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ORIGINAL PAPER

A recommendation system based on mining human portfolio for museum navigation

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Abstract In most developed countries, people now increasingly focus on leisure activities such as going to concerts, visiting museums, or sporting events. Because we live in an era of information technology, this technology can help us in leisure activities. While people enjoy attending exhibitions or visiting museums, many visitors go without a specific purpose or interest, thus making it difficult for them to retrieve useful information to efficiently guide them through a museum for example. In this paper, a system that integrates wireless Internet, RFID technology, and mobile devices is built to guide visitors through navigating museums with personal and adaptive content. The mobile guide system can classify visitors based on exhibition information, personal information, and visitor history; this allows it to provide more suitable information for users. The system also utilizes semantic web technology to connect with data such as user type or properties to create human portfolios, and uses a metadata method to provide user information automatically and appropriately. Obtaining user feedback in this system results in a more useful guide to the colorful content of a museum and gives users a more personal experience to fit their needs.

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1 Introduction

As leisure activities have become very popular, there are many guide systems for exhibitions and museums. Guide systems must be developed not only for adults but also for children, hence the completeness of a system is very important. In the following table, we compare several current guide systems with our proposed system. The comparison attributes are ubiquitous technology (RFID technology, WIFI technology, location-based technology), cloud computing, adaptive/personal content, multimedia resources (text, images, and video), and interaction (with the system). Ubiquitous technology is a commonly used technology in recent years, thus most of guide systems have integrated this. Cloud computing is a new data processing method that enhances data processing efficiency in information technology. Adaptive/personal content provides user with the most personalized and useful content. Multimedia resources indicate text, images, audio, and video content. Interaction indicates whether the system supports two-way interaction between the user and system. In traditional guides systems, only one-way interaction from the system to a user is supported. Our proposed system integrates all five factors, thus enhancing the completeness of the guide system. Based on the portable, small-scale nature of mobile devices (Roschell 2003), users can acquire information from the Internet or telecommunication networks and execute programs on these devices, e.g., cell phones, PDAs, notebooks, iPads. Since Metadata is very important to mobile devices, the Metadata was first defined at the Metadata Workshop Conference (http://zh.wikipedia.org/wiki/Metadata) and applies to data storage and data retrieval. Dublin Core is a simple (Hillman 2005), efficient, popular metadata standard that can quickly organize network resources and improve the precision of data search and retrieval. This provides a metadata format for experts from different areas to describe network resources, under which network resources are divided into 15 categories.

Categories for the description of works of art, CDWA, is a popular metadata definition for art exhibitions and museum categories (Agbabian et al. 1988). It was proposed by the Art Information Task Force, AITF, of the J. Paul Getty Trust. CDWA provides a scheme for describing the content of works of art such that we can establish a database based on these descriptions. There are 27 main categories and 233 subcategories in CDWA.

After establishing the metadata, ontology and semantic web were critical techniques to developing our BAR method. Ontology refers to a specific and existent type or the well-known philosophical concept (Gruber 1993; Arvidsson and Flycht-Eriksson 2008). In computer science, ontology represents knowledge as a set of concepts within a domain, and the relationships between those concepts. Common components of ontologies include individuals, classes, attributes, relations, function terms, restrictions, rules, axioms and events. Semantic web is a concept proposed by Tim Berners-Lee in W3C (Berners-lee et al. 2008). The main idea is to allow computers to "understand" text files on the Internet, that is, to recognize the semantics of text files. By using the semantic web technique, a search engine can utilize a unique and precise vocabulary to clearly mark text files that have been searched.

Since people go to museum or exhibition are willing to acquire several knowledge or information during their visiting, many museums provide visitors with different kinds of guides, such as human, audio guidance from portable device. With audio guide from portable device, visitors can enjoy personalized tour by choosing what they want to listen to or which galleries they want to visit. But most of the guidance content in current museum is fixed, deriving from a fixed content database and delivering fixed content to every visitor moreover is limited to audio-only. Since portable device and wireless network technology can provide visitors with a more personalized guide. Hence, our research aims to propose one a personalize guidance system that using a data storage format which allows exhibition organizers to store exhibition data and allows visitors to record their personal information. The proposed system also recommend real-time contents or information to user depends on user's background and visiting history by wireless network. Otherwise, our system also integrates with multimedia content including video and audio guidance to enhance its completeness. With the evaluation of proposed system, our research evaluated according to a best appropriate recommendation method (BAR) in this paper, the results will appear in this paper.

The remainder of this paper is organized as follows: in Sect. 2, we describe related work; in Sect. 3, we describe in detail the system's personal recommendation mechanism and the developed BAR method; in Sect. 4, we provide the interface of the developed system. The last section is consists of Conclusion and Future Research.

2 Related work

2.1 Recommendation system

With the rapid growth of Internet, the information on Internet is rich and abundant. However, the information is too much and complex, which makes people need to pay more attention on information retrieving. Data mining and information filtering techniques are generated to respond to this problem. Recommendation system is the application that can help people to filter out what they want by applied the information filtering techniques(Hung 2012; Hung et al. 2011).

Information filtering techniques are basically categorized into three types, Content-based Filtering, Collaborative Filtering and Hybrid Filtering. Content-based Filtering mainly analyzes the types of content, and compare with user's behavior and record in the past time, to find out the item the user may need in the future time (Belkin and Belkin 1992; Roy and Mooney 1999; Chien 2004). However, there may be some problem in the process of content-based filtering such as unclear definition of items, over-specialization problem, which indicates that content-based filtering can only analyze the data generated from past time and do not have the ability to recommend the item that user never accesses, or lower participant. Therefore, different from content-based filtering, collaborative filtering focuses on the compare of behavior similarity between users. Because it thinks that if people had some kinds of interests in the past time, he may keep up with them in the future, and system can categorize them into different categories according to their interests or specific behaviors (Cheng et al. 2012; Kenteris et al. 2010). For different categories of users, system can provide them different types of recommend items to fit their interests (Miller et al. 1997; Dumais et al. 1998; Sarwar et al. 2001). In collaborative filtering, the main problem is the lack of user information or data set, which makes the system unable to compare and analyze for the categorization. This kind of problem is called "Cold Star" or "Start Up" problem and needs to be solved by random recommendation or consider other features to categorize users (Huayue 2012; Song et al. 2011). Hybrid Filtering, or so-called Knowledge-based Filtering, combines the two methods and takes the advantage of them to have a better result of recommendation (Pin-Yu et al. 2010; Burke 2002). In the past time, recommendation system is mainly applied in the E-commerce system such as online shopping website, which can analyze user purchase records and browsing behaviors to predict user's requirements and interests and find out the related items for the user. Some other kinds of business applications start to use the recommendation mechanism such as music, books or movie (Jonghun et al. 2011).

