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A Personalized Multimedia Contents Recommendation Using a Psychological Model

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Abstract. With the development and diffusion of compact and portable mobile devices, users can use multimedia content such as music and movie on personal mobile devices, anytime and anywhere. However, even with the rapid development of mobile device technology, it is still not easy to search multimedia content or manage large volume of content in a mobile device with limited resources. To resolve these problems, an approach for recommending content on the server-side is one of the popular solutions. However, the recommendation in a server also leads to some problems like the scalability for a lot of users and the management of personal information. Therefore, this paper defines a personal content manager which acts between content providers (server) and mobile devices and proposes a method for recommending multimedia content in the personal content manager. For the recommendation based on user's personal characteristic and preference, this paper adopts and applies the DISC model which is verified in psychology field for classifying user's behavior pattern. The proposed recommendation method also includes an algorithm for reflecting dynamic environmental context. Through the implements and evaluation of a prototype system, this paper shows that the proposed method has acceptable performance for multimedia content recommendation.

Keywords: Multimedia Content Recommendation, Personalization, DISC Model, Dynamic Environmental Context.

1. Introduction

Recently, a great deal of information has become available and many people are sharing that information on the Internet thanks to the development of Internet technology. People can download and enjoy desired content conveniently, as multimedia content (music, video, pictures, etc.) have been

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digitized. In addition, personal computers can now store large volume of multimedia content with growth of computer performance. Many kinds of mobile devices are developed. In this environment, users want to use a multimedia content through a personal mobile device, anytime and anywhere. In IPTV application which is one of the applications for a multimedia content service, a user purchases a variety of multimedia content from a content service provider and stores that into a personal Set-Top Box. And then the user uses the stored content through personal mobile devices without a dependence on time and position.

In this environment, a user hopes to search and acquire multimedia content efficiently. Furthermore, the user expects that a mobile device automatically searches and proposes a customized content for the user. For these requirements, of course, it is the best solution to store all multimedia content in a personal mobile device, but that is unrealistic because of the storage-size problem of the mobile device. Another solution for acquiring a customized content is to access a content service provider through a personal mobile device directly. However this approach is not easy because the mobile device has limited resources like inconvenient I/O and tiny display. Moreover the content service provider should consider the searching and recommending service for many users. Therefore there are some problems like the scalability for a lot of users and the management of personal information.

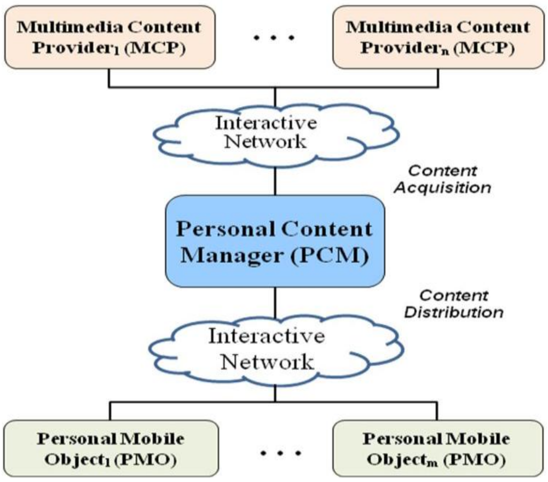


Fig. 1. Multimedia content service environment

This paper proposes the method to infer a multimedia content in a personal content manager (PCM) and recommend to a user's mobile device like Fig. 1

If the PCM recommends multimedia content, previous mentioned problems are solved naturally. Since the PCM intercommunicates between content providers and mobile objects, we can obtain available information for recommendation from two tiers.

This paper puts forward methods for solving the following issues for the customized multimedia content recommendation in the PCM.

How can personal characteristic and preference be applied to the recommendation?

There are a lot of previous researches in extracting user information from user history and profile and applying the information to a recommendation. However it is not sure that the reliability and satisfaction of their approaches have a high score because the studies about user history and information are in psychology and they are experts in computer engineering and science. Therefore we need to select and apply a verified method for manipulating user information. To extract user characteristics from user's behavior pattern, some methods are proposed and verified in psychology. Therefore we should adopt and apply one of the verified methods for the multimedia content recommendation. Although the recommendation service is based on user characteristics, users hope to obtain a different result by requesting the same recommendation service in the different time and position. In other words, users want to get a recommendation service based on user's dynamic context. Therefore we should consider how context information can be extracted and applied for the multimedia content recommendation.

This paper proposes a method to apply user characteristics to the content recommendation based on the consumption pattern derived from the user's behavior pattern, which has been thoroughly studied by the social and human sciences. The paper also proposes a method to reflect current user context to the recommendation by log history and environmental context information when the PCM accesses the content providers and the mobile objects connects the PCM, respectively. To evaluate our methods, this paper designs and implements a Jukebox based on proposed methods.

The remainder of this paper is organized as follows. Section 2 describes the related work and the DISC behavior pattern model. Section 3 explains the classification of DISC behavior patterns for our recommendation. Section 4 describes our methods for the multimedia content recommendation in detail. In Section 5, we design and implement a prototype system based on the proposed method and show the performance evaluation in Section 6. Finally, Section 7 provides concluding remarks.

