

Hypermedia Browsing Pattern Analysis

CHUEN-TSAI SUN AND YU-TAI CHING

*Department of Computer and Information Science
National Chiao Tung University, Hsinchu, Taiwan 30050*

Hypermedia course-on-demand has become a focus of distance education through computer networks. In this paper we propose a quantitative approach for hypermedia browsing pattern analysis. Although the importance of navigation behavior analysis has long been addressed, only a few researchers have discussed how to classify patterns based on objective, quantitative data recorded during a learning session. We show in this paper how to define measures based on graph theory and how to associate navigation information with other student learning activities in a hypermedia environment.

We first introduce a distant cooperative learning group project in Taiwan and the role of this study in it. We then define measurement indices for a hypermedia tutoring system. A quantitative approach to determining the similarity between navigation patterns is introduced based on the *Longest Common Subsequence* of two browsing paths. This partial resemblance, which, together with other metric measures, provides a sound basis for similarity analysis. A model for association, called a neuro-fuzzy classifier, is then described to complete this quantitative model. Preliminary experiment results are discussed. We believe that the proposed measures and models suggest an effective approach to student modeling in hypermedia-based distance education.

INTRODUCTION

This study is part of a distant cooperative learning project in National Chiao Tung University (NCTU), Taiwan. The target system of this group project is named CORAL, standing for *Cooperative Remotely Accessible Learning*. In this paper, we show a method to build an *intelligent student mode* for CORAL, in terms of *hypermedia browsing pattern analysis*. In the following, we first give a brief introduction to the CORAL system.

The shared focus of this research group in NCTU is distant cooperative learning which is based on a multimedia computer network environment. We believe that the technology of computer networking and multimedia is mature enough so that traditional Intelligent Computer Assisted Learning (ICAL) concepts can be extended to benefit distant cooperative learning. Learners who studied alone in the past can have partners now so that discussion becomes possible. Learning motivation and interest are expected to be largely increased in this environment. Moreover, teachers can enjoy an excellent instruction management environment by monitoring individual student's progress and obstacles. Assistance can be provided in time. From the viewpoint of education researchers, the information collected on multimedia networks can be used to build an objective and dynamic learning model without interrupting students' learning processes.

The first step of this project is to construct an appropriate environment of multimedia computer equipment and networks to support distant cooperative learning. Researchers can observe and record the learning behavior of students in this environment. Next, hypertext techniques are used to design multimedia courseware that is accessible through networks. Interface design factors based on cognitive psychology are taken into consideration so that students do not suffer from information overload. The effectiveness and efficiency of multimedia communication are improved in this project so that the environment encourage students' interest in mutual communication. A recording program is designed to collect students' behavior in terms of navigation paths in the hypermedia courseware. The collected information is used to construct types of learners.

To accomplish a dynamic, objective, and complete model of learning via communication, we need software to monitor the communication activities on the network. Digital information collected with this software is used for learning environment control and student model construction. We use fuzzy theory and neural networks to build student models. In addition, we apply other methods such as questionnaire, interview, and examination to discover personal factors of students.

The primary goal of this study in the CORAL system is to identify the relationship between a student's attitude, aptitude, performance factors and his learning patterns. The result of this study will be used to construct a database of pedagogical strategies. We have been developing a hypermedia courseware on the Internet. It can be used for self-paced learning by using a MOSAIC-like browser. In addition, we cooperated with a domestic company, the Be Young Co. Ltd., which is a successful multimedia title developer. They provided us their multimedia courseware product, Studio Classroom on CD-ROM, which is an award-winner English tutoring courseware. Furthermore, National Open University in Taiwan also has constructed a network-version English hypertext courseware. We collected students' learning activities when they were using these products. Then we analyzed the learning patterns to build student models.

The remainder of this paper is organized as follows: In the next section, we summarize some important concepts in student modeling and hypermedia as the basis of further discussion. In the Section on Navigation in Educational Hypermedia, we describe the issues in hypermedia learning pattern analysis. Next, in the Section on Navigation Indices, we define a number of indices to quantitatively represent the degree of nonlinearity of a hypermedia browsing path and the similarity between two paths. In the Section on Neuro-Fuzzy Analytical Model, we introduce our analytical approach. Preliminary experiment results are discussed in the Section Experiment Results and we close with concluding remarks.

