Proceedings of the 2nd International Conference on Information Technology for Application (ICITA 2004)

A Personalized e-Learning Material Recommender System

Jie Lu

Abstract--**E-learning environments are mainly based on a range of delivery and interactive services. Web-based personalized learning recommender systems can, as a kind of services in e-learning environment, provide learning recommendations to students. This research proposes a framework of a personalized learning recommender system, which aims to help students find learning materials they would need to read. Two related technologies are developed under the framework: one is a multi-attribute evaluation method to justify a student's need, and another is a fuzzy matching method to find suitable learning materials to best meet each student need. The implementation of this proposed personalized learning recommender system can support students online learning more effectively and assist large class online teaching with multi-background students.**

Index Terms--**Recommender systems, eLearning, Learning material, Multiple criteria.**

I. INTRODUCTION

E-learning environments are becoming increasingly popular in educational establishments. The rapid growth of e-learning has changed traditional learning behavior and presented a new situation to both educators (lecturers) and learners (students). Educators are finding it harder to guide students to select suitable learning materials due to more and more learning materials online. Learners are finding it difficult to make a decision about which of learning materials best meet his/her situation and need to read. Therefore, on the educator's side, educators need an automatic way to get feedback from learners in order to better guide their learning process. On the learner's side, it would be very useful an e-learning system could automatically guide the learner's activities and intelligently generate and recommend learning materials that would improve the learning [20].

Personalized recommendation approaches are first proposed and applied in E-commerce area for product purchase. Personalized product recommendations help customers find products they would like to purchase by producing a list of recommended products for each given customer [4]. Such recommendations are generated by recommender systems [12] which constitute a class of software. The basic principle of a recommender system is to use justifications to generate recommended products to customers, and ensure the customers like these products. These justifications can be obtained either from preferences directly expressed by customers, or induced, using data representing the customer experience [17].

Dr J. Lu is with the Faculty of IT, University of Technology, Sydney, PO Box 123, Broadway NSW 2007, Australia (email: jielu@it.uts.edu.au)

ICITA2004 ISBN 0-646-42313-4

Recommender systems have obtained success within the domain of E-commerce [15]. However, literature review shows less study to use recommender systems on e-learning sites. Recommender systems assist the natural process of relying on friends, classmates, lecturers, and other sources to make the choices for learning. Examples of the kinds of questions that could be answered by a recommender system include: what kind of materials should I read? What kind of exercises should I do? This study aims to explore the constructions of recommender systems in e-learning area to help students find learning material they would need particularly. Two key research issues involved in the study are how to identify a student's need, and how to accurately find the learning materials which match the student's need.

This study develops a framework for personalized learning recommender systems (PLRS). The framework introduces a personalized recommendation procedure by which we can generate recommendations effectively when applied to online teaching and learning sites. Once a learning material database, or a learning activity database, is created and a student's personal information is obtained, the PLRS can use a computational analysis model for identifying the student's learning requirement, and then use matching rules to generate a recommendation of learning materials (or activity) for the student. The provided recommendation is expected to have higher accuracy in matching student requirement to learning material, and thus higher acceptance by the students.

II. BACKGROUND

The research on recommender systems can be divided into three categories: technical system development research, user behavior research and privacy issues[13]. The study focuses on technical system development. A variety of recommendation techniques, such as data mining, agents and reasoning, have been developed and applied into recommender systems [2], [4], [8]-[10]. Recommender systems also have been implemented by many big web retailers, including Amazon.com and CDNow.com.

In general, existing recommender systems can be broadly categorized into content-based and collaborative, in e-commerce area. Content-based recommender systems provide recommendations to a customer by automatically matching his/her preferences with product content, such as recommendation of web pages and news items [6]. In content-based systems, products are described by a common set of attributes. Customer preferences are predicted by analyzing the relationship between the product ratings and the corresponding product attributes. A central problem in content-based recommender systems is the need to identify a sufficiently large set of key attributes. When the set is too small, obviously there is insufficient information to learn the customer profile. Therefore, content-based recommender systems can not be used for new customers who purchased only once, potential customers who visited the website but have not made any purchase, and customers who want to buy a product which is not frequently purchased.

