Design and Implementation of a User Profile Construction System Integrating Content and User Gesture Behavior (Postprint)

Authors: Wang Qiangbing, Zhang Chengzhi

Date: 2017-11-08T00:00:00+00:00

Abstract

【Purpose】To develop a mobile literature reading system that mines user interests and constructs user interest profiles by leveraging user gesture behavior data on mobile devices and the content corresponding to these gestures.

【Application Background】 A user profile construction system that integrates content and user behavior can mine user interests during literature reading and construct user profiles.

【Method】 Utilizing a Web reading system on mobile platforms as a tool, user models are constructed by collecting user gesture behavior data (including click, double-click, swipe, drag, zoom in/out, etc.) generated when users browse literature on mobile devices, together with the text content corresponding to these gestures, combined with the browsing time of the relevant text content.

【Results】 When using the literature reading system, users can discover their reading interests during the literature reading process and construct user interest profiles.

【Conclusion】 Preliminary research results indicate that user gesture behavior can, to a certain extent, reflect user reading interests and enable user modeling. These research findings can enhance the effectiveness of marketing and personalized recommendation systems.

Full Text

Constructing User Profiles by Integrating Content and Gesture Behaviors: System Design and Implementation

Wang Qiangbing[1,2], Zhang Chengzhi[1,2,3]
[1](School of Economics and Management, Nanjing University of Science & Tech-

nology, Nanjing 210094, China)
[2](Jiangsu Collaborative Innovation Center of Social Safety Science and Technology, Nanjing 210094, China)
[3](Jiangsu Key Laboratory of Data Engineering and Knowledge Service (Nanjing University), Nanjing 210093, China)

Abstract

[**Objective**] This paper develops a mobile literature reading system that mines user interests and constructs user interest profiles by leveraging gesture behavior data and corresponding content from mobile devices. [**Context**] A user profile construction system that integrates content and user behavior can effectively identify users' interests during literature reading and build corresponding profiles. [**Methods**] Using a mobile Web-based reading system as the tool, we collected user gesture behaviors (tap, double tap, swipe, drag, pinch in/out, etc.) generated while browsing literature on mobile devices, along with the text content corresponding to these gestures, and constructed a user model based on the associated browsing time. [**Results**] Users can discover their reading interests during the literature reading process, enabling the construction of user interest profiles. [**Conclusions**] Preliminary results demonstrate that user gesture behaviors can reflect reading interests to a certain extent and support user modeling. These findings can enhance the effectiveness of marketing and personalized recommendation systems.

Keywords: Gesture Behaviors, Mobile Device, Text Mining, User Modeling
Classification Number: G350

Introduction

As society and the economy continue to develop, mobile devices have become indispensable tools in daily life. With the widespread adoption and continuous improvement of mobile device capabilities, operations traditionally performed on computers are increasingly shifting to mobile platforms. User behavior on computers has been extensively studied, and leveraging computer-based user behavior data enables effective user modeling and reveals user interests. Due to the unique characteristics of mobile devices, users exhibit different gesture behaviors when using them. However, research on user modeling based on mobile device gesture behaviors remains limited. This study investigates how to utilize gesture behaviors generated on mobile devices for user modeling.

When users browse literature on mobile devices, they inevitably perform various gesture behaviors on the screen, such as tap, swipe up, swipe down, drag up, drag down, pinch out, and pinch in. Due to mobile device usage patterns and screen size limitations, a tap gesture indicates that the user is clicking on screen content; swipe up/down gestures indicate rapid content replacement on the screen; drag up/down gestures indicate slow content replacement, meaning the user is reading the screen content; and pinch out gestures indicate that the user is zooming in on local content for clearer reading. Guo et al. [1] demonstrated that mobile touch interaction—gesture behaviors on mobile devices—can reflect user interest in articles, and that dwell time on relevant content indicates interest level. This paper proposes that different gesture behaviors carry different weights in reflecting user interest, and that combining gesture behaviors with their corresponding content can reveal user interests. By integrating natural language processing techniques, Java Web technologies, and visualization tools, we constructed a mobile reading platform where registered users can read relevant literature. The system collects gesture behavior data during literature browsing and utilizes pinch in/out, drag, swipe, and tap gestures [2], combined with corresponding text fragments and browsing time, to discover user interests and generate interest cloud maps.

