13. THE KNOWLEDGE-NAVIGATION SYSTEM IN HYPERSPACE WITH NEURAL NETWORKS

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ABSTRACT

We propose a mechanism for the knowledge navigation based on the sub-symbolic approach to decide the appropriate navigation strategy. A neural network (NN) was used as a navigation strategy decision module in that system. In exploring hyperspace (HS), users often tend to be in undesirable states (e.g. "get lost" a.s.o). To improve these undesirable redundancies, we have constructed a sophisticated hypermedia system which can identify the user's needs a.s.o, and give some appropriate advice to the user in his/her exploring learning process.

Keywords

Hypermedia, Artificial Intelligence, Flexible Learning, Knowledge Based

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1. Introduction

Hypermedia is a tool for user-driven access to information. It provides an effective learning environment, where users can acquire knowledge by exploring the HS in his/her own way. But, often there appears the phenomenon of redundant information access. To improve these undesirable effects on users, many researches have been working to construct sophisticated hypermedia systems which can identify the user's interests, preferences and needs and give some appropriate advice to the user in his/her exploring learning process. In this paper, we propose a user model that represents exploring activities in HS and a mechanism based on a sub-symbolic approach, to decide appropriate navigation strategies. This paper also shows the training procedure of the NN and its result.

Adaptive hypermedia is a flexible system which infers the learning goal of the current learning state, by using the exploring history, the structural characteristics of the hypermedia a.s.o. As a result of its inference, this system changes its own performance to adapt to the user. The methods for adaptation are two types. One is the content-level adaptation (adaptive presentation). This method changes the contents of the node which the user will refer in next step. The other one is the link-level adaptation (adaptive navigation support). This method changes the links in the current node. The ELM-ART (Brusilovsky, 1996), which is an Intelligent tutoring system, is one of the most famous adaptive presentation systems. Its adaptation was realized based on a specific domain knowledge with a symbolic approach. So, the generality of the adaptation mechanism and the flexibility of the functional extension of this system are not high. The Adaptive HyperMan (Mathe et al., 1996) is one of the most famous adaptive navigation support systems. This system is an example of interactive adaptive hypermedia. The exploring characteristics of each user are acquired through conversation with him/her. This system is useful for a situation in which a frequent interaction between the system and the user is needed.

We have developed an adaptive educational hypermedia system based on the sub-symbolic approach. In cases of educational use, usually, as the exploring aim of students is usually fixed by a teacher in advance, frequent interactions with the system may be obstacles for the free exploring learning of a student.

2. Hyperspace Structure

2.1 Student exploring states

In this research, our purposes in giving guidance to the students for navigation towards their learning goal is *to support the smooth progress of the exploring study*. As a result of the observation of the exploring behavior of students and after interviewing them, undesirable cases, which are likely to happen during the learning process, are classified as follows : blind in HS, lost in HS and redundant or suboptimal references in HS. *Blind in HS* are the students who do not know how to

follow the links to go to the target nodes. The target nodes are not read before. The students can not infer the relation between the current node and the target nodes. *Lost in HS* are the students who do not know the relative position of the current node and referred nodes. *Redundant or suboptimal references in HS* are taken by students who follow a longer path than necessary to go to the target nodes or to achieve their learning goals. Two types of data are needed, to distinguish between the students who are in the undesirable learning states we described above, and the

Table 1: The indicators of the exploring activities and their computation ways

1.	validity of the reference (VR)	combination value of the importance of the already read nodes and the degree of relation between referred link and current node
2.	exploring stability (ES)	variance of the reading (reference) time of all referred nodes
3.	rate of understanding (RU)	mean value of the frequency of the reference of all referred nodes
4.	rate of glanced nodes (RGN)	ratio of nodes only glanced at, to thoroughly referred nodes
5.	rate of surface understood topics (RSUT)	ratio of topics, whose number of referred nodes is less than the ideal ratio of referenced nodes, to all topics
6.	rate of favorite topic (RFT)	ratio of the nodes in the topic, which has the maximal number of referred nodes, to all referred nodes

Table 2: The knowledge navigation strategies

1.	understanding the outline schema (UOS)	content-level adaptation	displays the hypermedia structure of the current teaching material
2.	magnification of the exploring concept (MEC)	link-level adaptation	recommends a node which has a link with the highest degree of relation to the current node
3.	focusing on the exploring concept (FEC)	link-level adaptation	recommends the unread nodes in the topic which has the maximal number of referred nodes
4.	changing of the exploring concept (CEC)	link-level adaptation	recommends the unread nodes in the topic which has the minimal number of referred nodes
5.	recognition of the exploring history (REH)	content-level adaptation	displays the explored nodes in order
6.	retreat (R)	link-level adaptation	recommends a node which has the greatest number of links among already referred nodes

other students. They are physical information on the exploring activity (e.g. reference time, number of referred nodes a.s.o), and semantic information on the exploring activity (e.g. degree of importance of the referred node, degree of relation between two nodes a.s.o).

