PORSCHE: A Physical Objects Recommender System for Cell Phone Users

Hideyuki Kawashima
Keio University
3-14-1 Hiyoshi
Yokohama, JAPAN
kawasima@ics.keio.ac.jp

Takaki Matsushita
Hitachi Corporation
Tokyo, JAPAN
matsuge@ayu.ics.keio.ac.jp

Satoru Satake
Graduate School of Keio University
3-14-1 Hiyoshi
Yokohama, JAPAN
satake@ayu.ics.keio.ac.jp

ABSTRACT

In web applications, recommendation algorithms such like collaborative filtering techniques are widely accepted for web users. To apply the algorithms for physical world objects such as books, three problems arise. The first problem is, how to input user ratings for physical objects ? The second problem is, how to measure user interests for physical objects ? The third problem is, how to consider the relationship between physical objects and users based on their locations ? In order to solve the problems, this paper proposes a physical objects recommender system for cell phone users, PORSCHE. As for the first problem, PORSCHE estimates the user ratings using user behaviors for physical objects. As for the second problem, PORSCHE changes the user ratings using both user behaviors and elapsed time. As for the third problem, PORSCHE adjusts the user ratings by continually monitoring the distance between physical objects and users. The result of experiments simulating a bookstore shows that PORSCHE detects user interests accurately and it also recommends proper books for the user.

1. INTRODUCTION

Web contents recommendation services such as Amazon.com provides attractive information with users analyzing user preferences. Techniques used in such web recommendation services can be divided into the following three categories. They are the collaborative filtering technique [6, 4], the contents based filtering technique [3], and the hybrid technique of the above two techniques [2]. This paper focuses on the collaborative filtering technique which has been well established through experiences in many companies including Amazon.com. GroupLens[6] is a representative research which uses the collaborative filtering technique, and it recommends news articles on web sites. On GroupLens, each user should evaluate news articles in 5 levels. Using the level information, GroupLens calculates correlations among users, and it recommends for a user X articles nicely evaluated by user Y whose preference feature is similar to user X's one.

To apply the collaborative filtering technique for physical objects, the following three problems arise. (1) Contents evaluation of physical objects should be conducted though it usually requires users to have more efforts rather than simply clicking web contents on a browser. (2) User interests for physical objects should be measured though sensing devices are required. (3) Locations of physical objects should be considered since location itself is essential for a physical object.

To realize a physical objects recommendation system, this paper proposes PORSCHE[1]. To solve problem (1), PORSCHE observes user actions from a sensor network constructed by ultrasonic tag systems, and it estimates user interests with physical objects by automatically analyzing user behaviors with the objects. To solve problem (2), PORSCHE dynamically revises evaluation values with physical objects by considering user behaviors or elapsed time after a user access. Furthermore, PORSCHE classifies user actions into three types, and it provides different weights with the actions for each type. To solve problem (3), PORSCHE decreases user interests with a physical object in accordance with the distance between a user and an object.

The rest of this paper is organized as follows. Section 2 describes preliminaries for PORSCHE including the review of the collaborative filtering technique and the details of sensor devices. Section 3 describes the design of PORSCHE constituted of a server and clients. Section 4 describes the evaluation of PORSCHE through experiment on a bookstore simulation and on user interests monitoring. Finally Section 5 describes concluding remarks and future directions.

2. PRELIMINARIES

2.1 Review of Collaborative Filtering

GroupLens[6] recommends news articles on web sites using the collaborative filtering technique. On GroupLens, user should evaluate news articles in 5 levels, and GroupLens stores the user evaluations in a certain form. An example of the form is shown in Table 1.

Now we describe how the collaborative filtering technique estimates (Q) in content 6 using already evaluated objects.

[1]Physical Object Recommendation System for Cell pHone usErs.

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Table 1: User Evaluation Example on GroupLens

Contents ID	User A	User B	User C	User D
1	1	4	2	2
2	5	2	4	4
3			3	
4	2	5		5
5	4	1		1
Average	3	3	3	3
New Content 6	(Q)	2	5	

Firstly, correlation coefficients between user A's evaluations and other users' evaluations are calculated. A correlation coefficient between user i and j, denoted as R_{ij}, is calculated in a fashion as shown in eqn. 1

$$R_{ij} = \frac{cov(i,j)}{\sigma_i \sigma_j} = \frac{\sum_{x=1}^{n'} (i_x - \bar{i})(j_x - \bar{j})}{\sqrt{\sum_{x=1}^{n'} (i_x - \bar{i})^2 \sum_{x=1}^{n'} (j_x - \bar{j})^2}} \quad (1)$$