Collaborative recommender systems estimate a customer's preferences for a product based on the overlap between his/her preference ratings for the product and those of other customers [13]. The main difference between collaborative and content-based recommender systems is that the collaborative systems track past actions of a group of customers to make a recommendation for individual members of the group. Using this approach, customers may now be able to receive recommendations for products that are dissimilar in content to those he/she has previously rated, as long as other like-minded customers prefer [6]. Collaborative filtering approach identifies customers (neighbors) whose interests are similar to those of a given customer, and recommends products the neighbors of the given customer have liked. One major limitation for this approach is sparsity [14]. It is hard for collaborative filtering based recommender systems to accurately compute the neighborhood and identify the products to be recommended. Also, an extreme form of the sparsity problem is the first-rater problem, which arises when a new product is introduced into the market and thus has no previous ratings information available [5].

One of the directions of learning is the theme of personalized learning [16]. Three issues are involved in the theme. First, learning should take into account student individual need to learn (and relearn) to improve not only their careers, but their personal lives as well. Second, learning should suit students' individual learning styles. Third, the learning environment continues to adapt and modify its behavior, based on interacting with each student over time. In order to create such learning environment, individual students' background, learning style and learning need will be first identified. After interacting with a small piece of learning materials and personal attributes, the learning environment would provide feedback on the learning materials and create a list of learning materials to the student, which would then be stored for future learning material recommendations. Therefore, whenever a student expresses his/her learning requests and knowledge background, needed information is presented in a way that takes advantage of the student's learning preferences. This is called a personalized learning environment [16].

A personalized learning environment facilitates students to achieve their learning objects by technological supports and suggestions [3]. Learning recommender systems can be as a personalized learning environment to deliver learning material recommendations to students in a format that best suits an individual student's personal preference, learning experience and need. Like product recommendations in E-commerce, the quality of learning recommendations has an important effect on a student's future learning behavior. Poor recommendations can cause two types of characteristic errors [5]: false negatives, which are learning materials that are not recommended, though the students need to study on them, and false positives, which are learning material that are recommended, though the student does not need them; or they are not suitable for the student. In an e-learning environment, the most important errors to avoid are false positives, because these errors will lead to angry students and thus they are unlikely to revisit the site.

III. FRAMEWORK OF PLRS

This section describes the framework of PLRS and analyses the main components of the framework.

A. Framework Description

This study proposes a framework of PLRS for recommending learning materials to students who may have different backgrounds, learning styles and learning needs. This framework is designed to have four main components 'getting student information', 'identifying student requirement', 'learning material matching analysis' and 'generating recommendation' respectively, shown in Fig. 1. The four components are connected with a user interface, a student database, a learning material tree database, and supported by a student requirement model and matching rules. The system starts getting student information and storing it into student database in component 1, student requirements across learning materials are analyzed in component 2. Student requirement analysis model is used in analyzing and identifying student requirements. In component 3 matching rules are used for discovering associations between student requirements and learning material tree. In component 4, a personalized learning material list for a given student is produced and recommended.

In the framework, information about student requirement can essentially be obtained in two ways: extensionally and intentionally expressed [18]. By intentionally expressed information, we mean some specifications by a student of what he/she specifically desires from the type under consideration, such as a title of a learning material. By extensionally expressed information we mean some information based on the actions of the student with respect to specific learning material, such as a list of learning materials the student accessed before. Two key issues dealt with in the framework are how to accurately identify a student's requirement which is handled by a student requirement analysis model, and how to accurately find out the learning materials which match the student's requirements, handled by matching rules.