2. Background and Related Work

2.1. Related Work

In general, there are three kinds of approaches in developing a recommender system: content-based, collaborative and hybrid ones[1]. Content-based recommendation is the technique whereby content is blocked or allowed based on analysis of its content, rather than its source or other criteria. [2, 3, 4, 5, 6, 7] propose a method for recommending TV programs for a user in

Personal Digital Recorder (PDR). For recommendation, [2, 4] uses implicit view history, explicit TV viewing preferences, and feedback information and [5, 7] propose an algorithm for estimating user preference score based on user history. The recommender system described in [3, 6] infer preference based on user profile and usage history and recommend a customized content.

Collaborative recommendation is recommended items that people with similar tastes and preferences liked in the past. It is categorized as a user-based collaborative recommendation[8] and an item-based collaborative recommendation[9]. Similar users and(or) items are sorted based on the memorized ratings. Relying on the ratings of these similar users and(or) items, a prediction of an item rating for a test user can be generated[10,11,12]. However they don't discuss applying personal information like user profile. Hybrid recommendations combine collaborative and content-based methods [13, 14, 15, 16, 17, 18]. They help to avoid certain limitations of content-based and collaborative systems. Even if their methods provide a personalized service based on the user preference, however, the result of their recommendation is the same when a user requests the same service in the different situations. In other words, a user wants to get a customized service based on current user situation like time, position, and weather. Therefore we need the recommendation method reflected user context. [19, 20, 21, 22, 23] propose a recommendation method based on user situation, although an application domain is not the same as ours. [19] proposes a method to apply user context by calculating context similarity among users and [22] deal with environmental context by using an ontology and rule. Especially [23] study that it is possible to infer the context from the existing data with reasonable accuracy in certain cases. Actually our approach using clustered-based method is similar with many model-based recommender systems, a classic reference of which can be found at [1]. However, previous researches are proposed each using user preference, history, and context information to the recommendation. Also there are not approaches that are optimized to apply user psychological characteristics.

This paper adopts the DISC Type to apply user psychological characteristics to the content recommendation. DISC Model is one of the popular methods to classify psychological characteristics based on user behavior pattern in psychological field [24, 25, 26]. By adopt DISC model for the multimedia content recommendation, we can expect a synergy effect in computer engineering and psychology fields.

2.2. DISC Model

Generally, people take action selectively based on their personality type and their own unique motivations - the influences that have affected them since birth. People act quite naturally and comfortably in their working or living environment, as those patterns form a kind of tendency, which is called a behavior pattern.

William Moulton Marston, a psychology professor at Columbia University, proposed the DISC behavior patterns in 1928, classifying behavior patterns into the D (Dominance) type, I (Influence) type, S (Steadiness) type, and C (Conscientiousness) type. Table 1 shows the psychological characteristics of each behavior pattern [24, 25, 26].

This paper classifies user's behavior patterns according to the DISC type, using the correlation between those four behavior patterns and the user's purchasing patterns, and proposes a new recommender system which provides a customized service for recommending a multimedia content based on user preference.

Table 1. Psychological characteristics by DISC type

DISC type	Description
D type (Dominance)	Independent, persistent, direct. Energetic, busy, fearless. Focus on own goals rather than people. Ask 'What?'
I type (Influence)	Social, persuasive, friendly. Energetic, busy, optimistic, distractible. Ask 'Who?'
S type (Steadiness)	Consistent, like stability. Accommodating, peace-seeking. Good listeners and counselors. Ask 'How?' and ask 'What?'
C type (Conscientiousness)	Slow and critical thinker, perfectionist. Logical, fact-based, organized, follows rules. Ask 'Why?' and 'How?'

[http://changingminds.org/explanations/preferences/disc.htm]

3. Classification of behavior patterns

To apply a personal characteristic and preference to the recommendation, the first issue described in the introduction, this paper proposes a method to extract and classify the characteristic and preference from user's behavior patterns based on the DISC type.

Originally, there are two methods of identifying a user's behavior pattern - an explicit method based on a questionnaire, and an implicit method that analyzes the user's purchase-making behavior pattern. The explicit method is a simple and traditional method that is used to identify the user's behavior pattern using the DISC questionnaire, based on data evaluated by the user. It is useful before user's initial behavior. However, it takes up the user's time and may cause inconvenience. On the other hand, the implicit method is convenient for users because the user's purchase-making pattern can be analyzed and identified without the user's direct involvement. However, one problem is that the user's psychological pattern cannot be identified if the user's initial purchase-making behavior cannot be understood.

The method proposed in this paper involves classification of behavior pattern according to the user's purchasing actions, by mixing those two methods. That is, the explicit method (using the summarized DISC questionnaire) is applied to users who have not purchased anything, whereas the implicit method is applied to users who have purchased something once more, in order to identify the user's behavior pattern.

Explicit method

In the explicit method, the summarized DISC questionnaire items are presented to analyze the user's behavior pattern. Normally, a description is given according to the category that best fits the behavior description, and the corresponding score is given. The user's behavior pattern is classified through the description category that the total score falls in.

Implicit method

The implicit method analyzes the user's purchase-making pattern in order to determine the behavior pattern. This section explains the implicit method, which determines the DISC behavior pattern using the search pattern in a music site with a search structure shown in Figure 2.

