

A METHOD FOR DETECTION OF LEARNING STYLES IN LEARNING MANAGEMENT SYSTEMS

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Each learner has his own learning style that helps him study easier. Many researchers have been concentrating in determining learners' learning styles to aim at efficiency in implementing adaptation in learning management systems. Automatic and dynamic detection of learning style has its attractive advantages in precision and time saving. In this paper, we propose a new method that automatically estimate learners' learning styles with respect to the Felder-Silverman Learning Style Model based on their behaviors in an online course. Our first tests were compared with those obtained through the Index of Learning Style questionnaire, and it shows a promising precision in inferring learning styles and the method can be used in other LMSs.

Keywords: adaptation, learning style detection, learning management system

1. Introduction

Learning preference, or learning styles, and their efficiency in learning process have been considered since 1970s, with the appearance of many learning style models. All of them admit that each individual has a learning style that helps them learn better. This is one of the reasons why some individuals find it easy to learn in a particular learning environment; whereas others find it difficult in the same one. Nowadays, although learning management systems (LMSs) have many advantages, most of them provide their learner with the same learning materials. This fact prevents learners from taking advantages of their learning styles. To overcome this disadvantage, the personalization in LMSs that provides each learner with his preferred learning objects is necessary; and it is becoming one of the hottest research and development.

Initially, students' learning styles were classified manually based on their answers of a particular questionnaire. This method is still helpful until now. Recently, some researchers concentrate on how to identify learners' learning styles automatically. There are two approaches in this trend including data-driven and literature-based. In our study, we choose the literature-based approach, which investigates learners' behaviours in their interactions with LMSs. The approach is

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the newest and has a noticeable promising result in identifying learning styles not only precisely but also automatically and dynamically. In terms of learning style model, we use the one proposed by Felder-Silverman. We introduce a new method to estimate the learning style based on the number of visits and time that learners spent on 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.

In the next section, we introduce related work. In Section 3 we present the material and methodology. Section 4 shows our results and discussion, while Section 5 draws on conclusions and future work.

2. Related work

2.1. The Felder-Silverman Learning Style Model (FSLSM)

Model. 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.

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 [16].

Measurement. The Felder-Soloman's Index of Learning Styles (ILS) instrument, which was developed in 1991, comprises 44 questions, 11 for each of the four previously described dimensions. This questionnaire can be easily done on the web [1] 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 a 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.

Comments. Sabine Graf et al. [19] presented the FSLSM's differences to other learning style models including describing learning style in more detail, representing also balanced preferences, and describing tendencies. Zywno [10], Livesay et al. [4], Felder and Spurlin [17] concluded that their reliability and

validity data justified a claim that the ILS is a suitable instrument for assessing learning styles, although both studies recommended continuing research on the instrument. Van Zwanenberg et al. [14] concluded that the ILS is the best used to allow individuals to compare the strengths of the relative learning preferences rather than offering comparisons with other individuals.

2.2. The automatic detection of learning styles

As mentioned in the previous section, many researchers developed a questionnaire corresponding to their learning style models, in which individuals fill their answers in order to identify their learning styles. This method is simple and manual. Its detection result can be applied to a traditional class or to an online course. But the method requires students to spend their time to answer, and it has a problem of inaccurate self-conceptions of students at a specific time.

Recently, there are two approaches that automatically detect learning styles: data-driven and literature-based. The detection is based on students' behaviours in an online course. The difference between the two approaches is expressed in using a certain kind of information for the learning style detection. These approaches are said to overcome the disadvantages of manual method. 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 [15]; (2) using Hidden Markov Models and Decision Trees [6]. The most remarkable research on the second approach was conducted by Graf et al. [19].

A. 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 behaviour 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 Cha et al. [6]. The authors investigated the use of Decision Trees (DT) and Hidden Markov Models (HMM) for detecting learning styles according to FSLSM. The behaviour of 70 learners was recorded during an online course in an intelligent learning environment based on specific patterns. The students were also asked to fill out the ILS questionnaire in order to evaluate both models. Two conclusions can be drawn, namely that DT and HMM seem to be suitable for detecting learning styles from the behaviour of students and that for certain dimensions of the FSLSM one approach is more suitable than the other. However, due to the restriction in using data, the proposed methods are only applicable for identifying students' learning

style preference when students have a moderate or strong preference on one or the other pole of the respective dimension.

