users' profiles and services under the same context automatically. Although the context history has been considered, the attributes of services are not taken into account such as distance and interest. The next service is recommended based on the users' preferences and association rules, but a sequence of services that is affected by service attributes is ignored.

In this paper, a navigation agent will replace existing association agent. An attribute-based scheme for service recommendation (ABSSR) is adopted. In our approach, association rules and ant colony algorithm are used to extract the relationship among the services or service sequences for recommending the navigation. The proposed scheme has some contributions for service recommendation. Firstly, we propose the service cluster and a cluster association model. On the basis of association rules, a ranking list of service clusters is recommended to the users before service selection. Secondly, based on the service cluster selection, an ant colony navigation model is proposed to calculate a ranking list of service using ant colony algorithm. In this model, the attributes of the service are taken into account. Furthermore, this probabilistic model reflects the users' interests dynamically.

The rest of this paper is organized as follows. In the next section, we present related work on the service recommendation. Section 3 presents our scheme, including the framework of ABSSR based on the preference management

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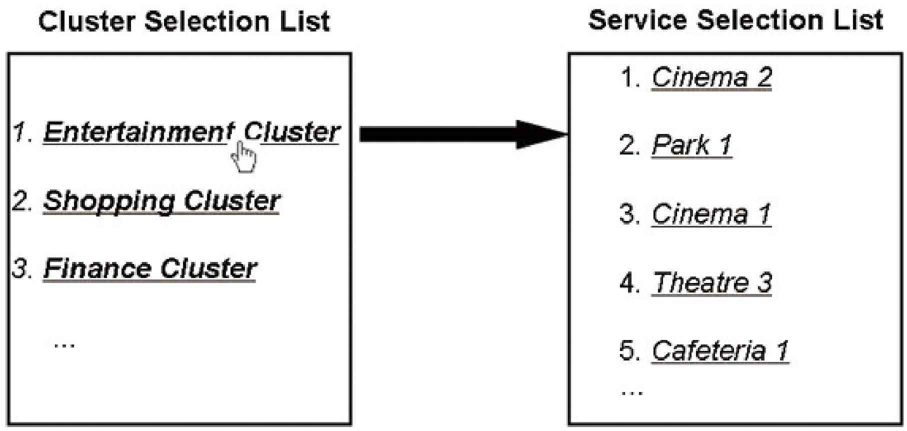

Fig. 1. The relationship between cluster selection list and service selection list.

layer in the CASUP and two models. Especially, the ant colony navigation model will be discussed in detail. In Section 4, the experimental results are reported to evaluate the effectiveness of our approach. Finally, we conclude this paper in Section 5.

II. Related work

During recent years, context-aware computing has been a field of intense research. Several interesting approaches have been reported. Some researchers focused on inference of high-level context such as users' current activities [5-7]. The context histories are exploited as one possibility for the prediction of future context, selection of devices and adaptation. On this basis, some researches for providing the personalized services using users' preference and the information from sensor data have been carried out [8-12]. The user profiles are estimated for service recommendations in efficient and manageable mechanisms. The CASUP, as mentioned above, is the most representative one.

The CASUP is a prototype system of an agent-based framework that offers the personalized services utilizing the extracted users' preferences and association rules. It is composed primarily of eight agents in four layers [4]. The data gathering layer is used for collecting sensor data, user data, and service data. The context management layer is used for inferring a high-level context from a low-level context, storing collected information into context history and classifying the user profiles and the selected services under the same high-level context. In the preference management layer, users' preferences are extracted from context history to infer the association rules for recommending the next services, and the application layer provides the personalized services to the mobile devices of the users. In the preference management layer, the decision tree algorithm is adopted to extract the preferences of users for each service and association rules are used to extract the relationship among the services. It has been recognized that capturing and inferring the users' preferences is important to offer the personalized services. However, little research has taken the attributes of services into account.

III. Attribute-based scheme for service recommendation

In this section, we present an attribute-based scheme for service recommendation (ABSSR) as a way of predicting users' navigation. The ABSSR consists of two models: Cluster Association Model and Ant colony Navigation Model. Before presenting the framework of ABSSR, some definitions are given.

A. *Definitions*

Firstly, several concepts are defined in order to describe the attribute-based scheme.

Definition 1 (Service Attributes): A list of attributes charactering a service. The attributes are the information of service themselves and the satisfaction from the users. Therefore, the services can be described by the service attributes such as introduction and location. Furthermore, the service attributes reflect influence on services from the users, including reputation of services, visiting frequency, spending time and so on.

