2013 International Conference on Advances in ICT for Emerging Regions (ICTer): 261 - 265

A Framework for Adaptive Learning Management Systems using Learning Styles

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Abstract*— Learning management systems (LMSs) are becoming increasingly popular in many educational establishments such as universities. However, they provide the same content for all learners in a given course. Educational theory suggests that learners possess different styles of learning. In this study, we propose a framework for adaptive LMSs that can tailor course content to the learning style of the individual learners. The Felder–Silverman learning styles model was used as the basis for our system implementation. Further, we present initial findings of application of the framework to a course conducted in Moodle LMS.

***Keywords*— e-learning, learning management systems, learning styles, Moodle**

I. INTRODUCTION

Education is a key to the knowledge economy, with the most educated attracted to the best jobs. Moreover, it broadens our horizons for a more wholesome life. Electronic learning (e-learning) has come a long way since the early days of electronic aids and television broadcasts.

E-learning is not limited to educational establishments such as universities. Private corporations are also embracing this technology for the cost-effective training of employees. With the advent of the Internet, the physical distance barrier is irrelevant in certain cases for education, as learning activities can be conducted over the World Wide Web. This has led universities to welcome learners from all over the world. People interested in courses can experience quality teaching, gain learning materials, and undertake fee-levying regular courses in the distance mode. Massive open online courses is one such recent addition to the e-learning space.

Two main issues must be addressed in the implementation of an e-learning infrastructure. The first is the software platform needed for e-learning, and the second is the digital content prepared to suit the platform. Learning management systems (LMSs) are a key category among the software platforms currently in use. Modular object oriented developmental learning environment (Moodle) [1], Blackboard [2], and Saba [3] are some of the leading software. Among these, Moodle is probably the most common, with over 83,000 sites providing for over 70 million users in 236 countries [1]. Reasons for its wide application include the ability to run on different infrastructure platforms and the cost of ownership factor. Being an open source product, Moodle also enables third-party enhancement of its functionality by the addition of modules.

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Despite the openness of such platforms, digital contents are offered in the same format to all learners within a particular course. LMSs tend to be course centric, rather than learner centric. This inability to personalize learning is often regarded as a limitation of most current LMSs, as noted by Graf and List [4]. Issues to be addressed to cope with this problem include learner expectations, motivation, and learning style [5]. Efforts to enhance the learning experience when using LMSs are already appearing in different ways. The ability to personalize LMSs by style templates and language is one such way. Another is the use of sharable content object reference model (SCORM) standards, which enable interoperability, accessibility, and reusability of web-based content.

Several recent studies have attempted to address the issue of identifying learning styles for personalizing the learning experience [6], [7]. These studies have adopted statistical as well as simple rule-based approaches. An important factor to consider here is that an individual learner's learning style may vary due to factors that are beyond the control of the course or LMS. Thus, the system must be capable of dynamically responding to such situations.

Here we present a framework that assists the learner to achieve his/her learning activities efficiently and effectively by adaptively changing the course material provided in Moodle. For this purpose, the learning style of the learner is extracted using a simple rule-based technique, which has been extensively documented by Graf et al. [8]. The learning style is categorized into four dimensions, each of which is formed by a pair of distinct trends: active–reflective, sensing–intuitive, sequential–global, and visual–verbal, as proposed by Felder and Silverman [9]. Data from two courses conducted at two educational establishments in Sri Lanka have been collected and utilized in our experimental study.

In this paper, Section II reviews related work on learning styles and adaptive learning systems, and Section III explains the Felder–Silverman learning style model (FSLSM) and the index of learning styles (ILS) as the basis of our study. Our proposed framework and functionality are presented in Section IV, and Section V describes our initial experiments. Conclusions and future work are given in Section VI.

II. RELATED WORK

Several definitions have been offered for the term "learning style." Honey and Mumford [10] defined learning styles as "a description of the attitudes and behaviors which determine an individual's preferred way of learning." Researchers have

suggested several models to classify learning, including Myers–Briggs [11], Kolb [12], and Honey and Mumford [13]. However, the model cited most frequently with respect to computer-based education systems is that proposed by Richard Felder and Linda Silverman, FSLSM [9], [14]. Graf et al. identified this model as the most appropriate for computer-based systems due to its ability to classify learners on the basis of their preferences over four dimensions [7], [15].

In addition, ILS, as developed by Felder and Soloman [14], can be used as an instrument to assess preferences in the four dimensions of FSLSM. This instrument consists of 44 questions, with 11 questions for each dimension. The results of the questionnaire provide an indication of an individual's learning preference in each dimension, with scores ranging from +11 to −11. This score can be read in the following manner. A score of 1–3 (either plus or minus) means that the learner is fairly balanced on the dimension of that scale. A score of 5–7 (either plus or minus) means that he/she has a moderate preference for one side of the dimension of the scale, and will learn more easily in a teaching environment that favors that dimension. A score of 9–11 means that he/she has a very strong preference for one dimension of the scale, and probably has considerable difficulty in learning in an environment that does not support that preference [14].