HYPERMEDIA STUDENT MODELING

Students should be the focus of instructional studies. As a result, student modeling is an indispensable module in any ICAL system. When we enhance ICAL systems with hypermedia capability which is supported by modern computer and networking technologies, the importance and complexity of student modeling become increased. Those traditional topics, such as cognitive models, communication models, motivation, expectation of learners, to name a few, have to be studied from a brand new angle. In addition, new phenomena, such as information overload and environmental factors, should be paid high attention. We should keep in mind that a student in a network-based hypermedia learning environment is not only a courseware learner but also a system user.

As indicated by Self (1988), a successful student model should enable an ICAL system to answer questions like: What the students can do, what they know about, what type of students they are, and what they do during a

learning process. He described a student model as a 4-tuple (P,C,T,H) , where P stands for procedural knowledge, C for conceptual knowledge, T for individual traits, and H for learning history. He introduced twenty functions of a student model which can be divided into six categories: *Corrective*, *elaborative*, *strategic*, *diagnostic*, *predictive*, and *evaluative*.

Since the CORAL system employs hypermedia courseware, we discuss student modeling in terms of hypermedia navigation. Multimedia is considered any combination of text, graphics, sound, animation, and video that are delivered by computer. A system that allows user to control what and when these elements are delivered, and provides a structure of linked elements through which the user can navigate, is called hypermedia (Vaughan, 1993). We can also consider hypermedia as a combination of hypertext and multimedia. In brief, hypermedia is a system of accessing information with a maximal degree of freedom in terms of navigation (Nielsen, 1990). In the past, a user can only read a document linearly. Nowadays, in contrast, there are many ways to unfolding information before users.

A hypermedia system works like a database system, it stores multimedia knowledge, and users retrieve the knowledge by navigating in the *hyper space*. A hypermedia system provides many methods for navigation. In addition to the traditional sequential search method, it supports associative links between related topics so that a reader can conveniently jump to wherever he feels interested in. Since a hypermedia system supports freedom of choice, many researchers believe that it can provide important measures for analyzing learning behavior (Dillon, McKnight, & Richardson, 1990).

To achieve the goal of student modeling in a hypermedia environment, we target on analyzing the *navigation paths* chosen by a student in a hypermedia tutoring system. The result will be used in design of pedagogical strategies, which will be implemented through access control in the tutoring system later on. The role of the student model in the CORAL system is shown in Figure 1. We emphasize on quantitative aspects, such as *staying time* on hypermedia nodes, *visiting sequence*, and so on. We expect this approach to provide us a complete profile of student behavior in a hypermedia network learning system.

The task of defining similarities among navigation patterns plays an important role in understanding a learning process in hypermedia. Several researchers have discussed such problems, but (dis)similarities between two students' navigation patterns were not quantitatively defined. Chen et al. (1995) developed the Standardized States Technique, a quantitative approach to analyzing student hypertext processing patterns. Since their data were binary, they used Jaccord's coefficient to determine the similarities between two students.

