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A novel mobile recommender system for indoor shopping

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ABSTRACT

With the widespread usage of mobile terminals, the mobile recommender system is proposed to improve recommendation performance, using positioning technologies. However, due to restrictions of existing positioning technologies, mobile recommender systems are still not being applied to indoor shopping, which continues to be the main shopping mode. In this paper, we develop a mobile recommender system for stores under the circumstance of indoor shopping, based on the proposed novel indoor mobile positioning approach by using received signal patterns of mobile phones, which can overcome the disadvantages of existing positioning technologies. Especially, the mobile recommender system can implicitly capture users' preferences by analyzing users' positions, without requiring users' explicit inputting, and take the contextual information into consideration when making recommendations. A comprehensive experimental evaluation shows the new proposed mobile recommender system achieves much better user satisfaction than the benchmark method, without losing obvious recommendation performances.

1. Introduction

In this age of information explosion, the recommender system is viewed as a powerful tool for people to obtain useful information on products and services (Adomavicius & Tuzhilin, 2005; Anand & Bharadwaj, 2011; Russell & Yoon, 2008). However, recommender systems are usually being used in web-based shopping only. Very few are designed for aiding physical shopping. With smart mobile terminals being deployed widely, mobile recommender system is considered to be an effective way for assisting physical shopping since mobile recommender systems have different characteristics, compared with web-based recommender systems. For example, some contextual information, such as location, time and weather, etc., can be captured in mobile recommender systems for inferring users' preferences, which improves the performance of mobile recommender systems in physical shopping environments.

As we know, indoor shopping is the most important physical shopping mode in retail business. For example, based directly on U.S. Commerce Department data, shopping centre-inclined sales measure sales at stores that are likely to take place at shopping centres. It is defined by the International Council of Shopping Centres (ICSC) that shopping centre-inclined sales include the following store types: General merchandise, Apparel, Furniture, electronic and "Other"; health and personal care; food and beverage; and building material and garden equipment and supplies (International Council of Shopping Centres, 2011). Referring to the released issued Annual Retail Trade Report by U.S. Census Bureau, in 2009, sales of the above mentioned types account for 57% of U.S. total retail sales (2,073,946/3,638,471 millions of dollars) (U.S. Census Bureau, 2011). In a sense, shopping centre still plays an important role in retail sales. The recommender system is one of key tools for the success of shopping. Since location is the key information for mobile recommender systems, mobile positioning technology has become the core technology for mobile recommender systems. However, currently existing mobile positioning technologies have some disadvantages or limitations for indoor shopping. Global Positioning System (GPS) is the most popular technology used in mobile recommender systems but inside buildings, GPS devices often lose signals; GPS-equipped mobile phones are generally unable to obtain indoor location information (Fano, 1998; Xu, 2003). This greatly limits the GPS positioning technology's usage in indoor shopping activities. Another positioning technology is RFID technology, which needs installation of RFID readers and RFID servers to identify RFID tags' positions (Bouet, 2008). Though many researchers and manufacturers have argued that the cost of RFID devices would drop quickly, search results (atlasRFIDstore, 2011) show that each RFID reader still costs

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250–4500 U.S. dollars. The high cost of RFID devices hinders large scale application of RFID positioning techniques for mobile recommender systems. Although Mobile Positioning System (MPS) technologies are an inexpensive approach, positioning accuracy is too poor to be used in mobile recommender systems (Liu, Darabi, Benrjee, & Liu, 2007).

In order to overcome the limitations of current positioning technologies and apply mobile recommender system for indoor shopping, in this paper, a novel mobile recommender system is proposed, based on a new positioning approach, received signal strength (RSS) pattern-mining positioning method. This positioning approach makes use of multiple mobile phone received signals to infer users' locations and to achieve store level accuracy. With the RSS pattern-mining positioning method, the new proposed mobile recommender system can capture some contextual information, such as users' location information, duration for which the user is staying in stores, to infer users' preferences, without requiring users' having to input information explicitly. When making recommendations, the new proposed recommender system not only considers users' preferences, but also users' contextual information such as location, time and stores' promotional offers, etc. At the same time, the new proposed mobile recommender system with the novel positioning approach overcomes the constraints and disadvantages of existing mobile recommender systems: better positioning accuracy compared with GPS method and lower cost compared with RFID method, since the method only uses the user's own mobile phone without expensive investment in RFID hardware. Comprehensive experimental evaluation shows the new proposed mobile recommender system achieves much better user satisfaction than the benchmark method, without losing obvious recommendation performance.

This paper is organized as follows. Section 2 reviews research works related to recommender systems. Recommender system architecture is presented in Section 3. Section 4 introduces the proposed mobile positioning approach. User preference learning and recommendation algorithms are described in Section 5. Section 6 reports results of a comprehensive experiment. The study's limitations are discussed in Section 7. Section 8 outlines conclusions.