In this research, some relevant attributes are extracted for describing service. We define *frequency*, *distance* and *reputation* as service attributes. *frequency* is the consumers' visiting times within a time window in the past. *distance* is denoted as the distance between two services' location, and *reputation* is the satisfaction degree that is received from the users in the past. *reputation* is calculated based on the method in [13].

Definition 2 (Service Cluster): A group of services that are similar to each other. The service cluster is the result of service classification based on similarity. Generally, it is too hard to manage the services due to huge quantity. Therefore, all of the services are classified into several service clusters based on how similar the services are. For instance, in the Restaurant Cluster, there are Chinese restaurants, Korean food restaurants and food courts; the Entertainment Cluster includes cinemas, cafes and bars.

Definition 3 (Service Recommendation List): A list of ranking services for users' selection. The service recommendation lists are ranking lists for user's selection. Because the

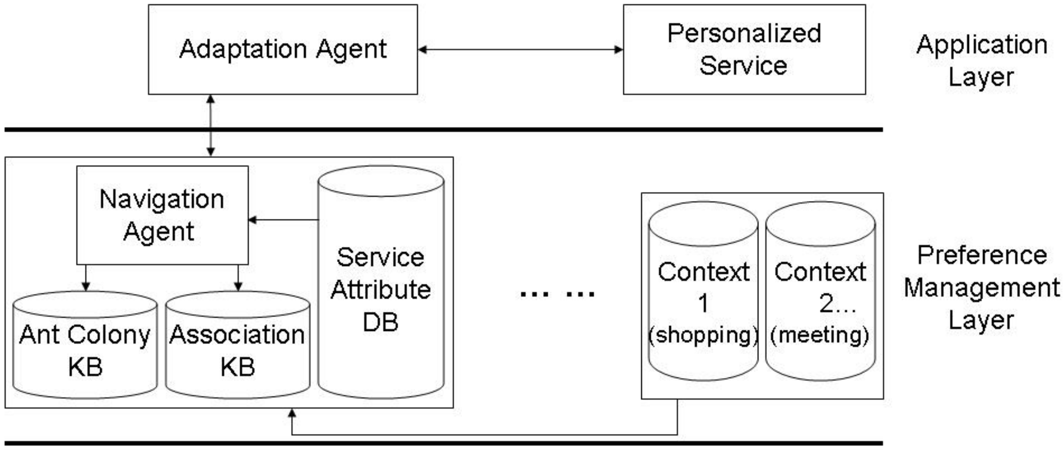

Fig. 2. The framework of scheme.

services are classified into service clusters, there are two lists, one is for cluster selection, and the other one is for relevant service selection. The users can make choices from the lists that are offered to PDA or mobile device. In each list, there are several service options that are sorted from the largest possibility to the smallest one. Meanwhile, a service search engine is provided to prevent the services that users want are not in the lists.

We present an example to make this definition precise. Once a user finishes dinner in *Chinese restaurant 1*, the system generates a cluster recommendation list based on the Restaurant Cluster. And then, if the user selects Entertainment Cluster in the cluster selection list, the service selection list will be generated based on the service attributes using ant colony algorithm. The example is illustrated in Fig. 1.

B. The Framework of ABSSR

Figure 2 shows the framework of the preference management layer in the ABSSR. Based on the preference management layer of the CASUP, existing association agent is replaced by a navigation agent. Meanwhile, an ant colony KB and a database for storing service attributes are added.

Tbl 1. Association Rule

Rule ID	Rule	Support	Confidence
R1	Restaurant → Finance	10.0	35.0
R2	Restaurant → Entertainment	12.0	37.0
R3	Sport → Shopping	3.0	15.0
...	...	...	...

Tbl 2. Selection Probability

Selection ID	Selection	Probability
S1	Shopping mall 2 → Cafeteria 3	45%
S2	Cafeteria 3 → Theatre 1	37%
...	...	...

In the CASUP, the association rule is used for recommending the next service after offering the previous service based on Apriori algorithm [14]. In this study, the services are classified into service clusters, and we use Apriori algorithm to provide the next service cluster based on previous service' cluster. Accordingly, the association rules in the association KB are changed, Tbl. 1 is an example. Based on a cluster selection, a service list is generated using ant colony algorithm [15]. From a service of previous cluster to another service of the next cluster, there is a probability based on the service attributes, *frequency*, *distance* and *reputation*. These probabilities are saved in the ant colony KB as Tbl. 2. Moreover, the probabilities are dynamic, they are updated at regular intervals based on the users' behavior.

