학습자 행위 선호도에 기반한 적응적 학습 시스템

김용세 [1],차현진 [2],박선희 [3],조윤정 [4],윤태복 [5],정영모 [6],이지형 [7]
성균관대 창의적설계추론 지적교육시스템 연구단 [1 2 3 4 5 6],
정보통신공학부 [7]
{yskim[1],lois6934[2],seonhp2[3],yunjung125[4],tbyoon[5],ewmhb[6],john[7]}@skku.edu

An Adaptive Learning System based on Learner's Behavior Preferences

Yong Se Kim[1], Hyun Jin Cha[2],Seon Hee Park[3],Yun Jung Cho[4],
Tae Bok Yoon[5],Young Mo Jung[6],Jee Hyong Lee[7]
Creative Design and Intelligent Tutoring Systems Research Center[1 2 3 4 5 6]
School of Information & Communication Engineering[7]
Sungkyunkwan University

요 약

Advances in information and telecommunication technology increasingly reveal the potential of computer supported education. However, most computer supported learning systems until recently did not pay much attention to different characteristics of individual learners. Intelligent learning environments adaptive to learner's preferences and tasks are desired.

Each learner has different preferences and needs, so it is very crucial to provide the different styles of learners with different learning environments that are more preferred and more efficient to them. This paper reports a study of the intelligent learning environment where the learner's preferences are diagnosed using learner models, and then user interfaces are customized in an adaptive manner to accommodate the preferences.

In this research, the learning user interfaces were designed based on a learning-style model by Felder & Silverman, so that different learner preferences are revealed through user interactions with the system. Then, a learning style modeling is done from learner behavior patterns using Decision Tree and Neural Network approaches.

In this way, an intelligent learning system adaptive to learning styles can be built. Further research efforts are being made to accommodate various other kinds of learner characteristics such as emotion and motivation as well as learning mastery in providing adaptive learning support.

Keyword : Intelligent Tutoring Systems, Adaptive systems, Learning styles, Learner's behaviors

1. Introduction

Interfaces that support customization and can adapt to each individual's specific preferences may be more effective than ones designed to be "one size fits all" [1]. In this context, it seems to be meaningful to explore the systems that can intelligently recognize the individual's learning styles through learner's behavior patterns on the user interface, and customize its user interface to fit the individual's specific preferences and styles. Felder & Silverman [2] have already performed research on classification of students, development of tutoring strategies, and the evaluation of learning strategies. By using the learning-style model, this study demonstrated a case of the learning environment where the learning styles are diagnosed using learner models, and customized user interfaces can be reconfigured in an adaptive manner to accommodate the learning styles.

2. Learner Model

Chen and Mizoguchi [3] emphasize that a learning system is considered to be “intelligent” if it can adapt its tasks to the learning content based on a learner model, so the learner model is a very important part in intelligent learning systems. Learner model is to be updated according to the analysis in a dynamic manner to provide an adaptive learning environment tailored to each learner. In this research, learner model has been designed: (i) it can provide the tutoring system with all relevant learner information, (ii) it will help in designing a tutoring system which can respond to the learner’s various activities and situations, and (iii) for learning interface adaptation, which is the focus of this paper, it provides a capability to look through the learner’s information and activities, and then extract the most appropriate learner aspects for designing the behavior-based user interface customization.

3. Adaptive Customization of Learning Interface

The *Index of Learning Style* (ILS) in a learning-style model by Felder & Silverman was adopted in this research as an appropriate category for designing the behavior-based learner diagnosis in that each learning style can be classified into two distinctive preferences [4]. The ILS has four dimensions; Global (G) vs. Sequential (Q) in terms of understanding process of information, Visual (V) vs. Auditory (A) in terms of information input, Sensory (S) vs. Intuitive (N) in terms of information perception, Active (C) vs. Reflective (R) in terms of information processing, and.

The distinctive characteristics in each dimension are described in Table 1. Among them, by using some of the characteristics which can be reflected on user interfaces, learner behavior patterns on learning interfaces were hypothesized for this research.