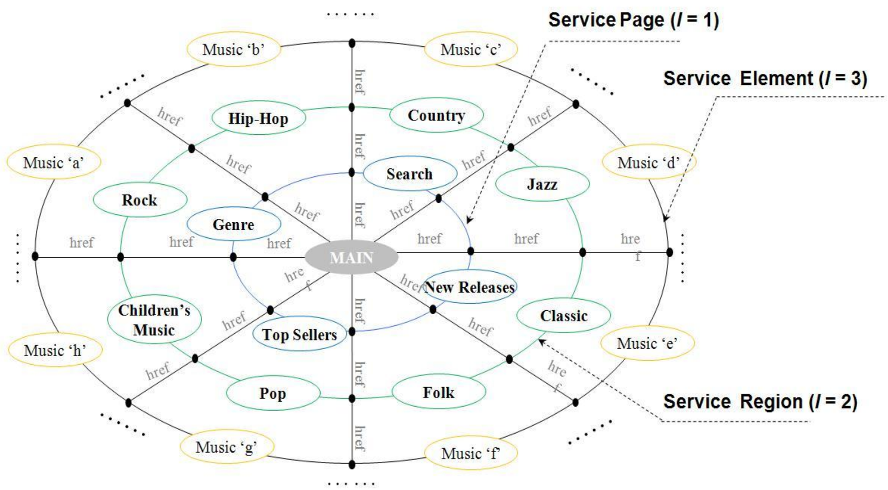


Fig. 2. The structure for searching content in a music website

Generally, websites that provide multimedia content are composed of three structural levels: a service page, a service region, and a service element. The main service page consists of one or more service pages and each service page includes one or more service regions. In addition, each service region also has at least one service element. For convenience, the service page, service region, and service element are here described as levels l=1, l=2, and l=3.

To classify the user's behavior pattern, this paper considers 'search depth', 'search variety', and 'staying time'. The 'search depth' is the number of accessing to levels for purchasing a multimedia content at level 3. For example, if a user's search path is main → new release (level: 1) → music 'A' (level:3) → genre (level:1) → music 'B' (level:3-purchase), then the 'search depth' is 3. In addition, 'search variety', which involves the number of movements to the same level or an upper level ($l=3 \rightarrow l=1$, $l=3 \rightarrow l=2$, $l=3 \rightarrow l=3$, $l=2 \rightarrow l=1$, $l=2 \rightarrow l=2$), becomes 1, because this involves movement to music 'A' (level: 3) → genre (level: 1) in the example. Lastly, 'staying time' is the total time taken to purchase certain content after logging in.

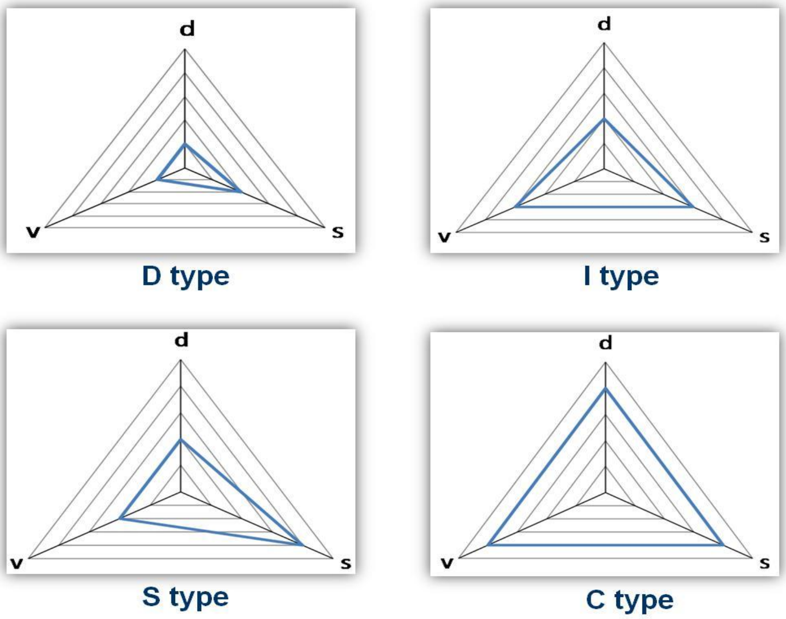


Fig. 3. Association of the *wLog* with the DISC type

Generally, in the normal web browser functions, it is difficult to extract the 'search depth', 'search variety', and 'staying time' from the client's side instead of the server's. Therefore, this paper proposes a specialized web browser to acquire this information by using the meta-tag [27]. The meta-tag is one of the methods that allow adding of information to a web page, and is not displayed on the web browser for the user. Using this tag, we can recognize the user's location and extract the final search depth. The 'search variety' also can be extracted by the meta-tag information. The 'staying time' can be checked, based on the time log that begins with accessing the page for searching and ends at the purchase time. However, it is assumed that users receive the confirmation message from the server at the time of purchase. The 'search depth', 'search variety', and 'staying time' obtained through our method are saved as the coordinate vector value on the personal content manager, instead of the server. This paper defines *wLog* to express this information as follows.

$$wLog = (d, v, s) \quad , \begin{Bmatrix} d = search\ depth \\ v = search\ \text{variety} \\ s = staying\ time \end{Bmatrix} \tag{1}$$

To find a relationship between the classification using the wLog and the DISC model, this paper defines the following hypothesis and verifies the hypothesis through an experiment.

Hypothesis:

D type - Short staying time and insufficient search variety because the intended information is definitive and a purchase decision is made quickly. Search depth is not deep because purchases are frequently made through a search.

I type - Search depth is relatively shallow because the user likes the multimedia content preferred by others, such as popular content, top-selling content, and recommended content. Search variety and staying time are normal.

S type - Staying time at frequently visited pages is consistently longer. Search depth is shallow and search variety is insufficient because the user prefers a specific genre or artist.