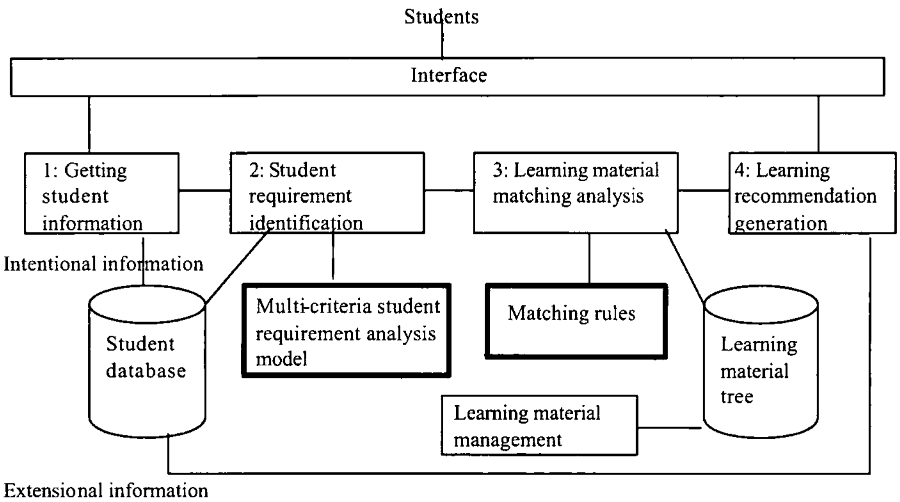

Fig.1. Framework of PLRS

B. Definitions

In the study, students are represented as a vector $X = (x_1, x_2, ..., x_n)$. The multiple criteria for evaluating student requirements are represented as independent variables and written as a criterion vector $C= (c_1, c_2, ..., c_m)$. A requirement of a student x_i for learning material is represented as a vector $R_{i1} = (r_{i1}, f_1, ..., f_p)$, $1<=i<=n$, r_{i1} is the requirement for learning content, $f_1, ..., f_p$ are features of the requirement in learning material, such as the degree of difficulty. The recommendations for the student x_i are to find a learning material set $L_i = (l_{i1}, l_{i2}, ..., l_{ik})$ from a learning material taxonomy. The learning material set L_i matches the student's requirement $R_i (i= 1, 2, ..., n)$ under a fuzzy matching rule $FM_m = \{(R_m, L_{mj}, \mu_{(R_m, L_{mj})})\}$, $m = 1,...,k$. In the fuzzy matching FM_m, $r_m \in R$ and $l_{mj} \in L$, $\mu_{(P_m, y_{mj})}$ is the membership of l_{mj} for r_m , r_m can be one, or one level, of learning material taxonomy, $m = 1,...,k$.

C. Component Analysis

There are four main components in the PLRS framework.

(1) Getting student information

The implementation of technologies for developing recommender systems is strongly dependent on the type of information that is being used[18]. This component aims getting student information and identifies if the student has registered in the student database. It performs the task based on two basic strategies. One is to get requirements from the most frequent students based on their individual learning history information. Another is to get information from the student directly, in particular for new registered learners. In order to supportstudent learning with different learning styles [1], the learning material recommender system will consider learning styles to be one of selection criteria forchoosing learning materials. Other features such as part-time students or full-time students are considered as well in choosing learning material.

Recent studies have suggested web usage mining as an enabler to reduce the need for registration-based personal preferences [11]. E-learning data contains a wealth of detail compared to off-line learning data. One important kind of data is click-stream which indicates the path of a visitor through a web site. Click-stream in an e-learning site provides information essential to understanding learning behavior of students, such as what materials they see and what materials they may interest. Through web usage mining to analyze click information will make a more accurate overall analysis of student requirements across all learning materials than does the analyzing of access records only. Furthermore, mining association rules from the click-stream will provide interesting relationships or associations, among learning materials. This component should also have the ability to get student click-stream information.

(2) Student requirement identification

Student requirement information is derived from multiple data sources. Student requirements are often too complex to be adequately captured by a set of keywords, and hard to justify using a single criterion. In particular, student requirements are, in many cases, hard to justify by precise values. Therefore, the multi-criteria analysis method will naturally be applied in the construction of a student requirement analysis model. This component will find out information from multiple information sources and apply a multi-criteria student requirement analysis model to identify the requirements of particular students, through using such information. Student database has records about learning styles, learning material access, and achievement of all groups of students (such as business faculty students, science faculty students). These records are used to identify individual students' preferences and neighbors of the group. Using this approach, students will receive recommendations for learning materials that most faculty-mates prefer. The component will also search for meaningful relationships, or associations, among data sources for student requirements in relating learning material classes.

The multi-criteria student requirement analysis model is proposed by using the concepts of multi-criteria decision models, and constructed for all target students. But each student may have different weight distribution for criteria as they may have different personal attributes and learning history. Once the model for a particular student has been generated and learned, his/her requirement is identified as a possible solution.

There are different methods for solving a multi-criteria problem. A rigorous approach is suggested to test various conditions and develop a comprehensive multiple criteria value function. Another is a simple linear weighted sum approach to develop the multiple criteria value function. In a real life situation, the criteria values are often uncertain and are described by linguistic terms such as 'important', 'more important', 'strong background', and 'weak background'. Fuzzy set technology is, therefore, used to handle such linguistic terms in achieving a solution for multiple criteria problems. The simple linear weighted sum approach with triangular fuzzy number which can handle linguistic terms will be used to obtain solutions for the multi-criteria student requirement analysis model. The outcome of the component for a particular student is her/his learning material requirement which contains learning contents and related features of required learning materials.