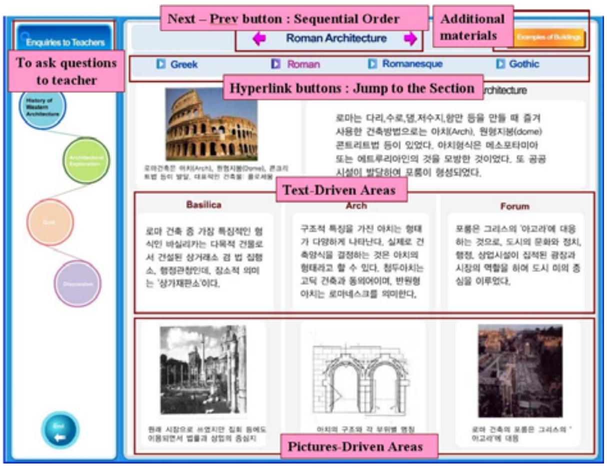
Table 1. Characteristics of ILS

([ ] is the characteristics incorporated for this research)

Global	Sequential
Jumping directly [G1]	Steady progression [Q1]
Intuitive leaps, Divergent thinking and synthesis	As presented, Convergent thinking and analysis
Big picture [G2]	Partial materials [Q2]
Visual	**Auditory**
Pictures & Demos [V1]	Words & Explanation [A1]
Sensing	**Intuitive**
Senses, facts and experimentation	Perception, principles and theories
Patient with details, Careful but may be slow [S1]	Bored by details, Quick but may be careless [N1]
By standard methods, empirical experimentation	Innovation, Logical inference, Dislike repetition
Active	**Reflective**
Work in groups [C1]	Work alone [R1]
Brief discussion or problem-solving activities, Practical [C2]	Occasional pauses for thought, Fundamental [R2]
Experimentalists	Theoreticians

G vs. Q: The ILS work states that the instructor should offer “the big picture of a lesson (G2)” before presenting the learning steps. From this viewpoint, if a learner wants to look through the overview of the contents, they may be Global learners. Thus, the overview buttons are located on the table of content screen for learners themselves to determine to look over the big picture. Furthermore, Global learners may want to jump to the section (G1) they are interested in by clicking the section hyperlinks rather than following the sequential order (Q1) that may be preferred by Sequential learners. Furthermore, on the content screen, Sequential style learners may study in a steady order by clicking the arrow buttons, while Global learners may jump to select the content that they want by choosing the section name buttons directly shown in Figure 1.

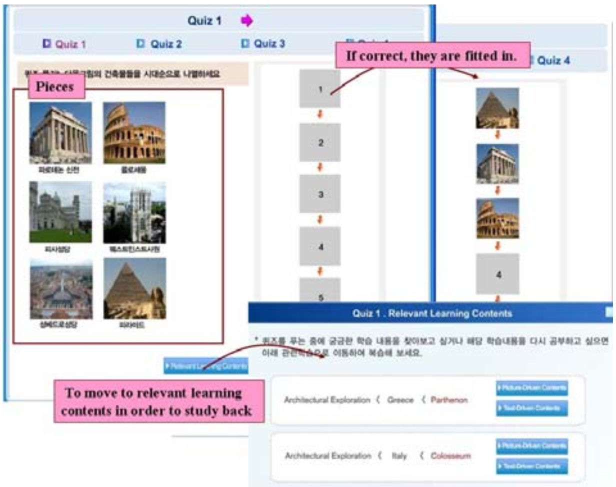
V vs. A: Felder & Silverman discuss that Visual style learners may prefer images (V1), while Auditory learners may prefer written texts (A1). Thus, the second interface layout in Figure 1 has content areas configured by both images and text. The learners can choose either picture-driven or text-driven areas. In the picture-driven area, the detailed explanations are mainly led by images in order to help the learners establish an understanding of the learning contents. On the other hand, the text-driven area is led by written texts.