2. Related works

Some mobile recommender systems have been proposed for physical shopping environments in extant research and these works can be divided into three major streams, in accordance with the methods of obtaining users' preferences.

2.1. Recommendation according to online ratings

Several researchers have tried to combine different ways of identifying users' preferences in the case of online shopping by obtaining users' preferences in physical shopping environments. Kurkovsky and Harihar (2006) propose a mobile recommender system prototype named SMMART which recommends items related to music. In this paper, the authors establish connections between users and the physical shopping environment by requiring recommendation from a store's server when identifying users entering the music store, although it requires users to explicitly input their preferences. Yang, Cheng, and Dia (2008) introduce a location-aware recommender system. They do not propose any particular positioning technology, but just list existing positioning technologies. This location-aware recommender system estimates users' preferences by analyzing web log data recorded in the mobile devices, and recommends products according to both users' preferences and distances between products and users. Pessemier, Deryckere, and Martens (2010) design a context-aware recommender system for mobile devices with the Bayesian classifier. The system adds a dimension in user profile to record contextual information such as mood, location and timestamp. When analyzing users' preferences, the system considers users' ratings in different contexts, segregated by the Bayesian classifier. Costa, Guizzardi, Guizzardi, and Filho (2007) develop a context-aware recommender system called COReS which is triggered by the user's context change and uses contextual information such as location, agenda, user profiles and users' evaluations to rank the recommendation results.

All these papers combine the online rating approach with physical shopping environment and need explicit user ratings or web log data to obtain user preferences. However, in physical shopping environment, people are either not willing to spend the time required to explicitly input their ratings or their behaviors cannot be captured through web log data.

2.2. Recommendation according to contextual information

Several recommender systems try to estimate users' needs based on contextual information. Fano (1998) proposed a shopping agent prototype equipped with a GPS receiver. This shopping agent is intended to support shopping in an outdoor mall having about 110 stores and can be applied only in outdoor shopping mall environment. As a shopping agent, it ignores users' preferences. It only recommends products with lowest prices. Park, Park, Kim, and Kang (2008) proposed a personalized recommender system which considers users' preferences and situations. This system infers the list of resources which considers users requirements by using ontology. Then, according to personalized information and contextual information, the system "reasons user-suitable resources from candidate resources." Although these papers obtain users' contextual information through users' locations, they do not learn each user's personal preferences from contextual information; they only provide non-personalized service, and their mobile recommendations only apply in outdoor environments.

2.3. Recommendation according to preference learning from contextual information

Several papers have used contextual information to obtain user preferences. Kawashima, Satake, and Shinagawa (2006) propose a recommender system which uses RFID senders and receivers to capture users' behaviors. The recommender system estimates users' ratings according to their distance from the objects, such as whether a user is near to an object or whether a user picks up an object or whether a user scans an object using a RFID reader device. Bohner (2008) proposes a recommender system called GECKO. GECKO updates the stereotype user model through use of visitor observation triggers that "capture the information required for predicting a visitor's activities and interests", and uses the spatial user model to "capture visitor's behavior suggested by the space." However, from the perspective of the positioning method, these papers use RFID or GPS to obtain users' behaviors. As we have argued before, RFID positioning can be very expensive due to its hardware cost, while GPS cannot work in indoor environments. From the perspective of recommendation method, these papers implicitly estimate users' ratings of each item and recommend items to users according to the distance between users and products. This kind of recommendation method requires awareness of the position information of each product which changes frequently and leads to huge data computing and accuracy losing of the user preference estimation when the position information of each product changes.

In summary, a majority of studies on mobile recommender systems have used online rating approach to obtain user preferences, which is not suitable for physical shopping environments. When using location and other contextual information for recommending items, researchers usually ignore users' past behaviors. Though there are several papers that have discussed use of contextual information to obtain user preferences, they are limited to a specific scenario due to limitations of positioning approaches. Based on literature review, we find that designing a more effective mobile recommender system for physical shopping process, especially indoor shopping process, is necessary.

3. System architecture & process

In this section, the architecture and process of the new proposed mobile recommender system, which can overcome the disadvantages of mobile recommender systems described in the literature above, are introduced.

3.1. System architecture

The whole system architecture is shown in Fig. 1. Generally, the system comprises three modules: mobile phone terminals, location server and recommendation server.

3.1.1. Location server

The RSS information of mobile phones from base stations is used to identify mobile phones' locations. RSS pattern database is used to store RSS patterns and their corresponding locations. When location information is required in recommendation, real time RSS information of mobile phones is captured, and the proposed RSS pattern-mining positioning algorithm matches the RSS information with RSS patterns in the pattern database, and infers mobile phones' locations there from. The detailed mechanism of the RSS pattern-based positioning algorithm is described in the section of RSS pattern-mining positioning approach.

