Design for Adaptive User Interface for Modeling Students' Learning Styles

Ashery Mbilinyi[1], Shinobu Hasegawa[2(✉)], and Akihiro Kashihara[3]

[1] School of Information Science, Japan Advanced Institute of Science and Technology, Nomi, Japan
ashery.mbilinyi@jaist.ac.jp

[2] Research Center for Advanced Computing Infrastructure, JAIST, Nomi, Japan
hasegawa@jaist.ac.jp

[3] The University of Electro-Communications, Tokyo, Japan
akihiro.kashihara@inf.uec.ac.jp

Abstract. Various researches have shown that providing adaptive support during students learning process improves student's motivational and learning outcomes. Therefore the effectiveness of e-learning systems can be determined based on how adaptive they are to the intended students. In this paper we describe a design for an adaptive user interface for a web-based learning system that can estimate students learning styles from their interaction with the web and use that information to guide them during their knowledge construction process.

Keywords: Adaptive user interface · Learning style · Web-based learning system

1 Introduction

A study conducted on 140,546 students participated in 4 Massive Open Online Courses (MOOCs) found that, despite the linear structure imposed on students – chronological ordering of weeks and learning sequences – learners predominantly navigate through MOOCs in a non-linear way, on average students skip 22 % of learning sequences entirely and perform a high number of back jumps, most often jumping from assessments back to earlier lectures [1]. This means, even though there are currently a large number of hypermedia-/hypertext based resources for learning purposes on the web [2], still students will have individual preferences on how they make choices on the learning resources no matter how structured they might be.

There are many factors that contribute to this individuality preferences but one thing common to all is, when they navigate through the hyperspace, they have to create a useful navigation path which influences their knowledge construction process [3]. But the problem is, so often the learners fails in creation of such navigation path due to cognitive overload, which is caused by diverse efforts not only in comprehending the contents of the webpages, but also in planning their own navigation process [4, 5].

Therefore, the provision of personalized or adaptive learning support for individual students is one of the important features to be provided by the e-learning systems [6] to help the students in their self-directed learning process. Adaptive learning systems can

S. Yamamoto (Ed.): HIMI 2016, Part II, LNCS 9735, pp. 168–177, 2016.
DOI: 10.1007/978-3-319-40397-7_17

either present personalized content for individual students or guide them to learn by providing a personalized path [7]. On our research we are focusing on a personalized path by developing a web-based system that can learn students behavior pattern called learning style and provide adaptive user interface to guide them.

Since it is difficult in applying adaptation on web-based learning systems based on students' learning styles because of the availability of students' behavior information on the web that can help to estimate their learning styles, we would like to examine the two following research questions;

- What kind data from student's interaction on the web can lead to recognition of their behavior pattern and therefore their learning style.
- What kind of user interface features can better adapt those recognized learning styles.

2 Related Works

2.1 Self-directed Learning

Adaptive presentation and adaptive navigation support has been two major technologies explored by adaptive hypertext and hypermedia systems [8] to help students in their self- directed learning. In systems with adaptive presentation, the pages are not static but adaptively generated or assembled for each student based on information stored on student model while in adaptive navigation support, the system assist their hyperspace orientation and navigation by changing the appearance of visible links to make it easier for students to choose where to go next and therefore help student find an "optimal learning path" [8]. There are many researches related to adaptation in self-directed learning. But two of the following works may be related to adaptation using learning style model.

AHA: The "Adaptive Hypermedia Architecture" system supports an on-line course with some user guidance through conditional (extra) explanations and conditional link hiding. In this system each time a user visit a page, the name of the page is passed to the adaptation engine, which updates a user model. The links are then displayed differently depending on the suitability of the link destination, which determined by an author-defined requirement, which express common relationships between concepts. The unvisited links are displayed blue color, purple is for visited ones, both of these are suitable links but the unsuitable or undesired links becomes black and not underlined [9].

