An Automatic Approach for Detecting Dynamic Learning Style For E-Learning System

[1]Rajesh Kangle, [2]Ashish Pawar, [3]Avinash Patil & [4]Vinay Tadkalskar

Department of Computer Engineering,
JSPM's Rajarshi Shahu College of engineering, Tathawade, Pune- 411033
rajeshkangle91@gmail.com, ashishpawar123@gmail.com, avpatil3@gmail.com, vinaytadalskar@gmail.com

Abstract: There are many learning management systems (LMSs) around us. Of them WebCT, Blackboard, and Moodle are widely and successfully used when e-education is concerned. They help teachers in creating and conducting online courses though the individual differences of learners are not considered. The learners possess different characteristics and requirements like motivation, learning styles, prior knowledge and cognitive abilities. Some of the characteristics such as learning styles, their effect on learning abilities can be supported by some of the recent learning systems. It makes learning easier according to some educational theories. Considering these facts, we focus on dynamically changed learning styles of students to provide them with a better learning material. This system will hopefully enhance the learning ability and quality of learners. Finally we propose to find differences between learning style detected by ILS questionnaires and detected those dynamically.

Keywords- e-Learning, personalization, learning style, motivation, knowledge ability.

I.INTRODUCTION:

Besides the term learning management system, many other terms exist with similar or equal meaning, such as course management system or e-learning platform. Teachers can use them to present content, provide students with communication tools such as discussion forums, chat, and video conferencing, create assignments and quizzes, evaluate and assess students' performance, and be supported in administration issues regarding content, courses, students, progress of students and so on. LMSs can be seen as "empty" environments which are developed for teachers to create and manage their courses and fill them with content. However, developers of LMSs decide on how learning can take place in the LMS and build the LMS based on pedagogical strategies. Such pedagogical strategies can be, for example, based on concepts of learning theories such as behaviourism, cognitivism, and constructivism. Another example is that LMSs can emphasize a more learner-centered approach or teacher-centered approach. One of these systems is Moodle whose design and development is guided by a social constructionist pedagogy, which is based on four concepts (Dougiamas, 2007): The evaluation aims, on one hand, at finding out how good LMSs support general functions and features as well as adaptation issues and on the other hand, at finding the LMS that is most suitable for using as a prototype and extending it to an adaptive LMS.

Every learner has some distinct characteristics that help them in learning. These characteristics are knowledge abilities, motivation, cognitive abilities, and so on. Since most of the e-learning offer same learning material to all students, they do not consider the influence of these factors. This results in the less optimal use of learning sysem. Thus, to improve the efficiency of e-learning systems that provides each learner with his preferred learning objects is necessary.

II.PROBLEM DEFINITION

The purpose of this study is to determine the effectiveness of E-Learning as well detecting learner's style as per his/her behavior. To detect exact style of learner we need to experiment on more than 6 week (test 3 times in week). Project work is on only logical behavior not include his physical activity during experiment. It is necessary to determine his seriousness about project.

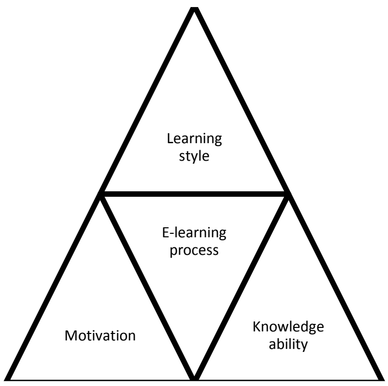
III.LITERATURE SURVEY

In order to use the information about working memory capacity to improve the detection process of learning styles, the relationship between learning styles and working memory capacity was investigated. Therefore, first, a comprehensive literature review was conducted, looking at studies that deal with the interaction of learning styles, cognitive styles, and cognitive traits. From these studies, indirect relationships between the dimensions of FSLSM and working memory capacity were concluded.

This paragraph introduces investigations dealing with how learning styles that can be automatically detected in LMSs based on information from student's behavior and actions. A general approach for automatic student modeling in LMSs with respect to learning styles was designed, implemented, and evaluated. For inferring learning styles from the behaviour and actions of students, two different approaches, a data-driven and a literature-based approach, were tested. According to the results of the evaluation, the literature-based approach achieved better results for identifying learning style preferences on each of the four dimensions of Felder-Silverman learning style model. Based on the results of the literature-based approach, the proposed concept for automatic student modeling can be seen as appropriate for detecting learning styles with high precision.

A.TRIPLE-FACTOR IN E-LEARNING PROCESS

It reflects relationship among three factors learning style, motivation and knowledge ability. The study proposed a model for e-learning system base on learning style, motivation, and knowledge ability called triple-characteristic model (TCM). The TCM model accommodates students' learning style, motivation and knowledge ability in their personalized learning activities.