C. The Models of ABSSR

In the models, the Apriori algorithm and ant colony algorithm will be used. The Apriori algorithm is the most prevalent techniques to locate association rule. Ant colony algorithm aims at exploring optimal course sequences since such sequencing can predicate several possible items for the next steps.

1) Cluster Association Model

On the basis of the concept mentioned above, all of the services are classified into several clusters. Once a user stops a service, navigation agent will employed to offer a recommendation of the next service. In order to achieve that objective, the cluster of next service must be inferred by navigation agent based on the sequence of the selected cluster in the past. That is, the cluster selection should be done before calculating the service selection list. The sequence of recommended service clusters is based on the association rules in Association KB. The navigation agent can infer next cluster according to "*Support*" and "*Confidence*" in Tbl. 2.

2) Ant colony Navigation Model

Real ants are capable of finding the shortest path from a food source to their nest based on the pheromone that they deposit on the ground. Ants choose their way probabilistically by the strong pheromone concentrations left on pheromone trails. For providing service recommendations, we regard consumers' service selections as artificial ants. The service selection depends on the attributes of services and consumers' behaviors and some values of attributes are dynamic. Therefore, an appropriate approach to recommending services should be treated as a dynamic probabilistic one, where probabilities are updated within a specified time window. Our proposed approach is based on the ant colony navigation model that analyzes the attributes of services and consumers' behaviors to recommend services. The most of parameters and functions used in this paper are same as the definitions in ant colony algorithm [15]. Furthermore, we modify heuristic information and the pheromone updating function by combining attributes of services.

a. Heuristic Information

In this research, the heuristic information η_{ij} indicates the degree of connectedness from service i to j.The heuristic information η_{ij} is defined as follow.

$$\eta_{ij} = \frac{C_{ij}}{\sum_{k=1}^{n} C_{ik}} \tag{1}$$

where C_{ij} is the degree of connectedness from service i to j. It represents the access times from service i to j. In the service cluster of service j, there are n different selections as the next service of the service i. This heuristic information is in fact the access proportion of the consumers from service i to service j among n services.

b. Pheromone Updating Function

The pheromone trail intensity τ_{ij} is the relational strength between the ith node and the jth node. The relational strength in this study is derived from the attribute values of services. We update pheromone in a way as Ant-quantity system [16] does for. Specifically, the pheromone is updated as long as ants move from one node to another. The pheromone τ_{ij}(t) is updated according to:

$$\tau_{ij}(t+1) = (1-\rho)\cdot\tau_{ij}(t) + \sum_{k+1}^{m} \triangle\tau_{ij}^{k} \tag{2}$$

where $0 < \rho < 1$ is the pheromone evaporation rate, $\triangle\tau_{ij}$ is the incremental intensity of locate pheromone trail from node i to j, and m is the number of consumers as ants. The value of $\triangle\tau_{ij}^{k}$ is related to the values of three service attribute defined above: *distance* between two services, *frequency* and *reputation* of service j. Furthermore, $\triangle\tau_{ij}^{k}$ is computed by:

$$\triangle\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{A_{ij}}, & \textit{if (i,j) is in the path of the } k^{th} \textit{ ant} \\ 0, & \textit{otherwise} \end{cases} \tag{3}$$

In Eq.(3), Q is a constant quantity of pheromone left on $path_{ij}$ as every time an ant goes from node i to j. Combining the three attribute values of the service i and service j, A_{ij} is defined as follow.

$$A_{ij} = \sqrt{\theta\cdot distance_{ij}^{2} + \mu\cdot\frac{1}{frequency_{j}^{2}} + \omega\cdot\frac{1}{reputation_{j}^{2}}} \tag{4}$$

A_{ij} takes into account these important features: $distance_{ij}$ is the distance between the service i and service j, and based on the practical experience, distance is from 0 to 5 kilometers. The larger $distance_{ij}$ is, the smaller τ_{ij} is. $frequency_j$ and $reputation_j$ are the attributes of service j, and their initial values are 1. The larger they are, the higher τ_{ij} is. *frequency* is a measure of the consumers' interest in a service. If a service is popular, in a time window, it will be visited more often by consumers than other services in the same cluster. Moreover, we adjust the time window to make *frequency* $\in [1, 50]$. Similarly, higher *reputation* of a service contributes to the consumers' prefer selection, with a value from 1 through 10. Furthermore, to protect the same order among $distance_{ij}^{2}$, $\frac{1}{frequency_{j}^{2}}$ and $\frac{1}{reputation_{j}^{2}}$

After using service i, the consumer selects the next service based on the remaining pheromone trail intensity on the path. Using $P_{ij}(t)$ to denote the probability of selecting service j from service i at the time t, we have

$$P_{ij}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ij}(t)]^{\beta}}{\sum_{k\in allowed_n}[\tau_{ik}(t)]^{\alpha}\cdot[\eta_{ik}(t)]^{\beta}}, & j\in allowed_n \\ 0, & otherwise \end{cases} \tag{5}$$

where $allowed_n$ is a set of selectable services after service i in the next step. α and β are the parameters that control the level of consideration of the pheromone trail.