CS383: This system dynamically creates HTML pages containing an ordered list of the educational resources, from the most to the least effective from the student's learning style point of view based on results from answering a dedicated questionnaire. CS383 follows 3 constructs of the Felder-Silverman Learning Model: Sensing/Intuitive, Visual/Verbal, Sequential/Global. For each category of resources (i.e. hypertext, audio files, graphic files, digital movies, instructor slideshows, lesson objectives, note-taking guides, quizzes, etc.), the teacher has to mention its suitability (support) for each learning style (by rating it on scale from 0 to 100). When a student logs into the course, a CGI executable loads the student profile, it then computes a unique ranking of each category of resources, by combining the information in the students profile with the resource ratings [10, 11].

Heritage Alive Learning System: is based on Felder-Silverman learning style model. Learning preferences are diagnosed implicitly, by analyzing behavior patterns on the interface of the learning system using Decision Tree and Hidden Markov Model approaches. Consequently the learning system interface is adaptively customized: it contains 3 pairs of widget placeholders (text/image, audio/video, Q&A board/Bulletin Board) each pair consisting of a primary and a secondary information area. The space allocated on the screen for each widget varies according to the student's learning style. [12, 13].

INSPIRE: Based on 4 Learning Styles in Honey and Mumford model [14], all learners in the INSPIRE system are presented with the same knowledge modules, but their order and appearance (either embedded in the page or presented as links) differ for each learning style. Thus for Activists (who are motivated by experimentation and challenging tasks), the module "Activity" appears at the top of the page, followed by links to examples, theory and exercises. In case of Pragmatists (who motivated by trying out theories and techniques), the module "Exercise" appears at the top of the page, followed by links to examples, theory and activities. Similarly, in case of Theorist the order is: theory, examples, exercises and activities while Reflectors the order is: examples, theory, exercises, and activities [11, 15].

2.2 Learning Style

Learning styles designates everything that is a characteristic to an individual when he/she is learning, i.e. a specific manner of approaching a learning task, the learning strategies activated in order to fulfill the task [13]. Learning style represents a combination of cognitive, affective and other psychological characteristics that serve as relatively stable indicators of the way a learner perceives, interacts with and responds to the learning environment [16]. For example, while approaching the same learning topic, there are students who would like to be presented first with definitions followed by examples, while others prefer abstract concepts to be first illustrated by a concrete, practical example. Similarly, some students learn easier when confronted with hand-on experiences, while others learn better alone [11].

There are over 70 learning style models in the literature [17]. Different models are used by various adaptive systems to classify learners. In our research, we are using Kolb's model.

Kolb's Model. Kolb's learning model which has been widely known as the Learning Style Inventory (LSI) [18] is probably the most famous model used in many disciplines, including education, management, computer science, psychology, medicine, nursing, accounting and law [19] to identify learning styles. Kolb's theory articulates that people learn from experience so the learning is a continual process which follows the cycle, so it is very unlikely that people will always have the same learning style, but changes during the knowledge construction process which involves a person and the environment they find themselves [20]. The cycle consists of 4 phases (Fig. 1), which are Concrete experience to Reflective observation to Abstract Conceptualization to

Active experimentation and back to Concrete experience. So at one time during the learning process a person can fall in one of the following learning styles [17]:

Accommodators: (Concrete experience + Active experimentation)

These types of students are practically oriented and get involved with unfamiliar and changeable circumstances. They are good at solving problems intuitively but sometimes seen by others to be overly proactive and somewhat impatient.

Assimilators: (Abstract Conceptualization + Reflective observation)

Assimilator likes inductive reasoning, logic and construction of theories; these learners are driven more by abstract ideas than by interaction with others.

Convergers: (Abstract Conceptualization + Active experimentation)

Students with a converging learning style are good at decision-making and problem solving; they prefer resolving technical issues compared to sort out interpersonal problems.

Divergers: (Concrete experience + Reflective observation)

Students with this learning style are imaginative and perceive situations from many perspectives; they are people-oriented and adapt by observation compared to direct action.