3.1.2. Recommendation server

The recommendation server is used to make recommendations. In it, user activity logging database is used to record users' past activities and corresponding contextual information, including such as the time spent in each store during every shopping process and corresponding promotional activities of each store when users enter. Weights of users' preferences which are stored in the user profile database are learnt by using these user activities logging data. When making recommendations, users' current position information from the location server, weights of preferences in terms of brand stores and store profile information together constitute the input of the recommendation algorithm, which is used to generate recommendations, and the recommendation results are transmitted to mobile phones. The preference learning algorithm and recommendation algorithm are presented in the section of user preference learning & recommendation algorithms

3.1.3. Mobile phone terminal

The mobile phone terminal has two functions. One is to capture mobile phones' real time RSS information and transfer it to a location server for identifying mobile phones' locations, which is implemented with a sub application. The other function is to display recommendation results. Due to limited size of the screen and the mobility, this mobile recommender system displays only necessary information.

3.2. System process

The new proposed mobile recommender system includes two main processes: learning process and recommendation process.

3.2.1. Learning process

Once a user enters the shopping mall, the mobile phone terminal will transfer its real time RSS information to the location server,

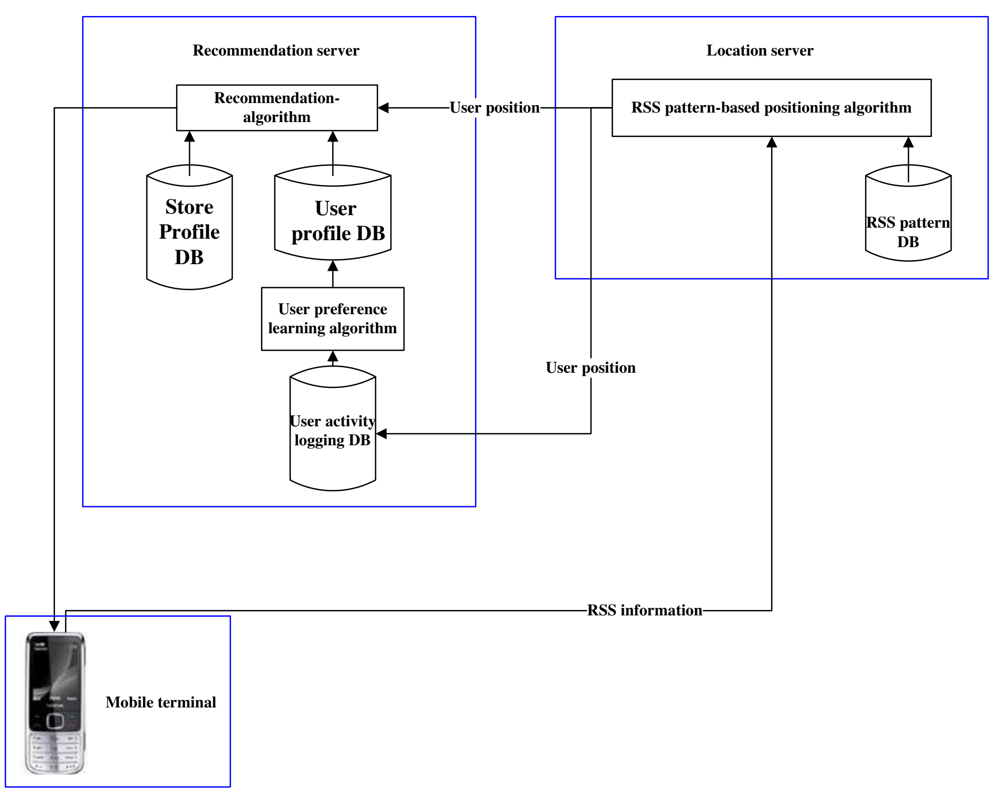


Fig. 1. Architecture of the proposed mobile recommender system.

and then the location server infers the user's position information. The position information is sent to the recommendation server. The recommendation server records real time contextual information in the user activity logging database. Then, using the logging data, user preferences are regularly updated by the user preference learning algorithm.

3.2.2. Recommendation process

Accordingly, when a user enters a shopping mall, the location server identifies his/her location and transfers this information to recommendation server. The recommendation server inputs the related context information, store profile information and weights of user preferences, and then the recommendation algorithm will generate a list of recommendations. Finally, these recommendations are delivered to the mobile phone terminal in a suitable way.

4. RSS pattern-mining positioning approach

To obtain users' locations, real time RSS information of mobile phones is transferred to the location server for inferring the positions by utilizing the RSS pattern database in the location server. The RSS pattern database stores the mappings between brand stores' locations and RSS patterns. According to primary field tests, a mobile phone can detect signals from about eight base stations nearby. Formats of the RSS patterns mappings are as shown in Fig. 2.