C type - The user reviews or listens to samples on various pages. The user takes a long time to make a purchase decision, checking price and performance. Search depth, search variety, and staying time are relatively deep, intensive, and long.

4. The recommendation of multimedia content

To determine the user's behavior pattern, this paper classifies users based on the *wLog* value. Target users are classified using the distance from the representative value of the defined behavior pattern group. The representative value is the centroid value of 3 clusters of vectors. The centroid is calculated by dividing the sum of the apex coordinates by the number of vectors. The following equation (2) is used to decide a user's type. The equation calculates the distance of the target user *u*'s purchase behavior pattern vector p_u from the vector P_j which is the vector composed by representative values of cluster *j*'s purchase behavior pattern. *k* is the attribute suffix (1:*d*, 2:*v*, 3:*s*) of the purchase behavior pattern vector.

$$d_{u,j}(p_u, P_j) = \sqrt{\sum_{k=1}^{3}(p_{uk} - P_{j_k})^2} \tag{2}$$

For example, if the *wLog* value of the user *x* is (*d*:5, *v*:2, *s*:18) and the representative value of $P_{j=D}$, $P_{j=I}$, $P_{j=S}$, and $P_{j=C}$ are (*d:4*, *v*:4, *s*:8), (*d:8*, *v*:16, *s*:16), (*d:8*, *v*:8, *s*:16), and (*d:16*, *v*:16, *s*:16), then the value of $d_{x,j}(p_x,P_{j=D})$, $d_{x,j}(p_x,P_{j=I})$, $d_{x,j}(p_x,P_{j=S})$, and $d_{x,j}(p_x,P_{j=C})$ are $\sqrt{105}$, $\sqrt{209}$, $\sqrt{49}$, and $\sqrt{321}$, respectively. Therefore, we can know that the user *x* is in the S type because the distance value of S type is the smallest.

To solve the issue for applying dynamic user's environmental context to the recommendation which is described in the introduction, this paper infers the user's preferred genre according to the context, using *uLog* which is the user's usage history of multimedia content on the mobile device. Figure 4 is the schema of the 'UsageData' which is defined in this paper to describe *wLog*, *uLog* and the metadata of a multimedia content.

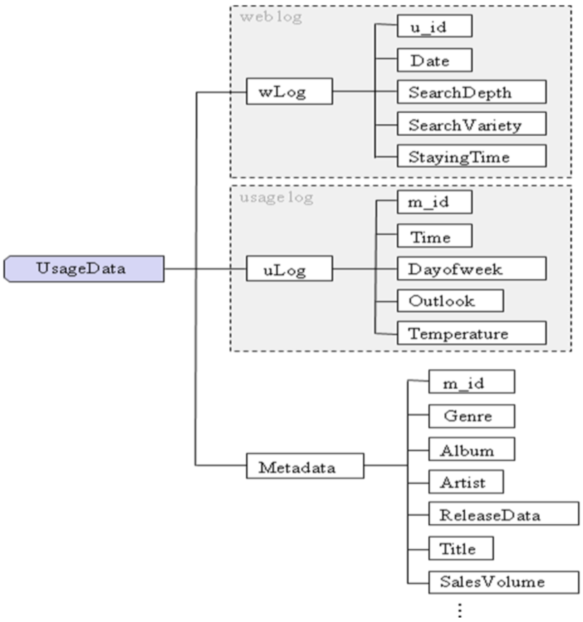


Fig. 4. The schema of the UsageData

Table 2. User Context information

	Outlook	**Time**	**DayOfWeek**	**Temperature(℃)**
1	Sunny	Dawn	Wed	15
2	Overcast	Afternoon	Sat	24
:	:	:	:	:
9	Rain	Morning	Mon	19
10	Sunny	Evening	Tue	23
:	:	:	:	:
14	Overcast	Night	Thu	22
15	Rain	Afternoon	Sun	21

As the algorithm for inferring the preferred genre, we use the decision tree algorithm. Table 2 and table 3 are an example of the user's context information included in *uLog* and of the decision tree structure for multimedia content, respectively.

Table 3. The decision tree for inferring a multimedia content

```
1:Dawn?
T-> 0:Overcast?
   T-> {'Folk': 1}
   F-> {'Country': 2}
F-> 1:Afternoon?
   T-> 3:24?
      T-> 0:Overcast?
         T-> {'Pop': 1}
         F-> {'Folk': 1}
      F-> {'Rock': 2}
   F-> 1:Morning?
      T-> 2:Tue?
         T-> {'Classic': 1}
         F-> {'Pop': 2}
      F-> 2:Sat?
         T-> 0:Overcast?
            T-> {'Hip-Hop': 1}
            F-> {'Classic': 1}
         F-> {'Jazz': 3}
```