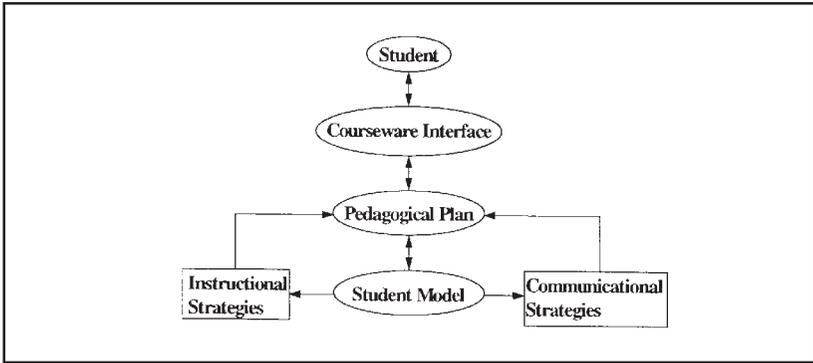


Figure 1. Role of student model

Providing good hypermedia tools has also become an important research area, such as shown in *LinkWay* (Beasley, 1992). With built-in recording functions, tutoring systems are able to collect hypermedia navigation information not only of users but also of authors. In general, the purpose of monitoring and analysis of hypermedia navigation is two-fold: The first is to answer substantial questions about how students use the courseware in terms of routes and methods of navigation. The second is to illustrate the systematic use of the monitoring and analysis tools, from a collection of raw data in the form of time-stamped protocols. Together, the results can shed light on substantial theoretical and pragmatic issues (Kornbrot & Macleod, 1990). We will discuss the issues in hypermedia navigation in more detail in the next section.

NAVIGATION IN EDUCATIONAL HYPERMEDIA

A navigation path can be decomposed into at least two components: The *navigation sequence* and the *staying time* at each hypermedia unit (node). Because each student has his own learning order and duration in visiting nodes in a hypermedia system, we take them as important measures. In this project we also adopt measurements about multimedia resources, such as how many times a function is applied, to realize what functions students prefer to use.

Horney (1993a) reported a case study with constructive hypertext. In that experiment, there were eight authors using *EntryWay* to create their bibliographies, to collect and categorize a set of images, or to create pre-

sentations. He identified five different navigation patterns in this study, *Linear Traversal*, *Star*, *Extended Star*, *Side Trip*, and *Chaotic*. It was observed that different purposes or different authors implied different construction styles.

We know very well that each student has his own way to read. Consequently, *degree of (non)linearity* of different students should be different. The concept of *degree of linearity* was studied in previous research, such as in (Horney, 1993b). In the following, we will give a computational definition of degree of nonlinearity, called *Hyper Degree*. Then, we will propose a method for computing it with the Longest Common Subsequence (LCS) algorithm.

Further, to analyze the properties of hypertext navigation, we need a standard for the purpose of comparison. A natural selection is to use the traditional *text* and consider it as a special case of hypertext. We consider that the traditional way of reading is linear, a reader proceeds to the next page after he finishes this one. In contrast, in a hypermedia courseware, students can read the contents with a nonlinear sequence. What is the degree of nonlinearity of a browsing sequence? This should be a meaningful indicator because we can know a student's tendency or reluctance to push himself to the limit of a given type of hypermedia.

Note that a hypermedia system is generally a directed graph (a *digraph*). The navigation pattern thus becomes a directed path in the digraph. Since each node can be labeled as a symbol, the directed path can be represented as a string. The similarity between two navigation patterns is thus reduced to the similarity between two strings. The longest common subsequence between two strings can then be applied to evaluate the similarity.

The LCS is defined as follows. A *subsequence* of a given string is any string obtained by deleting zero or more symbols from that string. A *longest common subsequence* of two strings is a subsequence of both that is at least as long as any other common subsequence. For example, "BCBA" and "BDAB" are the longest common subsequences of "ABCBDAB" and "BDCABA." The LCS is often used to represent the similarity between two sequences. For example, in data processing LCS is used to measure the differences between two files; and in molecular biology LCS is used to gain information about a new protein sequence. Similarly, the LCS can be applied to evaluate the similarity between two hypermedia navigation patterns. The longer the LCS, the more similar the two navigation patterns.

We have described the detailed algorithm for calculating LCS in another paper (Sun, Ching, & Lin, 1995). Thus, we neglect the algorithm and related proofs here. Now we propose several measures based on the length of the LCS between a pair of navigation paths. The primary advantage of these measures is that the hypermedia student modeling problem can now be formulated as a proximity problem or a clustering problem based on these measures.

NAVIGATION INDICES

We observed that most hypermedia courseware support *NEXT* links which together represent a default linear path for students who need guidance during navigation. We define a highest degree of linearity for students who follow the suggested path when visiting nodes. In brief, the degree of linearity of a browsing sequence is the degree of similarity between it and the sequence of the guidance path. When the browsing sequence is exactly the same as the default sequence, the degree of linearity should be 1; in other words, the Hyper Degree of navigation should be 0.

