Adaptive Learning Interface
Customization based on
Learning Styles and Behaviors

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Abstract. There exists an increasing demand for intelligent learning environments that are adaptive to learner’s preferences and tasks. This paper presents a study of an intelligent learning environment where the learner’s preferences are diagnosed using learner behavior patterns on user interfaces. In this research, a learning-style model by Felder & Silverman has been adopted as an appropriate basis for designing the behavior-based user interface customization.

Keywords: Adaptive user interface, Learner modeling, Learning styles

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, the learner’s behaviors are recognized, and customized user interfaces can be, finally, reconfigured in an adaptive manner to accommodate the learning styles.

1. 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 ontology has been designed as the first step of learner modeling for the following reasons: (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.
2. Learning Styles & User-Interface based Behaviors

The Index of Learning Style (ILS), introduced in a learning-style model by Felder & Silverman [2], has four axes; Sensory(S) vs. Intuitive(N) in terms of information perception, Visual(V) vs. Auditory(A) in terms of information input, Active(C) vs. Reflective(R) in terms of information processing, and Sequential(Q) and Global(G) in terms of understanding process of information. The discriminable characteristics that each learning style involves might be designed in customized interfaces. The ILS paper also proposes teaching techniques to address each dimension, discussing details of four dimensions of each learning style. Therefore, the learning-style model has been adopted in this research as an appropriate basis for designing the behavior-based user interface customization in that each learning style can be classified into two distinctive preferences. Based on the distinguishable characteristics of each dimension and the recommended teaching techniques, learner behavior patterns in learning contexts that seem to reflect each learning style preference have been hypothesized for this research.

3. Adaptive Customization of Learning User Interface

3.1 Hypothesized Behavior Patterns on the User Interface

Systems concerned with user modeling for the automatic adaptation of interfaces focus on monitoring events collected from the interface [4]. In this research, the learner’s behaviors for the interface would be 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]. Thus, user interfaces to reveal individual learning preferences have been designed using learning contents in an architecture domain.

G vs. S: The ILS work states that the instructor should offer “the big picture of a lesson” before presenting the learning steps. From this viewpoint, if a learner wants to look through the overview of the contents at the beginning, 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 of the learning contents. Furthermore, Global learners may want to jump to the section they are interested in by clicking the section hyperlinks rather than following the sequential order that may be preferred by Sequential learners. Furthermore, on the content screen (Figure 1), 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.

A vs. V: Felder & Silverman discuss that Visual style learners may prefer images on the screen, while Auditory learners may prefer written texts. 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.

S vs. N: ILS regards Sensory learners as having attentiveness to details and Intuitive learners as being bored by details 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, in problem solving situations where learners have to match two correct pieces, Sensory learners may spend more time on performing actions and may have higher rates of correctness than Intuitive learners. Felder & Silverman mention that while Sensory type learners are careful but may be slow, Intuitive learners are quick but may be careless. 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. Conversely, Reflective learners process information reflectively 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.
3.2 Behavior Pattern Extractions Module

In order to verify the hypothesized patterns and extract the hidden behavior patterns of learners in each learning style dimension, a pattern extraction module has been developed by using the Apriori algorithm [5]. The algorithm helps to find association rules that implies certain relationships among a set of objects [6]. There are three main steps in extracting the learner’s behavior patterns and verifying the patterns for this research, as illustrated in Figure 3. At first, after a learner conducts his or her learning actions in the ILS module, the learner’s events, such as clicking the buttons, the duration spent on the contents, etc. are recorded in an XML file. A collection of the individual events from the ILS module is defined as an array of actions. Then, all learners’ arrays of actions are compiled as a set of objects by counting the number of the same behavior patterns (e.g. the number of usages of the chat function), comparing opposite patterns (e.g. comparing total usage time of the picture areas to the usage time of text areas), etc. Among the set of objects, the Apriori algorithm is applied to find the associated relationships that occur together.

An experiment was conducted with 68 students, using an ILS module with the architecture learning content. Figure 4 describes the XML data that are derived from a learner by the ILS module. The XML record shows that the learner whose learning style is “SVRQ” clicked the first menu button [MmenuSC_F] and chose a sequential button [TSeqC] to study in a steady order.

3.3 Results of the Experiment

G vs. S: Global learners are strongly correlated to moving around the learning contents by clicking the global title button as hypothesized. However, sequential learners are also weakly correlated to using the global title button, rather than the sequential arrow buttons. It is assumed that most of learners who are accustomed to website styles may feel more comfortable with the global surfing. Another assumption is that the global title buttons on the user interface of the designed learning contents may be more attractive to the learners.

A vs. V: It is found that Visual learners have a strong correlation with studying the picture-driven contents, whereas Auditory learners want to study the text-driven contents more, [Auditory→ MainTxt_AS_ClickHigh in Figure 4] rather than additional learning contents. However, both Visual and Auditory learners tend to gain knowledge through both picture and text-driven areas.

S vs. N: It is interesting that sensory learners are very highly correlated to the completeness of all four quizzes [Sensing→FinishQ4 in Figure 4], while more than half of intuitive learners cannot complete the fourth quiz that is regarded as the most difficult one. Also, sensing learners are more correlated to returning to previous learning contents during the problem solving situation to review earlier materials than Intuitive learners. It is analyzed that sensory learners tend to solve problems by standard methods and be careful to do the tasks, but Intuitive learners tend to be quick and careless in problem-solving situations.

C vs. R: In the experiment, it was revealed the learning time given to the learners is too short. Many subjects said that they needed more time to complete all contents. Surprisingly, regarding the usage of the limited time, it is found that Active learners tend to spend time in activities, such as, chatting with friends and teachers, voluntarily sharing their opinions, and expressing their opinions. On the other hand, Reflective learners who tend to need time for thoughts spent more time on studying the learning contents.

Even if all the hypothesized behavior patterns are not verified, the findings from the experiment and verified differences between the learners in different learning styles must be a good starting point to derive the
learner’s preferences from their behavior patterns and intelligently customize the interface.

3.4 Adaptive Interface

It is shown that individual learning styles can be recognized based on the user interface-based behavior patterns. Therefore, it is possible to develop an intelligent tutoring system that is adaptive to the learning styles and preferences. In the CREDITS center, a prototype of an intelligent learning environment that is adaptive to learning styles has been developed on the subject of heritage alive of an old temple [7].

Conclusion

The learning environment demonstrated in this paper aims toward extracting learner’s behavior patterns for user interface, and developing an intelligent learning system that can enhance learning efficiency and experiences by providing effective user interfaces and learning contents according to the users learning style. To achieve the aim, firstly, some behavior patterns in different learning style dimensions were verified from the experiment with a learning content built based on the ILS theory. Based on the verified behavior patterns, the learner’s preferences can be determined by diagnosing their learning styles, and then an adaptive interface to accommodate the individual learning styles and support the learner can be developed.

Acknowledgements

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

References