With the rapid expansion of online information and the emergence of information overload, increasing numbers of websites are seeking ways to prevent users from getting lost in the information sea. Discovering user interests to recommend relevant information or content represents an effective solution. Consequently, many scholars have investigated how to leverage user-related information to obtain interests and achieve personalized recommendations. Joachim et al. [3] demonstrated that clickthrough data from search result pages can effectively mine user interest and preference information. Sun et al. [4] established user interest models based on browsing behaviors in computer Web browsers, determining user interest in a page through behaviors including scrollbar dragging, reading time, document saving, bookmarking, page printing, and hyperlink following. Zhao et al. [5] calculated user interest in specific pages based on content and behavior information during browsing, considering page browsing time and scrolling frequency using a multiple linear regression model. Huang et al. [6] improved retrieval effectiveness by combining mouse click behavior with mouse movement across different regions of search pages.

However, these studies focused on computer-based interactions. Users primarily rely on keyboards and mice on computers, whereas mobile device users depend mainly on finger gestures on touchscreens. Consequently, computer-based research cannot be directly applied to mobile devices. With the widespread adoption of mobile devices, scholars have shifted their attention to studying user gesture behaviors on these platforms. Guo et al. [1] compared touch operations on mobile devices with mouse and keyboard operations on computers, improving retrieval effectiveness by mining mobile user behaviors. Han et al. [7] utilized mobile gesture behaviors to discover the most relevant text fragments for users, thereby enhancing cross-device retrieval effectiveness. Research [8] has shown that when browsing an article, users are not necessarily interested in every paragraph but may only be interested in certain sections.

Building on these studies, this paper assigns specific weights to different gesture behaviors to reflect user interest levels in text fragments where gestures occur. By counting the types and frequencies of gestures on text fragments and combining them with browsing time, we identify keywords and corresponding interest levels within those fragments, ultimately calculating user interests across the entire literature browsing process. Finally, by integrating the set of literature browsed by the user, we discover the user’ s interest space and construct a user profile.

3.1 Design Approach

This study first determines user interest levels in different text fragments during article browsing based on gesture behavior data and reading time collected through the reading platform. Second, it identifies keywords of interest to users while browsing articles by synthesizing all text fragments where gestures occurred. Finally, it discovers user interests and constructs user models with visualization processing based on all articles browsed by the user. The design approach is illustrated in Figure 1 [Figure 1: see original paper].

3.2 System Architecture Design

Based on the design approach described above, the system architecture is divided into three layers, as shown in Figure 2 [Figure 2: see original paper].

(1) Data Layer
The data layer is responsible for storing data required for system operation, user behavior data generated during literature browsing, and personal information filled in during user registration.

(2) Processing Layer
The processing layer handles data processing tasks, including gesture collection, Chinese word segmentation, keyword extraction, interest calculation, profile construction, and data visualization. Gesture collection stores user gesture behavior data during literature browsing in the database. Natural language processing techniques such as Chinese word segmentation and keyword extraction identify user interest words. Based on these interest words, user interest profiles are constructed and displayed using data visualization tools.

(3) View Layer
The view layer includes user personal information management, literature reading, and visualization of user interest profiles.

3.3 Key Technical Descriptions

(1) Text Fragment Interest Calculation
This study analyzes user gesture behaviors and browsing time during literature browsing to obtain interesting text fragments and calculate their interest levels. We determined the weight of different gesture behaviors in reflecting text fragment interest. The pinch in gesture indicates zooming out content; pinch out indicates zooming in; drag indicates slow finger sliding; swipe indicates rapid finger sliding. Since swipe gestures represent rapid content replacement, their

contribution to reflecting text fragment interest is minimal [2]. Therefore, we set the weight of swipe to 0. We employed the Analytic Hierarchy Process (AHP) to determine weights for pinch in/out, drag, and tap. During article browsing, pinch in/out operations carry the highest weight, followed by drag operations, while tap operations carry the lowest weight. Based on this, we constructed a judgment matrix, as shown in Table 1 .