The DISC type classified by *wLog* and preferred genre inferred by *uLog* are used to recommend a multimedia content together. In other words, a different weighted value is given to each DISC type with regard to the ‘UsageData’, ‘Popularity’, ‘Artist’, and ‘Title’ of the multimedia content in the preferred genre which is inferred, in order to finally recommend specific multimedia content. For this recommendation, this paper defines the representative attributes that affect each behavior pattern, considering the fact that the user's purchase-making behavior pattern is closely related to the DISC type. For the D type, the ‘UsageData’ is selected as the representative attribute, because users with this behavior pattern are willing to accept a challenge, make a decision quickly, and show great interest in new content. That is, the ‘UsageData’ attribute of the multimedia attributes is the main attribute for D (Dominance) type users and a weighted value is given to recently released-multimedia content. I (Influence) type users like contact with people, and respect other people's opinions and comply with them. Due to these behavior pattern characteristics, weight is given to the ‘Popularity’ attribute from among the four attributes. In this paper, the ‘Popularity’ attribute is estimated by the ‘SalesVolume’ attribute in the metadata. S (Steadiness) type users perform consistently and have introspective and relaxed behavior pattern characteristics. For S type users, the ‘Artist’ attribute is representative, because they tend to show high loyalty towards their preferred artists. Lastly, C (Conscientiousness) type users show the behavior pattern of thinking analytically. C type users have the same level of preference for all multimedia content in the preferred genre inferred. Therefore, we define that the 'Title' is the representative attribute and weight is the frequency of the content used by the user.

The attribute vector (AV) for the multimedia content is equal to (*r, p, m, f*). Here, *r* is the release date of the multimedia content and has a value range of 1 to 12; *p* stands for the popularity of the content and has a value range of 1 to 5; and *m* stands for the number of items of the same artist and has a value range of 1 to 10. Lastly, *f* - the number of times the user has used the content, has a value range of 1 to 50. The attribute vector value, which has a different value range, can be normalized as *r', p', m', f'*, which are the values between [0, 1], using the equation (3). The evaluation value of the content according to the user's behavior pattern is calculated for the normalized attribute vector AV', using the equation (3). For example, if the AV of multimedia content *m* is (*r:*9; *p:*2; *m:*3; *f:*12) and the set of min_*n* and max_*n* pair of each attribute is (*r:*1,9; *p:*1,5; *m:*1,6; *f:*10,30), then AV' is (*r':*1; *p':*0.25; *m':*0.4; *f':*0.1).

$$n' = (n - \mathrm{min\_}n)/(\mathrm{max\_}n - \mathrm{min\_}n) \qquad n = \{r, p, m, f\} \tag{3}$$

Where, n stands for r, p, m, and f - the element of the attribute vector (AV), whereas min_n and max_n are the minimum and maximum values of each element.

$$w_{u,j} = \frac{1}{|\,1 - d_{u,j}(p_u, P_j)\,|} \qquad , j = \{1:D, 2:I, 3:S, 4:C\} \tag{4}$$

That is, $w_{u,j}$ shows the extent of the user's association with each behavior pattern.

$$r_{u,c} = \sum_{i=1}^{4} w_{u,j} \times AV'_{c,i}, i = \{1:r', 2:p', 3:m', 4:f'\} \tag{5}$$

The weight w_j is applied to the user's behavior pattern *j*, as shown in the equation (4). The user *u*'s preference score $r_{u,c}$ for the content *c* applied with the weight can be estimated by the equation (5). The equation (5) can be explained in detail as follows:

$r_{u,c} = (w_{u,D} \times AV'_{c,r'}) + (w_{u,I} \times AV'_{c,p'}) + (w_{u,S} \times AV'_{c,m'}) + (w_{u,C} \times AV'_{c,f'})$

For example, The weight $w_{x,j=S}$ of the user *x* which are described in the previous example is $1/(1-\sqrt{49})$. Also the preference score $r_{x,m}$ between multimedia content *m* and the user *x* is 7/24.

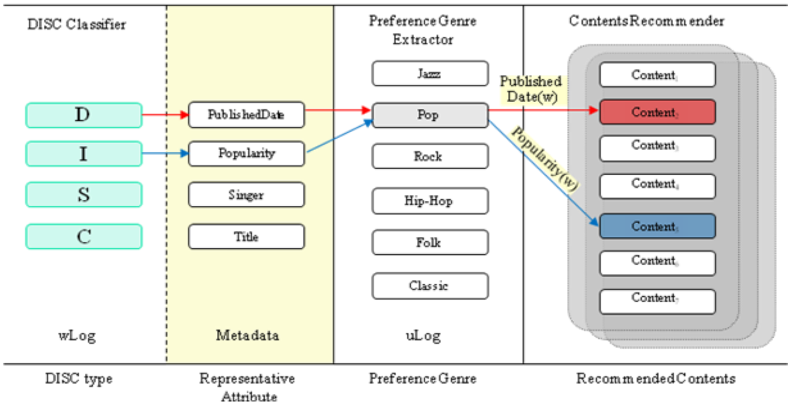


Fig. 5. An example of the schematic of the recommendation of the user's preferred multimedia content

Fig. 5 shows that the equation (5) gives different weight to each attribute value using the DISC type.

- The weighted value for the user is assigned as D type to the attribute *r'* to the extent that there is a similarity with the D type.
- The weighted value for the user is assigned as I type to the attribute *p'* to the extent that there is a similarity with the I type.
- The weighted value for the user is assigned as S type to the attribute *m'* to the extent that there is a similarity with the S type.
- The weighted value for the user is assigned as C type to the attribute *f'* to the extent that there is a similarity with the C type.

5. Personal Multimedia Jukebox

This paper proposes and implements the personal multimedia jukebox (PMJ) as an application system for the personal content manager described in the introduction. Fig. 6 shows the overall architecture of the system for providing personalized multimedia content recommendations in the mobile environment. The PMJ manages a lot of multimedia items purchased from the Content Provider (MCstore), and distributes the personalized service to mobile clients (mobile objects). The proposed Jukebox is composed of three modules. The Collecting Module (CM) collects and manages *wLog* (user's purchase behavior log), *uLog* (usage log of the mobile client), and multimedia content with metadata provided by the content provider. The Recommending Module (RM) classifies the behavior pattern using the information collected by the CA, and recommends personalized content based on the classified behavior pattern and context information. Lastly, the Propagating Module (PM) provides recommended content to the mobile client.