In this Internet generation, E-learning uses the power of Internet and provides abundant learning content to user and it faces the same problem of information overload. Therefore, recommendation system plays an important role in nowadays E-learning system, especially for the Open Course Ware, the pure online learning environment that has no instructor for advice. Course recommendation systems adopts different information filtering techniques and mainly use the data of user's background or learning portfolio (Lu 2004; Chen et al. 2005; Khribi et al. 2008) to analyze and induce user's interests or type, and recommend related content according to the analysis result. In recent years, the rapid growth of social networks and social network site bring something new to the research of recommendation system. Except for the traditional way of recommendation, which takes user's interests or previous records as a base to run the recommendation procedure, some online video or multimedia websites uses the social relationship such as the number of click or follower to adjust the recommendation result (Van Den Berg et al. 2007; Zhi et al. 2013; Zhenyu et al. 2013). This makes the researches of recommendation system start to notice the impact of social relationship, instead of focusing on user's information only.

2.2 Museum guide/navigation system

Most modern navigation relies primarily on positions determined electronically by receivers collecting information from satellites. Most other modern techniques rely on crossing lines of position or LOP (Sarwar et al. 2001). A line of position can refer to two different things: a line on a chart and a line between the observer and an object in real life. A bearing is a measure of the direction to an object (Deneubourg et al. 1990). If the navigator measures the direction in real life, the angle can then be drawn on a nautical chart and the navigator will be on that line on the chart. In addition to bearings, navigators also often measure distances to objects. On the chart, a distance produces a circle or arc of position. Circles, arcs, and hyperbolae of positions are often referred to as lines of position

With the navigation system in museum, it had been developed for a period because of the developed of wireless network, such as RFID, NFC, WIFI, GPS, Bluetooth and so on (Gavalas et al. 2011). The outcome is such as interactive tour-guide robot. It presents a modular and distributed software architecture, which integrates localization, mapping, collision avoidance, planning, and various modules concerned with user interaction and Web-based telepresence (Burgarda et al. 1999) and a museum guide system which is based on handheld devices which provides visitors good visual and audio experience with multimedia technologies (Wang et al. 2007), also a guide system for kids in museums. It uses a sensing board which can rapidly recognize types and locations of multiple objects, and creates an immersive environment by giving users visual and auditory feedback to their manipulations on the board (Kusunoki et al. 2002). Another application about e-learning, mobile guide systems (or electronic guidebooks) have also been adopted in museum learning, including those that combine learning strategies and the general audio–visual guide systems (Sung et al. 2010).

3 Adaptive recommendation system

3.1 Navigation path optimization

Designing a navigation path recommendation system that is intelligent and being capable of detecting the navigation status of visitors for efficient compensation has been a common issue. Developing adaptive navigation path for visitors with different capabilities and backgrounds has been a trend. To increase visitors' speed for navigating in a museum and diversities in navigation object selection, we propose the navigation concept map, reasonable navigation path, and navigation path optimization algorithm of adaptive recommendation systems to help visitors navigate museums efficiently and effectively.

We adopt the knowledge structure of course contents relevance and learner's knowledge patterns architecture analysis method that is based on knowledge space cognitive assessment (Doignon and Falmagne 1985; Albert and Lukas 1999) to infer the navigation concept map for navigation objects relevance in each navigation group. The navigation concept map is then used as the basis for inferring the navigation tree of reasonable navigation order. As shown in the example of Fig. 1, assume there are four navigation objects of tree relationship based on their relevance, parent nodes must be viewed before child nodes. For example, to navigate object numbered O_4, one has to navigate objects O_2 and O_1 in advance. To navigate object numbered O_2, then has to navigate objects O_1, for the same reason.

We can gradually deduce the set of all navigation objects architecture from an empty with no navigation object, and link to a number of different navigation path. Therefore, from the above example, it can be inferred many navigation paths and associations, as shown in Fig. 2.

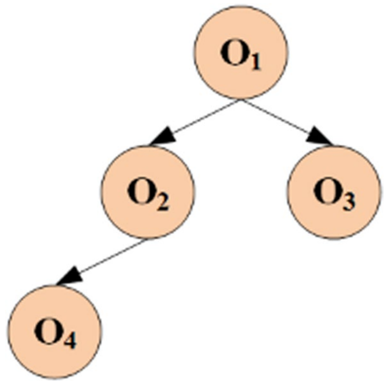

Fig. 1 An example of concept map of navigation objects

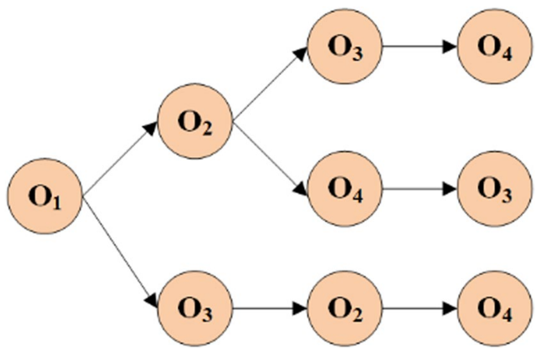

Fig. 2 Navigation paths of objects

For each navigation path or concept map of navigation objects, a parent navigation node is always the basis of all of its children navigation nodes except the root navigation node, and they are extended and reached root navigation node which is the basis of children navigation node. Therefore, a child navigation node has heavier relevance with its parent navigation node. The parent navigation node then has higher navigation weight, and the navigation weight is extended and reached root navigation node which has relative lighter navigation weight rate according to the child navigation node, for the same reason.

Definition 1 Assume there are N navigation objects numbered from O_i with i = 1, 2, 3, …, N. Based on the analysis of the navigation concept map, we have the hierarchical relationship concept diagram of the combination of navigation states. We then define the reasonable navigation path (NP) consisted of N navigation objects as $\mathbf{NP = (O_1 \rightarrow O_2 \rightarrow \ldots \rightarrow O_i \rightarrow \ldots \rightarrow O_N)}$, O_i represents the i-th navigation object.