Recently, several authors have utilized FSLSM in attempts to identify the learning styles of learners in an LMS. However, their approaches have varied. The methods used include data-driven approaches such as Bayesian networks [6], [16], [17], decision trees [18], hidden Markov models [18], clustering algorithms [19], as well as simple rule-based approaches [17], [20].

Most LMSs or similar systems are concerned with presenting the same course materials to numerous learners. Studies on adaptive learning systems have also been conducted. In these, the content of course material is adapted to individual learners with respect to their characteristics. Researchers have recently been focusing on developing such systems.

Despotovic-Zrakic et al. [19] presented a facility for adapting Moodle LMS course material to which a data mining technique was applied. Learners could be clustered into three groups on the basis of their behavior during a one-week period of their LMS use. Each cluster was a subset of preferences defined in FSLSM.

Adaptive quizzes in LMSs comprise another trial. Moodle supports a limited quiz feature that can adapt to the learning situation, e.g., giving some hints before asking the learner to try again [1].

III. Felder–Silverman Model

FSLSM is considered to be a powerful and reliable model for the computer-based analysis of learners' learning styles. It presents four key dimensions, as explained below [7].

The first dimension considers the processing of information preferred by a learner: active (ACT) or reflective (REF). Active learners work well in groups. They do not learn much in situations that require them to be passive and tend to be experimentalists. In contrast, reflective learners work better by themselves or with one other person at most. They do not learn much in situations that provide no opportunity to think about the information being presented and tend to be theoreticians.

The second dimension considers the type of information that is preferentially perceived by the learner: sensory (SEN) or intuitive (INT). Sensory learners prefer to learn facts and like to relate to practical, real-world situations. On the other hand, intuitive learners prefer abstract learning material, such as theories and their underlying meaning. Compared with sensory learners, intuitive learners are more comfortable with symbols.

The third dimension considers the sensory channel through which the external information is most effectively perceived: visual (VIS) or verbal (VER). Visual learners prefer pictures, diagrams, graphs, or demonstrations, whereas verbal learners prefer spoken information or audio. FSLSM does not consider other sensory channels, such as touch, taste and smell, as these are relatively unimportant in most educational environments.

The fourth and final dimension considers how the learner progresses toward understanding: sequential (SEQ) or global

