ICEB 2005 Proceedings

International Conference on Electronic Business (ICEB)

Winter 12-5-2005

An Adaptive Interface for Customer Transaction Assistant in Electronic Commerce

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An Adaptive Interface for Customer Transaction Assistant in Electronic Commerce

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Abstract: Personalized service and adaptive interface play important factors in electronic commerce. This work proposes an adaptive interface to for helping the customer transaction in electronic commerce. The adaptive interface collects the consumer behaviors by monitoring the customer operations, excluding unnecessary operations, and recognizing the behavior patterns. The interface uses the Bayesian belief network and the RBF neural networks to achieve the above tasks. The interface then evaluates knowledge and skill proficiency according to the customer behavior patterns. Finally, the interface generates the adaptive interface to the consumers for helping the transaction process.

Keywords: Web intelligence and web-based information technology, Adaptive interface, Proficiency evaluation

I. Introduction

Electronic commerce (EC) is the business activity that occurs over the electronic network. The customers purchase goods or services through the business platform of the EC systems. Personalized service and adaptive interface become the important factors to attract their customers. They should provide a friendly environment for the customer to buy goods according to the past consuming behaviors. Customer transaction behavior analysis becomes the important function in the system. Many systems have been proposed for applying the past user transaction history to different applications [3] [7] [8] [9] [10] [11] [13]. These systems are insufficiently specific regarding the analysis of the customer behavior. The system also did not provide the interaction activities analysis for effective customer behavior analysis. Some interface usability tools or systems were designed to overcome the above shortcomings [1] [2] [5] [6] [12]. Many problems still need to be solved. First, most systems use a resident monitoring program in the application system to collect user information from the interaction information between the end user and application system. The monitoring of user behaviors usually uses the cookies and the log files to record the user operations [5] [12]. Cookies were used to keep the user information in the client side. The drawbacks of cookies contain the limited amount of the information in the client side and the dangerous of information loss in the business session. Moreover, the drawbacks of log files include the collection of passive user request information and the complexity of interaction events. Second, most systems acquire the static and specific business information from the content of the web pages. They do not analyze the interaction operations of the user in the applications. Third, most systems assume the user is an experimented operator and may not commit wrong operations. The collected data are presumed correct and valid information. Finally, most systems lack the customer proficiency evaluation to provide an adaptive interface in the application domain.

This work proposes an adaptive interface for customer transaction assistant in electronic commerce. The system uses the customer transaction behaviors to provide an adaptive interface and transaction guidance. The interface analyzes the transaction behavior and excludes unnecessary operations by Bayesian network. The interface then uses the RBF neural networks to discriminate the behavior patterns based on customer operations. Finally, the interface evaluates the knowledge and skill proficiency of the consumer to provide the intelligent assistant. The interface provides three assistant functions for the customers based on the fuzzy degree of the knowledge and skill proficiency. The interface also provides guidance for the customer to complete the transaction.

II. System Architecture

The system architecture contains two modules, namely, interface manager and behavior analyzer (Fig. 1). The interface manager collects the interactions performed by the customer in the client-side and server-side. It captures the customer interactions from the browser and EC server and filters the customer operations from the customer interactions and recognizes the behavior patterns. It uses the Bayesian belief networks to exclude redundant and irrelevant operations. It then uses the RBF neural network for discriminating the customer behavior from the interaction message

The behavior analyzer uses the behavior patterns to evaluate the knowledge and skill proficiency degree of customer. The former uses the personal ontology and the latter uses the usefulness, precision, dependency, and efficiency measurements to evaluate the consumers. Finally, the interface provides three assistant functions for the customers based on the above evaluation to guide the customer for completing the transaction.

Proceedings of the Fifth International Conference on Electronic Business, Hong Kong, December 5-9, 2005, pp. 962 - 966.

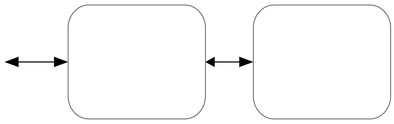

Fig. 1 System architecture

III. Interface Manager

The interface manager is responsible for collecting the transaction behavior and recognizing behavior patterns. First, the interface manager collects the interactions performed by the customer in the client-side and server-side. First, the interface manager captures the customer interactions from the browser and EC server. Fig. 2 shows the interaction pattern of the system. The interface manager then filters the customer operations from the customer interactions and recognizes the behavior patterns. It uses the Bayesian belief networks to exclude redundant and irrelevant operations. Redundant operations are those which the customer use the same operation for the same subtask. The irrelevant operations are those that are not effective in performing the subtask. The directed acyclic graph is used to represent the relationship among customer operations (Fig. 3). The circular node represents the operation of the customer and the link represents the relationship between operations. Both of two operations $<O_1, O_2>$ and $<O_3, O_4>$ can use to do the same subtask ST1. If the customer operates sequence is O1, O_3, O_2 and O_5. The operation O5 is the irrelevant operation and O_3 is the redundant operation for the subtask ST_1. The probability of the subtask ST_1, $P(ST_1)= P(O_1)*P(O_2)$. Redundant and unnecessary operations can be removed by computing the joint probability of the operations according to the causal relations of the Bayesian belief network.

