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

Authors: Wang Qiangbing, Cheng-Zhi Zhang

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

Abstract

Objective: 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 those gestures. Application Background: A user profile construction system that integrates content and user behavior can mine users' interests during literature reading and construct user profiles. Method: Using a Web reading system on mobile platforms as a tool, user models are constructed by collecting data on user gesture behaviors (click, double-click, swipe, drag, zoom in/out, etc.) generated when users browse literature on mobile devices, along with the text content corresponding to those gesture behaviors, combined with the browsing time of the corresponding 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 using user gesture behavior can reflect users' reading interests to a certain extent and enable user modeling. The findings of this study can improve 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 & Technology, 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 generated on mobile devices and the content corresponding to those gestures. [**Context**] A user profiling system that integrates content and behavioral data can effectively discover users' interests during literature reading and build corresponding user profiles. [**Methods**] Using a mobile Web-based reading system as the tool, we collect 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 combine this with browsing time data to construct a user model. [**Results**] Users can discover their reading interests during the literature reading process, enabling the construction of user interest profiles. [**Conclusions**] Preliminary research results demonstrate that user gesture behaviors can reflect reading interests to a certain extent and support user modeling. These findings can improve the effectiveness of marketing and personalized recommendation systems.

Keywords: Gesture Behaviors, Mobile Device, Text Mining, User Modeling

As economic and social development continues, mobile devices have become indispensable tools in daily life. With the widespread adoption and continuous improvement of mobile device functionality, operations traditionally performed on computers are increasingly shifting to mobile platforms. User behavior on computers has been extensively studied, and computer-based user behavior data has proven effective for user modeling and revealing user interests. Due to the unique characteristics of mobile devices, users exhibit different gesture behaviors when using them. Currently, research on user modeling using mobile device gesture behaviors remains limited. This paper investigates how to utilize gesture behaviors generated on mobile devices for user modeling.

When users browse a document on a mobile device, 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. Given the usage patterns and screen size limitations of mobile devices, 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. [**?**] demonstrated that mobile touch interaction—gesture behaviors on mobile devices—can reflect whether users are interested in the articles they read, and that dwell time on relevant content can reflect user interest levels. 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 users can read relevant literature after registration. The system collects gesture behavior data generated during literature browsing, utilizing pinch in/out, drag, swipe, and tap gestures [?], combined with corresponding text fragments and browsing time, to discover user interests and generate user interest word clouds.

With the rapid expansion of online information and the emergence of information overload, an increasing number of websites are considering how to prevent users from getting lost in the sea of information. Discovering user interests to recommend relevant information or content represents an effective solution. Consequently, many scholars have begun researching how to leverage user-related information to obtain interests and implement personalized recommendations. Joachims et al. [?] demonstrated that clickthrough data from search result pages can effectively mine user interest and preference information. Sun et al. [?] 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. [?] calculated user interest in specific pages based on content and behavioral information during page browsing, considering page browsing time and scroll operations, using a multiple linear regression model. Huang et al. [?] improved search effectiveness by combining mouse click behavior with mouse movement across different regions of search result pages.

These studies focused on computer-based research. User operations on computers primarily rely on keyboards and mice, whereas mobile device users mainly use finger gestures on touchscreens. Therefore, 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. [?] compared touch operations on mobile devices with mouse and keyboard operations on computers, improving retrieval effectiveness by mining mobile user behaviors. Han et al. [?] utilized mobile gesture behaviors to discover text fragments most relevant to users, thereby improving cross-device retrieval effectiveness. Research by Morita and Shinoda [?] indicates 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 the degree of user interest in text fragments where gestures occur. By statistically analyzing the types and frequencies of gesture behaviors occurring on text fragments, combined with browsing time, we identify keywords of interest to users within those fragments and their corresponding interest levels, ultimately calculating the keywords of interest during literature browsing. Finally, by combining the set of documents browsed by the user, we discover the user' s interest space and construct a user profile.