In Table 1, the value 3 in row 2, column 3 indicates that pinch in/out behavior is slightly more important/advantageous than drag behavior, while the value 5 in row 2, column 4 indicates that pinch in/out behavior is significantly more important/advantageous than tap behavior. After calculation, the weight for pinch in/out is 0.6267, drag is 0.2797, and tap is 0.0936. The consistency test result is 0.0825, confirming the validity of the calculation. The final weights for gesture behaviors in text fragment interest calculation are shown in Table 2 .

An article comprises different text fragments, and users spend varying amounts of time on each fragment. This study measures browsing time on text fragments using gesture behaviors. During literature browsing, the system automatically records the time when a gesture first acts on a text fragment. We define the browsing time of a text fragment as the difference between the time when a gesture first acts on that fragment and the time when the first gesture acts on another fragment after leaving it. The browsing time t_i for text fragment P_i is calculated as shown in formula (1).

it represents the moment when a gesture first occurs on text fragment P_i

jt represents the moment when a gesture first occurs on other text fragments after leaving P_i

The sum of browsing times across different text fragments in an article equals the total browsing time for that article. The total browsing time T for an article is calculated as shown in formula (2).

$$T = \sum_{i=1}^{n} t_i \tag{2}$$

where t_i represents the browsing time of text fragment P_i, and n represents the number of text fragments where gestures occurred in the article.

Browsing time can reflect user interest in a text fragment, and gestures occurring on a text fragment can also reflect interest. This study comprehensively calculates user interest in text fragments by combining time and gesture information. Let f_p, f_d, f_t, and f_s represent the occurrence counts of pinch in/out, drag, tap, and swipe gestures in text fragment i, respectively, with corresponding weights v_p, v_d, v_t, and v_s. Let t_i be the browsing time of text fragment P_i, and T be the total browsing time of the article containing the fragment. The interest level $W(i)$ of text fragment P_i is calculated as shown in formula (3).

$$W(i) = \frac{t_i}{T} \times (f_p \times v_p + f_d \times v_d + f_t \times v_t + f_s \times v_s) \tag{3}$$

(2) Text Fragment Keyword Extraction and Vector Space Representation

This study employs ICTCLAS[1] for keyword extraction from text fragments. ICTCLAS is a Chinese text processing package that performs word segmentation, keyword calculation, and new word discovery based on information entropy principles. After extracting keywords, we retain their weights and normalize them as shown in formula (4).

$$NC_i = \frac{C_i - C_{min}}{C_{max} - C_{min}} \tag{4}$$

where C_i represents the keyword weight of a word after ICTCLAS processing, C_{max} is the maximum keyword weight among all keywords in the text, C_{min} is the minimum keyword weight, and NC_i is the normalized keyword weight.

After extracting keywords from text fragments where gestures occurred, we obtain a keyword sequence representing the text fragment along with corresponding weights. We use a vector space model to represent the text fragment P_i as follows:

$$P_i = \{(K_1, NC_1), (K_2, NC_2), \dots, (K_n, NC_n)\}$$

where K_n represents the nth keyword extracted from fragment P_i.

(3) User Profile Generation and Visualization

After obtaining text fragment interest levels from gesture behaviors and browsing time, and extracting keywords from text fragments, we calculate user interest keywords and construct the user’ s interest space. Since users browsing specific literature are not interested in all content but focus on certain text fragments, we extract text fragments where gestures occurred and recombine them into literature D_i browsed by the user:

$$D_i = (P_1, P_2, \dots, P_n)$$

where P_n represents a text fragment in literature D_i where gestures occurred.