The behavior pattern recognition uses the RBF neural model as the behavior pattern classifier for discriminating the customer behavior from the interaction message. The RBF neural model contains three layers, namely, the input, hidden, and output layers (Fig. 4). Notably, the input layer uses 35 nodes to represent the interaction information. The input of the interaction information includes the interaction events, focus object, request method, and query items. The node number of the interaction information in the input layer is 9, 10, 6, and 10 correspondingly. Each interaction event uses three digits to represent the operation. Table 1 lists the code of the interaction event. The character of the focus object, request method, and query items are encoded following the sequence of the alphabetically. Each character then is normalized into a real number ranging between 0 and 1. For example, the request method of "Get" was coded into (7/26, 5/26, 20/26, 0, 0, 0). The interface manager forwards the behavior patterns for use by the behavior analyzer in customer behavior analysis [4].

IV. Behavior analyzer

The behavior analyzer uses the behavior patterns to analyze the activities and evaluate the proficiency level of the customer. First, it evaluates the knowledge and skill proficiency degree of customer. The knowledge proficiency degree *(KP)* evaluates the structure similarity between personal ontology and domain ontology. The *KP* is evaluated by using internal path length of the personal ontology and domain ontology.

$$KP = \frac{IPL_{Personal}}{IPL_{Domain}} \tag{1}$$

where $IPL_{Personal}$ and IPL_{Domain} are the internal path length of personal ontology and domain ontology. The *KP* is partitioned into three proficiency level, namely, novice, knowledgeable surfer, and expert (Fig. 5). Notably, the personal domain ontology stores the terminology and the relations between them of the application domain which was visited or used by the customer. It is constructed by using the merchandise name contained in the transaction operation [4]. The skill proficiency degree classifies customer's experience into one of the following three levels, namely, novice, skilled surfer, and expert. Figure 6 shows the fuzzy partition of the skill proficiency. Furthermore, the skill proficiency degree *(SP)* is computed by evaluating the skill measure.

$$\begin{aligned} SP &= F(U,P,D,E) = \\ &U*W_u + P*W_P + D*W_D + E*W_E \end{aligned} \tag{2}$$

where *U, P, D, E* refer to the measure of usefulness, precision, dependency, and efficient. W_U, W_P, W_D, and W_E are respective weights. The usefulness, U, evaluates the correctness and validity of the customer operations.

$$U = 1 - \frac{\sum_{i=1}^{n} e_i}{n} \tag{3}$$

where e_i represents the ratios of error or nullify operations, $e_i \in [0, 1]$ and n is the operation number.

Precision, P, computes the average number of operations for completing the tasks.

$$P = \frac{\sum_{i=1}^{n} t_i}{n} \tag{4}$$

where t_i represents the number of operations to achieve the ith task and n is the task number.

Dependency, D, represents the behavior correlation.

$$D = \frac{\sum_{i=1}^{n} B_i \Rightarrow B_{i+1}}{n} \tag{5}$$

where B_i and B_{i+1} represent the i^{th} and $(i+1)^{th}$ behaviors, $\Rightarrow$ represents the sequence relationships, and n is the behavior number.

Efficiency, E, measures the average time of the customer for completing the tasks.

$$E = \frac{\sum_{i=1}^{n} w_i}{n} \tag{6}$$

where w_i represents the time for completing the i^{th} task and n is the task number.