3.1 Design Approach

This paper first determines user interest levels in different text fragments during article browsing through collected gesture behavior data and reading time information. Second, we identify keywords of interest to users when browsing articles by synthesizing all text fragments where gesture behaviors occurred. Finally, we discover user interests by combining all articles browsed by the user, construct a user model, and perform visualization. The design approach is illustrated in [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: 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 management of user personal information, literature reading, and visualization of user interest profiles.

3.3 Key Technical Descriptions

(1) Calculation of Text Fragment Interest Level
This paper 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 user interest in text fragments. Pinch in/out gestures indicate users zooming out/in on screen content; drag gestures indicate slow finger sliding on the screen; swipe gestures indicate rapid finger sliding. Since swipe gestures represent rapid content replacement, their contribution to reflecting text fragment interest is minimal [**?**]. Accordingly, this paper sets the weight of swipe to 0. The Analytic Hierarchy Process (AHP) is used to determine the weights of pinch in/out, drag, and tap gestures. 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, a judgment matrix is constructed, as shown in .

In , 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. The calculated weights are 0.6267 for pinch in/out, 0.2797 for drag, and 0.0936 for tap. The consistency test result is 0.0825, confirming the validity of the calculation. The final weights for gesture behaviors in reflecting text fragment interest are shown in .

A document consists of different text fragments, on which users spend varying amounts of browsing time. This paper measures user browsing time on text fragments using gesture behaviors. Specifically, when users browse literature, the system automatically records the time when a gesture behavior first occurs on a text fragment. The time difference between when a gesture first occurs on text fragment Pi and when the first gesture occurs on another fragment after leaving Pi is used as the browsing time for that text fragment. The browsing time ti for text fragment Pi is calculated as shown in equation (1), where it represents the moment when the first gesture occurs on text fragment Pi, and jt represents the moment when the first gesture occurs on another text fragment after leaving Pi.

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 equation (2), where ti represents the browsing time of text fragment Pi, and n represents the number of text fragments in the article where gesture behaviors occurred.

Browsing time can reflect user interest in a text fragment, and gesture behaviors occurring on a text fragment can also reflect user interest. This paper combines time and gesture information to comprehensively calculate user interest in text fragments. If the numbers of pinch in/out, drag, tap, and swipe gestures occurring on text fragment i are fp, fd, ft, and fs respectively, with corresponding weights vp, vd, vt, and vs, the browsing time of text fragment Pi is ti, and the total browsing time of the article containing Pi is T. Let W(i) represent the weight of text fragment Pi. The interest level of text fragment Pi is calculated as shown in equation (3).

(2) Keyword Extraction and Vector Space Representation of Text Fragments

This paper uses ICTCLAS [?] 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, their weights are retained and normalized as shown in equation (4), where Ci represents the weight of a certain word after ICTCLAS processing, Cmax is the maximum keyword weight in the text, Cmin is the minimum keyword weight, and NCi is the normalized keyword weight.

After extracting keywords from text fragments where gesture behaviors occurred, we obtain a keyword sequence representing the text fragment and corresponding weights. The text fragment Pi is expressed using a vector space model as follows: Pi = {(K1, NC1), (K2, NC2), ···, (Kn, NCn)}, where Kn represents the nth keyword extracted from fragment Pi.

(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. When browsing specific literature, users are not interested in all content but focus on certain text fragments. We extract text fragments where gesture behaviors occurred and recombine them into literature Di browsed by the user: Di = (P1, P2, ···, Pn), where Pn represents text fragments in literature Di where gesture behaviors occurred.

Having obtained the interest level W(i) of text fragment Pi and keyword weight NCi, we set both weights to 0.5. The interest level of keyword K in fragment Pi is calculated as shown in equation (5): Keyword K Interest Level = 0.5 × NCi + 0.5 × W(i), where K represents a keyword extracted from text fragment Pi.

