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ADAPTIVE MOBILE CONTENT PERSONALISATION USING TIME-OF-DAY

Worapat Paireekreng and Kok Wai Wong

School of Information Technology
Murdoch University
South St. Murdoch
Western Australia 6150

ABSTRACT

The limitations of the hardware of the mobile devices and the content presentation screen size when using the mobile internet seem to be difficult for mobile users to handle the amount of information flowing to them. They have to scroll down several levels in order to obtain the most desired content. This paper proposes a personalised adaptive menu system that can bring the desire content for user by using the time-of-day information to facilitate the mobile internet usage. Users should not scroll down several levels from the list-oriented menu to obtain their interested information. Furthermore, by using the time-of-day information, the more desirable content can be display by using the users' lifestyle profile in order to deliver the content that are more relevant to the users at that time.. The results also show that the proposed adaptive menu system could provide around 80% accuracy in achieving the personalization experience.

Index Terms— Personalisation, Mobile internet, Adaptive menu, Context information

1. INTRODUCTION

Due to the busy life style, several communication medium have been adapted in order to respond to the increasing human needs. Mobile phones have emerged as an important gadget not just allowing people to make phone calls but also dealing with information of the world anytime anywhere. Mobile users can access many information and services via mobile internet as well. Furthermore, some users have also used the mobile device for entertainment. All these reasons have lead to the popularity of mobile internet.

Nevertheless, using mobile internet is not easy for many users due to some limitations such as the hardware and content presentation screen. The first problem concerns with the mobile devices' hardware, for example such as small screen size and input capability [2]. In addition, there are various screen types among different brands and models for different mobile devices. For example, some models have touch screen features while many still use the conventional screen with list-oriented display. As a result, the WAP developer and content provider have to deliver the content for customer in a listed-menu format. Secondly, the problem is related to the way content is presented. As a list display, users have to scroll down along the menu to several levels with many clicks until they can find the required information. In order to facilitate the usage of mobile internet, the problem mentioned should be resolved first. They would like to access the interested content as quickly as possible because data transfer on mobile is normally charge higher than other form of data transfer medium. Another characteristic of mobile internet users are mobility patterns. The users may have some similar usage patterns for the same time of day.

We therefore provide a solution for those problems by using adaptive list menu system that includes the information of the time-of-day. This paper explores a factor of time which is can be used for personalisation and adapting the menu of the content presentation for mobile internet users. The menu can be re-arranged according to the user's need based on the time-of-day information. The most desirable list menu at that time period will be shown. This can lead to reducing several clicks and searching for the desirable content.

The subsequent sections of this paper are organised as follows. Section 2 gives an overview of the personalisation with context information. In section 3, the proposed methodology is described. Section 4 presents the result of the research. Finally, this paper ends with some concluding remarks and proposed some future works.

2. LITERATURE REVIEW

2.1 Personalisation

The overload of information has been viewed as a draw back for many towards the use of information technology. Personalisation system could be one of the solutions to help users to obtain the information they want. Personalisation was defined by Ivar Jorstad et.cl. [8] as "*the mechanisms*

exist to allow a user U to adapt, or produce, a service A to fit user U's particular needs, and that after such personalization, all subsequent service rendering by service A towards user U is changed accordingly". They also presented the concept of personalisation in terms of individualized something to fit a specific person's need. It is evidence that personalisation can be used as a motivation for many tasks and services. Additionally, it might be better if user can be provided with that alternative [10].

2.1.1 Recommendation system

The implementation of the personalisation can be viewed as a recommendation system which is to propose the recommended products from the ordinary menu. The related work on recommendation system could be focusing on location-based service (LBS) [9]. It implemented the adjustment of recommendation by using user profile and history of the usage. Furthermore, applied symbolic machine learning is used to discover user's interest and preferences to construct the user profile [3]. The research also proposed ALKEMY algorithm for online decision-list learner. This work was implemented for infotainment TV show using recommender application. However, it tends to use extensive calculation which may consume too much time and could be inappropriate for most common content provider servers. In addition, the mobile users want quick response time when they are looking for information regardless what the processes are running at the back to gather the information.