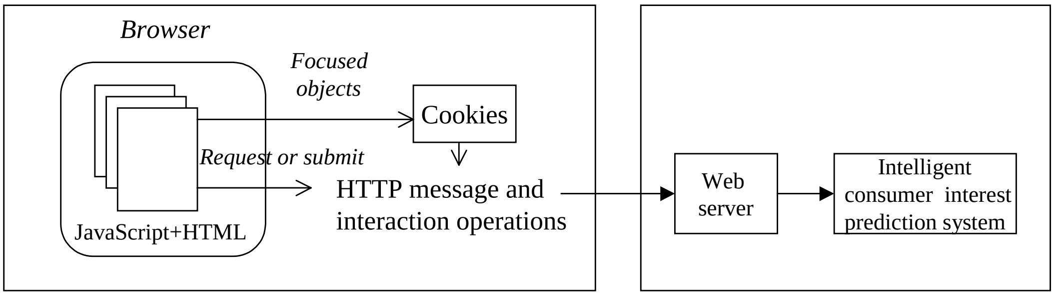

Fig. 2 Consumer interaction pattern

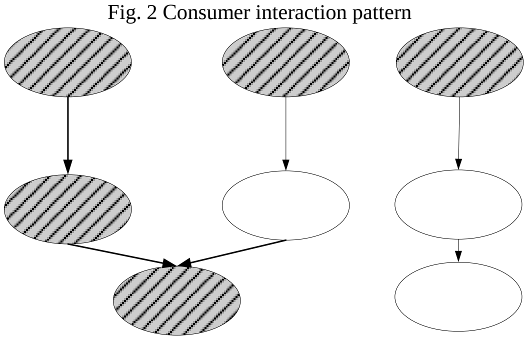

Fig. 3 Bayesian belief network

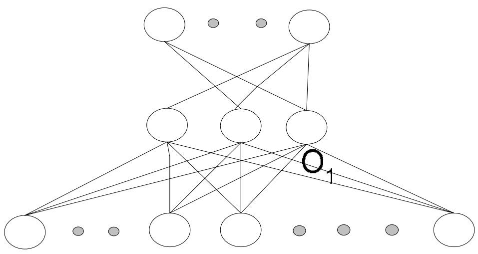

Fig. 4 RBF neural topology

Table 1 Code of the interaction event

Interaction event	Code
Form submission	001
Button clicking	010
Text input	100
Hyperlink clicking	101
Focus object	110
Mouse over	111

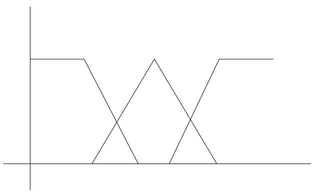

Fig. 5 Fuzzy partition of knowledge proficiency

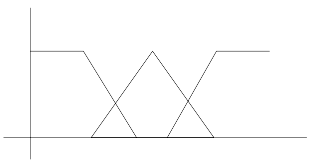

Fig. 6 Fuzzy partition of the skill proficiency

The system uses the values of KP and SP to help the customer for completing the transactions and customizing the interface. The intelligent interface provides three assistant functions for the customers, that is, transaction help, interaction style selection, and control panel expansion. Table 2 lists the assistant functions according to the knowledge and skill proficiency degree of customers. Basically, the transaction help provides three assistant types, namely, personal recommendations, collaborative ranking, and unconstrained transaction, for the customer. The transaction recommendations suggest the most possible merchandises for the customer according to the product hierarchy in the personal domain ontology. The collaborative ranking uses collaborative filtering to rank the possible business transactions for the customers. The unconstrained transaction didn’t provide any helps for experienced consumers. The interaction style selection provides three interaction patterns, that is, simple, weak, and strong, for the customers. The simple interaction provides transaction guidance to help the customer in completing the transaction tasks. The weak interaction uses distinct and click-and-selection interface elements, such as menu, radio, and combo buttons, to interact with customers conveniently. Moreover, the strong interaction provides advanced interaction patterns, such as, form fill in and checklists, to interact with experienced customers. Finally, the control panel expansion provides static, semi-adaptable, and fully adaptable interface for customers to insert new control panels in the interface. The static interface provides fixed control panel for the customer who can not modify the web page layout. The semi-adaptable interface provides the panel for the customer to add new personalized icons regarding as the shortcut for doing the transaction. The fully adaptable interface provides the entire control panels for the customer to rearrange the block layout of web page. Notably, the layout of web pages contains six blocks, that is, EC task bar, personalized icons, transaction behaviors, assistant function, recommendation, and guidance in the sequence of top-left and right bottom (Fig. 7).

V. Conclusions

This work proposes an intelligent interface for customer transaction assistant in electronic commerce. The system contains two modules, i.e, interface manager and transaction manger. The interface manager extracts the customer operations by analyzing the transaction behavior. The exclusion of unnecessary operations uses the Bayesian network to reduce the computation of irrelevant operations. The behavior pattern recognition uses the RBF neural networks to discriminate the behavior patterns based on customer operations. Finally, the behavior analyzer uses the knowledge and skill proficiency evaluation to provide the intelligent assistant. It provides three assistant functions for the customers according the fuzzy degree of the KP and SP. It also provides guidance for the customer to complete the transaction.

Acknowledgement

This project is partly supported by National Science Council of ROC under grants NSC 94-2745-E-030-004- URD.

References

[1] Aberg, J., Shahmehri, N.: The Role of Human Web Assistants in E-Commerce: An Analysis and a Usability Study. Electronic Networking Applications and Policy, 2000, 10(2), 114-125.

[2] Brusilovsky, P., Cooper, D. W.: Domain, Task, and User Models for an Adaptive Hypermedia Performance Support System. Proceedings of International Conference on Intelligent User Interface, San Francisco, 2002, 13-16

[3] Cho, Y. H., Kim, J. K.: Application of Web usage mining and product taxonomy to collaborative recommendations in e-commerce. Expert Systems with Applications, 2004, 26(2), 233-246.