Through these steps, we obtain the interest level of each keyword in every text fragment where gesture behaviors occurred in article Di. After obtaining keyword interest levels across fragments, we further calculate the user' s most interesting keywords in article Di. If a keyword appears in multiple text fragments where gesture behaviors occurred, we calculate its average interest level as the user' s interest level in that keyword when browsing article Di, as shown in equation (6), where Pi(NC) represents the interest level of the keyword in text fragment Pi, and n is the number of text fragments in article Di containing that keyword. The numerator represents the sum of interest levels across different text fragments.

This yields the keywords of interest and corresponding interest levels for article Di. We select the top 10 keywords with highest interest levels to represent the user' s most interesting keywords during browsing. The same method is applied to all articles browsed by the user, with each article containing the top 10 user-interest keywords. The processed articles form the user' s browsed document set D = (D1, D2, ···, Dn). In document set D, we calculate the frequency of each keyword across the document collection to obtain the user' s interest space. The user profile is represented as the following set: {(k1, m1), (k2, m2), ···, (ki, mn)}, where mi represents the frequency of keyword i.

After obtaining the user profile, we use data visualization tools to display it more clearly. This paper uses ECharts [**?**], a visualization tool provided by Baidu, to visualize user profiles. Character cloud diagrams from ECharts display user profiles, where keywords in the profile represent characters 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—whose interface is shown in [Figure 3: see original paper]. After registering, users can log in with their accounts to read relevant literature. During reading, users can perform actions such as commenting, forwarding, and liking. This paper focuses on mining user interest domains through gesture behavior information combined with browsing time.

The system can recognize gesture behaviors including pinch out/in, swipe, drag, and tap during page browsing, and records the corresponding text fragments and browsing times. We use a JavaScript open-source toolkit [**?**] to recognize user gestures. When designing the collection of text fragments corresponding to gesture behaviors, we referenced relevant JavaScript code from Han [**?**].

To test the system's 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 gesture data, corresponding text fragments, and other relevant data in the database, including user ID, document ID, gesture occurrence time, gesture type occurring on text fragments, text fragment content, and detailed gesture data (location, speed, timestamp, etc.). The gesture behavior sequence of user ID "user1" browsing article 32 is shown in (text fragment data is extensive and omitted for brevity).

4.2 System Application

After eliminating invalid data, we processed the gesture behavior sequences and corresponding text fragment timing information for users reading an article. Using the method described above to calculate text fragment browsing time, we then computed the types and frequencies of gesture behaviors occurring on each fragment. The results include readtime (text fragment reading time), dragtime (drag operation frequency), swipetime (swipe operation frequency), taptime (tap operation frequency), pinchintime (pinch in operation frequency), and pinchouttime (pinch out operation frequency), as shown in . This yields the keywords of interest and corresponding interest levels for user1 browsing article Di.

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

Iuser1 = {(Government Knowledge Management, 2), (Personal Information Management, 2), (Socialization, 1), (UTAUT, 1), (System, 1), (Trust, 1), (Trust Belief, 1), (Government, 1), (Patent Review, 1), (Model, 1), (Problem, 1), (Information, 1), (Smartphone, 1), (Problem Solving, 1), (Personal Information, 1), (Perceived Usefulness, 2), (Social Media, 1), (Technology Adoption, 1), (Microblog, 2), (Social Media Application, 3)}

Using ECharts to process this user interest space, the word cloud displays larger fonts for keywords of greater interest. The result is shown in [Figure 6: see original paper].

Conclusion

This paper constructed a mobile reading system using Java Web technologies that captures user gesture behaviors during reading. After registration, users can log in via mobile devices to read literature of interest. During reading, the system automatically records gesture behaviors, 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 construct user interest profiles and visualizes them using visualization tools.

This study did not compare mobile gesture behavior modeling with traditional modeling methods; such experiments will be conducted in future work. During article browsing, users perform additional behaviors beyond gestures, such as liking, forwarding, and commenting. This paper did not incorporate these factors when establishing user interest spaces; future work will combine these factors to more deeply investigate user interests and preferences.

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: Conceptualized the research, designed the research methodology, revised the final manuscript.
Wang Qiangbing: Processed the data, drafted the manuscript.

Conflict of Interest

All authors declare no conflict of interest.

Data Availability

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

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

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