Definition 2 Assume the navigation order of N navigation objects is encoded as (O_1, O_2, …, O_i, …, O_N) based on Definition 1, then the relation weight (RW) of every navigation object O_i and all navigation objects is represented as an 1 × N hierarchical matrix $RW_{O_i} = [W_{O_i\_O_1}, W_{O_i\_O_2}, \ldots, W_{O_i\_O_i}, \ldots, W_{O_i\_O_N}]$. The values within matrix RW_{O_i} are expressed the relation rates of the navigation object O_i with the relative order of every navigation object (O_1, O_2, …, O_i, …, O_N), and $0 \le W_{O_i\_O_1}, W_{O_i\_O_2}, \ldots, W_{O_i\_O_i}, \ldots, W_{O_i\_O_N} \le 1$. The "$W_{O_i\_O_1}$" then expresses the relation ratio values of navigation object O_i and O_1, for the same reason.

Each relation ratio in relation weight (RW) of every navigation object O_i represents how much rate of concept does come from the other navigation objects, that is to say, the values of relation ratio between the navigation object Oi and all navigation objects. Therefore, the relation ratio between the navigation node and itself is 1, which is the highest. The relation ratio between the navigation node and its parent navigation node is higher. But the relation ratios between the navigation node and the other navigation nodes are relatively lower and with all its child navigation nodes will be 0, which is the lowest. Accordingly, it can be seen that the relation weight (RW) of navigation object O_1 is regard as $RW_{O_1} = [W_{O_1\_O_1}, W_{O_1\_O_2}, \ldots, W_{O_1\_O_i}, \ldots, W_{O_1\_O_N}]$, the relation weight (RW) of navigation object O_2 is regard as $RW_{O_2} = [W_{O_2\_O_1}, W_{O_2\_O_2}, \ldots, W_{O_2\_O_i}, \ldots, W_{O_2\_O_N}]$, so to the relation weight (RW) of navigation object O_N is regard as $RW_{O_N} = [W_{O_N\_O_1}, W_{O_N\_O_2}, \ldots, W_{O_N\_O_i}, \ldots, W_{O_N\_O_N}]$.

As a result, based on the navigation concept map, we can analyze N navigation objects and obtain all navigation paths with reasonable navigation order. The best navigation order can be acquired with the relation weight (RW) between all pairs of navigation objects.

Definition 3 For N navigation objects with the navigation order (O_1, O_2, …, O_i,…, O_N), following Definition 1 and Definition 2, if there is a navigation path in which the navigation order of two adjacent navigation objects is defined as $O_t \rightarrow O_{t+1}$,t = 1, 2, 3, …, N − 1, and the relation weight (RW) of O_t, O_{t+1} and all navigation objects are defined as $RW_{O_t} = [W_{O_t\_O_1}, W_{O_t\_O_2}, \ldots, W_{O_t\_O_t}, W_{O_t\_O_{t+1}}, \ldots, W_{O_t\_O_N}]$ and $RW_{O_{t+1}} = [W_{O_{t+1}\_O_1}, W_{O_{t+1}\_O_2}, \ldots, W_{O_{t+1}\_O_t}, W_{O_{t+1}\_O_{t+1}}, \ldots, W_{O_{t+1}\_O_N}]$, then

1. The navigation relation value (NRV) of navigating order from O_t to O_{t+1} is defined as the sum of product terms (SOP) of relative relation ratio value in the two matrixes of relation weight (RW) between O_t and O_{t+1}. It is expressed as:

$$\mathrm{NRV}(\mathrm{O}_t \rightarrow \mathrm{O}_{t+1}) = (W_{\mathrm{O}_t\_\mathrm{O}_1} \times W_{\mathrm{O}_{t+1}\_\mathrm{O}_1}) + (W_{\mathrm{O}_t\_\mathrm{O}_2} \times W_{\mathrm{O}_{t+1}\_\mathrm{O}_2}) + \cdots + (W_{\mathrm{O}_t\_\mathrm{O}_t} \times W_{\mathrm{O}_{t+1}\_\mathrm{O}_t})$$
$$+ (W_{\mathrm{O}_t\_\mathrm{O}_{t+1}} \times W_{\mathrm{O}_{t+1}\_\mathrm{O}_{t+1}}) + \cdots + (W_{\mathrm{O}_t\_\mathrm{O}_N} \times W_{\mathrm{O}_{t+1}\_\mathrm{O}_N}) = \sum_{i=1}^{N} W_{\mathrm{O}_t\_\mathrm{O}_i} \times W_{\mathrm{O}_{t+1}\_\mathrm{O}_i}$$

2. For each navigation path, we can translate it into the sums of navigation relation value (NRV) with two adjacent navigation objects. It is expressed as:

$$\sum_{t=1}^{N-1} NRV(\mathrm{O}_t \to \mathrm{O}_{t+1}) = \sum_{t=1}^{N-1}\sum_{i=1}^{N} W_{\mathrm{O}_t\_\mathrm{O}_i} \times W_{\mathrm{O}_{t+1}\_\mathrm{O}_i}$$

3. The navigation path with the highest value of navigation relation value (NRV) is defined as the best navigation path, and the max value of navigation relation value (NRV) is defined as

$$Max\left(\sum_{t=1}^{N-1} NRV(\mathrm{O}_t \to \mathrm{O}_{t+1})\right) = Max\left(\sum_{t=1}^{N-1}\sum_{i=1}^{N} W_{\mathrm{O}_t\_\mathrm{O}_i} \times W_{\mathrm{O}_{t+1}\_\mathrm{O}_i}\right)$$

Therefore, if we want find out a best navigation order from these known reasonable navigation orders, such as the example of Figs. 1 and 2. There are four navigation objects as the arrangements of (O_1, O_2, O_3, O_4) that form binary trees based on the inference of navigation concept map. If the Relation Weight (RW) of every navigation object is separately regarded as

$RW_{O1} = [1, 0, 0, 0]$
$RW_{O2} = [0.5, 1, 0.3, 0]$
$RW_{O3} = [0.6, 0.2, 1, 0.1]$
$RW_{O4} = [0.2, 0.5, 0.1, 1]$

Thus, the sums of navigation relation value (NRV) based on Definition 3 for every recommended navigation path are respectively calculated as