Here x, $\bar{i}$, and $\bar{j}$ show a content, an evaluation average of user i for x, and an evaluation average of user j for x respectively. And, σ_i, σ_j, and $cov(i,j)$ show a standard deviation of i, a standard deviation of j, and a covariance of user i and user j respectively. Plus, n' shows a content which lacks one of evaluation values. From Table 1, R_{AB}, R_{AC}, R_{AD} are calculated as $R_{AB} = -0.8$, $R_{AC} = 1$, $R_{AD} = 0$ respectively. The result shows that A's interest and B's interest are in the inverse directions, while A's interest and C's interest are in the same direction. It furthermore shows that the relationship between A's interest and D's interest cannot be estimated.

User i's interest for content x, denoted as E_{ix}, is calculated in a fashion as shown in eqn. 2.

$$E_{ix} = \bar{i} + \frac{\sum_{j \neq i} (j_x - \bar{j}) R_{ij}}{\sum_{j \neq i} |R_{ij}|} \quad (2)$$

Since A's interest for content 6, E_{A6}, is calculated as 4.56. On GroupLens, for all of unknown contents are calculated, and consequently a content with the largest E is selected as a recommendation content for a user.

2.2 Sensor Devices

To obtain information of physical objects, we used positioning sensor devices and RFIDs. To show recommendation results, we used a cell phone as a displaying device. The details of them are described in the following.

An ultrasonic 3D tag system used for a object positioning system in this paper was developed by Nishida[5]. This paper denotes the system as U3D for simplicity. U3D is designed to be used in a room. The system is constituted of senders and receivers. U3D receivers (Fig. 2) should be equipped on a ceiling or walls, while U3D senders (Fig. 1) should be equipped on physical objects. We deployed receivers on the ceiling of a room in a mesh topology. Each receiver was 1 meter apart from its neighboring receivers.

To show recommendation results, this paper used a cell phone, FOMA M1000 developped by NTT Docomo (Fig. 3). The specifications of FOMA M1000 are Symbian OS 7.0, IEEE 802.11b wireless LAN, touch panel input interface, USB 2.0 and Bluetooth 1.1 output interface, and Opera 7.5 web browser. The emulator image is shown in Fig. 4.

Figure 1: U3D Sender

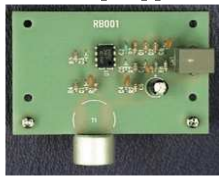

Figure 2: U3D Receiver

Figure 3: M1000

Figure 4: Emulator

Physical objects are assigned own identifier by an identical RFID chip. For RFID chips, this paper used μ chips developed by Hitachi corporation [1].

3. DESIGN OF PORSCHE

PORSCHE performs on a sensor network with U3Ds and RFIDs. PORSCHE is constituted of a PORSCHE server and PORSCHE clients. The PORSCHE server manages both of users' locations and physical objects' locations, and it continually calculates user interests for physical objects. On receiving a recommendation request from a user, the PORSCHE server generates a ranking list of recommendation objects using the collaborative filtering technique, and it returns the list to a PORSCHE client. Furthermore, the PORSCHE server stores information with physical objects including names, prices, manufactures, and URLs. A user obtains the information by scanning RFID tags.

3.1 PORSCHE Server

The PORSCHE server has three modules. They are a location management module, an interest measurement module and a collaborative filtering module. The details of them are described in the following.

The location management module obtains 3D positions of physical objects obtained from U3D, and it calculates each distance between a user and a physical object. On U3D, there is a problem to obtain the position. Each sender's location is calculated using the time from ultrasonic wave sending to its receiving. Therefore the order to obtain sender positions is not the same as the order of wave sendings in some cases. To revise this deficiency, the location management module uses sender devices' identifiers and physical objects' identifiers, and it matches sender-receiver pairs. Plus, this module calculates the change of the z-axis values for each object to provide it with the interest measurement module described in the following.

The interest measurement module estimates user interests for physical objects. PORSCHE classifies user interests for an object into the following 3 types.