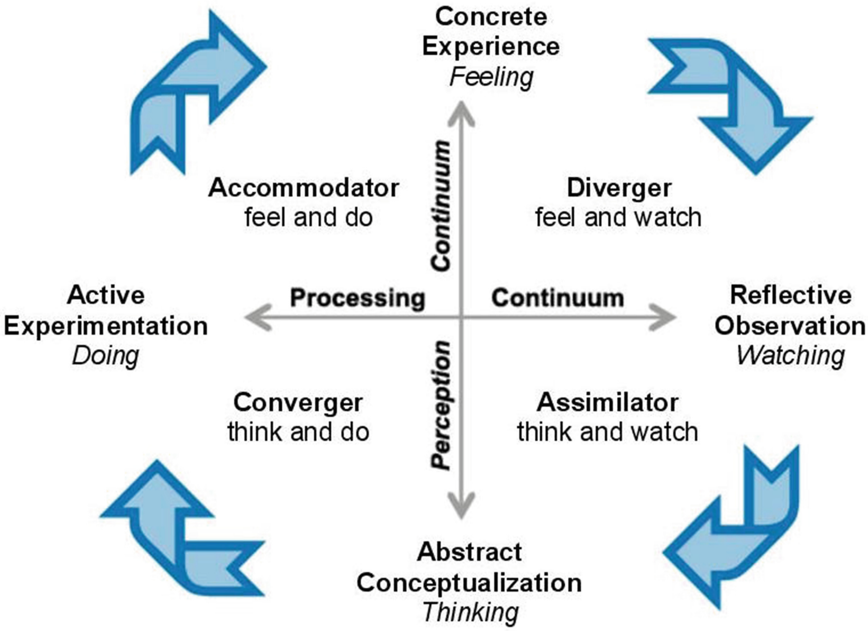

Fig. 1. Kolb's Learning Model (derived from http://www.learningexperience.org.uk/)

We have chosen Kolb's Model not just because it is well-accepted learning model among others over long time but also its foundation is on the idea that people are learning through experience so it accommodates the dynamism of learning styles involved during knowledge construction process of a person.

Honey and Mumford's Model. This model categorize four learning styles which are very similar to Kolb's model even though their model based on general individual behavior rather than learning in particular. Their learning style types are Activists (correlating to the "concrete experience" aspect of Kolb's experiential learning style), Reflectors (reflective observation), Theorists (abstract conceptualization) and pragmatists (active experimentation) [20]. Just like Kolb's, this model also illustrates that learning style is not a constant person's characteristics but dynamic one which changes due to the circumstances the learners experiences.

2.3 Target Learning Environment

Our system will be used to learn elementary school level mathematics. We will use Statistics subject in the prototype. Statistics offers flexibility in developing adaptive contents since among many mathematical subjects, few rival statistics in everyday applications [21]. The learning contents will be grouped in 4 modules, which are Examples, Theory, Exercise and Problem Solving Task. Each module should be tailored to give fully understanding of the specific learning topic. Once a student chooses a learning topic, the system should be able to guide him or her dynamically to the module that better suite his/her learning style at a particular time.

3 Modeling of Learning Style

3.1 In Preliminary Test: Initialization

At the initial stage when student creates their profiles in the system, we need to build a user profiles that will enable personalized interaction. Profiles should store both user-defined preference information and system detected user behavior pattern. Whenever the system detects a change in behavior pattern, it should update the profile [22].

Kolb's Learning Style Inventory (LSI) offers a questionnaire (Kolb's Test) which helps to identify the 4 mentioned learning styles types. At the initial point where the system does not have enough data from the users to recognize their learning style, the answers to this questions which will categorize their learning style will be the initial data to be stored on their profile as the user-defined preferences.

3.2 In Learning Process

During the students' learning process, our user modeling will involve tracking the interaction between the user and the system to recognize the users' behavior patterns and identify how these behaviors relate to their learning styles. This will help us to investigate whether Kolb model is appropriate for web-based learning or not. The data to be used will be the tracked users interface actions mainly frequency of clicking on learning modules, and navigation buttons and time intervals spent between modules.