2.1.2 Mobile content personalisation

In this area, the focus is on how to facilitate the use of mobile internet by distinguishing from the web browsing on a personal computer. It also focused on how to gather relevant information and presented them to the user. As user often moves around and accesses their mobile internet several times during the day, other relevant information (like time information) rather than user profile should also be considered as an important information to perform the mobile content personalisation This is sometime known as content filtering. This area makes use of the user profile and the other relevant information such as time of week [7] to predict the information that user will be interested when using mobile internet. Some other works including the navigation style prediction to predict how the user moves around each time they use the WAP portals by re-arranging the menu on the mobile phone. The details for this issue will be discussed in the next section.

2.2 User content usage prediction

User session refers to the time that the user connects to the mobile internet. This is the time when user connects until the user has disconnected with the server. Mobile internet usage time per session may not be long compared with normal web browsing on a desktop computer. It is normally use to browse for purposive information or services at that time. Furthermore, most of the times in one session, the user may browse several pages for relevant contents. This may include accessing from the main menu page to sub-pages. Therefore, if some techniques can be used to predict the contents or pages the user will be interested in the session, it will reduce the content access time. This can lead to higher user satisfaction.

2.2.1 User navigation prediction

The feature of hyperlink on mobile internet is often displayed as menu lists or options. The user has to click the option or menu item of interest to go to the desire content. These options or menus are known as user navigation. As can be seen from the content presentation or content filtering on mobile internet, personalisation can be achieved by predicting the user navigation.

The aim of the research in this area is attempting to reduce the click distance from the first option displayed menu and the desired option menu. It tried to display relevant topics which may be needed by the user to use them quickly [7,12,13]. Nonetheless most research focused on WAP portals and personalised same level of menu while our research try to propose the level-free content personalisation. In addition many works also implement techniques such as Markov model, Bayesian network and Naïve Bayes to predict the user navigation using profiling data [1,4,15].

To avoid computational complex techniques, which is a critical issue to consider for mobile application, we propose simple matching technique and case-base reasoning to enable the primary of mobile content personalisation.

2.2.2 Context information

The ambience information tends to be added for mobile personalisation due to the characteristic of ubiquity. The context was described as a situation similar to case-base reasoning for mobile [5,6]. The research mentioned that changing the environment leads to requirements of system adaptation. Contextual information played important roles towards information retrieval in successive search. From [14], it can be seen that by using time-framed information can improve the prediction of future browsing patterns. This research used time-framed separation of week and semester combined with matching session pages using association rules. [11] presented that user would prefer different kind of information during different time of the day. So, the displayed information on mobile device should be varied from time to time in order to match the users' need during different time of the day. For example, the result of this empirical study shows that user prefers to use information like weather forecast, news and breaking news in the morning while dining and MMS (including SMS) information were frequently used in the evening. As can be

seen from the context information, time is one of the important factors which can be used to predict and classify the mobile content usage for each user group.

2.3 System usability

To increase the mobile internet acceptance, it seems to be important to look at the Human-Computer Interaction (HCI) issues in terms of system usability. The content presentation in the mobile devices is also a concern at this point. Mobile device system usability aims to provide the requirement for new users to interact with the device easily with minimum learning and training. Many works are concerned with the human-interaction and usability. For example, the survey and interview methods were used in [16] to define the 'quality attribute'. It is related to the customer expectation levels and their contribution to personalization. This research work was based on mobile services. In usability test, the attributes concerning search time and the ease-of-use of the menu are defined by their quickness and correctness in responding to user's request. In addition to this area of the research, [2] also proposed 3 different styles of displaying news headline which was related to mobile usability. As can be seen from this work, although the work concentrated on data visualization, HCI and system usability should also be noted too.