1. $NRV(O_1 \to O_2 \to O_3 \to O_4) = \{(1 \times 0.5)+(0 \times 1)+(0 \times 0.3)+(0 \times 0)\} + \{(0.5 \times 0.6)+(1 \times 0.2)+(0.3 \times 1)+(0 \times 0.1)\} + \{(0.6 \times 0.2)+(0.2 \times 0.5)+(1 \times 0.1)+(0.1 \times 1)\} = 0.5+0.8+0.42 = 1.72$
2. $NRV(O_1 \to O_2 \to O_4 \to O_3) = \{(1 \times 0.5)+(0 \times 1)+(0 \times 0.3)+(0 \times 0)\} + \{(0.5 \times 0.2)+(1 \times 0.5)+(0.3 \times 0.1)+(0 \times 1)\} + \{(0.2 \times 0.6)+(0.5 \times 0.2)+(0.1 \times 1)+(1 \times 0.1)\} = 0.5+0.63+0.42 = 1.55$
3. $NRV(O_1 \to O_3 \to O_2 \to O_4) = \{(1 \times 0.6)+(0 \times 0.2)+(0 \times 1)+(0 \times 0.1)\}+\{(0.6 \times 0.5)+(0.2 \times 1)+(1 \times 0.3)+(0.1 \times 0)\} +\{(0.5 \times 0.2)+(1 \times 0.5)+(0.3 \times 0.1)+(0 \times 1)\} = 0.6 + 0.8 + 0.63 = 2.03$

So, the sum of navigation relation value (NRV) from $NRV(O_1 \to O_3 \to O_2 \to O_4)$ is the max value 2.03, then the navigation path of "$O_1 \to O_3 \to O_2 \to O_4$" is the best recommended navigation path, as shown by Fig. 3.

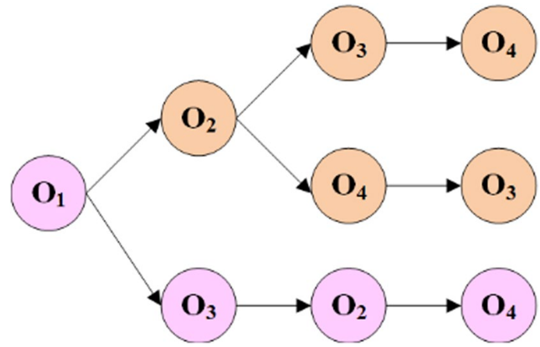

Fig. 3 The best recommended navigation path

3.2 System structure and procedure

For the recommend system in our research, we wanted to provide more personalized and adaptive content for visitors to a work of art. The personalized content may be based on user background, interests, visitation history or users with a similar background/visiting history.

For the exhibition/museum guide system in our study, we established a database of works of art using the Dublin Core and CDWA methods. Visitors must submit some of their personal data to the recommendation system before using it. The recommendation system evaluates this personal data using the BAR method and then finds works of art to recommend to the visitor. Visitors receive information on recommended works of art via mobile devices during their visit.

The mobile device's recommendation system also allows the visitor to rate the works of art after their visit. The results of this rating are then considered for further recommendations. As visiting history grows and the number of ratings increases, the more precise the recommendation system's BAR evaluation will be.

3.3 Database establishment

The recommendation system database included the following tables: art_multimedia, art_content, art_museum, art_relation, type, user_relation, user_experience, and user_portfolio.

Using CDWA, the table art_multimedia stored multimedia content related to a specific work of art; the table art_content stored detailed information on the works of art, including title, artist, year, type, location, dimensions, rating, and description; the table art_museum stored museum information and the museum's works of art; the table user_portfolio stored the visitor's personal information, including name, password, gender, e-mail address, birthday, occupation, educational degree, educational major, and interests; the table type stored information on the types in the system; the table art_relation stored information on the types of works of art in the exhibition; the table user_relation stored relationships between the visitor and the works of art. If the visitor liked a work of art and marked it in the system, this was stored in this table. Figure 4 represents the database structure of the recommendation system.