After we summarize the above computational criteria for Hyper Degree, we find that the LCS concept can be used here. LCS computes the length of the common subsequence in two strings s_1 and s_2 . We let s_1 be the learning path of a student, and s_2 be a predefined linear sequence, such as the path suggested by the *NEXT* links. Thus we propose the following equation for computing Hyper Degree.

$$\text{Hyper Degree} = 1 - \frac{|LCS(s_1, S)|}{|s_1|},$$

where S is an n -time repetition of s_2 , and

$$n = 1 - \frac{|s_1|}{|s_2|},$$

$\hat{e} s_1 \hat{e}$ denotes the length of s_1 .

We introduce the term n as a length scaling factor because in real applications a learning path is usually longer than the defined linear sequence s_2 . It is thus highly probable that the learning path contains a subsequence equal to s_2 . That is why we use S to replace s_2 .

Moreover, as mentioned above, the LCS can be used to evaluate the similarity between navigation patterns. We now define a metric based on the LCS. Note that a distance function between two navigation patterns is said to be a metric, if

1. the distance between two identical paths is 0,
2. for two paths $A \neq B$, the distance between A and B is greater than 0,
3. the distance from A to B is equal to the distance from B to A ,
4. the distance function meets the triangle inequality.

Given two navigation sequences $A = a_1, \dots, a_m$, and $B = b_1, \dots, b_n$, the distance function, denoted D_{lcs} , is defined as:

$$D_{\text{lcs}}(A, B) = m + n - 2|\text{LCS}(A, B)|.$$

Observe that, when two learning paths A and B have a long LCS, they have small $D_{\text{lcs}}(A, B)$.

The *elapsed time* is the time that a student spends browsing a node. In a hypermedia tutoring system, the elapsed time can be an important factor in the analysis of learning patterns. We now show that we can define a metric for the elapsed time.

Suppose there are N nodes in the hypermedia system and the elapsed time is given at each node. If a student has browsed a node more than once, the elapsed time is the accumulated time spent at the node; and the elapsed time is 0 if the node has not been visited at all.

Let A and B be two navigation patterns. The time they spend at nodes i are denoted by t_{a_i} and t_{b_j} , respectively. Since such time is user-dependent, t_{a_i} and t_{b_j} cannot be used to define the metric directly. For example, reading speed can differ greatly among students. Thus we need to normalize the elapsed time. Let $t_{a_{\text{total}}}$ and $t_{b_{\text{total}}}$ be the total accumulated time for the learning paths A and B , respectively. The normalized elapsed time is defined as follows:

$$T_{a_i} = \frac{t_{a_i}}{t_{a_{\text{total}}}}$$

$$T_{b_i} = \frac{t_{b_i}}{t_{b_{\text{total}}}}$$

Now the distance between two learning paths based on the elapsed time is defined as

$$D_{\text{time}}(A, B) = \sum_{i=1}^N |T_{a_i} - T_{b_i}|.$$

From time to time a student may leave the computer in the middle of browsing a certain node. Such action causes *noises* that may lead to biased conclusions. In order to record “noise-free” elapsed time, we need to define an upper bound and a lower bound for the time spent at a node. An upper bound can be used to detect the abnormally long browsing time. A lower bound is also needed since the users may want to go back to nodes traversed earlier. The time spent at the nodes on the path between the current node and the target node are of little use to us. Hence, time spent on such nodes is eliminated by using the lower bound. An elapsed time is recorded when it falls in between the lower bound and the upper bound. Other metrics have been defined in Sun, Ching, and Lin, 1995.

NEURO-FUZZY ANALYTICAL MODEL

Generally speaking, no matter which attributes are chosen, there is a certain method to group users, that is, students, into categories. A recent example is the *ElectroText* project (Horney & Anderson-Inman, 1994), in which students are categorized into six hypertext reading patterns: *Skimming*, *Checking*, *Reading*, *Responding*, *Studying*, and *Reviewing*. It was pointed out that reading patterns varied considerably on at least two dimensions and their frequency of occurrence was influenced by such factors as software design, instructional context, and student’s perception of the task. Statistical methods were frequently employed in previous work.