Table 2: Evaluation by User Actions

User Action	Evaluation Value
NEAR	2 (E_{ix_1})
PICK	3 (E_{ix_2})
SCAN	5 (E_{ix_3})

(1) Near an object (NEAR): When the distance between a user and a physical object is within 50 cm, the object is recognized as "NEAR" the user.
(2) Picking up an object(PICK): When a user picks up an object over 20 cm, the object is recognized as "PICK"ed up by the user.
(3) Scanning an object (SCAN): When a user obtains the data of physical object using a RFID reader device, the object is considered to be "SCAN"ed by the user.
On the detection of the above three actions, user i's evaluations for an object x are provided as shown in Table 2. These evaluation values decrease in accordance with elapsed time after providing, since latest evaluated objects should be prioritized than older objects. The decrease is calculated by the following sigmoid function shown in eqn. 3. In eqn. 3, a shows decreasing constant coefficient and t_1, t_2, t_3 show elapsed times after finishing "NEAR", "PICK", and "SCAN" respectively.

$$S(t_k) = \frac{2}{1 + \exp(a * t_k)}, (k = 1, 2, 3) \tag{3}$$

Now, a user interest E_{ix} (eqn. 2) is revised to E'_{ix} as follows. However, E'_{ix} will be furthermore revised to E''_{ix} in the explanation of the collaborative filtering module below.

$$E'_{ix} = \sum_{k=1}^{3} E_{ix_k} \times S(t_k) \tag{4}$$

The collaborative filtering module calculates user interests for unknown objects using user interests obtained from the interest measurement module. The collaborative filtering module deals with the following three tasks.

(1) Detecting target user
(2) Detecting recommendation objects
(3) Informing recommendation results

At first, collaborative filtering module receives a recommendation request from a user. Then it detects the user by its ID and calculates his/her interest similarities to other users. Finally, the collaborative filtering module generates a HTML file which describes recommendation objects sorted by the calculated user interests. The result shows physical objects which are unknown to the requested user, but are interesting for the user of which interests are similar to the requested user. Furthermore, the collaborative filtering module considers the distance between the requested user and physical objects. A user i's interest for object x E'_{ix} shown in eqn. 4 decreases in accordance with r, the distance between x and i. The interest E''_{ix} revised by r is calculated as shown in eqn. 5. Here, b is a decreasing coefficient.

$$E''_{ix} = E'_{ix} \times \exp(-b \times r) \ \ (r > 0) \tag{5}$$

3.2 PORSCHE Client

Table 3: Recommendation Candidates

Book ID	Book Name
B1	Pthread Programming
B2	Psychology for Problem Solving
B3	Programming Language C
B4	Teach Yourself JAVA
B5	HTML References
B6	Carte for Businessmen
B7	River without Bridge (Novel)
B8	Blue Sleep (Novel)

A PORSCHE client is constituted of a communication module which communicates with PORSCHE server, a scan module which obtains object information, and a view module which displays both of recommendation results and object information.

The communication module establishes a connection between the PORSCHE server and a PORSCHE client. It also provides the result of recommendation objects obtained from the PORSCHE server with the view module. After receiving the result, the view module displays it. Then a user obtains recommended object's information by scanning a RFID tag attached on a physical object. The information of read objects is provided with the communication module and it is transferred to the PORSCHE server. Since the communication module receives recommendation results in the form of HTML files, view module invokes a web browser to display the information[2].

The scan module reads RFID information attached on physical objects to obtain detailed information of them. Since the PORSCHE server manages detailed information of physical objects, the information can be obtained by using RFID information scanned by the scan module.

The view module performs as a user interface. It receives recommendation requests from a user, and it sends the requests to the PORSCHE server. After receiving recommendation results and detail information of physical objects related to the recommendation, it displays them for a user. The displaying can be invoked by a web browser or client applications.

4. EVALUATION

4.1 Application Example

We conducted an experiment to verify whether PORSCHE accurately detect user interests on books. Eight books are used in the experiment, and the titles and the contents of them are shown in Table 3. In our scenario, we assumed the number of users was five, four of them were already in a bookstore, and a new user called M has come into the bookstore. Then PORSCHE should provide recommendations for M. Before the arrival of M, PORSCHE stores evaluation values of other four users denoted A, B, C, D in Table 4. In the table, however, 0 shows missing values.

The detail of the experiment is explained in the following. At first, M behaved as follows.

[2]Browser was the best information displaying device in our environment, i.e. FOMA M1000

Table 4: Other Users Evaluation Values

User	B1	B2	B3	B4	B5	B6	B7	B8
A	9	2	2	2	2	1	3	4
B	6	7	5	8	1	9	7	7
C	2	3	2	2	8	4	8	2
D	4	5	5	7	9	5	3	0

Table 5: M's Interests

User	B1	B2	B3	B4	B5	B6	B7	B8
M	10		5	5	2			

(1) M viewed "Pthread Programming" several minutes, then picked it up, and moreover scanned it.
(2) M picked up "Programming Language C" and then viewed it.
(3) M picked up "Teach Yourself JAVA" and then viewed it.
(4) M moved to near "HTML Tag References" and then viewed it.