(3) Learning material matching analysis

This component uses fuzzy matching rules to find learning materials which match a given student requirement. In most Internet e-learning sites, the learning material taxonomy is available. Learning material taxonomy is represented in a practical way as a tree that classifies a set of low-level learning materials into a higher-level of a more general learning material. The leaves of the tree denote the learning material instances, and non-leaf nodes denote learning material classes obtained by combining several lower-level nodes into one parent node.

Decision tree techniques have already been shown to be interpretable and efficient [6]. Decision tree techniques are also recognized as highly unstable classifiers with respect to minor perturbations in the training data. Fuzzy set technique [19] can describe complex and uncertain relationships, and also can deal with unstable classifications such as classifications of learning materials described in a tree to makes data analysis tasks more efficient. Fuzzy set based fuzzy distance [21] can introduce an improvement in matching student requirements to learning materials due to the elasticity of fuzzy sets. Fuzzy set based fuzzy distance definition is therefore especially suitable for measuring uncertain matching, and therefore can be used for the representation of justifications rules. Fuzzy matching [18] approach has been proposed to evaluate the similarity of concepts. As student requirement and learning material information are all seen as concepts, the fuzzy matching approach is suitable for finding recommended learning materials based on student requirement.

In the component, given a set of requirements R_i of a student x_i, and an association rule implies the form $R_i \Longrightarrow L_i$, (find out L_i based on R_i) where L_i is a learning material set of a subject learning material taxonomy. The task of the component is to find out a learning material set $L_i = (l_{i1}, l_{i2}, \ldots, l_{ik})$ for a student x_i where l_{im} can be one or one class of learning materials at the same level, which has a fuzzy matching with R_i. The component may use a set of fuzzy matching rules to measure each student's requirements and candidate learning materials.

In the framework, learning materials in the same class may have different matching memberships for a given student since the memberships are computed at the learning material level. This membership reflects the degree of similarity association between the student requirements and the learning materials. When a fuzzy rule is applied, the system will able to choose which of the learning materials is to be recommended to the student.

(4) Learning recommendation generation

By using fuzzy matching rules for discovering associations between a student's requirements and a list of learning materials, the component will generate a personalized learning material recommendation list (N materials) for the student. This component also addresses how to determine the 'N' for top-N learning material recommendation, and the format of a recommendation. Recommendations are as records to be stored in student database.

D. Advantages of the Framework

While content-based recommendation and collaborative recommendation are complementary in nature, it would further boost the performance by integrating these two approaches [5]. The proposed framework implements the integration. The framework includes a model to identify student requirements using multiple criteria. The multiple criteria may include personal attributes, learning material access history, current interests, and other students' requirements. These criteria are used by content-based and collaborative approach respectively. By using the framework, a learning recommender system is expected to have the capability to optimize recommendations and reduce false positive errors which are learning materials that are recommended, but the student is not satisfied with them.

Sparsity is a key issue in personalized recommendations. In order to solve the problem, the proposed framework emphasizes the improvement of accuracy from two aspects: accuracy of identifying student requirements, and accuracy of finding recommended learning materials. To complete the first improvement, the proposed framework focuses on overall analysis of student requirements. It is designed to acquire and analyze a student's information in multiple aspects. To complete the second improvement, this proposed framework is designed to help find which of learning materials the students would like to read by suggesting a list of top-N recommended learning materials for each of them. Through developing and using the two technologies, the framework is accurately identifying the materials. By choosing the right level of learning material taxonomy tree and right learning materials each student needs, the system can provide a good quality of recommendations.

The framework is able to handle different learning materials (or learning activities) and student situations. This might include a learning material that students usually do not access often but has specific requirement related to that single access. In such a case, instead of only modeling a student's past requirements, the recommendation framework also uses other information, including the ephemeral information provided by a student at the time he or she is consulting the system for suggestions. The proposed recommender system can, therefore, assist a student to find out what he or she reallyneeds, by identifying the type of learning material requirement and describing the features of a learning material, neverread before. The framework can also deal with new learning material problems, that is, how to deliver new learning material information to students indiscriminately. By following the procedure of this framework, it is expected that, when a new learning material is introduced into the site and thus has no previous ratings information available, the fuzzy matching rules are able to find information of this learning material based on student requirements. Therefore, the proposed framework is able to handle effectively various situations for learning material recommendations.