[Figure 1] Interface Layout for Main Learning Contents

S vs. N: ILS regards Sensory learners as having attentiveness to details (S1) and Intuitive learners as being bored by details (N1) and an interface design has been devised to determine whether Sensory learners are patient with the additional materials when additional contents or examples are given as references. If students are interested in additional materials, they may click the button for additional materials on the interface. Furthermore, a quiz section was designed as a problem solving situation where learners have to select and insert a correct piece into a correct place on the problem. This has been suggested in that Felder & Silverman mention that while Sensory type learners are careful but may be slow (S1), Intuitive learners are quick but may be careless (N1). The user interface in Figure 2 works in the way that as soon as the students drag and drop a piece on the answer section, if correct, the piece is fitted in, but if wrong, it goes back to the original place. If student are careful to choose the answer, they may have low trials and high completion, but if they try it out carelessly, they may have high trials and low completion.

C vs. R: Felder & Silverman point out that an Active learner is someone who feels more comfortable with active experimentation (C2). Conversely, Reflective learners process information reflectively (R2) and tend to think about what others have told. From this viewpoint, if Active learners have arguments, they may expose their opinions freely to friends, but Reflective learners may have a time to think about it at first. The Active and Reflective learners may reveal differences between behaviors in situations that they can voluntarily participate in.



[Figure 2] Interface Layout for Problem Solving Situation

4. Experiment

Based on these interface guidelines, a learning content was developed in the architecture domain with Macromedia Flash [4] in order to verify the hypothesized behaviors. Systems concerned with user modeling for the automatic adaptation of interfaces focus on monitoring behaviors collected from the interface [5]. In this research, the learner's behaviors for the interface were also monitored in order to derive the learner's learning style preferences from the interface events, instead of using the ILS questionnaire for assessing learning preferences as in [2].

An experiment was conducted with 70 university students in this study. In the experiment, subject's learning styles were figured out by conducting the ILS questionnaire by Felder & Silverman. After the ILS questionnaire, the subjects studied the learning content in the architecture domain with the designed interfaces. All of their behaviors on the hypothesized user interface were recorded as XML files.

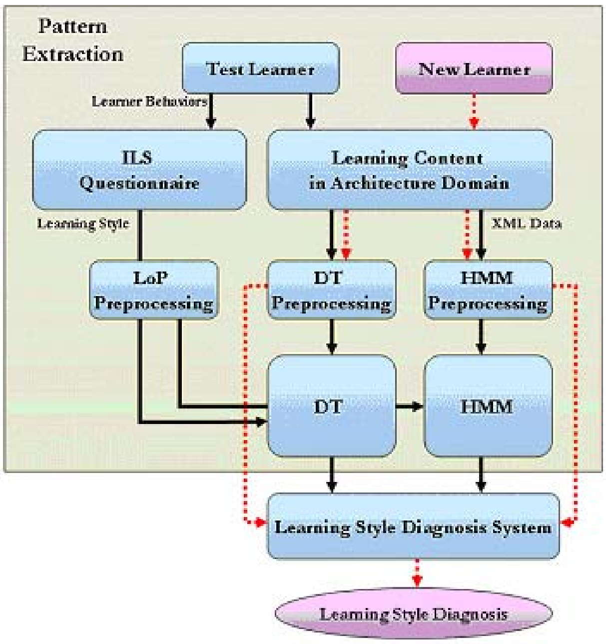
As the result of ILS questionnaire, we can get *Level of Preference* (LoP) which is the mark of how much the learners belong to the specific learning style. It is represented by odd numbers from 1 to 11 and a bigger number means a stronger preference. The data with higher LoP from 5 to 11 were used only.

5. Learning Styles Diagnosis

5-1. Behavior Pattern Extraction

In order to build learner models, we collect the learners' behaviors from the user interface, and analyze the data with *Decision Trees* (DT) and *Hidden Markov Models* (HMM). DTs produce the rules of the classification which are visible and easy to understand for the classification [6]. HMMs are a statistical method that uses probability measures to model sequential data represented by sequence of observations [7].

Figure 3 shows the detailed approach of this study in order to extract learners' hidden behavior patterns on the hypothesized user interface and derive a classification of the learning styles for each learner [4].