On most mobile phones, several channels of RSS can be detected, and these RSS always change very sensitively: when moving about 1.5 m away, the weakest signal will disappear, while a new signal will appear. Because the detected signals' channels are not labeled according to priority, and it is impractical to record the RSS information of a large number of points near to a brand store, the routine regression method is not very applicable here. So we adopt a simple but very effective method: the rule based algorithm to infer the position information with the mobile phone's RSS information and RSS pattern in database.

The main idea of the positioning algorithm is finding the nearest store of each user by computing the similarity between RSS information in each store and RSS information from each user. The form of this positioning algorithm is as follows.

Defined variables:

A vector V_{store_i} is used to label RSS near store i:

$$V_{store\_i} = (cell\text{-}id, ch1, ch2, ch3, ch4, ch5, ch7, ch7, ch8);$$

Here *cell-id* is ID of the main base station; *ch* is the channel number of each base station; these channels are in descending order, according to RSS. Similarly, a vector V_{user_j} is used to represent RSS of user j:

$$V_{user\_j} = (cell\text{-}id, ch1, ch2, ch3, ch4, ch5, ch7, ch7, ch8).$$

Set $S_{\_store\_i}$ and $S_{\_user\_j}$ are used to represent RSS information in unordered way

$$S_{\_store\_i} = \{cell\text{-}id_i, ch_i1, ch_i2, ch_i3, ch_i4, ch_i5, ch_i6, ch_i7, ch_i8\}.$$

$$S\_user\_j = \{cell\text{-}id_i, ch_i1, ch_i2, ch_i3, ch_i4, ch_i5, ch_i6, ch_i7, ch_i8\}.$$

A vector map is used to record the mapping between RSS information and store location information

$$Map = [V_{\_store\_1}, S_{\_store\_1:store_1;\ldots;} V_{\_store\_i}, S_{\_store_i:store_i;\ldots}].$$

The following positioning principle is used to identify the store that user j is located nearest to:

$$Nearest\ store = \underset{i \in store\_set \& card(S_{\_store\_i}, S_{\_user\_j}) \geq 8}{\arg\min} \left(\|V_{\_store\_i} - V_{\_user\_j}\|\right) \quad (1)$$

Here, the distance between vector V_{store_i} and $V_{user\_j} \| V_{store\_i} - V_{user\_j} \|$ is computed as: $\|Vstore_i - Vuser_j\| = \sqrt{\sum_{k=0}^{9}(d_{ij}k)^2}$. Here, if $cell\text{-}id_i \neq cell\text{-}id_j$, $d_{ij}0 = 1$, *else* $d_{ij}0 = 0$; *if* $ch_ik \neq ch_jk$, $d_{ij}1 = 1$, *else* $d_{ij}1 = 0$; $1 \leqslant k \leqslant 8$.

When making recommendations, the positioning algorithm utilizes RSS information from the mobile phone and data in the mappings between RSS patterns and stores' locations database to identify the mobile phone's location, and return the location information to the recommendation server, as described in Fig. 3.

5. User preference learning & recommendation algorithms

5.1. User preference learning

User preference learning is divided into two steps. The first step is users' behavior patterns learning. Users' behavior patterns can be automatically and gradually learned from contextual information during the process of physical shopping. In this mobile recommender system, a user's behavior pattern includes the average time of stay in a brand store (*pattern ST*), and the kind of promotional activities preferred (*pattern PR*). Fig. 4 shows some examples of user behavior pattern

$$Pattern\ PR_i = argmax \sum_{j=1}^{n} p_{ij} \quad (2)$$

Here p_{ij}: promotional offers of brand store j when user i enter.

$i \in$ *{stores a user has ever entered}*;

$j \in$ *{users}*.

The next step is estimating users' preference weightings. Users' preferences weightings of a brand are estimated by three factors: time spent in a brand store (*Factor ST*), frequency of entering the store (*Factor FR*), and matching between promotional activities in the brand store and user preference towards promotional activities (*Factor MA*).

Users' preferences learning are computed according to the following formulas:

Factor FR_{ij} frequency of user i entering store j in the latest month.

Factor $MA_{ij} = 0$; if in the latest month, the frequency of that particular promotional activity in brand store j matches Pattern PR i

Store name	Cell-id	Ch 1	Ch2	Ch 3	Ch 4	Ch 5	Ch 6	Ch 7	Ch 8
Esprit	60352	852	848	839	860	845	850	N/A	N/A
	60352	…	…	…	…	…	…	…	…
	60352	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…

Fig. 2. Mappings between RSS patterns and stores' locations database legend: *cell-id* = ID of main base station; *Ch* = the channel number of each base station; these channels are in descending order, according to RSS.

User id	Location	Time
23	Esprit	2010-12-07 15:02

Fig. 3. User real-time location information.