From the above actions, M's interests were obtained as shown in Table 5. After M sent a recommendation request to the PORSCHE server, he received results as shown in Table 6. Please note that four books M showed his interests were not recommended in Table 6 since PORSCHE recommends for an user only unknown books, in other words, potentially preferred objects.

Here we consider why the above results are calculated. At first, we consider the correlation coefficients. They are calculated as shown in Table 7. The range of correlation coefficients is from -1 to 1, however 1 shows completely similar preference and -1 shows completely dissimilar preference. From Table 7, user A and B have similar preferences to M while user C and D have dissimilar preferences to him. Table 4 shows that the scores on "Blue Sleep" are 4 for A, 7 for B, 2 for C, and 0 for D respectively. Since the preferences of A, B, and M were similar, "Blue Sleep" was recommended. The other results can be also understood naturally in this way.

4.2 User Interest Transition

We measured user interests for physical objects with changing the distance between a user and objects. On our experiment, the number of objects (O1, O2, O3) was 3, the number of user was 1, and time decreasing coefficient a on eqn. 3 was set to 0.005. On this condition, three objects were deployed in the distance of 1 m and an user behaved as follows.

(1) User stayed 10 seconds near O1.
(2) User moved from near O1 to near O2.

Table 6: Recommendation Results

Rank	Book	Preference
1	Blue Sleep	6.615943
2	Psychology for Problem Solving	5.836684
3	Carte for Businessmen	5.691086
4	River without Bridge	5.561519

Table 7: Correlation Efficient

User	Value
A	0.904534
B	0.580370
C	-0.703526
D	-0.883856

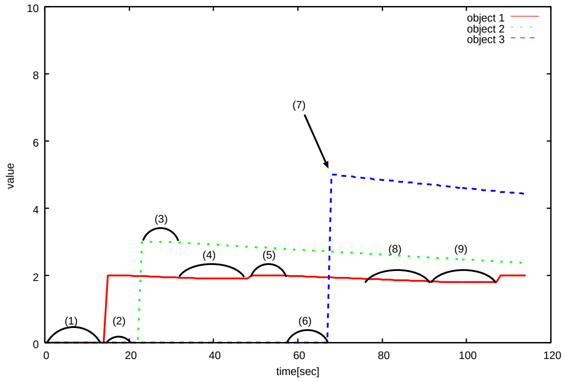

Figure 5: User Interest Transition

(3) User picked up O2.
(4) User put down O2 and moves to near O1.
(5) User stayed 10 seconds near O1.
(6) User moved from near O1 to near O3.
(7) User scaned O3.
(8) User moved from near O3 to near O1.
(9) User stayed 10 seconds near O1.

The transition of the user interest is shown in Fig. 5. In the figure, x-axis shows time (sec) and y-axis shows the user interest. On (1), NEAR is detected and interest for O1 is set to 2. On (3), PICK is detected and interest for O2 is set to 3, and interest for O1 decreases in accordance with time. On (4) and (5), NEAR is detected and interest for O1 is set to 2. On (6), user passed by O2 and is close to O3. Then interest for O1 is decreased. On (7), SCAN is detected and interest for O3 is set to 5. Finally on (8) and (9), interest for O1 is set to 2. From the above results, we complain that PORSCHE performed properly to show a user interest for physical objects.

5. CONCLUSION AND FUTURE WORK

This paper proposed PORSCHE, a physical object recommendation system for cell phone users. The problems to realize PORSCHE were (P1) efficient evaluation value input methods for physical world, (P2) the way to measure user interests, and (P3) location aware recommendation methods. To solve (P1), we applied ultrasonic 3 dimensional sensor devices. To solve (P2), we classified user behaviors into 3 types, and designed an module which automatically estimates user interests. To solve (P3), we incorporated time decreasing function into a user interest estimation module considering the distance between a user and physical objects. The result of experiments simulating a bookstore showed that PORSCHE detected user interests accurately and it also could recommend proper books for the user.

In future work, we plan to provide web contents related to recommended physical objects with users and also plan to track user gazes to improve the accuracy of estimations for user interests.

6. ADDITIONAL AUTHORS

Michita Imai (Department of Information and Computer Science, Faculty of Science and Technology, Keio University, JAPAN, email: michita@ics.keio.ac.jp).
Yasuhide Shinagawa (Department of Open and Environmental Science, Graduate School of Keio University, JAPAN, email: sinagawa@ayu.ics.keio.ac.jp).
Yuichiro Anzai (Department of Information and Computer Science, Faculty of Science and Technology, Keio University, JAPAN, email: anzai@ics.keio.ac.jp).

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