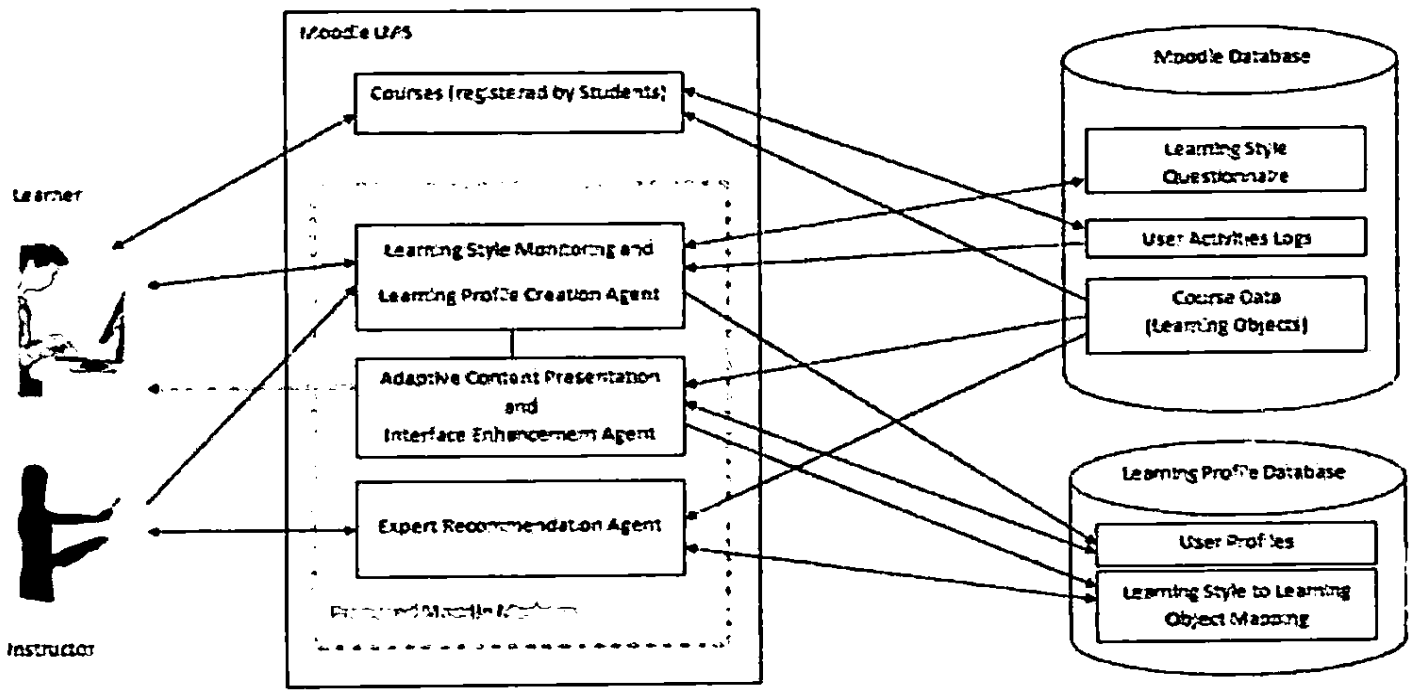

Figure 1: Proposed Framework

(GLO). Sequential learners learn in small increments, and therefore have a linear learning progress, tending to follow logical stepwise paths in finding solutions. Conversely, global learners use a holistic thinking progress and learn in large leaps. They tend to absorb learning material almost randomly without viewing connections; however, after learning sufficient material, they suddenly get the entire picture. They can solve complex problems and put things together in novel ways, but find it difficult to explain how they did it.

IV. Proposed Framework

To motivate the learner and hopefully achieve higher performance in learning, we propose a framework for adaptively changing course materials in response to the learner's learning style. Figure 1 shows the system organization.

When a learner registers for a course on the Moodle LMS, he/she can access course contents stored in a Moodle database. Activities performed by the learner are stored in the database as user-activity logs.

Three new modules are added to a conventional Moodle system. These are the learning style monitoring and learning profile creation agent (LLA), adaptive content presentation and interface enhancement agent (AIA), and expert recommendation agent (ERA), designed to facilitate the adaptive functionality to Moodle.

The LLA has two functions. First, it can suggest that the learner participates in the ILS questionnaire, which generates the learner's learning style on the basis of FSLSM. This information is stored as user profiles in a learning profile database. However, if the learner skips this questionnaire, his/her profile is generated by considering the log data of how he/she accessed the course material. This estimation is made upon several factors, as originally presented by Graf and Kinshuk [20] followed by Dung and Florea [21], and explained below. Each LMS course material may contain different learning objects such as videos, quizzes, and exercises. A factor for the determination of the learner's learning style concerns the time spent on each learning object in a course, $Time_{spent}$. In addition, the time expected for the corresponding learning object ($Time_{expected\_stay}$) is estimated, based on literature and expert knowledge.

The sum of the time values for all learning objects in the course is taken to obtain the following ratio, the ratio of time (RTLS) for the selected learning style.

$$RT_{LS} = \frac{\sum Time_{spent}}{\sum Time_{expected\_stay}}$$

Similarly, the number of learning objects visited by the learner ($LOs_{visited}$) is compared with the total learning objects (LOs) of the course. This forms the ratio of visits (RV_{LS}) for the given learning style, as given below.

$$RV_{LS} = \frac{\sum LOs_{visited}}{\sum LOs}$$

The average ratio (R_{AVG}), for each learning style is determined by the average of RT and RV. It can be used to express whether a learner has a weak, moderate, or strong preference for the selected learning style. This process is repeated for the eight learning styles.

Meanwhile, the ERA module is available to the instructor to fine tune the conditions for the determination of learning styles. Suppose the following values are obtained for the eight learning styles.

Dimension 1		Dimension 2		Dimension 3		Dimension 4	
ACT	REF	SEN	INT	SEQ	GLO	VIS	VER
0.77	0.1	0.2	0.35	0.8	0.72	0.75	0.3

Table 1: Sample scores (R_{AVG}) obtained for each learning style

Using two threshold values, threshold for moderate (T_M) and threshold for strong (T_S), where typically $T_M = 0.3$ and $T_S = 0.7$, each value for the eight learning styles is interpreted as weak, moderate, or strong. For the above example, this would yield the following (Table 2), where S, M, and W indicate strong, moderate, and weak, respectively. T_M and T_S may need to be fine-tuned depending on the content, but this remains as future work.

Dimension 1		Dimension 2		Dimension 3		Dimension 4	
ACT	REF	SEN	INT	SEQ	GLO	VIS	VER
S	W	W	M	S	S	S	W

Table 2 : Classification of learning styles on the basis of user preference

Once a learning profile is generated for a learner, AIA can recommend learning materials. The guidelines for recommendation are given in Tables 3 through 6.