Having obtained the text fragment interest level $W(i)$ and keyword weight NC_i, we set both weights to 0.5. The interest level of keyword K in text fragment P_i is calculated as shown in formula (5).

$$\text{Keyword } K \text{ Interest Level} = 0.5 \times NC_i + 0.5 \times W(i) \tag{5}$$

where K represents a keyword extracted from text fragment P_i.

Through these steps, we obtain the interest levels of keywords in each text fragment where gestures occurred in article D_i. To calculate the user' s most interested keywords in article D_i, we compute the average interest level for keywords that appear across different text fragments, using this as the user' s interest level in that keyword while browsing article D_i. The calculation method is shown in formula (6).

$$\text{Interest}(K) = \frac{\sum_{i=1}^{n} P_i(NC)}{n} \tag{6}$$

where $P_i(NC)$ represents the interest level of the keyword in text fragment P_i, and n is the number of text fragments in article D_i containing the keyword. The numerator represents the sum of keyword interest levels across different text fragments.

This yields the keywords of interest to the user in article D_i and their corresponding interest levels. We select the top 10 keywords with the highest interest levels to represent the user' s most interested keywords during browsing. Using the same method for all articles browsed by the user, each article contains the 10 most interesting keywords. The processed articles form the user' s browsed article collection $D = (D_1, D_2, \dots, D_n)$. In this article collection, we calculate the frequency of each keyword across the document collection to obtain the user' s interest space. The user' s interest profile is represented as the following set:

$$\{(k_1, m_1), (k_2, m_2), \dots, (k_i, m_n)\}$$

where m_i represents the frequency of keyword occurrence, with $i = 1, 2, \dots, n$.

After obtaining the user profile, we use data visualization tools to display it more clearly. This study employs ECharts[1], a visualization tool provided by Baidu, to visualize user profiles. We use word cloud charts in ECharts to display user profiles, where keywords in the profile represent words in the cloud, and their frequencies serve as weights to control font size.

4.1 System Development

To collect user gesture behaviors during browsing, we developed a mobile reading website—the Literature Reading System—with an interface shown in Figure 3 [Figure 3: see original paper]. After registering, users can log in with their accounts to read relevant literature. During reading, users can comment, share, and like articles. This study focuses on mining user interest domains through gesture behavior information combined with browsing time.

The system recognizes pinch out/pinch in, swipe, drag, and tap gestures during page browsing, and records the corresponding text fragments and browsing times. We use a JavaScript open-source toolkit[2] to recognize user gestures. When designing the collection of text fragments corresponding to gesture behaviors, we referenced Han' s [9] related JavaScript code.

To test system feasibility, we recruited a graduate student from our research group for an experiment. Before the experiment, we introduced the system' s basic functionality and usage. The participant browsed relevant literature according to their interests.

The system stores collected user gesture data, corresponding text fragments, and other relevant data in a database, including user ID, article ID, gesture occurrence time, gesture type acting on the text fragment, text fragment content, and detailed gesture data (position, speed, timestamp, etc.). Table 3 shows the gesture behavior sequence for user ID "user1" browsing article 32 (text fragment data is extensive and omitted for brevity).

Table 3. Gesture Behavior Sequence

userID	documentID	time	type	touchHtml
user1	32	2016-01-10 13:47:01	drag	paragraph1
user1	32	2016-01-10 13:47:02	drag	paragraph1
...	...	...	...	...

(Note: The number i after "paragraph" does not represent the ith paragraph in the article but only distinguishes different text fragments.)

4.2 System Application

After eliminating invalid data, we obtained gesture behavior sequences and corresponding text fragment time information when the user read an article.

Using the method described above to calculate text fragment browsing time, we first computed the browsing duration for each fragment. Next, we calculated the types and frequencies of gestures occurring on each text fragment: readtime (text fragment reading time), dragtime (drag operation count), swipetime (swipe operation count), taptime (tap operation count), pinchintime (pinch in operation count), and pinchouttime (pinch out operation count). The results are shown in Table 4 , yielding the keywords of interest and their corresponding interest levels for user1 browsing article D_i.

