2012 International Conference on Education and Management Innovation
IPEDR vol.30 (2012) © (2012) IACSIT Press, Singapore

An approach for detecting learning styles in learning management systems based on learners' behaviours

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Abstract. Automatic detection of learning styles in learning management systems (LMSs) is an important problem in which many researchers have proven their interest because it enhances learning efficiency by implementing adaptation dynamically. In an attempt to find out an effective solution for the problem, we propose a new literature-based method to estimate students' learning styles automatically. We used recorded data of learners' behaviours during their interactions with learning objects and a mapping rule to infer learning styles with respect to the Felder-Silverman Learning Style Model. The results of our method obtained through an experimental course were compared with those obtained through the Index of Learning Style questionnaire. The comparison showed a high precision of our method in identifying learning styles. Moreover, the method does not depend on a particular LMS. These characteristics indicate that the proposed method is promising and capable for wide use.

Keywords: adaptation, personalization, learning style detection, learning system

1. Introduction

Individuals have different learning preferences that help them learn better. These preferences are named learning styles. Many educational theorists and researchers consider learning style as an important factor that affects the learning process. The difference is one of the reasons why some learners find it easy to learn in a particular learning environment, whereas others find it difficult in the same one. Although learning management systems (LMSs) have many advantages, most of them provide their learner with the same learning materials. To improve efficiency of the learning process, the personalization in LMSs that provides each learner with his preferred learning objects is necessary; and it becomes one of the hottest research and development nowadays.

Beside the use of a questionnaire, there are two approaches that automatically detect learning styles: data-driven and literature-based. These approaches do not require learners to waste their time on completing a questionnaire. They are free from the problem of inaccurate self-conceptions of students at a specific time, and they also allow tracking changes in learning styles. Some methods associated with their research results presenting for the first approach are: (1) using Bayesian Network [14]; (2) using Hidden Markov Models and Decision Trees [5]. The literature-based approach is the newest and it is still studied by few researchers. It investigates learners' behaviours in their interactions with LMSs. The most remarkable research on this approach was conducted by Graf et al. [16]. This approach has a noticeable promising result in identifying learning styles not only precisely but also automatically and dynamically. This character is worth considering because learning styles may change over time.

In our study, we use a well-known learning style model proposed by Felder-Silverman. We promote a new method to estimate the learning style based on the number of visits and time that learners spent on

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learning objects. The method was experimented in our own web-based LMS called POLCA. Our results in discovering learning styles and matching learning objects with suitable learners are promising.

The rest of this paper is organized as follows: Section 2 introduces related work. In Section 3 we present the material and methodology. Section 4 shows our results and discussion, and Section 5 draws on conclusions and future work.

2. Related work

2.1. The Felder-Silverman Learning Style Model

Several authors proposed different definitions for learning style. For example, James and Gardner (1995) define learning style as the "complex manner in which, and conditions under which, learners most efficiently and most effectively perceive, process, store, and recall what they are attempting to learn" (p. 20). Merriam and Caffarella (1991) present Smith's definition of learning style, which is popular in adult education, as the "individuals' characteristic way of processing information, feeling, and behaving in learning situations" (p. 176) [8].

Some well-known learning style models have been proposed by Myers-Briggs, Kolb, and Felder-Silverman. In our research, we concentrate in the Felder-Silverman learning style model (FSLSM) [15] because the authors provide the questionnaire and a completed guide to use it. Moreover, this model has been proved to be effective in many adaptive learning systems [2] [4] [9].

The learning style model was developed by Richard Felder and Linda Silverman in 1988. It focuses specifically on aspects of the learning styles of engineering students. Three years later, a corresponding psychometric assessment instrument, the Felder-Soloman's Index of Learning Styles (ILS), was developed.

Their model permits classify students in four categories, Sensory/Intuitive, Visual/Verbal, Active/Reflective, and Sequential/Global. The dimensions Sensory/Intuitive and Visual/Verbal refer to the mechanisms of perceiving information. The dimensions Active/Reflective and Sequential/Global are concerned with processing and transforming information in understanding [1].