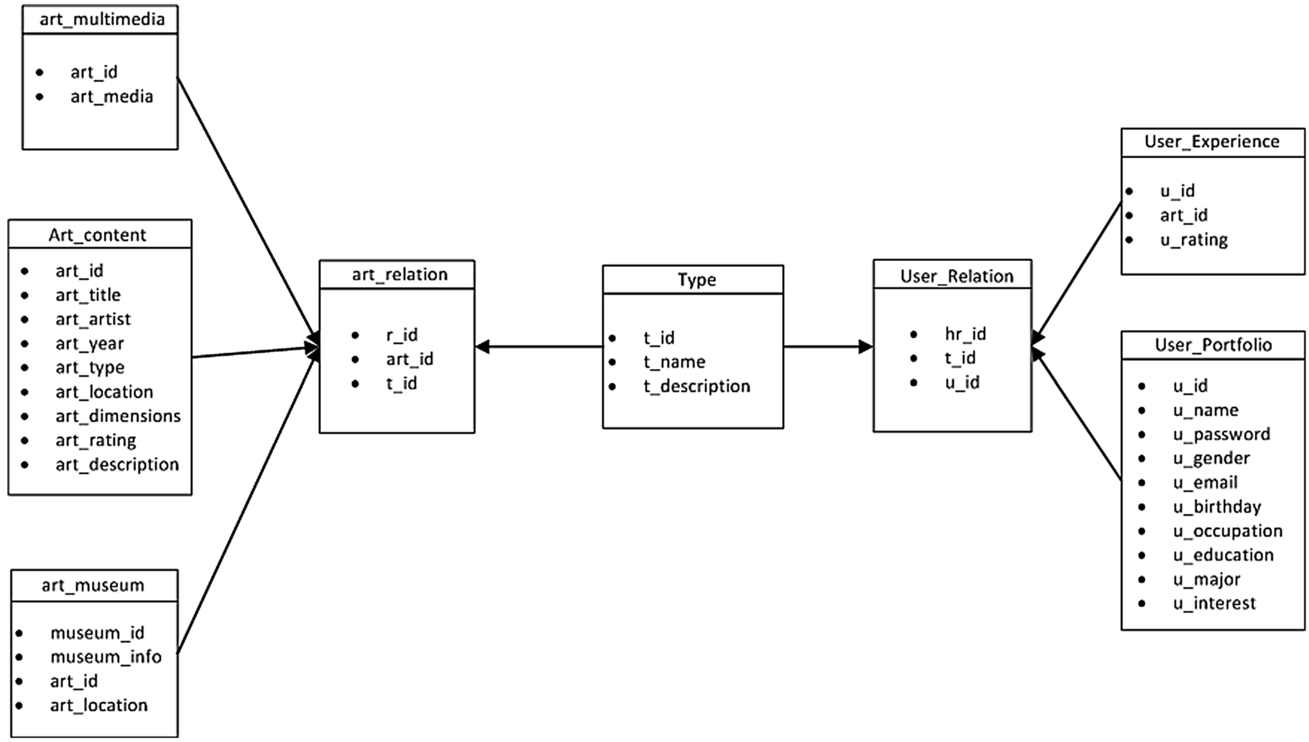

Fig. 4 Database structure of the recommendation system

Figure 5 below is the process flow of the database. Our research proposed two main database structures, a user database and art database. The user database is mainly store user related date and are divided into two database, user portfolio and user experience. The art database mainly stored information related to works of art and was divided into three databases: art content, museums, and multimedia. In the system the two databases were constantly connected to one another. When users logged into the recommend system, their portable devices would send local visitor data to the database to ensure that visiting history was completely synchronized with the database. In the museum, RFID technology was used to detect current work of art that the user was currently visiting. At the same time, the database would send all information on the work of art and user information to the system, and provide adaptive and personalized content to the user. After the visit, all related information would be sent back to the database, such as rating data.

3.4 Personalized content for visiting users

Different users may have different reasons for visiting a museum—some users just want to browse the works of art in the museum, while others may want to study the works of art in very great detail. Hence, this study provides personalized content on mobile devices for users of different backgrounds to visit the museum. We also provide a multimedia guide on mobile devices to enhance the completeness of the recommend system.

When users first use the system, the system requires that they submit personal data to allow the system to create a user portfolio and recommendations. Additionally, several studies indicate that different types of content may affect the efficiency of user comprehension. For example, some people like to read text-based content, while but others may like audio or video content. Our study held that utilizing users' preferred content on a mobile device would enhance their interest and comprehension efficiency. In the recommendation system, users can select their preferred content type when registering in the system, and they can later change this in the system settings. Figure 6 below shows the personalized multimedia content with audio and video.

For visitors who are not familiar with the works of art in the museum, the system also provides recommendations to the user. If the user does not have a history of previous visits, the system will recommend the most popular works of art to the user. If the user has a visiting history, the system will follow their previous ratings. The system utilizes a ratings scale of 1 through 5 stars, with 1 star being the lowest rating and 5 stars being the highest rating. If a user does not rate a work of art after visiting, the text "Rate this object" will appear next to the stars. For the recommendation mechanism, our research assigned different weighting to each star rating. 5 stars

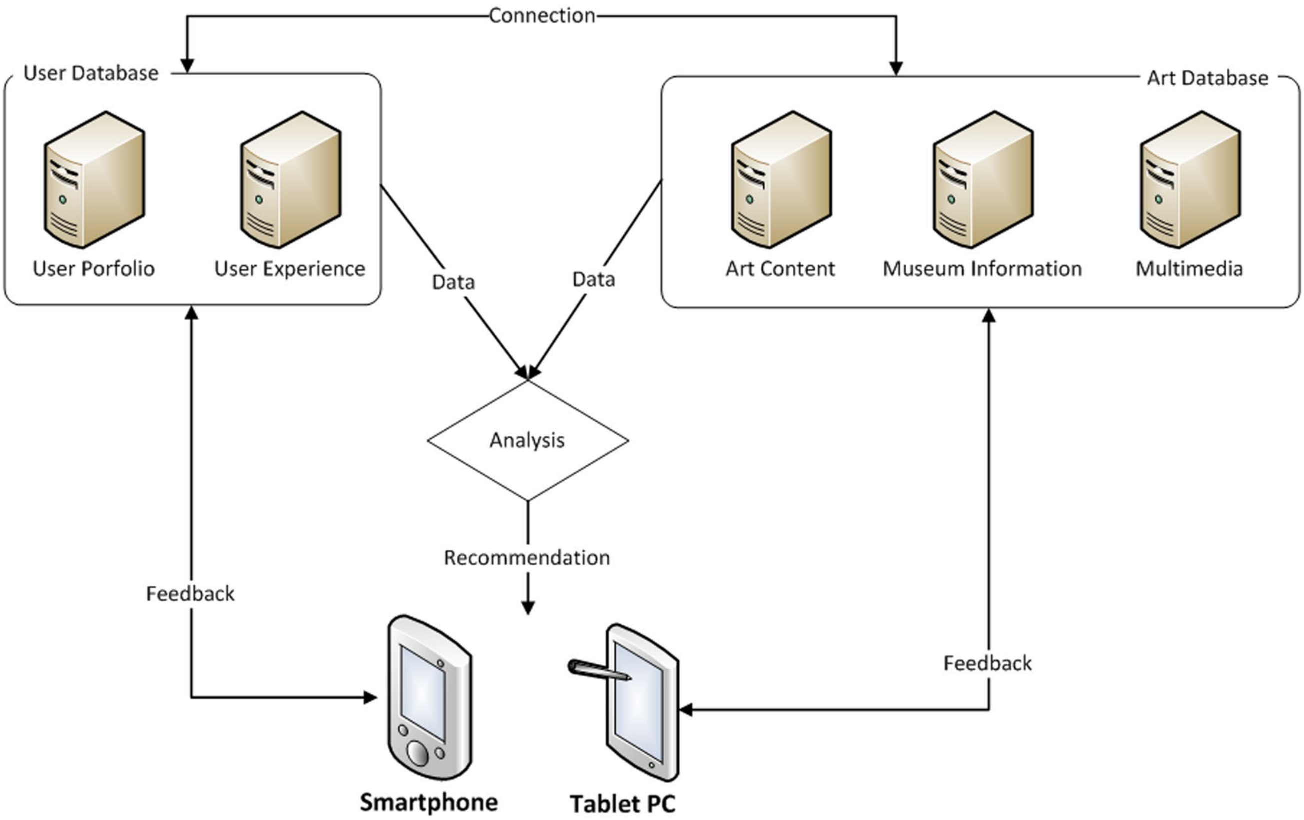

Fig. 5 Database process flow

Fig. 6 Personal multimedia content on mobile device (audio and video)

indicated a weight value of 1; 4 stars indicated a weight value of 0.8; 3 stars indicated weight value 0.6; 2 stars indicated a weight value of 0.4; and 1 star indicated a weight value of