First we want to track the student's first choice of learning module (first link click), after the system has displayed the learning modules available for the topic. Their first click on the specific learning module would likely mean that no matter the chronological arrangement suggested to students by the system, that learning module might be their preferable one. Then as he/she continues learning, time spend on each module would also let the system learn his/her behavior. The less interval time he/she spend on a certain module since his/her first click action before jumping to another module would mean he/she didn't prefer the previous module. At last the students will be given an open test in which they will be able to review any module or information to help them answer this test, the back jumps frequency to a particular module will give information on what kind of learning materials each student think they better help him/her in understanding of the learning topic. We have designed a "Weak User Model" (Fig. 2) to model the above-mentioned user behavior. We have called it a "Weak User Model", since we are still investigation if these kinds of data would be enough to give full recognition of students learning style.

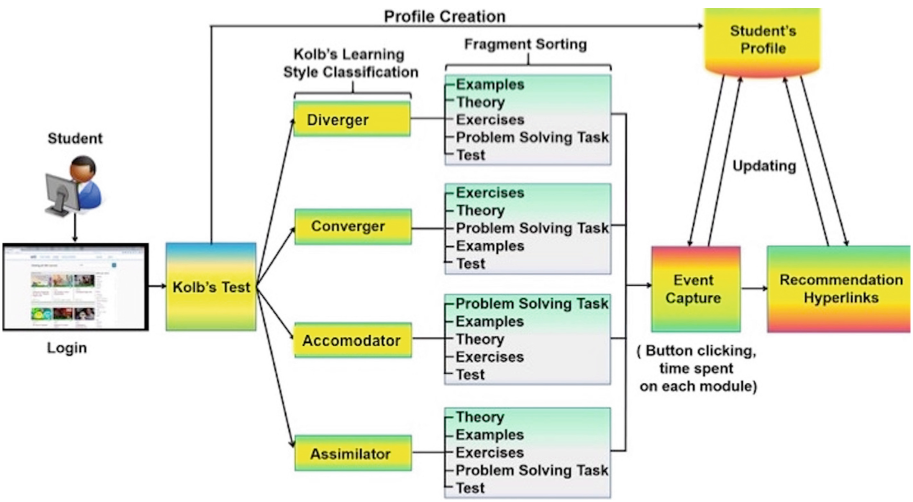

Fig. 2. Weak User Model

4 Design for Adaptive User Interface

4.1 Learning Style Adaptation

One of the main difficulties on designing of adaptive hypermedia systems is linking learning styles with the hypermedia applications [23]. For our system, adaptation will be in two levels, which are adaptive contents and adaptive user interface. For the contents, each module will be designed to give a full understanding of the learning topic so that when a user access the contents he/she prefer can get to understand the topic. For the user interface, we want the system to provide different arrangement of learning modules to each user's learning style so it can be easy for users to find the modules they prefer and also as they continue to learn, thus their preference behaviors changes, we want a system to dynamically provide different recommendation links to each learning style recognized so as to guide their knowledge construction process.

4.2 User Interface Adaptive Features

Fragment sorting is the technique in which educational resources are presented in different order considered suitable for each student [7]. So for each learning style identified after Kolb's Test (Fig. 1), students will be presented different order from the most suitable module at the top to the least one at the bottom. The fonts size and color of each link to the module will also be different with the top one larger and bottom one smaller in descending order. The arrangement is derived from INSPIRE system but will follow the Kolb's learning styles teaching suggestions as follows:

Accommodator: The arrangement will be Problem Solving Task ⇒ Examples ⇒ Theory ⇒ Exercises ⇒ Test, because this student can be taught better through making at integration between experiences and application, so problem solving task should be at the top.

Assimilator: Making facilitation for concept formulation is better way to teach this kind of student so the arrangement is Theory ⇒ Examples ⇒ Exercises ⇒ Problem Solving Tasks ⇒ Test.

Converger: Making personalization by practice is suitable for this learning style so the arrangement is Exercises ⇒ Theory ⇒ Problem Solving Task ⇒ Examples ⇒ Test.

Divergers: Are better taught by making connection between experiment and pre-existing knowledge so the arrangement is Examples ⇒ Theory ⇒ Exercises ⇒ Problem Solving Task ⇒ Test.