3. METHODOLOGY

This research used the server log file from a mobile content provider in Thailand to illustrate the concept. The log file provided several type of content related to entertainment of mobile phone including Java Games, Theme, Wallpaper, Ring tone, Video clip etc. The log file was gathered from 9,644 unique user and 60,000 transactions. When user connects through WAP server, the content visitor page will appear Later, content visitor page, category visitor page, list visitor page and detail visitor page will be accessed respectively. There are 2 types of customer; member and non-member. Member customer can download unlimited content by monthly payment while non-member has to pay per-time charge when downloading the content. Additionally, the member can click to download the content via list visitor page, but non-member should download the content via the payment and charge page. Both types of customer session usage or any pages access will be recorded in the server log file. Half of the data was divided for training by adding time-separation factor with 4467 unique user including 29998 transactions are used. The other parts of data would be used to test the result. There is a total of 29,998 records in the training data set, and 30,002 records in the testing data.

The design of this experiment was started with pre-processing data stage. From the server log file, the data cleaning method was applied to obtain appropriate data format for analysis. Then, it was imported to database for the experiment. After that, the factor of time-of-day was classified in order to know which item would be used within the period. The periods were separated in the following clusters: 1.) 5:01-11:00 were assigned as 'Morning' 2.) 11:01-16:00 were assigned as 'Afternoon' 3.) 16:01-21:00 were assigned as 'Evening' and 4.) 21:01-5:00 were assigned as 'Midnight'. Next, the period was appended and classified into the data according to time-of-day, follow by sorting the top 7 items which was frequently used at that period.

After that, the irrelevant data are removed, due to some mobile phone models that cannot download the content so that the content name and content type in the database would be left as a blank data. When the data was filtered again, the remaining data can be used to analyse by categorisation corresponding to period. It can be divided into 4 periods and kept it as follows:

$$P_i = \{C_1, C_2, C_3, \ldots, C_7\}$$

where P_i is the set of top 7 content name at the period *i* and C_n is the content name of WAP page which was ranked according to the most frequently used at the period *i*

The training data is used during the pre-processing stage in order to obtain the primary results of the personalised mobile menu. These will be submitted to customers according to their connection periods. As for the testing data, user's usage sessions were grouped. The testing data is used to verify that the personalization system which was created using the training data. The test data was organised in the same way as the training data by removing irrelevant record which cannot be downloaded by that mobile devices. Next, the classification of mobile internet usage session was managed by grouping the user which was using the mobile internet at that time. It was then separated into user by user and session by session as follows:

$$US_j = \{C_1, C_2, C_3, \ldots, C_n\}$$

where US_j is the user who connects through the mobile internet in each session and C_n is the content page identification or content name which was used in session *j*

In addition, user session was referred to a record of user click and content page usage at the time user connects mobile internet. The user may access one content page in the session or several pages. It depends on how easy user can find the most wanted content. For example, user may access only one WAP page if the page and content were displayed at the first page of mobile internet. In contrast, it may take a

long time or scroll down several level if user cannot find the desired content in the appeared pages.

The accuracy rate was calculated by counting the number of matching content name between period and user's session. If there is at least one content name in the period content set (P_i) which is directly match to the content in US_j , it was counted as 1. The overall sessions would be calculated whether there is at least one content matching or not. It can be explained as follows:

$$\textit{Number of matching session} = \sum_{j=1}^{n} \begin{cases} 1 : P_i \cap US_j \neq \varnothing \\ 0 \end{cases}$$

The results of this experiment will be discussed in the next section.

4. RESULTS

The results are shown in this section. Table 1 shows the result of classified content name, content type and content category with an accumulated frequency of user's click. As the data is confidential and therefore the name of the content cannot be disclosed, the content name is represented by content id instead.