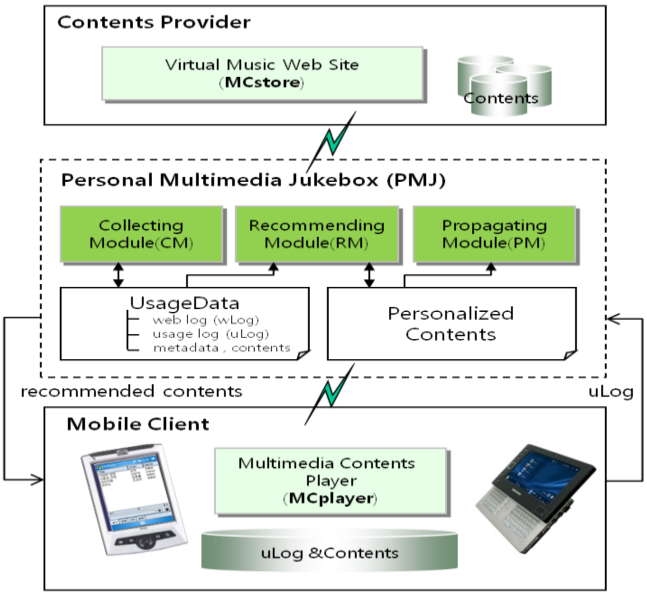


Fig. 6. The system architecture for providing personalized multimedia content recommendations

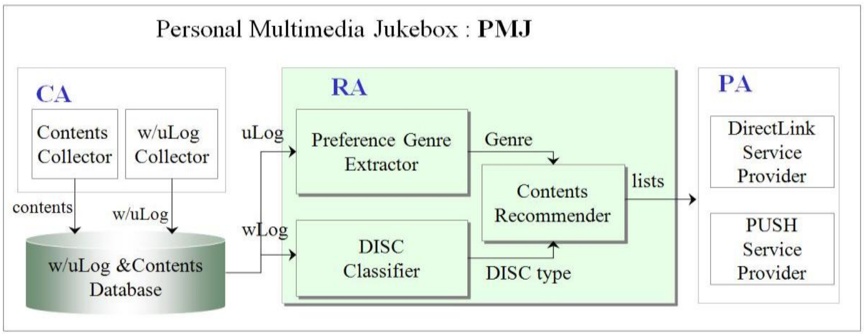


Fig. 7. The architecture of the Personal Multimedia Jukebox

Fig. 7 shows the architecture of our PMJ in detail. The CM collects *wLog*, *uLog*, and metadata regarding the content from the content provider and mobile clients. *wLog* includes the *d*, *v*, and *s* records and *uLog* is the user's usage history. Lastly, the metadata contained in the content is collected and saved. The RM recommends personalized content using the usage data collected by the CM. For recommendation, this paper uses the DISC type obtained by using the user's web log, namely *wLog* and the preferred genre obtained by using the user's usage log, namely *uLog* by the DISC Classifier and Preference Genre Extractor, respectively. The Contents Recommender generates a list of multimedia content for a user based on extracted the DISC type and the preferred genre. The PM provides a recommendation service to mobile client through wire or wireless network.

6. Experimental Results

6.1. Prototype implementation

For evaluation of our system, this paper built the music website (MCstore) in the server system like Fig. 7 and implemented a multimedia content player (MCplayer) on a mobile client like Fig. 8.

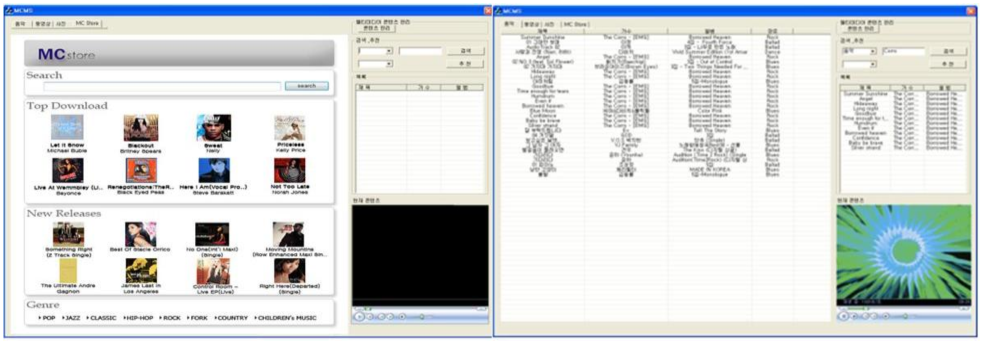


Fig. 8. The interface of the MCstore

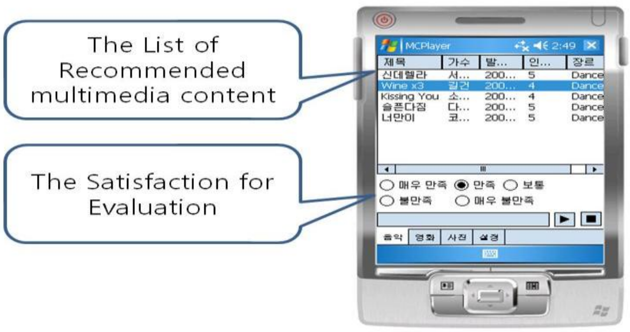


Fig. 9. The emulator for evaluating our recommendation

MCstore was implemented using MySQL 5.0 as the DBMS to store wLog and the content on Windows XP, and Tomcat 5.5 was used as an application server for Java and JSP. To install PMJ on a personal computer, MySQL 5.0 was used to store uLog and wLog, and the content of Windows XP was also used. MCplayer is a multimedia player that can be run on a PDA that supports Windows Mobile 5.0.