Table 1 The visiting history with average rating for a specific user

Item	Content	Average rating	Visiting times
Artist	***Da Vinci***	***0.85***	***4***
Artist	Jean-François Millet	0.7	2
Artist	Monet Claude	0.67	3
Artist	Michelangelo	0.67	3
…	…	…	…
Type	***Fresco***	***0.93***	***3***
Type	Oil on Paper	0.84	5
Type	Oil on canvas	075	4
Type	Oil on wood	0.67	3
…	…	…	…
Style	***Renaissance***	***0.77***	***6***
Style	Baroque	0.7	4
Style	Gothic	0.67	3
…	…	…	…
Year	***15 Century***	***0.85***	***4***
Year	16 Century	075	4
Year	17 Century	0.74	3
Year	19 Century	0.67	3
…	…	…	…

The item with bold and italic means the most high score in averaging rating

Fig. 7 The recommend content on mobile device

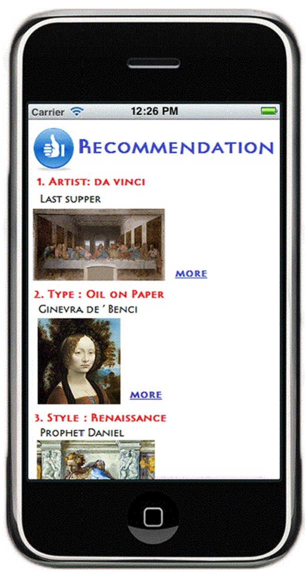

Fig. 8 The recommend work of art from average rating

0.2. Information is recorded using the rating system for the work of art currently being visited. For example, a visitor might be currently visiting the Mona Lisa and give it 4 stars. Information on the Mona Lisa would be (1) Artist: Da Vinci, (2) Type: Oil on Paper, (3) Style: Renaissance (4) Year: 16th century. The information would be given a weight value of 0.8 for Da Vinci, Oil on Paper, 16th century, and small size. Hence, the greater a user's visiting experience, the more accurate his/her recommendation will be. For further example, for a user Jason who has already visited many works of art, his visiting history with ratings would be as follows:

Table 1 indicates the user Jason's visiting history and rating history. The system records the user's rating and time of visiting by artist, type, style and year. When a user visits the museum, the system will obtain the most highly rating item from the database. For example, in Table 1, when the user visits a museum, the system obtains the highest average rated items by artist, type, style and year. It will match the highest average rated items with works of art in the current museum to determine if it contains works of art from the corresponding artist, type, style, and year. If so, the system will recommend those works of art to the user. If there are no matching works of art, the system will recommend the most popular works of art in the museum to the user. An example is shown in Figs. 7 and 8.

3.5 Best appropriate recommendation method

The BAR method includes two phases: (1) when the visitor initially establishes his/her personal data, BAR determines their initial weights for recommendation; (2) when the visitor rates a work of art, BAR evaluates the attributes of the work and the user's personal data to update the weights for more precise recommendations. The following Table 2 indicates how the weight evaluate on user's data.

In Phase 1, we first evaluate the weights using the following variables of personal data:

```
UA  user's age
UD  user's education degree
UI  user's interest
UE  user's occupation
UH  user's major
WUA weight of user's occupation
WUD weight of user's major
WUI weight of user's interest
WUE weight of user's occupation
WUH weight of user's major
```
$P=\{H_i \mid 1 \le i \le n\}$ a set of user_portfolio database where Hi means the ith human data from human_portfolio database.

The user's age is divided into 3 intervals: less than 19, 20–40, and greater than 40, and we assign a weight of 1, 2, or 3 to each interval respectively. The user's educational

Table 2 The weight of user's data

Item\value	+1	+2	+3	+4	+5
Age (WUA)	0–19	20–39	39~	None	None
Education (WUD)	Primary school	Junior high school	Senior high school	College	Others
Interest (WUI)	No related	Art related	None	None	None
Occupation (WUE)	No correlation	Partial correlation	Perfect correlation	None	None
Major (WUH)	No correlation	Partial correlation	Perfect correlation	None	None

```
Input  user's personal data values in database

Output user's weight values WP

Set new user, WP = 0, WUA = 0, WUD = 0,

WUI = 0, WUE = 0, WUH = 0

// evaluate weight of user's age

If  0<UA≤19

   WUA = WUA + 1

else If  20≤UA≤39

   WUA = WUA + 2

else

  WUA = WUA + 3

// evaluate weight of user's education degree

If  UD = "primary school"

   WUD = WUD + 1

else If  UD = "junior high school"

   WUD = WUD + 2

else If  UD = "senior high school"

WUD = WUD + 3

else If  UD = "college"

   WUD = WUD + 4

else

WUD = WUD + 5

// evaluate weight of user's interest

If  UI = art related options

WUI = WUI + 2
else

WUI = WUI + 1

// evaluate weight of user's occupation
If UE = "perfect correlation"
WUE = WUE + 3

Else if UE = "partial correlation"

WUE = WUE + 2

Else if  UE = "no correlation"

WUE = WUE + 1

//evaluate weight of user's major of education

If UH = "perfect correlation"

WUH = WUH + 3

Else if UH = "partial correlation"

WUH = WUH + 2

Else if  UH = "no correlation"

WUH = WUH + 1

// add all weights

WP = WUA + WUD + WUI + WUE + WUH

Store  WP to user's profile
```

degree is classified by primary school, junior high school, senior high school, college, or vocational school, and we assign a weight from 1 to 5 for each degree respectively. Options for user interests include art, music, sports, etc., divided into art-related and non-art-related, and assigned a weight of 2 and 1 respectively. The user's occupation and educational major are classified by following three levels: (1) perfectly correlated with art, (2) partially correlated