From these information, from the behavioral features of students in undesirable states and from the structural model of the HS, we defined 6 indicators which represent the exploring activities in HS (Kayama et al., 1997). The labels and meanings of each indicator are shown in Tab.1. The needs of the students who are in undesirable states are considered to determine the strategies, which will support their smooth progress during the exploring study. The structure model of the teaching material and the methods of presentation of the needed information are also considered, in order to develop the 6 knowledge navigation strategies. The labels and functional details of these strategies are shown in Tab.2. Our system makes its adaptation by using both methods, the link-level adaptation and the content-level adaptation. To the first type of adaptation belong UOS and REH, to the other type MEC, FEC and CEC. The adaptability of our system is increased by including both types of adaptation.

Figure 1: The partial structure model of Hyperspace

2.2 The structure model

Fig.1 represents the structure model of the HS. A topic has two attributes : the set of nodes which are included in it, and the ideal ratio of referred nodes (IRR). A node has four attributes: identification number (ID), degree of importance (DI), and the standard and minimum necessary time for reading (SNT, MNT). DI is defined as the degree of contribution towards the achievement of the current learning goal. Its values are integers from 0 to 5. A link has only one attribute, the degree of relation (DR) between two nodes. DR is defined as the strength of the relation between the contents of linked nodes. Its values are integers from 1 to 5. This value is used to evaluate the efficiency of referring that link between the nodes.

Our knowledge navigation system supports an educational hypermedia system with all of the attributes mentioned above. So, the teacher who wants to use our navigation system needs to arrange his/her hypermedia which is used as a teaching material. There are no limitations or rules to set concrete values for each attribute. Using those attributes of items of the HS, we describe the formulas of each of the indicators mentioned above (kayama at al. 1997).

3. System Configuration

The prototype navigation system is working and the selected theme for the teaching material is “The positioning at tennis (for doubles)”. Our system has five modules and two databases and is shown in Fig.2. The system interferes only when the user wants to be guided in determining his/her next exploring activity. Our system is implemented for educational use, so we do not attempt to interfere in the students’ learning. Only direct navigation requests from the students can trigger the interference of our navigation system.

Each exploring state (ID and reference time) of a student is recorded by the exploring data recording module as a piece of the history exploring database. When a student requests navigation guiding from the system, the exploring activity evaluation module develops the model of the current state of the student. This model is expressed by the six indicators which were mentioned above. The student model is handed over to the next module, the navigation strategy decision module, which contains a NN as an inference engine. Only one navigation strategy is selected by the navigation strategy decision module from the output of the NN. The definite content of the navigation guidance information is created in the definite

Figure 2: The structure of the navigation system

Figure 3 : An example of the navigation

contents building module by using the strategy determined by the NN engine and the knowledge of the HS attributes from the HS structure database. Then, the results of the processing are shown to the student by the navigation guide visualization module as the current navigation guidance information. Fig.3 shows an example of navigation guidance information (the guidance message and recommended nodes).

4. Navigation Strategy Decision Module

4.1 The algorithm and input data of the neural network

In this research, a sub-symbolic approach is taken to develop the navigation strategy decision module. To infer the appropriate navigation strategy, the expertise on knowledge navigation is learned by a supervised NN. This expertise is formed by the pair {learning state of the student; adapted strategy, which should help him/her find the right exploring path}. By using this sub-symbolic approach of inference with the NN, it is possible for the system developer to improve the flexibility and the generality of the mechanism of the navigation strategy decision processes. In the case of using a symbolic approach, like a production system for implementation of a navigation strategy decision module, expertise is represented as production rules. When the items of the condition part in those rules are changed, it is needed to re-arrange the expertise. The more the number of the exploring indicators or the values of the indicators increase, the more difficult it is to express the rules, because of the

explosion of the possible combinations between exploring states, which are expressed by the exploring state indicators, and the navigation strategies. It is hard to represent the production rules which cover the whole domain world. On other hand, in case of using a sub-symbolic approach, the extraction of the expertise is equivalent to the collecting of the training data for the NN. The training phase of the NN means the arrangement of the expertise. These embedded processes make the task of experts and system developers easier. It is thought in knowledge navigation systems that the load of extracting and arranging expertise is reduced The NN which is used in our system is a supervised multi-layer feed-forward model. The engine learned pairs consisting of possible student states in exploring learning and the appropriate navigation strategies, by using the back-propagation (BP) learning rule. The input pattern is the student’s learning state and the output pattern is the corresponding navigation strategy.