[Figure 3] Learning Style Diagnosis for Adaptive Interface

5-2. Decision Tree

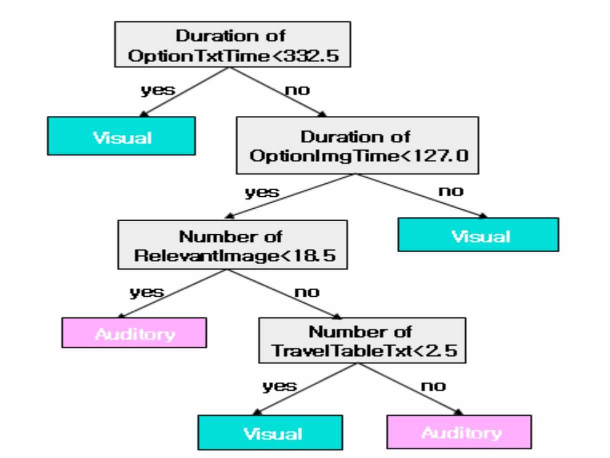
In machine learning, a decision tree describes a tree structure of which leaves represent classes and branches represent conjunctions of features that lead to those classes. A decision tree can be generated by splitting the data set into subsets based on the information gain [8].

The learner's data directly collected from the user interface may not be proper to use for building a user model. We removed anomalous and erroneous data, discarded the data with an LoP of 1 or 3, and transformed some data into more usable format. For instance, the actions of the same type (e.g. chatting with friends and asking to teachers) were combined into an instance, and durations in the events of the same properties (e.g. time spent on picture-driven contents) were added and put into an instance. In addition to these, it was also considered how correct the students solved the quiz or how carefully they tried to solve it. From the data, we collected the attributes for building DTs such as the number of interface icon clicks, the durations of some activities, the correctness of solving quizzes, the number of opinions that they wrote or read, and so on.

The preprocessed data were divided into two sets. Seventy percent of them were used for training and thirty percent of them were used for testing. Table 4 shows the number of data which was used in each learning style dimension. For example, 49 learners among 70 learners had a LOP larger than 3 in the V vs. A dimension. Among the 49 data, 35 were used for training (i.e. building a DT) and 14 for testing the built tree.

The DT obtained for the V vs. A dimension is shown in Figure 4. The DT in the example illustrates that the root classifier is the duration on the text-driven contents by moving through the optional text button for choosing text-driven contents. If learners spent their learning time on the text-driven contents chosen by the optional button less than 332.5 seconds, they are regarded as Visual style learners. Otherwise, the DT is to check the duration on the picture-driven contents. If the learners spent their learning time on the picture-driven contents greater than 127 seconds, they are also classified into a Visual group. If not, the next step is to count how many times the learners clicked a button for moving to the relevant picture-driven content. The DT will determine the learners to be an Auditory group if the number of the counts is less than 18.5. Lastly, depending on the number of text buttons clicks (2.5) on the table of content rather than moving through image buttons, DT will classify the learners into the Auditory group or the Visual group. Those rules obtained by DT correspond to the hypothesized behaviors on the user interface. This DT was validated with the 14 testing data in order to test the accuracy of the trees and rules, and the error rate is 0% in the DT for the data.

Similarly, the decision trees in S vs. N (SN) and G vs. Q dimensions (GQ) were also analyzed and validated with quite low error rates (SN: 22.22%, GQ: 28.57%), but C vs. R dimension had a quite high error rate (33.33%).



