Learning Styles Diagnosis based on User Interface Behaviors for the Customization of Learning Interfaces in an Intelligent Tutoring System

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Abstract. Each learner has different preferences and needs. Therefore, 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, and then user interfaces are customized in an adaptive manner to accommodate the preferences. A learning system with a specific interface has been devised based on the learning-style model by Felder & Silverman, so that different learner preferences are revealed through user interactions with the sys-tem. Using this interface, learning styles are diagnosed from learner behavior patterns on the interface using Decision Tree and Hidden Markov Model approaches.

1 Introduction

Individual learners have different preferences and learning styles, and these preferences are related with learner behaviors on user interface of learning environments. Thus interfaces that can adapt to each individual's specific preferences would be desired in intelligent learning environments [1].

The objective of this research is to develop an intelligent tutoring system that can diagnose 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 different tutoring strategies, and the evaluation of learning strategies. By using the learning-style model by Felder & Silverman which is more comprehensive, this study demonstrated a case of learning environment where the learning styles are diagnosed using learner models and the learner's behaviors, and customized user interfaces can be, finally, 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 appropriate learner aspects for designing the behavior-based user interface customization.

3 Learning Styles & Hypothesized User-Interface Behaviors

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, and Sensory (S) vs. Intuitive (N) in terms of information perception, and Active (C) vs. Reflective (R) in terms of information processing.

The distinctive characteristics in each dimension suggested by Felder & Silverman 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.

3.1 Global vs. Sequential (G vs. Q)

The ILS work states that the instructor should offer "the big picture or goal of a lesson" before presenting the learning steps (G2). From this viewpoint, it has been hypothesized that if a learner wants to look through the overview of the contents at the beginning, they may be Global learners. Thus, as seen in Fig. 1, 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 (G1) they are interested in by clicking the section hyperlinks on the "table of content" screen rather than following the sequential order that may be preferred by Sequential learners. In main content areas (Fig. 2), Sequential style learners may study in a steady order (Q1) by clicking the "next/previous" buttons, while Global learners may jump to select the content that they want by choosing the "section name" buttons directly.

Table 1. Characteristics of ILS (The characteristics incorporated are annotated with brackets)

Global	Sequential
Jumping directly [G1]	Steady progression [Q1]
Big picture [G2]	Partial materials [Q2]
Visual	**Auditory**
Pictures & Demonstrations [V1]	Words & Explanation [A1]
Sensing	**Intuitive**
Patient with details, Careful but slow [S1]	Bored by details, Quick but careless [N1]
Active	**Reflective**
Work in groups [C1]	Work alone [R1]
Brief discussion or problem-solving activities, Practical [C2]	Occasional pauses for thought, Fundamental [R2]