Recommendation Hyperlinks: will follow some adaptive navigation support techniques of Brusilovsky's taxonomy of adaptive hypermedia technologies as follows: -

Adaptive link hiding and generation: During "Event Capturing" phase in our system (Fig. 2), we recorded two parameters, time spend on each module and frequency of click on a module. The links of two learning modules corresponding to the highest value of those two parameters or the one link if both parameters favor it will be displayed this time at the top followed with link for the "Test" at the bottom. If the students test score will be less than 60 %, after learning through the module or modules given, the system should generate another mostly likely link for the student to choose from the hidden links, this time will be only one link with the highest parameter value of the either two parameters among the hidden links. Otherwise if the score is above 60 %, only one most preferable link will be shown together with Test for the next learning topic. Through this way, the system will keep on narrowing the recommendation links choices until the one link of the module that mostly preferred by the student will be recognized at the end.

5 Experiment Plan

5.1 Preliminary Experiment

We want to evaluate if Kolb's model is effective to be used in Web-based Learning Systems or not. If it is effective there must be close correlation between the learning style class the system placed a student during a fragment sorting phase and the learning modules the system will detect that a student prefer most, after the "event capturing" and "recommendation hyperlinks" phase. For example, if the student is Accommodator type of learning style that means at the end the mostly preferable link to him should be "Problem solving task".

5.2 System Experiment

We want to evaluate whether the system's adaptive features have been of assistance to student in guiding him to his/her preferred modules during navigating the hyperspace or have been limiting students. We will use confidence questionnaire to ask students how satisfied they were with the navigation support the system provided. We will also evaluate the effective of our systems by comparing the average learning time and test scores on learning topics assigned to students when using system with adaptive features and when there is no adaptive features.

6 Conclusion and Future Work

In this paper, we have described the design of adaptive user interface for modeling students' learning styles with two research questions in hand (i) What kind data from student's interaction on the web can lead to recognition of their learning pattern and therefore their learning styles (ii) What kind of user interface features can better adapt those recognized learning styles. The key idea is that adapting students' way of learning has a positive effect their learning process, leading to increased efficiency, effectiveness and/or learners satisfaction [11]. While we are still investigating if the set of input parameters we are using can be of enough information about users behaviors in learning, in the future we would like to have a "Stronger User Modeling" and propose a learning styles based on web-based learning environment. To do that we are expecting to broaden our behavior identification techniques by performing association rule mining [24] on clusters that represent group of users that interact similarly with the interface [25]. This process involves extracting the common behavior pattern in terms of class association rules (CAR) in the form of $X \rightarrow c$, where X is a set of feature value pairs and c is the predicted class label (that is, the cluster) for the data points where X applies. We also want to broaden the evaluation of effectiveness of the adaptive user interface through tracking feedback expression of users expression by observing face recognition and eye tracking data.

Acknowledgements. This work is supported in part by Grant-in-Aid for Scientific Research (B) (No. 26282047), from Ministry of Education, Science and Culture of Japan and Japan International Cooperation Agency (JICA) under ABE Initiative Program.