We believe that introducing the concept of fuzziness is important in learning pattern analysis because most types of student grouping are fuzzy in nature. Several analytical models based on fuzzy theory have been proposed in the past. For instance, Panagiotou et al. (1993) considered the fuzzy logic theory is appropriate for developing student model. Torres et al. (1993) used fuzzy rule of the form *IF browsing-pattern THEN problem-solving-strategy*. We now introduce a more flexible numerical models based on fuzzy logic and neural networks for navigation pattern analysis.

In many pedagogical studies it is desirable to associate navigation patterns to other measures of learning behavior. This is where *fuzzy classification* (Zadeh, 1978) can demonstrate its strength. A fuzzy classifier considers the boundary between two neighboring classes a continuous, overlapping area within which a pattern has partial membership in each class. This viewpoint not only reflects the reality of many education applications,

but also provides a simple representation of the potentially complex cause-effect relations.

We use *fuzzy if-then rules* to describe a classifier. A typical fuzzy classification rule is like:

if X_1 is A and X_2 is B then Z is C ,

where X_1 and X_2 are attributes; A , B are *linguistic terms* (Zadeh, 1975) characterized by appropriate membership functions, which describe the attributes of a pattern Z . The *firing strength* or the degree of appropriateness of this rule with respect to a given pattern is the degree of belonging of this pattern to the class C .

As such, a fuzzy rule provides a meaningful representation of the qualitative aspects of human recognition. Based on the result of pattern matching between rule antecedents and forthcoming navigation patterns, a number of fuzzy rules are triggered in parallel with various values of firing strength. Individually invoked conclusions are considered together with a combination logic.

Further, we want the system to have learning ability of updating and fine-tuning itself based on new information. Recently, researchers have been trying to automate the classifier construction process based on a training data set. We propose a method of using adaptive networks for this purpose.

An adaptive network is a multi-layer feed-forward network in which each node performs a particular function (*node function*) based on input signals and a set of parameters pertaining to this node. The type of node function may vary from node to node; and the choice of node function depends on the overall function that the network is designed to carry out.

Figure 2 demonstrates the adaptive-network-based classifier architecture. The first two layers group the input patterns into several clusters. The next two layers perform a nonlinear mapping between the clusters to an output variable. In this case each input is represented as three linguistic terms.

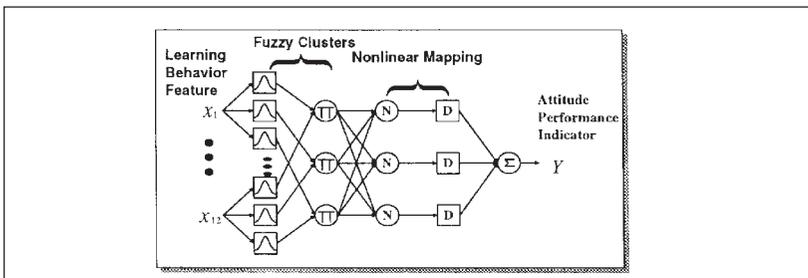


Figure 2. A neuro-fuzzy classifier

In our model the nodes in the same layer have the same type of node function.

Each node in *Layer 1* is associated with a parameterized bell-shaped membership function represented as

where X_i is one of the input variables, A is the linguistic term associated with this node function, and $\{a_i, b_i, c_i\}$ is the parameter set. Each node in *Layer 2* generates a signal corresponding to the conjunctive combination of individual degrees of match. The output signal corresponds to the firing strength of a fuzzy rule with respect to an object to be categorized. We take the linear combination of the firing strengths of the rules at *Layer 3* and apply a sigmoidal function at *Layer 4* to calculate a degree of belonging to a certain class.

In summary, important attributes in patterns can be fuzzified first in the model so that inherent fuzziness in human behavior is handled properly. The adaptive network completes the task of association. For more details about this model, see Jang and Sun, 1995 and Sun, 1994.

$$\mu_A(X_i) = \frac{1}{1 + \left[\left(\frac{x_i - c_i}{a_i} \right)^2 \right] b_i}$$

EXPERIMENT RESULTS

In this section, we present our instructional experiment with Studio Classroom on CD-ROM, shown in Figure 3, which is a popular commercialized courseware. It works on PC with MS-Windows, tutoring English. The content of the Studio Classroom covers both articles and conversation. The ways of presentation include text, voice, pictures, music, video and graphics.