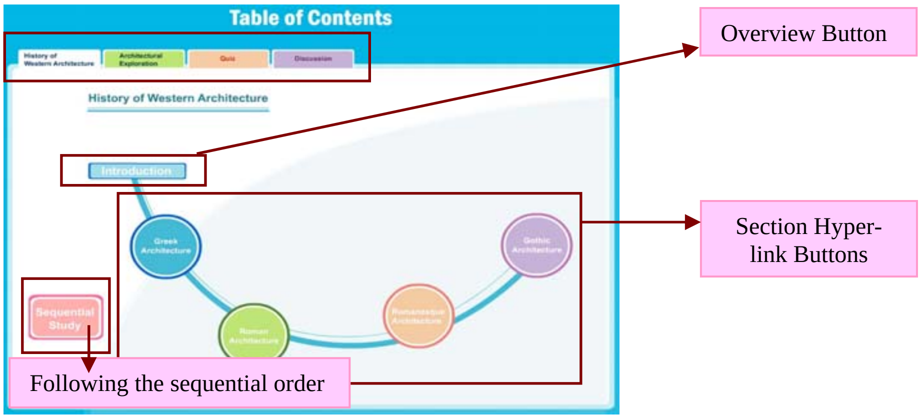

Fig. 1. Interface Layout for Table of Contents

3.2 Visual vs. Auditory (V vs. A)

Felder & Silverman discuss that Visual style learners may prefer images or demos (V1) on the screen, while Auditory learners may prefer written texts or explanations (A1). Thus, the second interface layout in Fig. 2 has content areas configured by both images and text with similar contents information. The learners can choose either picture-driven or text-driven areas according to their preferences. 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. Therefore, comparison in button clicks and durations between text-driven and picture-driven contents can be led to diagnosing the learner's learning style in the V vs. A dimension.

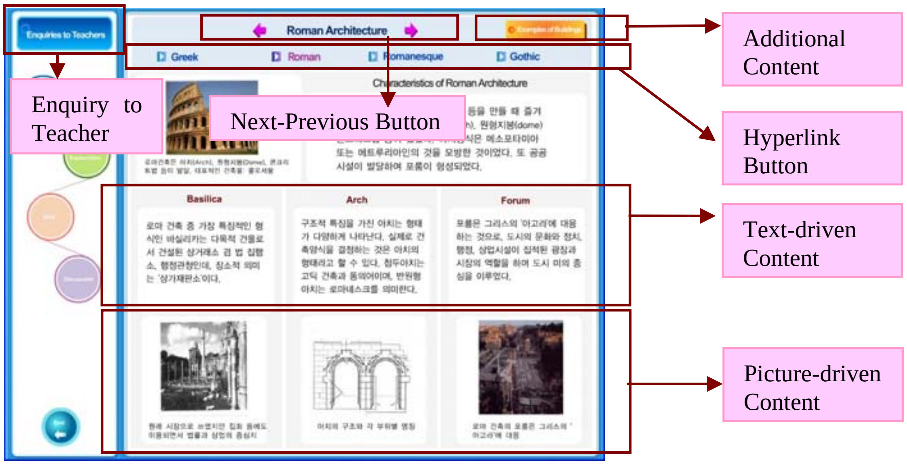

Fig. 2. Interface Layout for Main Learning Contents

3.3 Sensing vs. Intuitive (S vs. N)

An interface design has been devised to determine whether Sensory learners are patient with the additional materials and spend more time on studying the details of the references when additional contents or examples are given for reference learning materials as illustrated in Fig. 2.

A button for "Additional material" on the top right in Fig. 2 can be chosen by learners who want to study the detailed examples for the Architectural style (i.e. Roman Architecture in Fig. 2). If they clicked the button, the additional contents also have many different examples and details, so the students also go into deeper information if they are interested. It is based on that ILS regards Sensors as having "attentiveness to details (S1)" and Intuitors as being "bored by details (N1)".

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), so the interface design shown in Fig. 3 has been devised to verify the assumption. The user interface 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.

To illustrate, if students are careful to choose the answer and move to the puzzle section, they may have low trials and high correctness and completeness, but if they try it out without care, they may have high trials and low correctness and completeness. Therefore, the learner's learning style in Sensing vs. Intuitive dimension can be recognized from the differences in the number of trials and the correctness on the user interface of the quiz section.