Active	Reflective
• Self-assessment tests • Chat, forum posting • Multiuser mind map tools • Multiple choice questions • Guessing exercises	• Outline of lecture/session • Case studies • Slide shows • Forum viewing • Using online help • Content viewing • Examples • Single-user mind map tool • Summaries of lecture/session • Result pages view

Table 3: Learning styles to learning object (activity) mapping for dimension 1

Sequential	Global
• Detailed questions • Step-by-step exercises • Pages with few links	• Outline of lecture/session • Lecture/session summaries • Pages with multiple links • Overview questions • Navigation skip • Navigation overview pages

Table 4: Learning styles to learning object (activity) mapping for dimension 2

Visual	Verbal
• Graphics • Tables • Flowcharts, charts • Images • Demonstrations/videos • Colored or highlighted text • Slides with multimedia and animations	• Text-based material • Audio objects • Lesson objectives and Content objects • Text slideshows with audio

Table 5: Learning styles to learning object (activity) mapping for dimension 3

Sensing	Intuitive
• Examples • Exercises • Self-assessment tests • Questions about facts • Detail questions • Hands-on activities • Practical material • Slideshows • Case studies • Navigation using arrows	• Content viewing • Questions about concepts • Concepts and theories • Conceptual maps • Definitions • Algorithms

Table 6: Learning styles to learning object (activity) mapping for dimension 4

We structure our recommendation for the learner by introducing a matrix for the learning styles of each dimension. However, recommendations are not given to all cases since some do not make sense. While the basic principle under ILS is to identify dimensions where the learner is "out of balance," i.e., he/she has a very strong preference for one style and dislikes the other, there would be the opportunity to give conditional recommendation in some other situations.

We introduce two conditional thresholds for this purpose: conditional threshold for strong ($CT_S = T_S - T_M = 0.4$) and conditional threshold for moderate ($CT_M = T_M = 0.3$) for situations where the two learning style levels are adjoined. Suppose, for a given dimension, the level of learning style 1 (element on one side) is moderate, and that of learning style 2 (element on another side) is weak; if their learning style levels are separated by a score of more than CT_M, we decide to recommend materials that are relevant to learning style 1.

Table 7 shows the recommendations to be provided for each pair of learning styles in a certain dimension *i* (*i* can be 1–4). LS1 indicates learning style 1 and LS2 indicates learning style 2; for example, for dimension 1, LS1 is Active and LS2 is Reflective. NR indicates that no recommendation is possible. An underlined item indicates a conditional recommendation. Situations where CT_M is used are denoted by an asterisk (*), whereas those where CT_S is used are denoted by a plus sign (+).

		Learning Style 2 Level		
		Weak	Moderate	Strong
Learning Style 1 Level	Weak	NR	LS2*	LS2
	Moderate	LS1*	NR	LS2+
	Strong	LS1	LS1+	NR

Table 7: Recommendation matrix for a given learning style dimension i

V. Initial Experiments and Results

On the basis of the above framework, we are conducting experiments using two learner groups at two educational establishments in Sri Lanka. The pilot study involved 22 students who followed a course on Introduction to Information Technology. Using our framework, we compared the predicted learning styles (LLA functionality) to the results obtained using the ILS questionnaire. For each dimension, we considered the percentage of learners whose preference was accurately predicted by our framework.

Table 8 shows the experiment results. Our precision rate is compared with the results obtained by previous researchers who have conducted similar trials. However, the conditions of calculating the precision rate may not be exactly the same across trials. We are now fine tuning our thresholds and calculation scheme to further improve the precision of our method.

Authors	ACT/REF	SEN/INT	VIS/VER	SEQ/GLO
Garcia et al. [6]	58.00%	77.00%	-	63.00%
Graf and Kinshuk [7]	79.33%	77.33%	76.67%	73.33%
Dung and Florea[21]	72.73%	70.15%	79.54%	65.91%
This study	**63.64%**	**77.27%**	**72.73%**	**77.27%**

Table 8 : Precision rate comparison

VI. Conclusions and Future Work

This paper introduces a new framework for detecting learners' learning style in an LMS. The framework is based on FSLSM and has been implemented on a Moodle LMS. Our pilot study reveals that the system is comparable with previous studies when considering the learning profile creation. We are currently in stage II of the development of our system, which involves presenting content based on the learner's profile. We also plan to compare our present results using the simple rule-based approach with approaches that utilize sophisticated data mining techniques. Finally, the possibility of embedding learning style preference for SCORM content is also one of

our aspirations. This would allow the content to be reused without the need to re-tag content for its learning style preference.

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