We invited 20 students in computer science major and 30 students in foreign literature major to participate in our experiment. The students in computer science were junior, most of them male and they are familiar with operations on personal computer. In contrast, the students in foreign literature were freshman, most of them female and first-time MS-windows users.

We collected not only the learning activities of students, but also their background data. The Studio Classroom has twenty one lessons, we chose three lessons from them for our experiment. We analyzed the collected browsing data lesson by lesson. After analyzing browsing patterns in one lesson, we analyzed the difference of learning skills of students between lessons.



Figure 3. Studio classroom overview

Our experiment followed the schedule below to collect background data of student and browsing pattern of three lessons. A student was asked to fill a table and to do a pre-test, when they first participated in our experiment. The table is for student background. The data include age, gender, education, and ability of using computer, among others. The pre-test was for identifying prior knowledge of students. At the end of experiment, we had a questionnaire to collect response from students. The questionnaire asked for the students' impression of using Studio Classroom and of learning with computer.

We now briefly discuss the results by using neuro-fuzzy classifiers. There were 12 learning behavior features, including the features described above and other items such as the maximum number of opened windows, total number of key strokes, and so forth.

We had three entries of the students' background information as the output of the fuzzy neural network. These three items of background information are:

1. How long the student has been using computer.
2. What the student uses computer for.
3. What operating system the student has used before.

Table 1
Modeling Errors in Fuzzy Neural Networks

Item	Fuzzy clusters	Training Error	Checking Error
1	10	0/35	1/5
2	15	6/35	1/5
3	17	2/35	1/5

We found that the fuzzy neural network had good performance, as shown in Table 1.

In all three cases it provided a one-out-of-five prediction error. However, we cannot draw any strong conclusion here because of the small number of samples. Rather, we use this pioneer experiment as an example to demonstrate the use of the proposed neuro-fuzzy model.

CONCLUDING REMARKS

Since the visiting sequence of a navigation pattern is a primary factor for learning path analysis in educational hypermedia, we adopted a very useful quantitative measure, the Longest Common Subsequence, to define a number of similarity indices. Based on LCS, we defined an important measure, called the Hyper Degree, to indicate the nonlinearity a student shows in his navigation. We found that this measure provided many useful information for clustering students into different types. It can help us to identify the reasons behind the reluctance of a student to use hypermedia. Based on the results, remedies of design can be suggested for hypermedia courseware authors.

We also defined a couple of metric properties to evaluate the similarity between two navigation patterns. These extracted attributes can be used to build student models so that a new student who shows a similar pattern can benefit from the accumulated experience. In other words, dynamic pedagogical planning becomes possible.

We used a fuzzy neural network to achieve a mapping between the student profile, such as attitude, aptitude, and performance, and the student behavior, in terms of navigation patterns. In general, neural networks allow many attributes (traits, features) to be analyzed at the same time, thus more complex and subtle interactions among input attributes can be identi-

fied automatically. Traditional statistical methods usually make many assumptions about the data, in contrast, a neural network can be considered as a *non-parametric* tool because we do not need *a priori* knowledge about its internal parameters, represented by the weights, it can identify them via a learning algorithm.

The adaptive neuro-fuzzy classifier has several advantages over the traditional neural networks. One is that it provides a way to interpreting the learning results. Because the meaning of layer 1 and layer 2 in the model are membership functions and fuzzy rules, respectively, we can easily extract fuzzy rules or clusters after learning. The fuzzy table is embedded in neural network in a natural way. Another advantage is that it needs much less training samples, because it use fuzzy membership functions to partition the feature space. This partition largely reduces the number of parameters to be modified. Thus, the serious problem of over-fitting in traditional neural network.

TRAINING CAN BE ALLEVIATED

Since our focus is educational hypermedia, we tried to develop a general mechanism that can be used in different hypermedia courseware. Thus, we provided ideas and specifications for our group project to design a general recording program in the CORAL system. After determining the courseware and setting up the recording items, we arranged experiments to have subjects to use the courseware. Although we did it in a quantitative and automatic manner, the experiments for recording student learning behavior were still very time-consuming. That is why the amount of our collected data is still limited.