User id	Pattern ST	Patten PR
1	30 minutes	Discount
2	20 minutes	New arrival
3	50 minutes	no

Fig. 4. User behavior pattern.

User id	Store 1	Store 2	……	Store n
1	1	4/3	……	0
2	7/3	0	……	2
……	…….	…….	……	……

Fig. 5. Users' preferences weights table.

when the user enters the store j is over 50% of the total frequency of the user entering store i;

Factor $MA_{ij} = 1$; if in the latest month, the frequency of promotional activity in brand store j matches Pattern PR i when the user enters the brand store is below 50% of the entire frequency of the user entering the store

$$Factor\ ST_{ij} = \frac{MAX\_DURING_{ij} - patternST_i}{patternST_i} \qquad MAX\_DURING_{ij} = max\{tg_{ij} - te_{ij}\} \tag{3}$$

Here te_{ij}: Time when user i gets out of store j; tg_{ij}: Time when user i enters store j; Then user's preference is calculated as:

$$Preference_{ij} = \frac{Factor\ ST_{ij} + Factor\ FR_{ij} + Factor\ PR_{ij}}{3} \tag{4}$$

There is an example showing user preference learning. If the average time user i spends in each brand store ever entered in the latest month is 30 min, the longest time user i spent was 60 min at store j, and user i has entered store j 3 times in the latest month, and the preferred promotional activity of user i is discount, and there is a discount activity in store j in the latest month, then

Pattern $ST_i = 30\ min$;
Pattern PR_i: *discount*;
$MAX\_DURING_{ij} = 60$ min;

$$Factor\ ST_{ij} = \frac{MAX\_DURING_{ij} - pattern\ ST_i}{pattern\ ST_i} = \frac{60-30}{30} = 1$$
Factor $FR_{ij} = 3$;
Factor $MA_{ij} = 0$;

$$Preference_{ij} = \frac{Factor\ ST_{ij} + Factor\ FR_{ij} + Factor\ PR_{ij}}{3} = \frac{1+3+0}{3} = \frac{4}{3}$$

Weights of preferences are as shown in Fig. 5.

5.2. Recommendation algorithm

As the classical recommendation algorithms, which have been widely used in online recommendation, such as content-based, collaborative filtering and so on, need huge number of records, they do not apply physical shopping scenario because of the limited number of stores. So a simple and effective rule-based recommendation algorithm is used to recommend right brand stores to right users, and the rules are set according to the following two assumptions. One, the higher a user's preference weighting of a brand is, the more likely he/she is to buy the brand. The other, when the user's preferences towards two brands are the same, he/she will enter the brand store with promotional offers. The following is the formal description of the proposed recommend algorithm:

First, some variables are defined.

$Preference_{ij}$: user i's preference weighting of a store j.
RP_{ij}: ordinal of $Preference_{ij}$
PB_{ij}: if brand store j is making a promotional offer that User i likes (0 No; 1 Yes).
Here $i \in \{user\}$; and $j \in \{store\}$.
$R(i)$: User i's preference weights of all brand stores he/she ever enters.
$R(i) = \{store_{i1}, store_{i2} ... store_{ik} ... store_{in}\}$,
Here $k \in \{$brand stores user i ever enters$\}$; $RP_{i1} > RP_{i2} > \cdots > RP_{ik} > \cdots > RP_{in}$
$P(i)$: results recommended to user i.
$P(i) = \{user\ id, store_1, store_2, store_3 ... store_n\}$

Then, the following rules are used:

Rule 1: *IF* $RP_{ij} \leqslant 5 \Rightarrow i \in P(i)$;
Rule 2: *IF* $RP_{ij} > 5 \wedge i \leqslant length(R(j))/2 \wedge PB_{ij} = 1 \Rightarrow i \in P(i)$;
Rule 3: *IF* $RP_{ij} > 5 \wedge i \leqslant length(R(j))/2 \wedge Card\ (P(i)) \leqslant 10 \Rightarrow i \in P(i)$;
Rule 4: *IF* $RP_{ij} > 5 \wedge i > length(R(j))/2 \wedge Card\ (P(i)) \leqslant 10$ *AND* $PB_{ij} = 1 \Rightarrow i \in P(i)$;
Rule 5: *Under other conditions* $\Rightarrow i \notin P(i)$.

Explanations of rule 1–5:

When user i's preference weighting of store j is high enough, store j will be recommended to user i.

When user i's preference weighting of store j is not so high but it is not too low, and brand store j is making a promotional offer that user i likes, store j will be recommended to user i.

When user i's preference weighting of store j is not so high but it is not too low, and the number of stores which have been recommended is no more than 10, store j will be recommended to user i.