[4] Deng. C. W.: The Design and Implementation of an Intelligent User Modeling Management System. Master Thesis, Fu-Jen Catholic University. Taiwan, 2003.

[5] Etgen, M., Cantor, J.: What Does Getting WET (Web Event-logging Tool) Mean for Web Usability. Proceedings of the 5th Conference on Human Factors and the Web. Maryland. Available at: http://zing.ncsl.nist.gov/hfweb /proceedings/etgen-cantor/

[6] Fischer, G.: User Modeling in Human-Computer Interaction. User Modeling and User-Adapted Interaction, 2001, 11(1-2), 65-86.

[7] Goecks, J., Shavlik, J. W.: Learning Users' Interests by Unobtrusively Observing Their Normal Behavior. Proceedings of the International Conference on Intelligent User Interfaces (IUI-2000), New Orleans, 2000, 129-132.

[8] Kenichi, Y.: User Command Prediction by Graph-Based Induction. Proceedings of the Sixth International Conference on Tools with Artificial Intelligence, LA, CA, 1994, 732-735.

[9] Kim, W. Song, Y. U., Hong, J. S.: Web enabled expert systems using hyperlink-based inference. Expert Systems with Applications, 2005, 28(1), 79-91.

[10] Kim, Y. S., Yum, B.-J., Song , J., Kim, S. M.: Development of a recommender system based on navigational and behavioral patterns of customers in e-commerce sites. Expert Systems with Applications, 2005, 28(2), 381-393.

[11] Liton F., Schaefer, H.P.: Recommender System for Learning: Building User and Expert Models through Log-Term Observation of Application Use. User Modeling and User-Adapted Interaction, 2000, 10(2-3), 181-207.

[12] Paganelli, L., Paterno, F.: Intelligent Analysis of User Interactions with Web Applications. Proceedings of the International Conference on Intelligent User Interface, San Francisco, 2002, 111-118.

[13] Seo Y., Zhang B.: A Reinforcement Learning Agent for Personalized Information Filtering. Proceedings of the International Conference on Intelligent User Interface (IUI-2000), New Louisiana, 2000, 248-251.

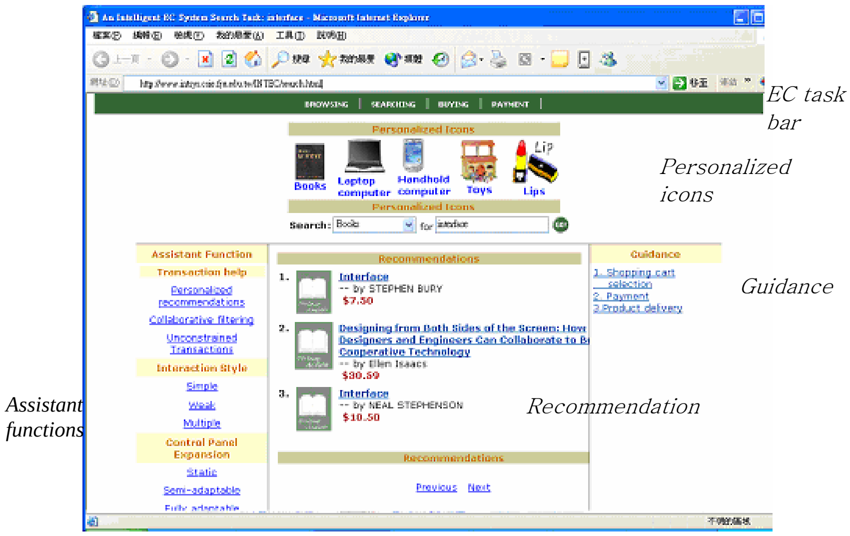

Fig. 7 Novice knowledge and skilled surfer proficiency interface

Table 2 Assistant functions for different knowledge and skill proficiency level

KP \ *SP*	Assistant function	**Novice**	**Skilled surfer**	**Expert**
Novice	*Transaction help*	Personal recommendations	Personal recommendations	Personal recommendations
	Interaction style	Simple	Simple	Weak
	Control panel expansion	Static	Semi-adaptable	Semi-adaptable
Knowledgeable surfer	*Transaction help*	Personal recommendations	Collaborative ranking	Collaborative ranking
	Interaction style	Weak	Weak	Strong
	Control panel expansion	Static	Semi-adaptable	Fully-adaptable
Expert	*Transaction help*	Collaborative ranking	Unconstrained transaction	Unconstrained transaction
	Interaction style	Weak	Weak	Strong
	Control panel expansion	Static	Semi-adaptable	Fully-adaptable