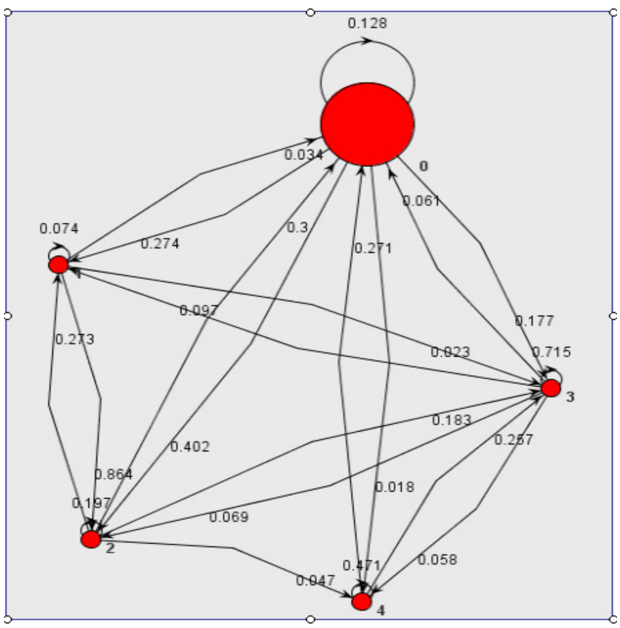
[Figure 4] An Example of the Final DTs

5-3. Hidden Decision Tree

HMMs are a statistical method, usually used for modeling a system with sequences of the system outputs. HMMs assume that the system to be modeled is a Markov process with unknown parameters, and determine the hidden parameters from the observable parameters, i.e. the system outputs. While DTs do not consider the sequence of learner's actions, HMMs do.

In order to train HMMs, we need sequential information. Since the learners' data collected from our learning system are the sequences of buttons or menus clicks, we can easily apply the data to HMMs. We also discarded the data with a number of data with low LoP (e.g.1-3). We also transformed the data. For example, to prepare the data for the G vs. S, we abstracted the menu button clicks with menu hierarchy.

We built two HMMs for each learning style dimension. For example, one HMM for Visual shown in Figure 5 and one HMM for Auditory were trained for the V vs. A dimension. As we did for building DTs, we divided the data into the training set and the test set with a ratio of 7:3. For example, among the 42 data, 30 were used for training and 12 for testing in the V dimension. In order to verify the HMMs, we apply a test data to each HMM and evaluate the probabilities for each HMM to accept the data. If the probability of the V HMM is higher, we conclude that the learner of the data is Visual and vice versa. The V and the A HMMs correctly classify 12 data among 14 (i.e. the error ratio is 14.28%). The HMMs for the G vs. S (GS) dimension and S vs. N (SN) dimension were also validated and showed low error rate (GS: 14.28%, SN: 22.22%). However, the C vs. R dimension showed a little high error rate (33.33%).



[Figure 5] HMM for a Visual Learning Style

5-4. Result Analysis

To diagnose user's learning style, two different kinds of machine learning techniques were utilized. One is an approach of the DT which was focused on button click counters and durations on the learning interface and the other is HMM which has an advantage of analyzing the sequential information of a user's learning process.

In the V vs. A case, our methods showed 0% (DT), and 14.28% (HMM) error rates. This result illustrates that the hypothesized interfaces are well designed to classify Visual vs. Auditory learners. Since the variety of attributes, such as the number of button clicks, the time for learning, etc. are more useful than sequence information of attributes for the V vs. A dimension, DTs show better results than HMMs.

In the G vs. Q case, DTs show 28.57% error rate and HMMs show 14.28% error rate. The sequential information is one of the essential data to extract learner's G vs. Q behavior patterns, so HMMs are better for analyzing data than DTs. However, in S vs. N (SN) and C vs. R (CR) dimension, the results of two methods show the same error rates. Therefore, it needs to be considered which methods will be utilized for the diagnosis of the learning style in those two dimensions.

For the S vs. N dimension, it might be possible that both methods are applied to identify the learner's style. Then, if the results of both methods are the same, it is obvious to determine whether she/he is sensing or intuitive. However, if not, a decision-making process is needed: (i) A gap value of probabilities derived from the S and N HMMs with "each testing data" is calculated, and then the average of the gap values with "all of the testing data" is produced. (ii) A gap value of probabilities in "a new learner's data" whose learning style is diagnosed can also be calculated by using the S and N HMMs. (iii) If the gap value from the new learner is greater than the average value, the result from the HMMs is more trustworthy. Otherwise, DTs will be chosen.

In terms of the C vs. R, the same decision-making process as the S vs. N dimension can be utilized. However, the error rates in both the DT and HMM methods are very high. It may be caused by the lack of data. We extracted Quiz & Discussion related button clicks from learners' data, and trained DTs and HMMs for the C vs. R dimension. In fact, most of learners tended to focus on the main learning rather than the discussion and quiz parts due to limited time. It was statistically proved that most of learners spent on the discussion part less than 10 percent of whole experiment time. Therefore, not enough data to train DTs and HMMs were obtained from this viewpoint. To cope with this problem, we are adjusting the experiment time and the amount of learning subject in on-going research.