The ILS instrument comprises 44 questions, 11 for each of the four previously described dimensions. This questionnaire can be easily done on the web [13] and provides scores as 11A, 9A, 7A, 5A, 3A, 1A, 1B, 3B, 5B, 7B, 9B or 11B for each of the four dimensions. The score obtained by the student can be:

- 1-3, meaning that the student is fairly well balanced on the two dimensions of that scale;
- 5-7, meaning 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 strong preference for one dimension of the scale and he probably has a big difficulty in learning in an environment that does not support that preference.

The letters "A" and "B" refer to one pole of each dimension.

According to this model, there are 16 different types of combination of learning style dimensions. They are:

- active/sensing/visual/sequential
- active/sensing/visual/global
- active/sensing/verbal/sequential
- active/sensing/verbal/global
- active/intuitive/visual/sequential
- active/intuitive/visual/global
- active/intuitive/verbal/sequential
- active/intuitive/verbal/global
- reflective/sensing/visual/sequential
- reflective/sensing/visual/global
- reflective/sensing/verbal/sequential
- reflective/sensing/verbal/global
- reflective/intuitive/visual/sequential
- reflective/intuitive/visual/global

- reflective/intuitive/verbal/sequential
- reflective/intuitive/verbal/global

2.2. The automatic detection of learning styles

In order to implement adaptation in LMSs, students' learning styles must be found out first. Many studies aim at the automatic detection of learning styles to avoid intentional or unintentional wrong answers, and to save students' time on filling in a questionnaire. Some studies use data-driven approach, while others use literature-based approach. The difference between the two approaches is expressed in using a certain kind of information for the learning style detection.

2.2.1. The data-driven approach

This approach uses sample data in order to build a model that imitates the ILS questionnaire for identifying learning styles from the behaviours of learners. The advantage of the approach is that the model can be very accurate due to the use of real data. However, the approach strictly depends on the available data. Therefore, it may be difficult to have a good data set used for detecting learning styles because the data are scattered on different courses.

One of the studies in this approach is conducted by Garcia et al. [14]. The authors observed the behaviours of learners during an online course in the SAVER system and performed two experiments to show the effectiveness of Bayesian networks for identifying learning styles based on the behavior of students. The approach considered the active/reflective, sensing/intuitive, and the sequential/global dimension of FSLSM. The result showed that the Bayesian network obtains good results for the sensing/intuitive dimension and can detect the active/reflective and sequential/global dimension provided that students have some learning experience in web-based courses and that they are encouraged to communicate with each other via communication tools.

2.2.2. The literature-based approach

The idea of the literature-based approach is to use the behaviours of students in order to get hints about their learning style preferences and then apply a simple rule-based method to calculate learning styles from the number of matching hints. This approach is similar to the method used for calculating learning styles in the ILS questionnaire and has the advantage to be generic and applicable for data gathered from any course, due to the fact that FSLSM is developed for learning in general. However, the approach might have problems in estimating the importance of the different hints used for calculating the learning styles.

A method using this approach was proposed by Graf et al. [16]. The authors analysed the behaviours of 127 learners during an object oriented modeling course in LMS Moodle. This study is also based on Felder-Silverman learning styles model. Behaviour patterns associated with thresholds are determined according to frequent activities on LMS. By summing up all hints and dividing them by the number of patterns that include available information, a measure for the respective learning style is calculated and then it is normalized to detect learning styles for each dimension of the FSLSM on a 3-item scale, for example, between an active, balanced, and reflective learning style. The precision for all the dimensions of the FSLSM of the proposed method compared with the ILS questionnaire range from 73.33% to 79.33%, demonstrating a promising use in identifying learning styles.

3. Material and Methodology

We developed an architecture for multi-agent adaptive learning systems (figure 1). We implemented the LMS POLCA based on that architecture to do the experiment on estimating learning styles and adapting learning materials to the learners. In the system, each learning object can be 1 to several PowerPoint slides, 1 animation that illustrates the concept, 1 picture or several pictures, 1 multiple choice exercise, 1 input text exercise, 1 programming exercise (make a short program, modify a program, or find the output of a program), 1 http address (a web page), 1 article, and so on.