When we used the neuro-fuzzy model to map the learning activities to the background data, we found that a perfect recognition rate is difficult to achieve. This is not surprising, though, because human beings are very complicated. We could not be really sure that the student background can be represented by our currently collected data. We believe that more information and better feature extraction are necessary to improve the current mechanism. Up to this point, all completed experiments, defined indices, and constructed models are only a partial student model. To realize how learning activities correlate with student background based on categorization of learning paths, we have a lot of work to do.

References

- Beasley, R.E. (1992). A methodology for collecting navigation data using IBM's LinkWay: A hypermedia authoring language. *Journal of Educational Multimedia and Hypermedia*, 1(4), 465-470.
- Chen, D.T., Horney, M.A., & Anderson-Inman, L. (1995). The standardized states technique: A utilization of cluster analysis in analyzing students' hypertext processing patterns. *Journal of Educational Multimedia and Hypermedia*, 4(1).
- Dillon, A., McKnight, C., & Richardson, J. (1990). Navigation in hypertext: a critical review of the concept. In D. Diaper et al., (Eds.), *Human-Computer Interaction—INTERACT '90*, (pp. 587-592). Elsevier Science Publishers B.V. (North-Horlland).
- Horney, M.A. (1993a). Case studies of navigational patterns in constructive hypertext. *Computers in Education*, 20(3), 257-270.
- Horney, M.A. (1993b). A measure of hypertext linearity. *Journal of Educational Multimedia and Hypermedia*, 2(1), 67-82.
- Horney, M.A. & Anderson-Inman, L. (1994). The ElectroText project: Hypertext reading patterns of middle school students. *Journal of Educational Multimedia and Hypermedia*, 3(1), 71-91.
- Jang, J.S. & Sun, C.T. (1995). Neuro-fuzzy modeling and control. *Proceedings of the IEEE*, 83(3), 378-406.
- Kornbrot, D. & Macleod, M. (1990). Monitoring and analysis of hypermedia navigation.
- In D.Diaper et al., (Ed.), *Human-Computer Interaction - INTERACT '90*, (pp. 401-406). Elsevier Science Publishers B.V. (North-Horlland).
- Nielsen, J. (1990). *Hypertext & Hypermedia*. Academic Press.
- Panagiotou, M., Grigoriadou, M., & Philokiprou, G. (1993). Fuzzy student model. In *Proceedings of AI-ED 93-World Conference on Artificial Intelligence in Education*, p. 579.
- Self, J.A. (1988). Student models: What use are they? In P. Ercoli and R. Lewis (Eds.), *Artificial intelligence tools in education*, (pp. 73-85). Elsevier Science Publishers B.V. (North-Holland).
- Sun, C.T. (1994). Rulebase structure identification in an adaptive network based fuzzy inference system. *IEEE Trans. on Fuzzy Systems*, 2(1): 64-73.
- Sun, C.T., Ching, Y.T., & Lin, F.X. (1995). Modeling hypermedia navigation: An AI approach. In *Proceedings of the 7th World Conference on Artificial Intelligence in Education 95* (in press).
- Torres, E., Iida, T., & Watanabe, S. (1993). Adapting skill acquisition sessions through fuzzy rules that match student learning patterns with problem-solving. In *Proceedings of AI-ED 93—World Conference on Artificial Intelligence in Education*. p. 591.

- Vaughan, T. (1993). *Multimedia: Making it Work*. Osborne McGraw-Hill.
- Zadeh, L.A. (1975). The concept of a linguistic variable and its application to approximate reasoning. *Information Sciences*, 8, 199-249.
- Zadeh, L.A. (1978). Fuzzy sets and their application to pattern classification and clustering analysis. In van Ryzin, J., (Ed.), *Classification and clustering*, (pp.251-299). New York: Academic Press.

Notes

1. Research supported by National Science Council, Taiwan, ROC, Grant No. NSC84-2511-S-009-003CL.