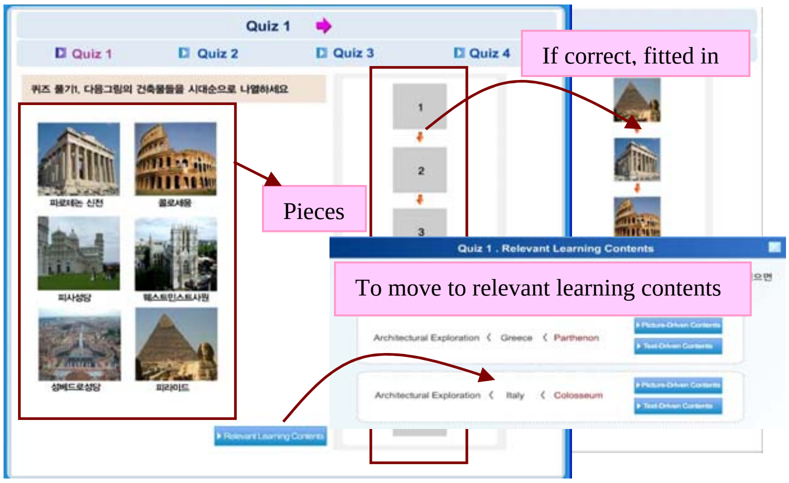

Fig. 3. Interface Layout for Problem Solving Situation

3.4 Active vs. Reflective (C vs. R)

Felder & Silverman point out that an Active learner is someone who feels more comfortable with active experimentation, and enjoys brief discussion and problem-solving activities (C2). Conversely, Reflective learners process information reflectively and want to have intervals to think about what others have told (R2). From this viewpoint, Active learners may want to participate in activities such as quiz, chatting (C1), and brief discussion, whereas reflective learners may be more interested in reviewing other learners' and professional opinions (R1) rather than doing real activities. In the discussion section, different buttons are provided based on the different characteristics.

4 Experiment

Based on these interface guidelines, a learning content was developed in the architecture domain with Macromedia Flash [4] in order to collect and 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].

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. We used data with higher LoP only as described in Table 2.

Table 2. Data Collection for Learning Styles Diagnosis

	G	Q	V	A	S	N	C	R
Number of data with low LoP [1-3]	22	20	14	8	22	12	30	17
Number of used data	20	8	42	7	27	9	14	9

5 Learning Styles Diagnosis & Pattern Extraction

5.1 Behavior Pattern Extraction

The first step in providing adaptive learning interface customization seems to build a model for learning styles [6]. In order to build one, 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 pattern recognition and classification [7]. HMMs are a statistical method that uses probability measures to model sequential data represented by sequence of observations [8, 9].

Fig. 4 shows the detailed approach of this study in order to extract learners' hidden behavior patterns. First of all, the data was collected from the experiment where the learners with different learning styles studied the learning content of architecture domain with the hypothesized interfaces, and the learners' behaviors on the learning content were recorded in XML files. Secondly, a preprocessing of the data based on the XML files was performed in order to make the data more appropriate for mining, exploring the characteristics of DT & HMM. Based on the preprocessed data, DTs and HMMs are constructed for each learning style dimension.

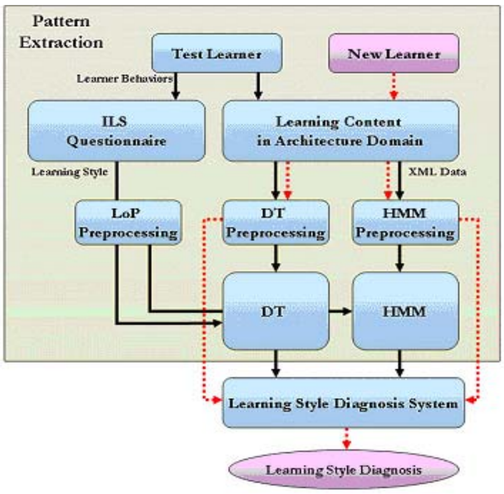

Fig. 4. Workflow of Learning Style Diagnosis for Adaptive User Interface Customization

5.2 Decision Tree

Preprocessing. The learner's data directly collected from the user interface may not be proper to use for building a user model. There can be errors or missing attributes, so some transform may be needed [10]. We removed anomalous and erroneous data, discarded the data with a 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 taken into consideration how correct the students solved the quiz or how carefully they tried to solve it. From the data, we collected the attributes for building decision trees 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, the trial rate of the quiz, and so on.