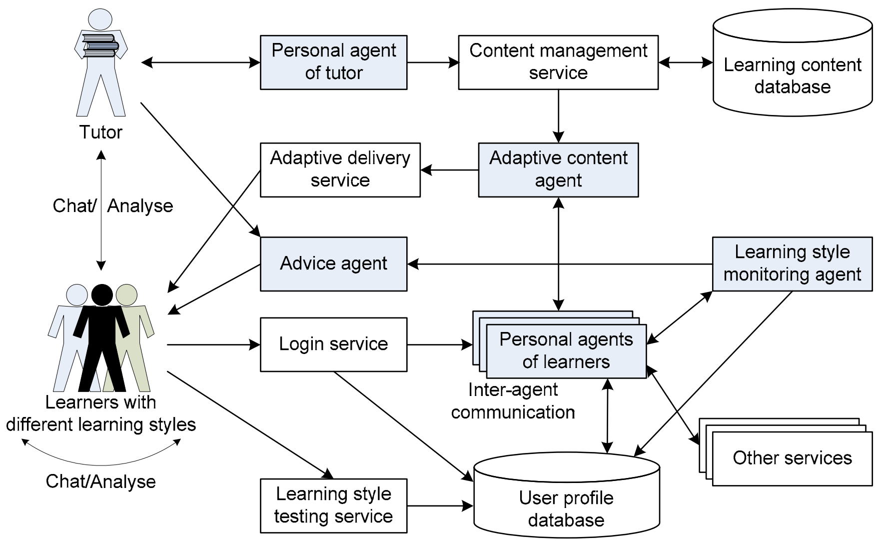

Fig.1: Architecture of adaptive learning style e-learning system based on intelligent agents and services

The learning objects we use are organized in the four-dimension learning style space. This organization makes it possible to do statistics served for Felder-Silverman learning style discovery. Ideally, interchangeable learning objects, which cover all learning preferences, are sufficient for each learning content. The process of updating learners' models and estimating their learning style is performed automatically and frequently. Once the learning style of a learner is identified, the system automatically implements adaptation by delivering learning objects that fit his new detected learning style.

3.1. Labeling learning objects

Each learning object is labeled with one subtype of any element in the set of 16 types of combination mentioned in the section 2.3. For example, learning object 1 is labeled as ActiveSensingVisualSequential, while learning object 2's label is Visual only.

Based on the theoretical descriptions about leaning styles' characteristics of Felder-Soloman [1], and on the practical research of S. Graf et al. [16], Hong H. and Kinshuk [4], and E. Popescu et al. [3], the learning objects in the POLCA system are labeled as described in Table 1.

Table 1. Labels of learning objects in POLCA

Active	Reflective	Sensing	Intuitive	Visual	Verbal	Sequential	Global
Self-assessment exercises, multiple-question-guessing exercises	Examples, outlines, summaries, result pages	Examples, explanation, facts, practical material	Definitions, algorithms	Images, graphics, charts, animations, videos	Text, audio	Step-by-step exercises, constrict link pages	Outlines, summaries, all-link pages

3.2. Estimating learning styles

Completing the Felder-Silverman questionnaire at the first time logging in the system is an optional choice for each learner. If he takes that entry test then the system can deliver learning materials adaptively for him right afterward. Otherwise, the adaptation for the learner will start only from the point when the system identifies his learning style automatically.

We used a literature-based method to estimate learning styles automatically and dynamically. Expected time spent on each learning object, $\mathtt{Time}_{\mathtt{expected\_stay}}$, is determined. The time that a learner really spent on each learning object, $\mathtt{Time}_{\mathtt{spent}}$, is recorded. These pieces of time are also the ones calculated for each learning style labeled for the learning objects. For instance, if $\mathtt{Time}_{\mathtt{expected\_stay}}$ of a ReflectiveSensing learning object is 30 ms, then $\mathtt{Time}_{\mathtt{expected\_stay}}$ 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 $\mathtt{Time}_{\mathtt{spent}}$ for each of all eight learning style elements of the learner is calculated. Then we find out eight respective ratios:

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

We use the same manner to find out the ratios $\mathtt{RV}_{\mathtt{LS\_element}}$ 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.