6.2. Performance Evaluation

In order to evaluate our user pattern classification and recommendation performance by comparing with conventional methods, we distributed the programs (PMJ.exe, MCplayer.exe) to 80 students enrolled at Chungnam National University and have collected their usage history during six months.
In order to verify our user behavior pattern classification developed with adopting the DISC, we test the hypothesis regarding the association between the purchase-making pattern established by this study and the DISC obtained from the DISC psychological pattern questionnaire as seen in Fig. 10. In the figure, the D type and S type show a relatively higher degree of accuracy of classification than the I type and C type. This fact proves that the proposed method of classification of the D type and S type behavior patterns is more efficient. In addition, the accuracy of all the classification types increases after the initial evaluation.

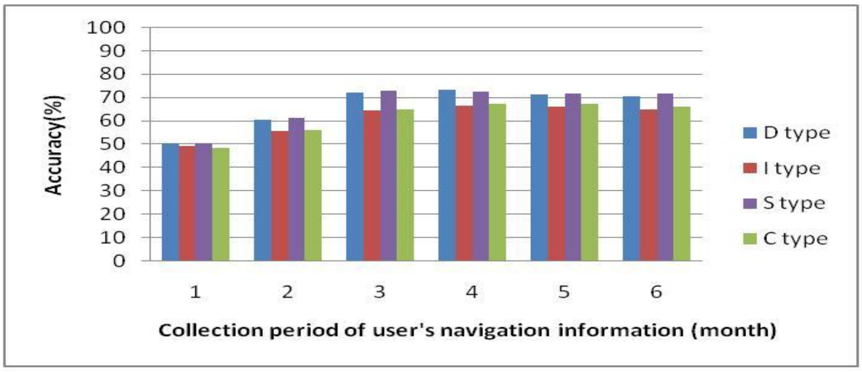


Fig. 10. Performance of user behavior pattern classification based on DISC type

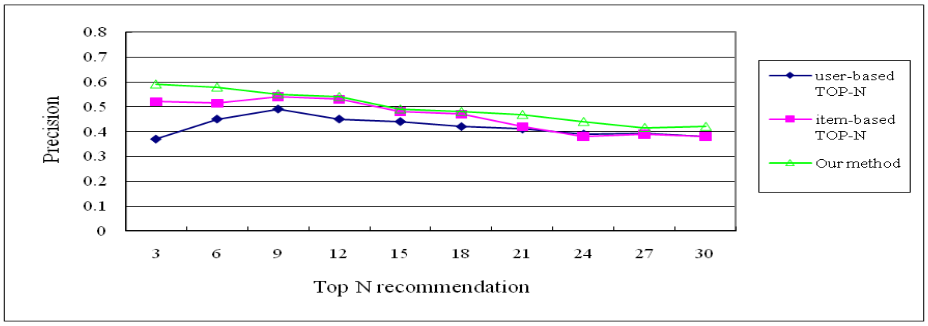
To evaluate our recommendation performance, we compare the performance of our method with conventional methods such as user-based Top-N and item-based Top-N. Also, we chose the precision and recall [28, 29, 30] as a metric of the classification performance, widely used for measuring the recommendation performance in information retrieval applications. The equations (6) and (7) are the formula of estimating the precision and recall performance respectively. Let the set of music items relevant to a query be denoted as {Relevant}, and the set of music items retrieved be denoted as {Retrieved}. The set of music items that are both relevant and retrieved is denoted as {Relevant} $\cap${Retrieved}.

$$precision = \frac{|\{Relevant\} \cap \{Retrieved\}|}{|\{Retrieved\}|} \tag{6}$$

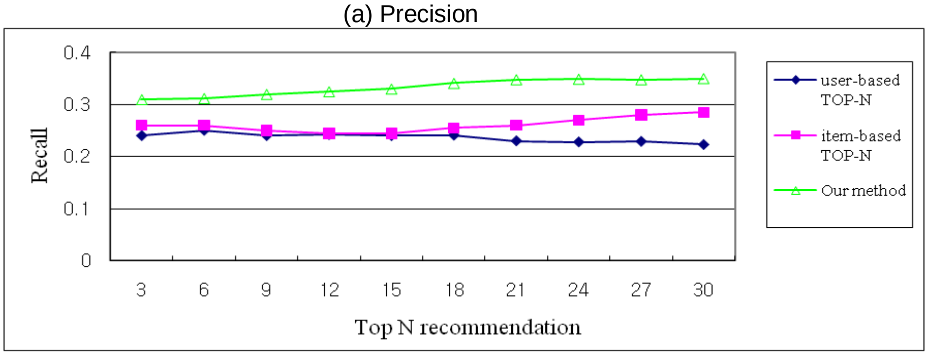
$$recall = \frac{|\{Relevant\} \cap \{Retrieved\}|}{|\{Relevant\}|} \tag{7}$$