Table 4. Processed Gesture Behavior Sequence Results

userID	documentID	readtime	dragtime	swipetime	taptime	pinchintime	pinchouttime	touchHtml
user1	32	0:22	...	...	...	...	...	paragraph1
...	...	...	...	...	...	...	...	...

Using the same method to process other articles read by user1, we formed the user' s browsed article collection. The resulting user interest space is:

$$I_{user1} = \{(\text{Government Knowledge Management}, 2), (\text{Personal Information Management}, 2), (\text{Socialization}, 1),$$

We processed this user interest space using ECharts. In the word cloud, larger font sizes indicate greater user interest in a keyword. The result is shown in Figure 6 [Figure 6: see original paper].

This study constructed a mobile reading system using Java Web technologies that captures user gestures during reading. After registration, users can log in via mobile devices to read literature of interest. During reading, the system automatically records gestures, their timestamps, and corresponding text fragments, storing this data on the server. After obtaining user gesture data, the system employs natural language processing techniques to build user interest profiles and visualizes them using visualization tools.

This study did not compare mobile gesture-based modeling with traditional modeling methods; such experiments will be conducted in future work. In addition to gestures, users also perform other behaviors while browsing articles, such as liking, sharing, and commenting. This study did not incorporate these factors when building the user interest space; future work will combine these factors for deeper investigation of user interests.

References

[1] Guo Q, Jin H, Lagun D, et al. Mining Touch Interaction Data on Mobile Devices to Predict Web Search Result Relevance [C]//Proceedings of the 36th International ACM SIGIR Conference on Research and Development in Information Retrieval. 2013: 153-162.

[2] Han S G, Hsiao I H, Parra D. A Study of Mobile Information Exploration with Multi-Touch Interactions[C]//Proceedings of the 7th International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction. 2014: 269-276.

[3] Joachims T, Granka L, Pan B, et al. Accurately Interpreting Clickthough Data as Implicit Feedback[C]//Proceedings of the 28th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval. 2005: 154-161.

[4] Sun Tieli, Yang Fengqin. An Approach of Building and Updating User Interest Profile According to the Implicit Feedback [J]. Journal of Northeast Normal University: Natural Science Edition, 2003, 35(3): 99-104.

[5] Zhao Yinchun, Fu Guanyou, Zhu Zhengyu. User Interest Mining of Combining Web Content and Behavior Analysis [J]. Computer Engineering, 2005, 31(12): 93-94.

[6] Huang J, White R W, Dumais S T. No Clicks, No Problem: Using Cursor

Movements to Understand and Improve Search [C]//Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 2011: 1225-1234.

[7] Han S G, Yue Z, He D Q. Understanding and Supporting Cross-Device Web Search for Exploratory Tasks with Mobile Touch Interactions [J]. ACM Transactions on Information Systems, 2015, 33(4): Article No. 16.

[8] Morita M, Shinoda Y. Information Filtering Based on User Behavior Analysis and Best Match Text Retrieval[C]//Proceedings of the 17th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval. 1994: 272-281.

[9] Han S. PITT (PIck-up The Touches) -A Javascript Plugin to Track Your Website Visits [EB/OL]. [2016-06-25]. http://www.pitt.edu/~shh69/pitt.html.

Author Contributions

Zhang Chengzhi: Proposed research ideas, designed research methodology, revised final manuscript.
Wang Qiangbing: Processed data, drafted manuscript.

Conflict of Interest

All authors declare no conflict of interest.

Supporting Data

Supporting data is self-archived by the authors, E-mail: 1906439961@qq.com, zhangcz@njust.edu.cn.
[1] Wang Qiangbing, Zhang Chengzhi. userdata.mdb. User Gesture Behavior Data.

Received Date: 2016-08-25
Revised Date: 2016-11-07

[1]http://ictclas.nlpir.org/
[1]http://echarts.baidu.com.cn/
[2]http://hammerjs.github.io/

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.