Table 3: The extracted navigation knowledge

redundant 390					
necessary 339					
	UOS	MEC	FEC	CEC	REH
	9	81	60	90	18
					81

4.2 *Extracting expertise on navigation from experts*

The pairs of learning state and navigation strategy are prepared from the results of

experiments whose subjects are experts in some educational fields. In preparation for this experiment, experts are given the explanation of the means and the ways of calculation of each exploring indicator, and the ways of navigation for each navigation strategy. Experts’ understanding of the indicators and navigation strategies is confirmed by researchers. According to the questionnaire method, the sets of learning states are gathered from experts. The experts are required to answer in pairs of learning state and suitable navigation strategy. Also, the experts attach to each learning state grades for the indicators. During this process, learning states which are not needed to express a certain strategy are allowed to be included in the experts’ answer. By arranging the results of this experience, all learning states are classified. The results look as in Tab.3. The learning states extracted are the ones computed by selecting the answer of the majority from the collected results. The rest of the data are classified as being “redundant” states for the navigation. Subjects are 5 teachers who all have already used the hypermedia system for their teaching. The pairs of data are teachers’ expertise on navigation. This knowledge is independent of the teaching domain. The extracted knowledge is used as training patterns for the NN. The way of extracting the navigation knowledge from teachers is closely related to the navigation strategy decision module performance. The learning result of the NN determines the validity of our navigation system. The functional distinction area of the NN which is trained by supervised learning is approximately defined by the boundary lines between the sets of training data with the same output patterns. Therefore, an efficient NN training needs patterns which have an even (normal) distribution of the input data. In this experiment, 3 categories (“high”, “middle” and “low”) are used to represent the score of each indicator and there are 729 (= 6_{indicators}^{3 categories}) learning state patterns in total.

4.3 The
neural network
structure

Table 4: The fine tuning parameters of the network

parameter	value
number of units in the hidden layer	16
learning rate	0.3
momentum	0.5

The NN in the navigation strategy decision module has 3 layers. The input layer has 12 units. One indicator is assigned two units so that 3 categories of

evaluation can be expressed. The output layer has 7 units. These represent the 6 navigation strategies and the “redundant” output. The number of the hidden layer units are determined by successive training simulations. The final number of neurons in this layer is the number which assures the highest performance. Moreover, other parameters are needed to be tuned in order to achieve a better efficiency of the NN. These NN parameters are the learning rate and the momentum. The fine tuning parameters are shown in Tab.4. All of the navigation knowledge is learned by the NN. It means that this trained NN can decide upon an unique appropriate navigation strategy for each exploring state at the rate of 100 %. When the navigation strategies are changed or the relation between the learning state and the appropriate navigation strategy is changed, the system developer has only to retrain the NN. The training of the NN has to be done before replacing the old NN engine with the new one.

Figure 4: The structure teaching material and exploring paths of students

5. Example
of the user
model

An investigation was made on several real users to evaluate the appropriateness of the student model. The real users were graduate and undergraduate students who have played tennis for a few years. The students have used this navigation system to

confirm their knowledge of the positioning at doubles play. To evaluate the appropriateness of the student model in our system, we have been recording data about users' exploring activities and about the navigation guidance information for 14 days. Data we recorded are as follows : the student's exploring state when he/she requests the system to give a navigation guidance, the name of the navigation

strategy applied for the user, the shown navigation guidance (guidance message and recommended nodes or topics), the node IDs which are accessed in the next step and the reason for having demanded navigation guidance. 25 users have used the navigation system during this experiment. Navigation guidance was requested in total for 154 times. The mean time of learning with our system was of 37 minutes per student.

Appropriateness of the student model in the navigation system : Paths in Fig.4 show the actual paths of students' exploring. The nodes with the circled numbers express the nodes searched by the students. The students who follow Path1 are searching for the contents of a specific topic intensively. The students who follow Path2 are searching for items relevant to each node one after another. We describe the results of the evaluation of the exploring activities of our system.

Path2 (1-2-3-4-8-9-10-7) : The navigation guidance was demanded when the user could not find any more nodes related with his/her learning goal. As a result of referring the nodes which were of related contents one after another, the RSUT has become high and RFT has become low. The low value of the VR is due to the low importance of the accessed nodes. The navigation strategy which was applied to this student is the FEC. The shown navigation message was "You have referred nodes on many topics. How about learning more details on a specific topic?". The topics of the accessed nodes were recommended as a next destination to explore.

6. Conclusion

By using our approach, our navigation goal, supporting the smooth progress of the exploring study, is achieved. To realize the other purpose, encouraging students to maintain a positive attitude toward exploring learning, the students' exploring intention has to be added to the user model. As a result of the integration, we expect that the adaptability of our system will increase. This is but one of our future works.

7. References

- Brusilovsky, P. (1996). ELM-ART : An intelligent tutoring system on world wide web, Proc. of ITS'96, 261 -- 1269 .
- Kayama, M., and Okamoto, T. (1997). Mechanism for knowledge-navigation in hyper-space with neural networks, SIG-IES-9702, 9 -- 16.
- Mathe, N., and Chen, J. (1996). User-centered Indexing for Adaptive Information Access, User Modeling and User-adapted Interaction, 6, 6, 225-261.

8. Biography

Miss Kayama received her Master of Engineering from University of Electro-Communications. Presently, she is a doctoral course student at Prof. Okamoto's Lab. Her main research field is Artificial Intelligent and Education (Intelligent Teaching Environment with Neural Network).

Dr. Okamoto received my Dr. of Engineering from Tokyo Institute of Technology. Presently, he is a Professor in the Information System Laboratory, Univ. of Electro Communications, engaged in AI, ITE, CAI research. He is a member of the Board of CAI Society, of the Japanese Society of Educational Technology, a.s.o. and have a lot of important official functions for promoting the field of computers and education in Japan.