Also the F-measure is a measure of a test's accuracy. It considers both the precision and recall of the test to compute score. The precision and recall metric is inversely related. To overcome this drawback of precision and recall metric, F-measure measure is used. Equation (8) is the definition of F-measure which considers both precision and recall.

$$F - measure = \frac{recall \times precision}{(recall + precision)/2} \tag{8}$$



(a) Precision



(b) Recall

Fig. 11. Performance comparisons of our method, user-based Top-N, and item-based Top-N

A higher value of precision metric indicates that most of the recommendation is correct and a higher value of recall indicates that most of the similar music items are recommended. Also, we repeated the performance measure as varying the number of recommended music items, *N*. As seen in Fig. 11(a) (b), our method outperforms the conventional methods. For instance, at *N*=3, user-based Top-N and item-based Top-N have the precision of 0.37 and 0.52, while our method has a precision of 0.59.

From the analysis of the performances of user-based Top-N and item-based Top-N, their poor performances are due to the lack of sufficient rating information on the music items recommended. In other words, the target users have very few similar users who have rated music items. The item-based Top-N shows a slightly improved result than the user-based Top-N because the recommendation is made based on the music items that are similar to other music items the target user has liked. Also, it is possible to retain only a small subset of music items to provide good prediction quality and similarities between the music items that are relatively static. As the number of music items recommended increases, the performance is degraded. It is because less similar music items are recommended in the recommendation process. As seen in the figures, our method outperforms user-based Top-N and item-based Top-N because our method considers the semantic relations among music items, which can compensate the drawbacks of user-based Top-N and item-based Top-N addressed above by reflecting user's current psychological mind (DISC).

The application of DISC leads our method to achieve an improved result when compared to user-based Top-N and item-based Top-N. When the number of recommended products is low our method performs the best (i.e. the highest value for precision is 0.59 when N=3). When the number of recommended music items increases, we found that the inclusion of less similar music items to the recommendation list degrades the performance slightly.

Table 4 shows the F-measure of different methods for different top N recommendations. In general, F-measure depends on the value of corresponding precision and recall values of top N recommendations. The higher value of our method for F-measure implies that the proposed method can provide better recommendation than the other methods.

Table 4. F-measure for Top N recommendation

N / Met	3	6	9	12	15	18	21	24	27	30
user-based Top-N	0.29114754	0.32142857	0.32219178	0.31473988	0.31058823	0.30626323	0.2946875	0.28776699	0.28910789	0.28106136
item-based Top-N	0.34666666	0.34532299	0.34177215	0.33416020	0.32353591	0.33062069	0.32117647	0.31569230	0.32597014	0.32571428
Our method	0.40644444	0.40524943	0.40459770	0.40578034	0.39439024	0.39873325	0.39917647	0.38925221	0.37897382	0.38181818

Also we evaluate user's satisfaction of our recommendation algorithm. As shown in Fig. 9, there are five radio buttons at the bottom of the interface of the mobile device that allows the user to evaluate his/her degree of satisfaction with the recommended multimedia content. Users are able to give a top score of 5 (very high satisfaction) and a bottom score of 1 (very high dissatisfaction).

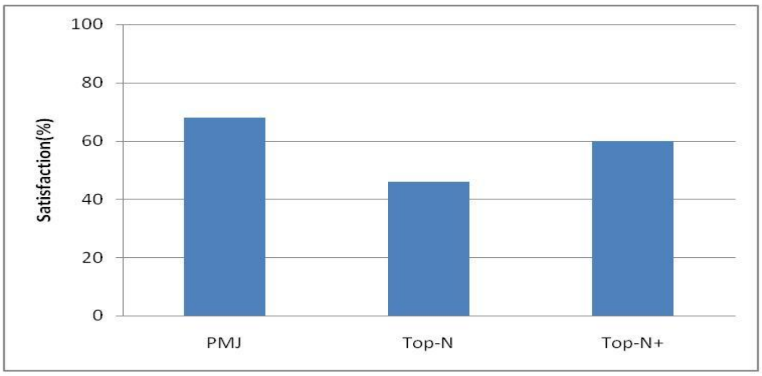


Fig. 12. Comparing Satisfaction with our method, user-based Top-N, and item-based Top-N

Fig. 12 is a graph of the average degree of satisfaction with our recommendation technique, user-based Top-N and item-based Top-N algorithm. According to the results of the experiment, the user-based Top-N method shows a level of satisfaction of 46%, whereas the item-based Top-N method shows a level of satisfaction of 60%. The PMJ shows the highest level of satisfaction at 68%.

7. Conclusion

This paper proposed the method for recommending multimedia content in a personal content manager. Our method can be used to solve a scalability problem and a limited resource problem of a server system and a mobile device, respectively. Main contributions of this paper are threefold. The first, we proposed a method to adopt and apply the DISC model verified in psychology field for the content recommendation. The second, we proposed an algorithm for reflecting dynamic environmental context to the recommendation. The third, we implemented a prototype system and showed that our method is reasonable for multimedia content recommendation through the performance evaluation. To the best of our knowledge, it is hard to find previous studies for applying user's psychology to multimedia content recommendation. However, our performance evaluation showed that the DISC model is closely related to the purchase pattern and the user's psychology is one of the useful factors for recommendation.

In our current version, the prototype system dealt with music content only. However, it will be extended and applied to various types of multimedia content.

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