6. Adaptive Interface

As shown above, learning styles of individual learners are diagnosed based on behaviors obtained from specially designed interfaces using machine learning approaches such as DT and HMM. It means that individual learning styles can be recognized based on the user interface-based behavior patterns. Therefore, based on the learning styles diagnosis, it is also possible to develop an intelligent tutoring system that is adaptive to individual learner's learning styles and preferences. In this CREDITS research center, a prototype of an intelligent learning environment that is adaptive to learning styles and situations has been developed on the subject of heritage alive of an old temple [9].

7. On-going Research & Future Work

Further research efforts are being made to extend beyond simple data (e.g. button clicks, the duration on a page alone, etc.) to more additional data collection (e.g. different attention on either text-driven or picture-driven contents, etc.), by means of eye movements with an eye-tracker device. Sibert & Jacob [10] point out that eye gaze interaction is a reasonable addition to computer interaction. In this research, a preliminary experiment with the eye-tracker device also demonstrated the detailed eye movements of the learners while they are interacting with the learning content. A remote eye-tracker, “iView X System” produced by SMI, was used for this study.

For the future work, in addition to the classification methods like DT and HMM, clustering methods can be approached in order to partition the learners into 16 different learning styles groups. In that the four dimensions may have influences on one another, the learning style analysis conducted in each dimension separately needs to be extended to the combinations of those four dimensions.

8. Conclusion

This paper describes learning styles diagnosis based on behavior patterns for user interfaces, and developing an intelligent learning system which can enhance learning efficiency and experiences by providing effective user interfaces and learning contents depending on the learner’s preferences. To achieve the aim, some machine learning approaches like DT & HMM were utilized. First of all, DTs extracted some behavior patterns for each dimension and provided if-then rules which are possible to make a classification of the undefined learners into different learning styles groups. Furthermore, HMMs also produced some useful machines that help to make the classification with sequential information of the user’s learning process. Based on the diagnosis of learning styles with the machine learning approaches, this study also exemplified how the different learning styles and learner’s preferences can be adapted to the user interface layout in intelligent learning environments.

Acknowledgement

This research was supported by the Korean Ministry of Science & Technology through the Creative Research Initiative Program.

References

1. Karger, D. R., Quan, D.: Prerequisites for a Personalizable User Interface, Proc. of Intelligent User Interface2004 Conf., Ukita (2004)
2. Felder, R., Silverman, L.: Learning and Teaching Styles in Engineering Education, Engineering Education (1988) 78(7) 674–681
3. Chen, W., Mizoguchi, R.: Communication Content Ontology for Learner Model Agent in Multi-agent Architecture, Proc. of the 7th International Conference on Computers in Education (1999) 95-102
4. Cha, H. J., Kim, Y. S., Park, S. H., Cho, Y. J. Pashkin, M.: Adaptive Learning Interface Customization based on Learning Styles and Behaviors, Proc. International Conference on Computers in Education, Singapore (2005)
5. Branco, P., Encarnacao, L. M.: Affective Computing for Behavior-based UI Adaptation, Proc. of Intelligent User Interface2004 Conf., Ukita (2004)
6. Margaret, H. D.: Data Mining Introductory and Advanced Topics, Pearson Education Inc., New Jersey (2003)
7. Fok, A. W. P., Wong, R. H. S., Ip, H. H. S.: Adaptive User Interface for Personalized Education based on Hidden Markov Model, Proc. of the 9th Global Chinese Conference on Computers in Education, Hawaii (2005)
8. Mitchell, T.: Machine Learning, WCB/McGraw-Hill, USA (1997)
9. Kim, Y. S., Kim, S. A., Cho, Y. J., Park, S. H.: Adaptive Customization of User Interface Design Based on Learning Styles and Behaviors: A Case Study of a Heritage Alive Learning System, Proc. of ASME Computers & Information in Engineering Conf., California (2005)
10. Sibert, L., Jacob, R.: Evaluation of Eye Gaze Interaction, Proc. of the SIGCHI Conf. on Human Factors in Computing Systems, Hague (2000) 281-288