Attributes. A total of 58 attributes as shown in Table 3 has been devised so that DT based diagnosis can be constructed. For example, "GQ_7_MainCntsGlobal" in the G vs. Q dimension, represents the number of clicks for contents selection through hyperlink buttons as in Fig. 3. A global learner would move to other content with the hyperlink (MainCntsGlobal) button rather than moving in a sequential order.

Table 3. Diagnosis Attributes for DTs in G vs. S dimension

Learning Style	Attribute List	
Global vs. Sequential	GQ_1_TableofCntMenuClick GQ_2_TableofCntTabClick GQ_3_TableofCntSeqClick GQ_4_TableofCntMenuFirst GQ_5_MainMenuSymbolFst GQ_6_MainCntsSequence	GQ_7_MainCntsGlobal GQ_8_MainScreenMove GQ_9_DetailGlobal GQ_10_DetailSequence GQ_11_SubCntsGlobal GQ_12_SubCntsSequence

Training & Test. 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 decision tree) and 14 for testing the built tree [11].

Table 4. Training Data and Test Data

	G vs. Q	V vs. A	S vs. N	C vs. R
Number of training set	21	35	27	17
Number of testing set	7	14	9	6

The decision tree obtained for the V vs. A dimension is shown in Fig. 5. The decision tree in the example (Fig. 5) 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. In the learning system used, a user can choose either picture-driven or text-driven contents, and there are many buttons for choosing either one. 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.

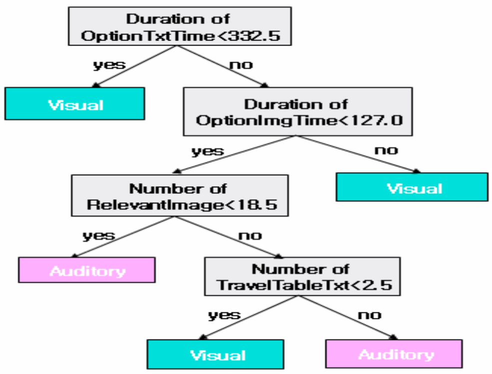

Fig. 5. An Example of the Final DTs

Those rules obtained by DT correspond to the hypothesized behaviors on the user interface. This decision tree 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 decision tree for the data. Similarly, the decision trees in Sensing vs. Intuitive (SN) and Global vs. Sequential dimensions (GQ) were also analyzed and validated with quite low error rates (SN: 22.22%, GQ: 28.57%), but Active vs. Reflective dimension had a quite high error rate (33.33%). Table 5 shows the detailed information about test sets with error rates in each dimension.

Table 5. Results of DTs (Error Rates)

DTs	G vs. Q	V vs. A	S vs. N	C vs. R
Error Rate	28.57%	0.0%	22.22%	33.33%

5.3 Hidden Markov Model

While DTs do not consider the sequence of learner's actions, HMMs do. For example, if a learner clicks button A, B and C sequentially, DTs can handle only click counters of each button, but HMMs can handle the sequence of clicks. In this viewpoint, DTs and HMMs are complementary each other.

Preprocessing. In order to train HMMs [8.9], 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 removed anomalous and erroneous data, and 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. If there are two top-level menu buttons such as m_1 and m_2, sub-menus m_{11} and m_{12} under m_1, and m_{21} and m_{22} under m_2, and a learner sequentially clicks m_1, m_{11}, m_2, m_{21}, and m_{22}, we converted this sequence into m_1, m_1, m_2, m_2 *and* m_2. That is, we use only the highest level information. On the other hand, we do not perform this kind of transformation for the V vs. A because button clicks for the V vs. A would be meaningful.

Attributes. The collected data from the experiment consist of a variety of learning activities on the learning content. Therefore, in order to analyze separately the data in each dimension with HMM, learning activities were filtered and redefined into four different sequential data sets as a preprocessing step. Table 6 shows the sequential attributes for four different dimensions of learning styles. First of all, learner's sequential information on studying the history of western architecture abstracted in a high level, explained in the preprocessing section, was extracted to make the G vs. Q HMMs, consisting of 9 attributes (e.g. GQ_1_Main1: studying Greek architecture, GQ_2_Main2: studying Roman architecture, etc.).