In another study, Garcia et. al. [15] observed the behaviour 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 tools.

B. The literature-based approach

The idea of the literature-based approach is to use the behaviour 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. [19]. The authors analysed the behaviors of 127 learners during an object oriented modeling course in LMS Moodle. This study is also based on Felder-Silverman learning styles model. Behavior 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

In an effort to find out an efficient, automatic method for identifying students' learning styles, we used a literature-based approach that track learners' behaviours to labeled learning objects. In our research, we concentrate in the Felder-Silverman learning style model (FSLSM) 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, 5, 10, 17, 19]. We construct our own learning management system, POLCA, to serve our study and to be used conveniently in the future. We describe our method and its experiment result in following subsections.

3.1. Labeling learning objects

Each learning object is labeled with one subtype of any element in the set of 16 types of combination of four learning style dimensions, recalled Sns/Int, Vis/Veb, Act/Ref, and Seq/Glo. 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 [16], and on the practical research of S. Graf et al. [19], Hong H. and Kinshuk [5], 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, $Time_{expected_stay}$, 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:

$$RT_{LS_element} = \frac{\sum Time_{spent}}{\sum Time_{expected_stay}} \quad (1)$$

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.

$$RV_{LS_element} = \frac{\sum LOs_{visited}}{\sum LOs} \quad (2)$$

Finally, we calculate the average ratios:

$$R_{avg} = (RT + RV)/2 \quad (3)$$

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 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. We will finish this subsection 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 implemented the LMS POLCA to do the experiment on estimating learning styles and adapting learning materials to the learners. In the system, each learning object can be: one to several PowerPoint slides, an animation that illustrates a concept, a picture or several pictures, a multiple choice exercise, an input text exercise, a programming exercise (make a short program, modify a program, or find the output of a program), a http address (a web page), an article, etc.

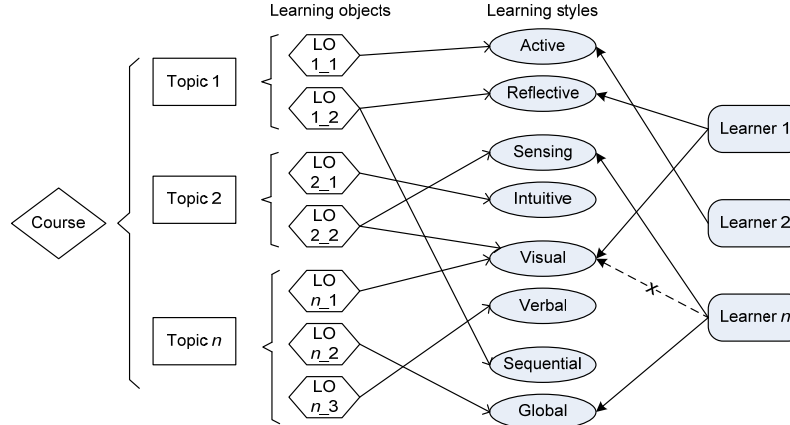


Fig. 1. The adaptation in the system

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. A simulation of the adaptation is shown in Figure 1. The removed dashed-arrow derived from Learner n means that his learning style can be re-identified.

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 the university 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 formula (4) proposed by García et al. [15], 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.

$$Precision = \frac{\sum_{i=1}^n Sim(LS_{determined}, LS_{ILS})}{n} \quad (4)$$

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. [15], which is 58%, 77%, 63% for Act/Ref, Sen/Int, Seq/Glo dimensions, respectively, when using Bayesian networks. Compared with S. Grab's outcome [19], 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 2.2, 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 adaptive LMS with respect to FSLSM was developed to take advantage of initiative. Adaptation experimented in the system also has a very good result.

For the future work, we will carry on extensive tests to firmly validate the proposed system and the efficiency of the method. We also study the ontological representation of learning objects to take its advantages in machine-readable and reasoning capabilities.

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