D. The algorithm of ABSSR

In the following, we present our approach in the form of the algorithm. We suppose that the user is using service S and he wants to stop it.

Step 1: Service Cluster Selection

Based on the service S, we know the service cluster of S is sc_1. The cluster selection list is generated using association rules. Suppose the user selects sc_2 as the cluster of next service.

Step 2: Parameters Initialization

This step is pre-processing, in which the parameters of $\theta, \mu, \omega, \alpha, \beta$ and Q are initialized for ant colony navigation model. Moreover, a time window for *frequency* is set.

Step 3: Heuristic Information Calculation

The heuristic information η is evaluated according to the connectedness between S and some feasible services in sc_2. Suppose there are n services denoted as $S_1, S_2, \ldots, S_n$, can be as the next selection from service S, a set of heuristic information $\{\eta_{SS_1}, \eta_{SS_2}, \ldots, \eta_{SS_n}\}$ is calculated using Eq.(1).

Step 4: Pheromone Trail Intensity Calculation

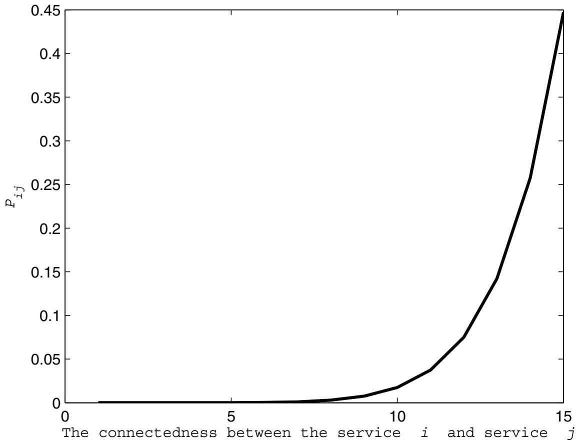

Fig. 3. P_{ij} variations by different value of the connectedness.

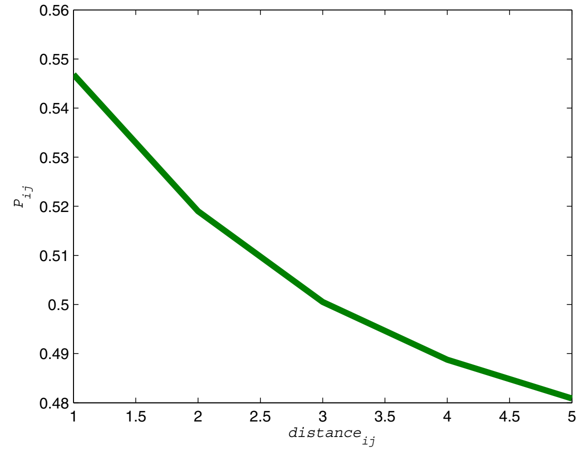

Fig. 4. P_{ij} variations with the increment of $distance_{ij}$.

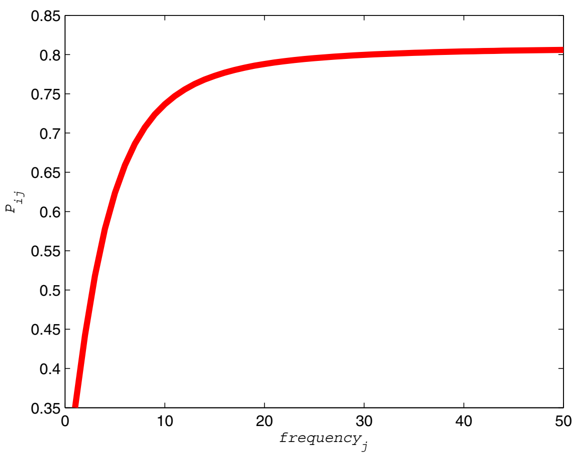

Fig. 5. P_{ij} variations with the increment of $frequency_j$.