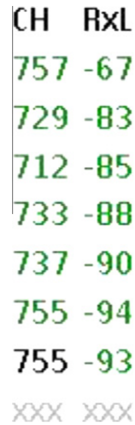
When user i's preference weighting of store j is low but the number of stores which have been recommended is no more than 10 and brand store j is making a promotional offer that user i likes, store j will be recommended to user i.

Under other conditions, store j is not recommended user i.

6. Experimental evaluation

6.1. Experimental setting

To prove the performance of the new proposed mobile recommender system, we conduct an experimental evaluation in a big shopping mall. As in indoor shopping scenario, without location information and web log data, mobile recommender system has to require users to explicitly input their ratings of items. Moreover, GPS does not work in indoor environments and accuracy of the traditional MPS positioning approach is far below the store level. Therefore, it is meaningless to compare the new proposed mobile recommender system with a system using the MPS or with a system using the GPS. RFID positioning requires each user to hold a RFID reader, and at the same time, RFID tags have to be placed in each store. Alternately users have to put tags themselves, and at the same time, RFID readers have to be placed in each store. Therefore, it is impractical to compare the new proposed system with a



CH	RxL
757	-67
729	-83
712	-85
733	-88
737	-90
755	-94
755	-93
XXX	XXX

Fig. 6. RSS information. Legend: *CH* = channel, RXL = received signal level.

User id	19
shiseido	59.25521634
mtmjapan	54.97605974
Cle de Peau Beaute	37.53063914
jurlique	29.11992093
guerlain	23.62376455
Erno laszlo	9.666593455
Giorgio Armani	3.329453108
joyce	2.593015594
Bobbi Brown	2.461234351
Royal Selangor	1.922468702

Fig. 7. A user's preference weightings of stores.

system using the RFID. So we just compare the new proposed mobile recommender system with a mobile recommender system using explicitly inputting (explicit rating-based mobile recommender system), from objective and subjective perspectives.

From objective perspective, recommending right products to right users is the key task of a recommender system (Mobasher, Cooley, & Srivastava, 2000; Adomavicius & Tuzhilin, 2005), and the metrics of measuring the accuracy of recommendation are precision, recall and F-measure (Miyahara & Pazzani, 2000; Carterette & Bennett, 2008). Precision is the percentage of the recommended relevant products over all recommended products. Recall is the percentage of the recommended relevant products over all relevant products. *F*-measure is weighted average of precision and recall

Group		N	Mean	Std. Deviation	Std. Error Mean
Precision	0	20	0.9400	0.15694	0.03509
Precision	1	20	1.0000	0	0

Fig. 8. Group statistics for precision. Legend: Group 0 = experiment group; Group 1 = contrast group.

should not be very obvious because the new proposed mobile recommend system can accurately learn users' preferences. To obtain relatively objective analysis results, we conduct a survey to inquire users' favorite stores during their shopping process in both groups. Then we measure precision, recall and *F*-measure of both mobile recommender systems.

From subjective perspective, the technical acceptance model (TAM) states that users' intention to use a system depends on two main factors: perceived usefulness and perceived ease of use; users' continuous intention depends on users' satisfaction (Davis, Bagozzi, & Warshaw, 1989; Bhatacherjee, 2001). Because the new proposed mobile recommender system does not require users' explicit inputs, we hope it can improve users' perceived usefulness, perceived ease of use and satisfaction.

This experiment was conducted in a big shopping mall. Before the experiment, some preparatory works are done. First, the RSS pattern of every store's door in the shopping mall is recorded to build the mappings between RSS patterns and stores' locations database. Second, stores' profile information is collected, including products' information, promotional offers and so on.

$$Precision = \frac{(\text{a user's favorite brand stores}) \cap (\text{stores system recommending to him/her})}{\text{stores system recommending to him/her}}$$

$$Recall = \frac{(\text{a user favorite stores}) \cap (\text{stores system recommending to him/her})}{\text{a user favorite stores}}$$

$$F\text{-}measure = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

As the new proposed mobile recommender system can learn users' preferences by capturing and analyzing users' activities, the new proposed mobile recommender system may lose a little of precision, recall and *F*-measure, compared with explicit rating-based mobile recommender system. But the loss in objective measures

Forty students and research assistants are chosen as experiment participants. Twenty participants are in the experiment group who use the new proposed mobile recommender system, and the other twenty participants are in the contrast group who used explicit rat-

		Levene's Test for Equality of Variances		t-test for Equality of Means		
				95% Confidence Interval of the Difference		
		F	Sig.	t	df	Sig.(2-tailed)
Precision	Equal variances assumed;	15.211	0.000	-1.710	38	0.095
Precision	Equal variances not assumed			-1.710	19.000	0.104

Fig. 9. Independent samples test for precision.

group		N	Mean	Std. Deviation	Std. Error Mean
F-measure	0	20	0.9613	0.10230	0.02308
F-measure	1	20	1.0000	0.00000	0.00000

Fig. 10. Group statistics for *F*-measure. Legend: Group 0 = experiment group; Group 1 = contrast group.