IV. APPLICATIONS OF PLRS

'Database Principles' is a subject offered for non-IT students who come from many other faculties, such as Business Faculty, Engineering Faculty and Science Faculty. They, therefore, have very different knowledge backgrounds, learning styles, and demands and needs of learning. For example, business students have learnt ER-model from a business subject but no experience about computer languages. Science students have good knowledge in relational algebra but are struggling with understanding business rules. Most engineering students have learnt at least one computer language but no experience in RE-modeling. As a result, most business students feel database design part easier to handle than database implementation part, while most engineering students need more readings and practice in ER modeling. In order to deal with the multi-background student situation, lecturers often indicate many choices of learning materials for each topic of the subject, and students often rely on incomplete information, from their classmates and friends, when deciding which of the indicated learning materials to read and which of exercise questions to do.

The proposed PLRS is expected to support students in learning material choosing and can therefore handle such situation. Table 1 and Table 2 show two main tables in the subject student database. Fig. 2 shows the learning material tree of subject where five topics taught in the subject. There are four levels in the learning material tree. The level of the root node is zero, and the level of any other note is one plus the level of its parent. For each leaf note, which is a learning material, including difficulty degree, length, location and so on. Table 3 shows three examples of recommendations. Access possibility means the intensity of recommendation.

Table 1: An example of student information

SID	Name	Background	Style	Type	...
102	J. Lee	Business	A	PT	
103	P.Chin	Engineering	B	FT	
104	C.Miller	Science	B	FT	
...	...	...	...	...	

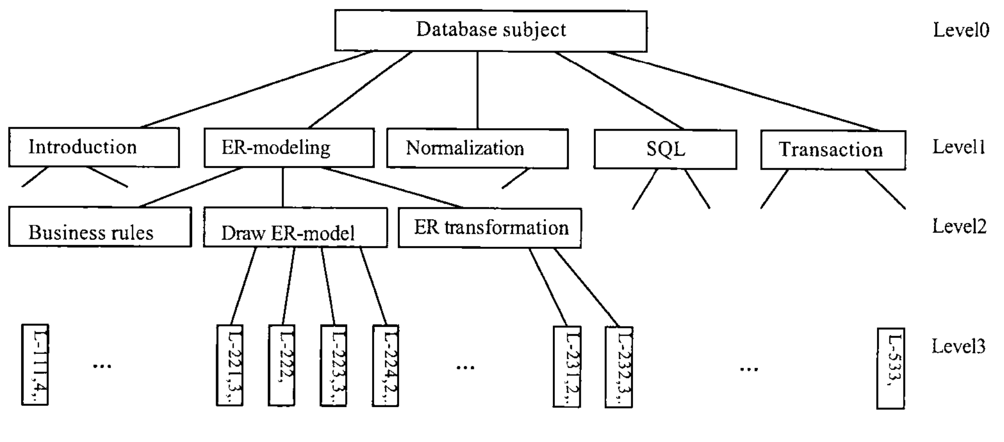

Fig. 2. Learning material tree

Table 2: An example of material access history

SID	Material	Date
102	L-221	05/05/03
102	L-234	07/06/03
104	L-133	03/04/03
...	...	...

Table 3: An example of recommendations

SID	Access possibility	List
102	96	L-234, L-343, L-335,
103	90	ER transformation
104	80	L-311, L-322

V. CONCLUSIONS AND FURTHER STUDY

This paper presents a personalized learning material recommendation framework and discusses related technology. The framework has good characteristics in supporting students choosing learning materials by providing recommendations. The framework will be implemented as an online system and is generally applicable to any student learning activity recommender systems.

REFERENCES

[1] B. Bates and J. Leary, "Supporting a range of learning styles using a taxonomy-based design framework approach" *Proceedings of the 18th annual conference of the Australasian Society for computers in learning in Tertiary education*, 9-12 December 2001, pp. 45-53.

[2] S.W. Changchien, and T. Lu, "Mining association rules procedure to support on-line recommendation by customers and products fragmentation" *Expert Systems with Applications* Vol. 20 (2001), pp. 325-335.

[3] D.T. Chen and D. Hung, "Personalised knowledge representations: the missing half of online discussions" Educational Administration Abstracts; Vol. 38 (2003), pp. 355-357.

[4] K.W. Cheung, J.T. Kwok, M.H. Law and K.C. Tsui, "Mining customer product ratings for personalized marketing" *Decision Support Systems* Vol. 35 (2003), pp. 231-243.