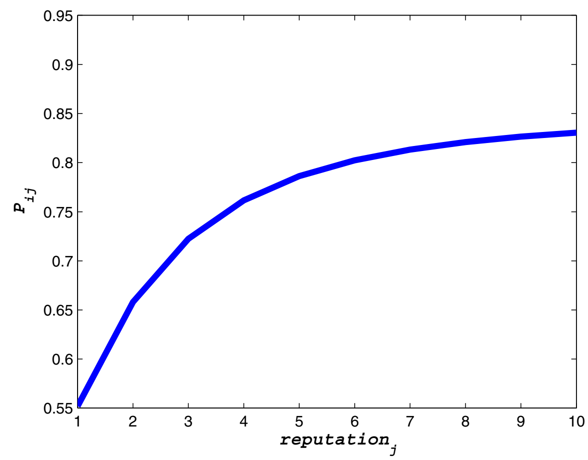

Fig. 6. P_{ij} variations with the increment of $reputation_{ij}$.

Based on the attributes of service (*distance*, *frequency* and *reputation*), a set of the pheromone trail intensity $\{\tau_{SS_1}, \tau_{SS_2}, \ldots, \tau_{SS_n}\}$ is calculated, according to Eqs.(2-4).

Step 5: Probability Calculation and Service Selection

In this step the set of probability $\{P_{SS_1}, P_{SS_2}, \ldots, P_{SS_n}\}$ are calculated on the basic of $\{\eta_{SS_1}, \eta_{SS_2}, \ldots, \eta_{SS_n}\}$ and $\{\tau_{SS_1}, \tau_{SS_2}, \ldots, \tau_{SS_n}\}$ using Eq.(5). The service selection list is generated in decreasing order of $\{P_{SS_1}, P_{SS_2}, \ldots, P_{SS_n}\}$. Suppose that the user selects service S' in the list as the next service he wants.

Step 6: Updating

After the user selects a service S' in the service selection list, the values of three attributes should be updated, including the connectedness between service S and S', $frequency_S$ and $reputation_S$.

IV. Experimental Results

To evaluate the effectiveness of ABSSR, we utilize attribute-based service recommendation to test the proposed ant colony navigation model. In the model, the probability in ant colony KB is related to the values of attributes of services.

Experiment 1: In this experiment, the impact on the probability from different values of the heuristic information η_{ij}. In Eq.(1), η_{ij} is affected by the connectedness from service i to j. Without lose of generality, we set C_{ij} from 1 to 15. In addition, in the service cluster of service j, there are four other services as the next service of service i, and they are set randomly between 1 and 15.

With the parameters $\alpha = 1$ and $\beta = 8$, the probability variation is illustrated in Fig. 3. From the result, with the same pheromone trail intensity, the more C_{ij} is, the higher P_{ij} is.

Experiment 2: In experiment 2, based on the same heuristic information η_{ij}, the relationship between P_{ij} and the attributes will be analyzed. The change of attributes will impact on pheromone trail intensity τ_{ij}. In the ABSSR, three attributes are considered: *distance*, *frequency* and *reputation*. If all of the attributes are inconsistent in the experiment, the results are confused. Consequently, we observe one attribute with two other remaining attributes be constant. To protect the same order among attributes, we fixed the parameters $\theta = 10$, $\mu = 2500$, $\omega = 1000$, $\alpha = 2$ and $\beta = 1$.

In Fig. 4, the *distance* between the service *i* and *j* is increased from 1 to 5 (kilometers) with the same values of other attributes. From the figure, we can observe that the probability is decreased with the increment of the $distance_{ij}$, and vice versa. Similarly, we varied the values of the $frequency_j$ and $reputation_j$ to analyze the influence of P_{ij} ($frequency_j$ is from 1 to 50, and $reputation_j$ is from 1 to 100.). The results are given in Fig. 5 and Fig. 6. The probability has an increase corresponding to the growths of $frequency_j$ and $reputation_j$.

V. Conclusion

As the number of the users of networks has been increased greatly nowadays, the proactive service recommendation in m-commerce becomes an important issue. It is computed by the contextual information from sensor nodes. Although some researchers focus on context history, the attributes of a service have been ignored. In this paper, we have presented an attribute-based scheme for recommending services for consumers. For this end, we grouped all of the given services into several clusters, employed a cluster association model and an ant colony navigation model to track the consumers' behaviors, and then calculate the degree of the influences from the attributes of services in relation to the recommendation. After these, a service recommendation list is generated for consumers. The proposed models were implemented and the experimental results have shown that the varieties of the attributes do have affects on ranking lists. By refining the system, the proposed scheme could be further analyzed and potentially get its own place in practice.

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