Training & Test. We used on HMM program which is implemented in Java, JahmmViz [12]. We built two HMMs for each learning style dimension. For example, one HMM for Visual and one HMM for Auditory were trained for the V vs. A dimension. Fig. 6 shows the trained HMMs for the V and A where hidden states were used. As we did for building DTs, we divided the data into the training set and the test set with a ratio of 7:3. Table 7 shows the number of data which was used in each learning style dimension. For example, among the 42 data, 30 were used for training and 12 for testing in the Visual 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 Visual HMM is higher, we conclude that the learner of the data is Visual and vice versa. The Visual and the Auditory 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%).

Table 6. Diagnosis Attributes for HMMs in G vs. S dimension

Learning Style	Attribute List	
Global vs. Sequential	GQ_1_Main1 GQ_2_Main2 GQ_3_Main3 GQ_4_Main4 GQ_5_Main1add	GQ_6_Main2add GQ_7_Main3add GQ_8_Main4add GQ_9_TopicChange

Table 7. Results of HMMs (Error Rates)

HMMs	G vs. Q	V vs. A	S vs. N	C vs. R
Error Rate	14.28%	14.28%	22.22%	33.33%

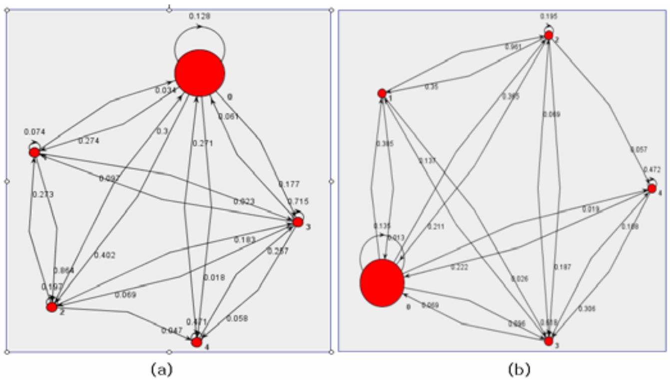

Fig. 6. (a) HMM for a Visual Learner Style and (b) HMM for an Auditory Learner Style

5.4 Result Analysis

To diagnose user's learning style, two different kinds of machine learning techniques were utilized. DT was used with focus on button click counters and durations on the hypothesized learning interface and HMM was used to analyze the sequential information of a user's learning process.

G vs. Q: 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 Global vs. Sequential behavior patterns, so HMMs are better for analyzing data than DTs.

V vs. A: 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, the rates of a correct answer, and trial of solving the quiz, etc. are more useful than sequence information of attributes for the V vs. A dimension, DTs show better results than HMMs. Thus, the DT technique can be utilized in order to diagnose the individual learning style in the V vs. A dimension.

S vs. N: It might be possible that both methods; DTs & HMMs 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 for the diagnosis of the learning style: (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 regarded as more trustworthy. Otherwise, the result from the DTs will be chosen.

C vs. R: It seems that the error rates in both the DT and HMM methods are very high. 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 part 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.

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 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 [13].

7 Concluding Remarks

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. Based on the diagnosis of learning styles with the machine learning approaches, this study also exemplified how the different learning styles can be adapted to the user interface layout in intelligent learning environments.

We are currently conducting a learning style diagnosis experiment as discussed in paper with about 600 students using an interior design-related content. We believe that a bigger pool of student data would provide more beneficial learner modeling results. Further research efforts are being made to extend beyond simple data (e.g.

button clicks, the duration on a page alone, etc.) to 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.

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. Furthermore, another future work will also be directed to extending the learner modeling by considering the various other kinds of learner characteristics such as emotion and motivation as well as learning mastery in providing adaptive learning support.

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