B. THE FELDER-SILVERMAN LEARNING STYLE MODEL

FSLSM dimensions can be categorized into four dimensions, namely:

1. Active: Self-assessment exercises, multiple-questions guessing exercises.

Reflective: Examples, outlines, summaries, result pages.

2. Sensing: Examples, explanations, facts, practical material.

Intuitive: Definitions, algorithms.

3. Visual: Graphics, images, charts, videos, animations.

Verbal: Text, audio.

4. Sequential: Step-by-step exercises, constrict link pages.

Global: Outlines, summaries, all-link pages.

C.FINDING THE LEARNING STYLES AND AFFECTIVE STATES OF LEARNER

For the learners learning style recognition in a e-learning system currently questionnaires, self reports and automatic approaches are used. Similarly for the affective state recognition verbal (questionnaire, self report),nonverbal (heart rate, blood pressure, and skin conductance etc.), intrusive (speech, facial expression, and gestures), and nonintrusive (automatic) approaches are used. The benefit of automatic approaches whether it is used for learning style or affective state recognition is that it is free from uncertainty as it avoids students' involvement in providing explicit feedback about their preferences.

The ILS questionnaires consists of 44 questions, eleven for each of the four dimensions. The questionnaires can be completed on the WWW and supplies scores as 11A, 7A, 9A, 5A, 3A, 1A, 1B, 5B, 3B, 7B, 9B or 11B for each of the four dimensions. The score obtained by the learner ca be:

- 1-3, signifies that the learner is fairly well balanced on the two dimensions of that scale.
- 5-7, signifies that he has a moderate preference for one dimension of the scale and will learn more easily in a teaching environment that favors that dimension,
- 9-11, meaning that he has a very powerful preferences for one dimension of the scale and he probably has a difficulty in learning in an environment that does not support that preference.

The options "A" and "B" refers to one polarity of each dimension.

According to this model, there are 16 distinct types of combination of learning style dimensions are as follows:

- active/sensing/visual/sequential

- active/sensing/visual/global

- reflective/sensing/visual/sequential

- reflective/sensing/visual/global

- active/sensing/verbal/sequential

- active/sensing/verbal/global

- reflective/sensing/verbal/sequential

- reflective/sensing/verbal/global

- active/intuitive/visual/sequential

- active/intuitive/visual/global

- reflective/intuitive/visual/sequential

- reflective/intuitive/visual/global

- active/intuitive/verbal/sequential

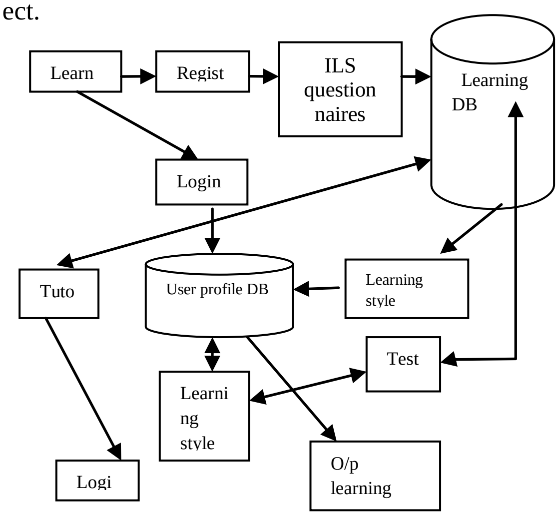
- active/intuitive/verbal/global

- reflective/intuitive/verbal/sequential

- reflective/intuitive/verbal/global

IV.SYSTEM DESIGN OF E-LEARNING SYSTEM

Our system aim to recognize the learning style of learner (student) as per his/her behavior .system consist (active/reflective, sensing/intuitive, visual/verbal, and sequential/global) four learning style along with learning object.



Having a more detailed information about the students' learning styles allows providing more accurate adaptivity. Content objects are used to present the content of the course. These content objects can have different formats, depending on the LMS. For example, content can be presented as html-files or pdf-files. Patterns related to the content objects include the number of visits (content_visit) as well as the time learners spent on content objects (content_stay). Additionally, the time learners spent on content objects including graphics were tracked. Furthermore, patterns regarding outlines of chapters were considered since outlines are explicitly mentioned in FSLSM. Therefore, the number of visits of outlines (outline_visit) and the time learners spent on it (outline_stay) were included as patterns. Another feature dealt with examples. Examples aim at illustrating the theoretical content in a more concrete way. Again, the number of visits (example_visit) and the time learners spent on these objects (example_stay) were used as patterns.

V.MATERIAL AND METHODOLOGY

Our system consists of four modules, i.e. ILS questionnaires LS detection module, learner's behavior pattern module, detection of three factors module and personalization course content module. We implemented a LMS based on developed architecture to do the experiment on adapting course materials to learners and estimating learning factors.

We divided the learning objects in the four-dimension learning style space. This organization cover all learning preferences, which are enough for each learning content. We update learner's models and estimate their learning factors automatically and dynamically.