[5] T.H. Cho, J. K. Kin and S. H. Kim, "A personalized recommender system based on web usage mining and decision tree induction" *Expert Systems with Applications* 23 (2002), pp. 329-342.

[6] J.K. Kim, Y.H. Cho, W.J. Kim, J.R. Kim, and J.H. Suh, "A personalized recommendation procedure for Internet shopping support" *Electronic Commerce Research and Applications* Vol. 1(2002), pp. 301-311.

[7] P. Korhonen, "A visual reference direction approach to solving discrete multiple criteria problems" *European Journal of Operational Research* Vol. 34 (1988), pp. 152-159.

[8] O.B. Kwon, "I know what you need to buy" context-aware multimedia-based recommendation system" In *Expert Systems with Applications*, 2002, (Article in Press).

[9] L. Lee and TC. Lu, "Intelligent agent-based systems for personalized recommendations in Internet commerce" *Expert Systems with Applications* Vol. 22 (2002), pp. 275-284.

[10] R.D. Lawrence, G.S. Almasi, V. Kotlyar, M.S. Viveros and S. Duri, "Personalization of supermarket product recommendations" *Data Mining and Knowledge Discovery* Vol. 5 (2001), pp. 11–32.

[11] B. Mobasher, R. Cooley and J. Srivastava, "Automatic personalization based on web usage mining" *Communications of the ACM* Vol. 43 (2000), pp. 142–151.

[12] P. Resnick and H.R. Varian, "Recommender systems" *Communications of the ACM* Vol. 40 (1997), pp. 56-58.

[13] T.H. Roh, K.J. Oh and I. Han, "The collaborative filtering recommendation based on SOM cluster-indexing CBR" *Expert Systems with Applications*, 2003, (Article in press).

[14] B., Sarwar, G. Karypis, J. Konstan, and J. Riedl, "Item-based collaborative filtering recommendation algorithm" *Proceedings of the Tenth International World Wide Web Conference*, 2001, pp. 285–295.

[15] J.B. Schafer, J.A Konstan and J. Riedl, "E-commerce recommendation applications" *Data Mining and Knowledge Discovery* Vol. 5 (2001), pp. 115–153.

[16] C. Steed, "Why personalized is the way ahead for learning" *IT Training*. Sept, 2002.

[17] R.R Yager, "Fuzzy logic methods in recommender systems" *Fuzzy Sets and Systems* Vol. 136 (2003), pp. 133-149.

[18] J.D. Yang, and D.G. Lee, "Incorporating concept-based match into fuzzy production rules" *Information Sciences* Vol. 104 (1998), pp. 213-239.

[19] L. A. Zadeh, "Fuzzy sets" *Inform & Control* Vol. 8(1965), pp. 338-353.

[20] O.R. Zaiane "Web usage mining for better web-based learning environment" In Prof. of *Conference on Advanced Technology for Education*, pp 60-64, Banff, AB, June 2001.

[21] G.Q Zhang "On fuzzy number-valued fuzzy measures defined by fuzzy number-valued fuzzy integrals I" *Fuzzy Sets and Systems* Vol. 45 (1992), pp. 227-237.

Second International Conference on Information Technology & Applications

Conference Organising Committee

Conference Chair Prof Shi Guangfan Heilongjiang University, China

Conference Vice-Chair Dr. Fu Yuzuo Shanghai Jiao-tong University, China

Technical Chair Dr. Sean He University of Tech Sydney, Australia

International Advisor Dr Dapeng Tien Charles Sturt University, Australia

ICITA 2004 is organised by:

Heilongjiang University, Harbin, China

http://www.hlju.edu.cn

And supported by:

Shanghai Jiao Tong University, Shanghai, China

http://www.sjtu.edu.cn

IEEE, NSW Section, Australia

http://ewh.ieee.org/r10/nsw/

IEEE, CS Chapter, Beijing, China

http://www.cie-china.org/ieee-beijing/

Saora Inc., Japan

http://www.saora.com/

ICITA 2004 Harbin, China http://www.[illegible]

Second International Conference on Information Technology & Applications

ICITA 2004

Harbin, China

8-11 January 2004

http://[illegible].org

[illegible], China

[illegible] University, China

[illegible] Section, Australia

[illegible] CS Chapter, Beijing, China

Saora Inc., Japan

papers published at the ICITA2004 will be EI indexed.

Saora
Illuminating Interfaces