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Players' Interest Measurement Based on Visiting Time in a Location-Based Game

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***Abstract*—In this paper, we propose a model which can measure players' interest in visited places based on visiting time and we apply the model to a typical location-based game. The results in the conducted experiments show that our model works well in both simulation and a real game and that it outperforms an existing model.**

Keywords—location-based game; visting time; degree of interest

I. INTRODUCTION

A location based game [1, 2] is a type of game in which the information on players' positions is utilized in the gameplay. The game content varies depending on how the information on the players' positions is used. In this paper, we use a location based game in which a player is shown a number of photos about targeted places. The player then has to select one photo and go to the place s/he considers most related to the selected photo.

Those photos may be randomly chosen and shown to a player by the game. And if so, sometimes the game may show the player series of photos about places s/he does not have an interest in, which can decrease the player's play motivation. Therefore, we consider it is necessary for the game to give higher priority to places which the player may be interested in, so s/he can enjoy the game better.

II. PLAYER INTEREST MODEL

In order to measure the player's interest, we based our work on a model proposed by Bohnert et al. [3], but we added a modification. In Bohnert's model, once the visiting time, of each place visited by a player of interest, u, is known, the player's interest can be inferred using a measure called Relative Interest (RI) defined by

$$RI_{ui} = \frac{T_{ui}}{T_{u*}} - \frac{1}{n_{*i}} \sum_{v \in U} n_{vi} \frac{T_{vi}}{T_{v*}} \quad (1)$$

where

- T_{ui} : the time player u stayed at place i
- T_{u*} : the average visiting time of player u
- n_{*i} : the number of players that visited place i
- U : the set of players, and

$$n_{vi} = \begin{cases} 1: \text{if player } v \text{ has stayed at place } i \\ 0: \quad\quad\quad\quad\quad\quad\quad\quad \textit{otherwise} \end{cases}$$

Formula (1) is based on the assumption that players often spend more time on places they have an interest in. By this assumption, when all players spend long time at a particular place, the system will infer that all of them have an interest in that place. However, there is a case in which such a place just merely requires more visiting time than the others although the players do not like the place at all (e.g., because of longer introduction time, etc.). This formula has the second term, the term after minus, to indirectly cope with this issue. To directly deal with the issue, we propose a modified formula for measuring the relative interest as follows:

$$RI_{ui} = \frac{T_{ui}}{T_{u*}} \frac{T_{ui}}{T_{*i}} - \frac{1}{n_{*i}} \sum_{v \in U} n_{vi} \frac{T_{vi}}{T_{v*}} \frac{T_{vi}}{T_{*i}} \quad (2)$$

This formula has a newly introduced variable T_{*i} which measures the average time spent on place i among all players who have visited place i. The role of this variable is to further regulate the time intrinsically required by place i.

III. EXPERIMENT WITH A SIMULATION

In order to compare the performance of our model with Bohnert's model in inferring players' interest using the visiting time, we first ran a controlled experiment on simulated dataset generated as follow. First, we generated 12 places (with ids from 1 to 12) and their corresponding typical visiting time as: 50, 60, 70, 80, 90, 100, 110, 120, 140, 160, 180 and 200, respectively. Then, assuming that there are 100 players, we randomly generated the visiting time for each player on each place based on the aforementioned typical visiting time, and we then slightly increased or decreased those values according to the assumed preference ranking by each player, which was also randomly generated, as shown in Table I.

TABLE I. TIME MODIFICATION VALUES FOR EACH RANKING

Ranking	1	2	3	4	5	6
Time	+25	+20	+15	+10	+5	0
Ranking	7	8	9	10	11	12
Time	0	−5	−10	−15	−20	−25

TABLE II. PERFORMANCES OF THE TWO MODELS ON SIMULATED DATA

Existing Model	Proposed Model
0.833	0.920

Table II shows the performances of Bohnert's model and our model on this simulated dataset. The performance of each model was evaluated by the average value of the Kendall tau rank correlation coefficient between the ranking by the players and the ranking by each of the two models. Note that the range of the Kendal tau rank correlation coefficient is from -1 to 1 with higher values for higher degrees of similarity. From Table II, we can see that our model performs better than the existing model on this dataset. As a result, we anticipated similar results could be obtained for data from a real game, which is described in the following section.

IV. Game Implementation

The game that we implemented for this research is a typical location-based game in which the targeted players are freshmen students and the targeted places are laboratories in our department, Human and Computer Intelligence Department, College of Information Science and Engineering. The players' task is to correctly find and go to the laboratories shown in or hinted by the photos displayed by the game. Each player is given a handheld device which has the game implemented on it, so s/he can easily interact with the game while moving around on two floors where our department is located.

Fig. 1 shows a sample quiz screen of the game on which multiple photos, individually representing a laboratory which a player has not visited yet, are shown at a time. The player must then choose one photo and go to the laboratory s/he thinks most related to the photo. The size of the photos is relative to the value of relative interests of the player in them, i.e., the higher value of the relative interest, the bigger the photo. We used collaborative filtering [3] and the proposed relative interest for predicting players' interest in unvisited places, but this mechanism is, however, beyond the scope of this paper.

Fig. 2 shows a map screen displayed by the game while a player is moving. On this map, the player can see the name and position of each laboratory and which laboratories s/he has visited. When the player taps a laboratory on the map, the game displays a screen with some hints about that laboratory.

Fig. 1. A quiz screen.

Fig. 2. A map screen.

To check which laboratory a player has entered, the game uses the id of a local wireless LAN router, located at each laboratory in advance, that the handheld device is connected with when the player enters a laboratory. This id information is sent to the game server located at the author's laboratory via the university's wireless LAN. The game then reports to the player whether s/he has come to the right laboratory.

V. Experiment in a Real Game

In this experiment, at the end of the game, each participant was asked to rank the laboratories. There were 26 students participated in the experiment. Among them, 13 participants returned us their ranking results. These results were compared with the ranking inferred from either formula (1) or (2), by calculating the Kendall tau rank correlation coefficient between them.

Table III shows the performances of the existing model and our model in terms of the average value of the Kendall tau rank correlation coefficient between the ranking made by the players and the one inferred by the corresponding model. From this table, one can see that the proposed model outperforms the existing model for this dataset.

Additionally, we also observed the players' interest in the game. The results of our questionnaire showed that about 60% of the participants reported that they found this game very interesting to play.

TABLE III. THE PERFORMANCES OF TWO MODELS ON REAL-GAME DATA

Existing Model	Proposed Model
0.262	0.405

VI. Conclusions and Future Work

According to the results from both simulated data and real data, the performance of our model is better than the existing model in inferring the players' interest. This is because of our modification to the existing relative interest. Namely, our modification more directly takes into account the average time spent on each place than the existing one.

We are now studying the effect of the use of collaborative filtering and the proposed relative interest for predicting players' interest in unvisited places in order to accordingly adjust the size of each photo shown to the player. These findings will be reported elsewhere. In addition, we plan to find other mechanisms that exploit predicted players' interest in places for giving the players more entertaining experiences.

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