References

1. Guo, P.J., Reinecke, K.: Demographic differences in how students navigate through MOOCs. In: Proceedings of the First ACM Conference on Learning' Scale Conference, pp. 21–30 (2014)
2. Hasegawa, S., Kashihara, A.: An adaptive support for navigation planning in hyperspace. In: Proceedings of World Conference on Educational Media and Technology, Association for the Advancement of Computing in Education (AACE), pp. 2548–2555 (2006)
3. Hammond, N.: Learning with hypertext: problems, principles and prospects. In: McKnight, C., Dillon, A., Richardson, J. (eds.) Hypertext: A Psychological Perspective, pp. 51–69. Ellis Horwood Limited, Chichester (1993)
4. Cunningham, D.J., Duffy, T.M., Knuth, D.A.: The textbook of the future. In: McKnight, C., Dillion, A., Richardson, J. (eds.) Hypertext: A Psychological Perspective, pp. 19–49. Ellis Horwood Limited, Chichester (1993)
5. Thuering, M., Hannemann, J., Haake, J.M.: Hypermedia and cognition: designing for comprehension. Commun. ACM **38**(8), 57–66 (1995)
6. Tseng, J.C.R., Chu, H.C., Hwang, G.J., Tsai, C.C.: Development of an adaptive learning system with two sources of personalization information. Comput. Educ. **51**(2), 776–786 (2008)
7. Brusilovsky, P.: Adaptive hypermedia. User Model. User-Adap. Interact. **11**, 87–110 (2001)
8. Brusilovsky, P., Peylo, C.: Adaptive and intelligent web-based educational systems. J. Artif. Intell. Educ. **13**, 156–169 (2003)
9. De Bra, P., Aerts, A., Berden, B., De Lange, B., Rousseau., B., Santic, T., Smits, D., Stash, N.: AHA! The adaptive hypermedia architecture. In: Proceedings of the Fourteenth ACM Conference on Hypertext and Hypermedia, pp. 81–84 (2003)
10. Carver, A., Howard, A., Lane, D.: Enhancing student learning through hypermedia course and incorporation of student learning styles. IEEE Trans. Educ. **42**, 33–38 (1999)
11. Popescu, E., Badica, C., Moraret, L.: Accommodating learning styles in an adaptive educational system. Informatica **34**, 451–462 (2010)
12. Cha, H.J., Kim, Y.S., Park, S.-H., Yoon, T.-b., Jung, Y.M., Lee, J.-H.: Learning styles diagnosis based on user interface behaviors for the customization of learning interfaces in an intelligent tutoring system. In: Ikeda, M., Ashley, K.D., Chan, T.-W. (eds.) ITS 2006. LNCS, vol. 4053, pp. 513–524. Springer, Heidelberg (2006)
13. Popescu, E., Trigano, P., Badica, C.: Towards a unified learning style model in adaptive educational systems. In: Seventh IEEE International Conference on Advanced Learning Technologies, pp. 804–808 (2007)
14. Honey, P., Mumford, A.: The Manual of Learning Styles Maidenhead. Peter Honey Publications, Oxford (1992)
15. Papanikolaou, A., Grigoriadou, M., Kornilakis, H., Magoulas, D.: Personalized the interaction in a web-based educational hypermedia system: the case of INSPIRE. User-Model. User-Adap. Interact. **13**, 213–269 (2003)
16. Keefe, J.W.: Learning style: an overview. In: NASSP's Student Learning Styles: Diagnosing and Prescribing Programs. National Association of Secondary School Principals, Reston, VA, pp. 1–17 (1979)

17. Coffield, F.D., Moseley, E., Hall, E., Ecclestone, K.: Learning Styles and Pedagogy in Post-16 Learning: A Systematic and Critical Review. Learning and Skills Research Centre, London (2004)
18. Kolb, D.A.: Experiential Learning: Experience as the Source of Learning Development. Prentice Hall, New Jersey (1984)
19. Mainemelis, C., Boyatzis, R.E., Kolb, D.A.: Learning styles and adaptive flexibility: testing experiential learning theory. Manag. Learn. **33**(1), 5–33 (2002)
20. Brown, E.: The use of learning styles in adaptive hypermedia: thesis submitted to the university of Nottingham for the degree of doctor of philosophy (2007)
21. Minsky, M.: What makes mathematics hard to learn (2008). http://web.media.mit.edu/~minsky/OLPC-1.html
22. Liu, J., Wong, C., Hui, K.: An adaptive user interface based on personalized learning. IEEE Intell. Syst. **18**(2), 52–57 (2003)
23. Franzoni, A.L., Assar, S.: Student learning styles adaptation method based on teaching strategies and electronic media. Educ. Technol. Soc. **12**(4), 15–29 (2009)
24. Zhang, C., Zhang, S.: Association Rule Mining: Models and Algorithms. Springer, Berlin (2002). doi:10.1007/3-540-46027-6
25. Conati, C., Samad, K.: Student modeling: supporting persSonalized instruction, from problem solving to exploratory, open-ended interactions. AI Mag. **34**(3), 13–26 (2013)