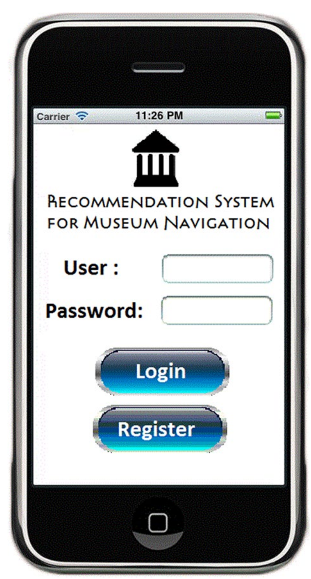

Fig. 9 Login interface

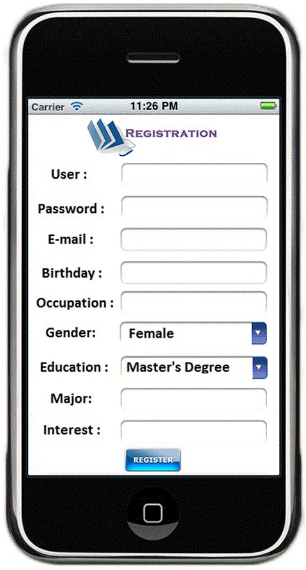

Fig. 10 Registration Interface

with art, (3) non-correlated with art, and assigned a weight of 1, 2, or 3 respectively.

Initial weights are evaluated in Phase 1 based on which the recommendation system recommends works of art to the visitor. The visitor then marks some works of art that he/she likes. When the visitor visits an exhibition and marks some works of art that he/she likes, the recommendation system receives these rankings and a BAR evaluation is used to update the visitor's weights. This method is described in Phase 2 of the BAR method. Some definitions of variables used in Phase 2 are as follows.

$A=\{A_i \mid 1 \le i \le n\}$ set of art database where Ai means the ith author data from author database.

$S=\{S_i \mid 1 \le i \le n\}$ a set of art database where Si means the ith style data from style database.

$MAI=\{VA_i \mid VA_i \in A, 1 \le i \le k\}$ author' s identification of the work of art which user marked

$MSI=\{VS_i \mid VS_i \in S, 1 \le i \le k\}$ style identification of the work of art which user marked

$RAI=\{RA_i \mid 1 \le i \le n\}$ Record the frequency of author' s identification of the work of art which user marked

$RSI=\{RS_i \mid 1 \le i \le n\}$ Record the frequency of style identification of the work of art which user marked

---

In Phase 2 of the BAR method, when the visitor marks a work of art, the recommendation system retrieves its author and style attributes from the database. After the visitor finishes with his/her visit, the recommendation system evaluates which author and style the visitor graded the highest, and then stores this information in the visitor's database. Therefore, when the visitor visits another exhibition, the recommendation system can make good recommendations using these data.

3.6 Linking semantic web

During the visit, the mobile device carried by the visitor can receive the marks he/she assigns and provide the visitor with information and recommendations of works of art. Moreover, by using the techniques of semantic web and wireless networking, the visitor can receive more information through the mobile device by connecting to other websites. The Semantic Web is a collaborative movement led by the international standards body, the World Wide Web Consortium (W3C 2011) The standards body promotes common data formats on the World Wide Web. By encouraging the inclusion of semantic content in web pages, the Semantic Web aims at converting the current web—dominated by unstructured and semi-structured documents—into a "web of data". The Semantic Web stack builds on the W3C's Resource Description Framework (RDF). According to the W3C, "The Semantic Web provides a common framework that allows data to be shared and reused across application, enterprise, and community boundaries." (Berners-Lee et al. 2001) The following is the method of integrating the semantic web with the BAR method.

```
Input  user marked author MAI,
user marked style MSI
Output the highest author and style value
For i = 1 to i = k  do
Set  RAi = 0, RSi = 0

// count the frequency of authors and styles that the
visitor marked
For i = 1 to i = k  do
For j = 1 to j = n  do
IF  VAi = Aj  do  RAi += 1
IF  VSi = Sj  do  RSi += 1
// find which author and which style that the visitor
likes most
```

$$RAI_{\max} = \arg\max \{RA_i \mid 1 \le i \le n\}$$
$$RSI_{\max} = \arg\max \{RS_i \mid 1 \le i \le n\}$$

```
Store  RAImax, RSImax
```

4 Interfaces of the appropriate recommendation system

4.1 System interface

The visitor must first log into the appropriate recommendation system to use the system. The system will generate the visitor's database and store the visitor's information. The login interface of the recommendation system is shown in Fig. 9. When a visitor first uses the appropriate recommendation system, he/she must enter some personal

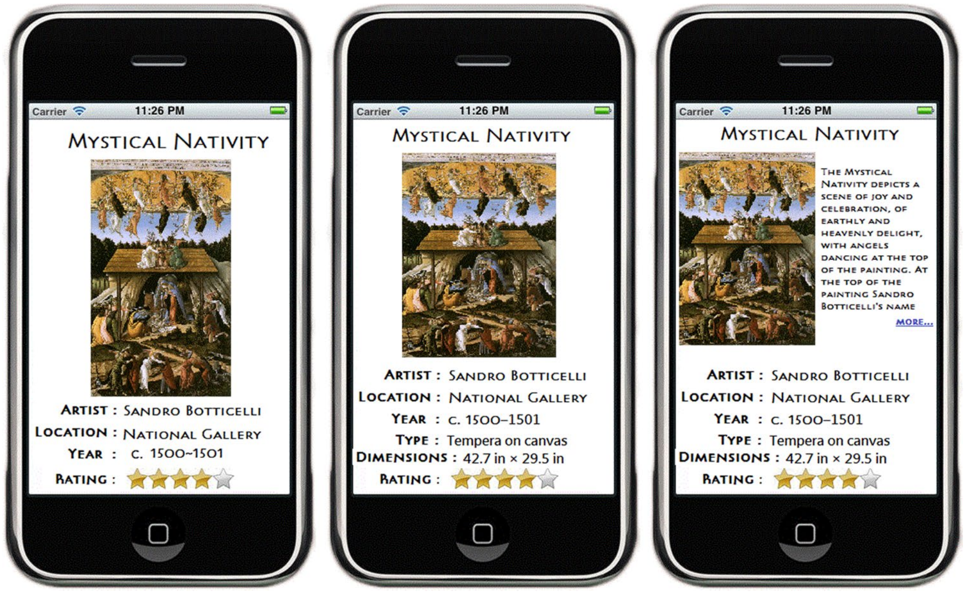

Fig. 11 Information shown to different level visitor on mobile device

Fig. 12 Another example of information shown to different level visitor on mobile device

information to complete the registration process. The registration interface is shown in Fig. 10.