Content id	Type	Category	Frequency
Game 33	Java Games	Action	106
Ring tone 7	True Tone	Sport	92
Game 133	Java Games	Card&Casino	31
Game 129	Java Games	Action	25
Game 204	Java Games	Action	25
Game 250	Java Games	Action	20
Game 251	Java Games	Action	17

Table 1: The contents are ranked by the frequency of user's click according to period 1 (P_1)

Content id	Type	Category	Frequency
Ring tone 7	True Tone	Sport	401
Game 33	Java Games	Action	322
Ring tone 14	True Tone	True Tone	117
Game 133	Java Games	Card&Casino	85
Game 250	Java Games	Action	70
Game 251	Java Games	Action	68
Theme 24	Theme	Cartoon	57

Table 2: The contents are ranked by the frequency of user's click according to period 2 (P_2)

Content id	Type	Category	Frequency
Ring tone 7	True Tone	Sport	1527
Game 33	Java Games	Action	755
Ring tone 14	True Tone	True Tone	307
Game 133	Java Games	Card&Casino	243
Theme 24	Theme	Cartoon	209
Ringtone 13	True Tone	True Tone	184
Game 250	Java Games	Action	172

Table 3: The contents are ranked by the frequency of user's click according to period 3 (P_3)

Content id	Type	Category	Frequency
Ring tone 7	True Tone	Sport	1630
Game 33	Java Games	Action	729
Ring tone 14	True Tone	True Tone	326
Game 133	Java Games	Card&Casino	241
Theme 24	Theme	Cartoon	227
Game 204	Java Games	Action	203
Game 250	Java Games	Action	186

Table 4: The contents are ranked by the frequency of user's click according to period 4 (P_4)

The next result is related to the accuracy rate of the personalised adaptive menu system according to time-of-day of WAP content page as compared with the user's session. The list-oriented menu will be changed by bringing the top 7 from the P_i to display on the first page. If there is at least one page matches what the user wants during the session, the accuracy rate will be increased. As can be observed from table 5, the percentage of matching session was higher than 77% and it reached 81% in period 2 which is the most number of user's session compared with other periods. In overall 1, its number of user's session was higher than the number in overall 2, because some users might use the mobile internet overlapping the time-of-day period. For example, user id 3233 might use mobile internet from period 2 to period 3. As a result, the accumulative number in the overall came from the sum of the sessions in all period, while the Overall 2 presented the distinct user id for all period and compared it with the unique session as well. The accuracy rate for the distinct user id could reach the accuracy rate at 80.81%

Period	1	2	3	4	Overall 1	Overall 2
user's session	730	858	589	1044	3221	2902
match session	573	695	469	804	2541	2345
Accuracy rate (%)	78.49	81.00	79.63	77.01	78.89	80.81

Table 5: the accuracy rate of proposed personalised adaptive menu

Moreover, it can be seen from the ranked content in each period, in period 1 (Morning), the users aim to download Java Games more than other content type, 6 out of 7 of the top rank is Java Games in this period. While, the other periods the top downloaded content types varied such as Java Games, True Tone or Theme. It can imply that users do not have too much time in the morning to customise their mobile phone. They only need relaxing content like games in the morning, while for other time periods user may customise their mobile phone by using content related to the device such as ring tone or theme.

5. CONCLUSIONS

The paper proposed a method which facilitates mobile device users when they connect to the mobile internet. The personalization system allows users to access their interested content without scrolling down several levels of menus and pages. Furthermore, this can help user reduce the connection time of the mobile internet as well. The research adapted from the server log file of a mobile content provider in Thailand. As can be seen from the results, if the contents were separated by period using time-of-day, users' WAP menu can be adapted to suit users' needs. Additionally, it increases higher user satisfaction by providing the appropriate content for user in each period. The results show that adaptive menu reach an accuracy of 80.81% and each period provided matching user's session at around 77%. Content category can be varied in each period or time-of-day. It can be inferred that user will use different category in different period of the day.

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