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

Finally, we calculate the average ratios:

$$\mathtt{R}_{\mathtt{avg}} = (\mathtt{RT} + \mathtt{RV})/2$$

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	Strong

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 $\mathtt{R}_{\mathtt{avg}}$ 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. We will finish this sub-section by showing the learning style of a learner's example result presented in following table:

Table 2: An example result of calculated R_{avg}

	ACT	REF	SNS	INT	VIS	VRB	SEQ	GLO
R_{avg}	0.5	0.6	0.25	0.2	0.8	0.15	0.8	0.9

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.

3.3. Delivering learning objects

Once a learner's model is updated, the system delivers only the learning objects that match his learning style to him. The match can be explained as: Learning objects with learning style LS will match a learner with learning style moderate/strong LS. For the learner in the previous example, he will receive only learning objects, whose learning style labels consist in Active, or Reflective, or Visual.

Learning style discovered at the moment is compared with the previous one. If there is no difference, then the adaptation stays the same. Otherwise, the system notices the user and automatically applies adaptation according to his newly detected learning style.

3.4. Experiment

We chose an Artificial Intelligence course to evaluate our method. The duration for the experiment was nine weeks; that is enough for studying nine sections with 204 learning objects included. The learning objects are sufficient as described above. The parameter `P` was set to four weeks. 44 undergraduate students in the field of Computer Science from Politehnica University of Bucharest participated in the study. They were finally asked to fill in the ILS questionnaire and to give feedback about the system adaptation.

4. Results and discussion

To assess the precision of our method, we use the following measure proposed by García et al. [14], in which Sim is 1 if the values obtained with our method and ILS are equal, 0 if they are opposite, and 0.5 if one is neutral and the other an extreme value; and n is the number of students.

$$Precision = \frac{\sum_{1}^{n} Sim(LS_{determined}, LS_{ILS})}{n}$$

The comparison results are shown in Table 3.

Table 3. Results of comparison

Act/Ref	Sen/Int	Vis/Vrb	Seq/Glo
72,73%	70.15%	79.54%	65.91%

The ratios of matching in four dimensions are all over 65%. This result is a bit higher than the outcome found out by García et al. [14], which is 58%, 77%, 63% for Act/Ref, Sen/Int, Seq/Glo dimensions, respectively, when using Bayesian networks. Compared with S. Grab's outcome [16], which is (79.33%, 77.33%, 76.67%, 73.33%), our result can be considered as approximate. Regarding to the adaptation process, 91% of participating students evaluated that the system dynamic adaptation is good and very good.

The method is based only on indications gathered from the learners' behavior during an online course and it uses a simple mapping rule. It does not depend on any aspect of the system architecture. Therefore, together with the advantages of literature-based approach mentioned in Section 1, our result shows that the proposed method can be used to find out learning styles in any LMS.

5. Conclusions and future work

In this paper, we presented a new method based on literature to estimate learners' learning styles automatically and dynamically. The proposed method refers to all four dimensions of FSLSM, as well as to their preference levels. Together with the advantages of time saving, automatic detection and system architecture free, its high precision in learning style estimation makes the method become promising and capable for wide use. An architecture suitable for adaptive learning systems and an adaptive LMS with respect to FSLSM was developed to take advantage of initiative. Adaptation experimented in the system also has a very good result.

Our future work will concentrate on larger experiments, on in-depth analysis, and also on the efficiency of dynamic learning style estimation and learning adaptation. Another aspect we will do is representing learning objects by ontologies to take advantage of machine-readable and reasoning capabilities from ontologies.

6. References

[1] B. A. Soloman and R. M. Felder. *Index of Learning Styles*. 1997. Available: http://www.engr.ncsu.edu/learningstyles/ilsweb.html

[2] C.I. Peña, J.L. Marzo, and J.L. Rosa. *Intelligent Agents to Improve Adaptivity in A Web-Based Learning Environment*. StudFuzz 178. 2005, pp. 141–170.