When the visitor completes the registration process, the appropriate recommendation system will evaluate the visitor's personal information using the BAR method to generate the visitor's weight. Then visitors are classified into 3 groups: high-end visitors, mid-end visitors, and low-end visitors. A visitor is classified as a high-end visitor if his/her personal weight is between 10 and 13; a visitor is classified as a mid-end visitor if his/her personal weight is between 6 and 9; a visitor is classified as a low-end visitor if his/her personal weight is between 1 and 5.

The appropriate recommendation system shows different information on a work of art to a visitor depending on the group to which the visitor belongs. For a high-end visitor, the recommendation system shows all the information on the work of art on the visitor's mobile device, including a detailed description and the title, artist, year, type and dimensions of the work. For a mid-end visitor, the recommendation system shows some information on the work of art on the visitor's mobile device, including the title, artist, year, type, location, year and dimensions of the work. For a low-end visitor, the recommendation system shows basic information on the work of art on the visitor's mobile device including the title, artist, location and year of the work. Figures 11 and 12 are examples of the information shown to different types of user. The left screen is a low-end visitor, the middle is a mid-end visitor, and the right is a high-end visitor.

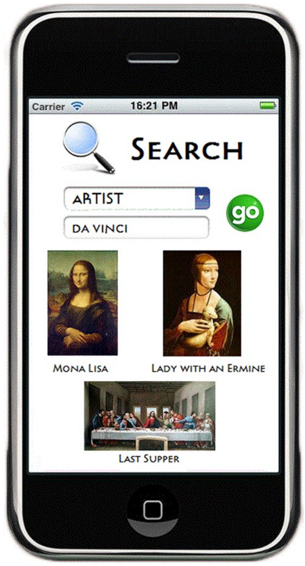

Fig. 13 Searching interface on mobile device

Additionally, the recommendation system also features a search function. In this function, we provided the ability to search for works of art by keywords and according to, artist, type, style, year and museum. Users need only enter a keyword into the smartphone and select the items they wish to search for. The results will be listed on the screen. Figure 13 show the search function interface of the recommendation system.

The bottom of the interface also provides visitors with the ability to note whether or not he/she likes the work of art. As described above, this information will be retrieved by the system and evaluated in Phase 2 of the BAR method to generate and update the user's personal information. Therefore the appropriate recommendation system will provide suitable information to the visitors.

4.2 Comparison to other navigation systems

Recently many methods for mobile navigation have been introduced, including navigation by staff, navigation by paper notes, navigation by voice and navigation by multimedia. The mobile devices used in all types of navigation mostly use RFID technology. These navigation systems using RFID belong to passive navigation systems—that is, the visitor obtains exhibition information by tracking the mobile device itself. The appropriate recommendation system we designed is an active system, in which the visitor obtains information and marks his/her opinions on the works of the art. The system also recommends works of art to the visitor by using his/her personal information and opinions.

In contrast with most recent navigation systems using RFID devices, the appropriate recommendation system we designed can be used on most popular mobile devices, e.g., smart phones, PDAs, notebooks, iPads, etc. Visitors can install the recommendation system on their own mobile devices and use it at any exhibitions, provided the exhibition information is in the system database.

The appropriate recommendation system provides information depending on the visitor group—this differs from most recent navigation systems, which provide all information to all visitors. Instead, the appropriate recommendation system provides suitable information to the visitors. Table 3 lists the comparison of the appropriate recommendation system and the other navigation systems.

Table 3 Comparison of appropriate recommendation system and other navigation system

	Recent navigation system	Appropriate recommendation system
Mobile device	Specified RFID devices	Popular personal mobile devices
Content provide	Passive	Active
Content	All information to all visitors	Information depending on visitor group

Table 4 The Questionnaire Survey

Item	Ratings				
I. General opinion					
I think enabling recommendation in an museum guide system can facilitate the visiting process	1	2	3	4	5
I think enabling more interactions in implemented system can motivate users	1	2	3	4	5
I am willing to acquire related knowledge & information in an recommendation system	1	2	3	4	5
I am willing to share information (e.g., knowledge, expertise, etc.) with others to lead more related information in museum	1	2	3	4	5
II. Recommend mechanisms & multimedia content					
I can receive more useful information for visiting in the implemented system	1	2	3	4	5
I can obtain extra information correlated to a specific art in the implemented system	1	2	3	4	5
I can improve my visiting performance in museum through the recommendation system	1	2	3	4	5
The recommended multimedia content attract me to use it more in specific art	1	2	3	4	5

Table 5 The results of questionnaire survey

Item no.	Scores	Average scores
Part I		
Question 1	4.88	4.36
Question 2	4.53	
Question 3	4.28	
Question 4	3.75	
Part II		
Question 1	4.52	4.33
Question 2	4.12	
Question 3	4.41	
Question 4	4.26	

4.3 Questionnaire survey

After using the implemented recommended system in museum, we also provided a e-survey to let user filled questionnaire on mobile device. The questionnaire form is in following table. The following Table 4 is the content of our questionnaire survey and the Table 5 is the results of questionnaire survey.

In this questionnaire, we have 82 people (43 female and 39 female), Their average age is 34.6. The results reveal that most people agree that the recommendation mechanism and interactions in an online recommended system may assist their visiting process. As to the implemented system in Part 2, we receive a positive result, around 4.33 score in 5 in average, which shows that proposed automated mechanisms and multimedia content may meet the needs of visiting.

5 Conclusion and future work

For a leisure-centric generation, leisure activities are the increasing focus of many users. Using mobile device navigation systems in leisure activities has recently become very popular for exhibitions and museums. With the progress of wireless technology, the semantic network technique and personal mobile devices have also become well-developed. Visitors can obtain more information using mobile devices than ever before. In this study, the proposed appropriate recommendation system provides adaptive and personalized information on works of art to visitors according to their specific background and visiting history stored on their own mobile devices.

The appropriate recommendation system could be improved by integrating the visitors' own experiences into the BAR method evaluation, such that the system recommends works of art to visitors more precisely. The appropriate recommendation system could be extended to a community system. Visitors could share and exchange their experiences and interact more with the exhibitions or museums in the system. These are all for future studies.

In the future, we plan to integrate location-based information technology such as GPS and NFC into our system. Doing so will enable devices to provide more detailed and personalized information for users to conduct their leisure activities.

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