Construct	Number of Items	Reliability
PU	5	0.975
PE	6	0.972
S	4	0.992

Fig. 12. Construct reliability. Legend: PU = perceived usefulness; PE = perceived ease of use; S = satisfactory. All item loadings were significant at $p = 0.001$ level.

ing-based mobile recommender system. Participants in both groups have similar age, sex and education background distributions; ten are 20–25 years old and the other ten are 25–30 years old; ten are male and the other ten are female in each group; ten are awarded master's degree, and ten have PhD degree in the two groups. Participants of the two groups go shopping in a big mall with a mobile phone equipped with a recommender system. But the mobile recommender system in experiment group learns users' preferences according to users' positions and other contextual information, and explicit rating-based mobile recommender system requires users to explicitly rate each brand store in the shopping mall by clicking on mobile phone screens. The experiment is conducted in the following steps:

Step 1: The participants are told about the experiment process.
Step 2: Participants of the experiment group go shopping in the big shopping mall for two weeks, to capture their shopping activities for learning their preferences.
Step 3: Participants of the experiment group go shopping in the big shopping mall and the new proposed mobile recommender system recommend brand stores to them.
Step 4: Participants of contrast group explicitly input ratings assigned to each brand store.
Step 5: Participants of contrast group go shopping in the big shopping mall with mobile phones and the explicit rating-based mobile recommender system recommend brand stores to them.
Step 6: Two surveys asked experiment participants which brand stores are their favorites and their feelings about using mobile recommender systems.

6.2. Experimental result and discussion

Fig. 6 shows an example of RSS information captured by the proposed system, and Fig. 7 shows a user's preference weightings of each brand store learnt by the proposed system.

The average precision of new proposed mobile recommender system is 94%; the average recall of new proposed mobile recommender system is 100%; and the average precision of new proposed mobile recommender system is 96.11%. The average precision, recall and precision of the explicit rating-based mobile recommender system are all 100%.

To compare the new proposed mobile recommender system with mobile recommender system using explicit input from objective perspective, the following hypotheses are tested:

H1. *There are no significant differences between precision of the new proposed mobile recommender system and of explicit rating-based mobile recommender system in the scenario of shopping in a big shopping mall.*

H2. *There are no significant differences between recall of the new proposed mobile recommender system and explicit rating-based mobile recommender system in the scenario of shopping in a big shopping mall.*

H3. *There are no significant differences between F-measure in the new proposed mobile recommender system and explicit rating-based mobile recommender system in the scenario of shopping in a big shopping mall.*

The average recalls of both groups are 100%, so *Hypothesis* 2 is supported.

To test Hypothesis 1 and Hypothesis 3, we conduct independent sample *T* tests to compare precision, recall and *F*-measure of both groups. Figs. 8–11 show the results of the comparison of the two methods.

Fig. 9 shows that in Levene's Test for Equality of Variances, $F = 15.211$ and $P = 0.00$. We can infer that variances of precision in both groups are not equal. So we choose the *t*-test when equal variances are not assumed. For two independent samples test, $t = -1.710$, $P = 0.104$, $P > 0.05$, so *Hypothesis* 1 is supported.

		Levene's Test for Equality of Variances		t-test for Equality of Means		
				95% Confidence Interval of the Difference		
		F	Sig.	t	df	Sig.(2-tailed)
F-measure	Equal variances assumed;	14.232	0.001	-1.678	38	0.102
F-measure	Equal variances not assumed			-1.678	19.000	0.110

Fig. 11. Independent samples test for *F*-measure.

Construct	Group	Number	Variable Mean	Standard Deviation	F	Sig
PU	0	20	6.02	0.71052	49.009	0
	1	20	3.48	1.45877		
PE	0	20	6.3333	0.76089	43.774	0
	1	20	4.0333	1.35573		
S	0	20	6.0625	0.85021	35.297	0
	1	20	3.65	1.60468		

Fig. 13. Measurement model. Legend: PU = perceived usefulness; PE = perceived ease of use; S = satisfactory; Group 0 = experiment group; Group 1 = contrast group.

From Fig. 11, since Levene's Test for Equality of Variances shows $F = 14.232$ and $P = 0.001$, we can infer that variances of precision in both groups are not equal. So we choose the *t*-test when equal variances are not assumed. For two independent samples test, $t = -1.678$, $P = 0.110$, $P > 0.05$, so Hypothesis 3 is supported.