A.ILS Questionnaires LS Detection Module

In this module, ILS questionnaires are provided to a student when he/she logged in to the system for the first time. ILS questionnaires consist of 44 questions which are again divided into four dimension learning style space, each consisting of 11 questions. Students are required to answer the questions. Based on their answers, identify students learning style. Then offers the course material to students very first time based on identified learning style.

B.Behavior Pattern Module

Store the information of learning behavior patterns and manage it in a database(test result, learning log and forum log). Test results have score of tests, quizzes, self assessment tests. A learning log has the time spent on learning objects, number of visits to the forum and how long to stay in the forum.

C. AUTOMATIC DETECTION OF THREE FACTORS MODULE

1.Estimating Learning Style Preferences:

We used a literature-based method to estimate learning styles automatically and dynamically. Expected time spent on each learning object, $Time_{expected\_stay}$, is determined. The time that a learner really spent on each learning object, $Time_{spent}$, is recorded. These pieces of time are also the ones calculated for each learning style labeled for the learning objects. For instance, if $Time_{expected\_stay}$ of a ReflectiveSensing learning object is 30 ms, then $Time_{expected\_stay}$ assigned for Reflective, as well as for Sensing is 30 ms. After a period P, which is passed as a system parameter (for example, six weeks), sums of $Time_{spent}$ for each of all eight learning style elements of the learner is calculated. Then we find out eight respective ratios:

$RT_{LS\_elements} = \sum Time_{Spent} / \sum Time_{expected\_stay}$

We use the same manner to find out the ratios $RV_{LS\_element}$ those are considered about the number of visits aspect. Number of learning objects visited and total of learning objects with respect to each learning style element are counted for the calculation.

$RV_{Ls\_elements} = \sum Los_{visited} / \sum Los.$

Finally, we calculate the average ratios:

$R_{avg} = (RT + RV)/2$

Learning styles are then estimated based on the following simple rule:

R_{avg}	LS Preference
0-0.3	Weak
0.3-0.7	Moderate
0.7-1	Small

The mutual results for two learning style elements of the same dimension, which are both strong, are rejected. Obviously, a learner cannot have both strong Active and strong Reflective learning style. One other ability is that R_{avg} for both two elements of one dimension are less than 0.3. At the current round of adaptation, we no longer consider this dimension because it is no need to provide the learner with learning materials that match this part. Applying the rule, we define that the learning style of the learner is moderate Active/Reflective, and strong Visual. In this situation, the pair SEQ/GLO is rejected, and the pair SNS/INT can be ignored.

2.Estimating Motivation(High/Low):

A student having high or low motivation state can be indicated by the number of learning activities in an e-learning system. Identification of motivational factor using the data from learning log and forum log.

3.Estimating Knowledge Ability:

A student can use the self assessment test, quiz to measure his/her level of understanding of learning material that has been learned. Then the student can answer the questions provided by e-learning system. The system calculate the number of correct answers to decide the class of knowledge ability, namely: poor(0-50)/ average(50-74)/ good(75-100).

VI. CONCLUSION AND FUTURE WORK

The objective of this system was to combine the advantages of learning management systems (LMSs) with those of adaptive systems. While LMSs focus on supporting teachers in creating, administrating, and managing online courses, such systems provide only little, or in most cases, no adaptivity for learners. On the other hand, adaptive systems support learners by providing courses that are tailored to their needs and characteristics but are rarely used in practice due to their lack of support for teachers. In order to provide adaptivity based on learning styles in LMSs, the learning styles of learners need to be known first. Therefore, an automatic student modelling approach for detecting learning styles from the behaviour and actions of learners was developed. For each of the four learning style dimensions of the FSLSM, relevant patterns of behaviour were selected, which were based on commonly used features in LMSs. In order to improve the automatic detection of learning styles, investigations were conducted about using also other sources of information. Once learning styles are known, adaptivity can be provided. Within this thesis, a concept for providing adaptive courses in LMSs was developed. This concept was implemented in Moodle, enabling Moodle to automatically generate and present courses that fit students' learning styles. The evaluation showed that students, who were presented with a course that matches their learning styles, spent significantly less time in the course but yield on average the same grades than students who were presented with a mismatched or standard course.

In future we develop the system which recognizes the physical appearance or behavior of learner to find better accuracy. It may required good quality web-camera.

VII. REFERENCES

[1] Pham Quang Dung, "An approach for detecting learning styles in learning management system based on learners' beahviours", 2012 International conference on Education and Management Innovation.

[2] Zainal. A. Hasibuan. "A dynamic personalization in e-learning process based on triple factor architecture", 2012 8th international conference on (Volume:1)

[3] Sabin Graf, Silvia Rita Viola, "Automatic student modeling for detecting learning style preferences in learning management system", 31.963/46-VII/9/2002.

[4] Farman Ali Khan, "Implementation of Affective states and learning styles tactics in web-based learning management systems", 2010 10th IEEE international conference on advanced learning technologies.