[3] E. Popescu, P. Trigano and C. Badica. Relations between Learning Style and Learner Behavior in an Educational Hypermedia System: an Exploratory Study. *Proc. of the 8th IEEE International Conference on Advanced Learning Technologies, (ICALT'08)*. 2008, pp. 725-726.

[4] Hong H. and Kinshuk. Adaptation to student learning styles in web based educational systems. *Proc. of the World Conference on Educational Multimedia, Hypermedia & Telecommunications (ED-MEDIA)*. 2004, pp. 491-496.

[5] H. J. Cha, Y.S. Kim, S.H. Park, T.B. Yoon, Y.M. Jung, and J.-H. Lee. Learning Style Diagnosis Based on User Interface Behavior for the Customization of Learning Interfaces in an Intelligent Tutoring System. *Proc. of the 8th International Conference on Intelligent Tutoring Systems, Lecture Notes in Computer Science*. Springer-Verlag Berlin Heidelberg, Vol. 4053. 2006, pp. 513-524.

[6] H. Shi, O. Rodriguez, Y. Shang, and S. Chen. Integrating adaptive and intelligent techniques into a Web-based environment for active learning. In: *Intelligent Systems - Technology and Applications*. Six Volume Set. CRC Press LLC. 2003, pp. IV-229 to IV-259.

[7] J. W. Keefe. Learning Style: An Overview. In: J.W. Keefe (ed.), *Student Learning Styles: Diagnosing and Prescribing Programs*. Reston, VA.: National Association of Secondary School Principals. 1979.

[8] James et al. as cited in Bettina Lankard Brown. *Learning Styles and Vocational Education Practice. ERIC Clearinghouse on Adult, Career, and Vocational Education*. [on-line], Columbus, OH. 1998. Available: http://www.calpro-online.org/eric/pab.asp

[9] M. S. Zywno. A Contribution to Validation of Score Meaning for Felder-Soloman's Index of Learning Styles. *Proc. of the American Society for Engineering Education Annual Conference & Exposition*. 2003.

[10] M. Yaghmaie and A. Bahreininejad. A context-aware adaptive learning system using agents. In: *Expert Systems with Applications journal*. Elsevier, Volume 38 Issue 4. April 2011, pp. 3280-3286.

[11] Min, Wei, and Lei. Research of Ontology-based Adaptive Learning System. *Proc. of the International Symposium on Computational Intelligence and Design (ISCID '08)*. 2008, pp. 366-370.

[12] N. Atman, M. Inceoğlu, and B. Aslan. Learning Styles Diagnosis Based on Learner Behaviors in Web Based Learning. *Proc. of the International Conference on Computational Science and Its Applications (ICCSA 2009)*. Springer-Verlag Berlin Heidelberg, Part II, LNCS 5593. 2009, pp. 900–909.

[13] N. Capuano, M. Gaeta, A. Micarelli, and E. Sangineto. Automatic student personalization in preferred learning categories. *Proc. of the 3rd International Conference on Universal Access in Human-Computer Interaction (UAHCI 2005)*. MIRA Digital Publishing, 2005.

[14] P. García, A. Amandi, S. Schiaffino, and M. Campo. 2007. Evaluating Bayesian Networks' Precision for Detecting Students' Learning Styles. In: *Computers & Education*. Elsevier. 2007, **49** (3): 794-808.

[15] R. M, Felder. Learning and Teaching Styles in Engineering Education. In: *Journal of Engineering Education*, vol. 78, nº 7. 1988, pp. 674-681.

[16] S. Graf, Kinshuk, and T.C. Liu. Identifying Learning Styles in Learning Management Systems by Using Indications from Students' Behaviour. Proc. *of the 8th IEEE International Conference on Advanced Learning Technologies. (ICALT'08)*. 2008, pp. 482-486.

[17] S. Sun, M. Joy, and N. Griffiths. The use of learning objects and learning styles in a multi-agent education system. In: *Journal of Interactive Learning Research*. 2007, **18** (3): 381-398.

[18] X. Wei and J. Yan. An E-learning System Architecture Based on Web Services and Intelligent Agents. *Proc. of the 9th International Conference on Hybrid Intelligent Systems*. 2009, pp. 173-177.