To compare the new proposed mobile recommender system with the explicit rating-based mobile recommender system from subjective perspective, the following hypotheses are tested:

H4. *The new proposed mobile recommender system will bring users more perceived usefulness than explicit rating-based mobile recommender system in the scenario of shopping in a big shopping mall.*

H5. *The new proposed mobile recommender system will bring users more perceived ease of use than the explicit rating-based mobile recommender system in the scenario of shopping in a big shopping mall.*

H6. *The new proposed mobile recommender system will bring users more satisfaction than explicit rating-based mobile recommender system in the scenario of shopping in a big shopping mall.*

To test the above hypotheses, we conduct an ANOVA test to compare the perceived usefulness, perceived ease of use and satisfaction of both groups.

The reliability of each variable in the second survey is validated as follows: Fig. 12.

The differences of each variable in the two groups are shown in Fig. 13:

From Fig. 13, according to one factor ANOVA, for perceived usefulness, $F = 49.009$, $P = 0$, $P < 0.05$, so Hypothesis 4 is supported.

For perceived ease of use, $F = 43.774$, $P = 0$, $P < 0.05$, so Hypothesis 5 is supported.

For satisfaction, $F = 35.297$, $P = 0$, $P < 0.05$, so Hypothesis 6 is supported.

In summary, from the objective perspective, there are no significant differences between accuracy of recommendation of the new proposed mobile recommender system and the explicit rating-based mobile recommender system, although the new proposed mobile recommender system only uses users' locations and other contextual information to infer preferences, without requiring users' explicit inputs. And from the subjective perspective, participants using the new proposed mobile recommender system feel significant more usefulness, more ease of use and more satisfaction than participants using explicit rating-based mobile recommender system.

7. Limitations

In this paper, the core technology of mobile recommender system is the new positioning approach based on mining RSS patterns. Although this technology does not incur any extra hardware cost, it needs to build mappings between RSS patterns and stores' locations database by collecting RSS information of each brand store. This will lead to some manpower cost, but usually the RSS patterns can be provided by operators of shopping malls, so this cost is not high. In the experiment, we compare the new proposed mobile recommender system with the one based on users' explicit inputs. Comparisons with mobile recommender systems based on other indoor positioning approaches are not involved in the experiment due to cost consideration; these will be taken up in future work. Moreover, experimental evaluation should be at a larger scale in the future.

8. Conclusion

Traditional online recommender systems cannot provide recommendations for physical shopping and existing mobile recommender systems suffer impractical positioning technologies and cannot recommend accurate information to users in indoor shopping scenario. In this study, a novel mobile recommender system is proposed for indoor shopping. The new proposed positioning approach involving mining RSS patterns avoids the shortcomings of extant positioning approaches, and can obtain users' position information, to implicitly estimate users' preferences. So this recommender system can effectively recommend products/brands to users by using both users' preferences and contextual information. A comprehensive experiment is conducted to evaluate performance of this mobile recommender system, and the evaluation results show no significant differences between accuracy of recommendations by the proposed mobile recommender system and mobile recommender system using explicit inputs. But participants using the mobile recommender system showed significantly higher interest than those using the benchmark system, in different aspects: perceived usefulness, perceived ease of use and user satisfaction. This study shows the mobile recommender system using this novel positioning approach can be a better choice in practice to assist users' shopping activities in big shopping malls.

Appendix A

Perceived usefulness

Using this recommender system more in my shopping would enable me to accomplish shopping more quickly. 1 2 3 4 5 6 7

Using this recommender system more would improve my shopping performance. 1 2 3 4 5 6 7

Using this recommender system would enhance the effectiveness of my shopping. 1 2 3 4 5 6 7

Using this recommender system more would make shopping easier. 1 2 3 4 5 6 7

(*continued on next page*)

I find this mobile recommender system useful in my shopping. 1 2 3 4 5 6 7

Perceived ease of use

Learning to operate this mobile recommender system would be easy for me. 1 2 3 4 5 6 7

I find it easy to get this mobile recommender system to do what I want it to do. 1 2 3 4 5 6 7

My interaction with this mobile recommender system is clear and understandable. 1 2 3 4 5 6 7

I find this recommender system to be flexible to interact with. 1 2 3 4 5 6 7

It would be easy for me to become skillful at using this mobile recommender system. 1 2 3 4 5 6 7

I find this mobile recommender system easy to use. 1 2 3 4 5 6 7

Satisfaction

I feel very satisfied when I use this mobile recommender system. 1 2 3 4 5 6 7

I feel very pleased when I use this mobile recommender system. 1 2 3 4 5 6 7

I feel very contented when I use this mobile recommender system. 1 2 3 4 5 6 7

I feel absolutely delighted when I use this mobile recommender system. 1 2 3 4 5 6 7

Measurement scales for perceived usefulness, perceived ease of use and satisfaction.

Legend: 1 = extremely unlikely agree, 2 = quite unlikely agree, 3 = slightly unlikely agree, 4 = neutrality, 5 = slightly likely agree, 6 = quite likely agree, 7 = extremely likely agree.

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