A literature-based method to automatically detect learning styles in learning management systems

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ABSTRACT

Efficiency and effectiveness of learning process can be improved by adaptations to learners' learning styles. But for the time being, most of existing education systems lack of adaptation or personalization; every learner is delivered the same learning contents. Many researchers have been studying to find out an efficient way of students' learning style identification for a better personalization. In our study, we concentrate on intelligent agents that can provide the learners with personal assistants to carry out learning activities according to their learning styles and knowledge level. In this paper, we present a new literature-based method that uses learners' behaviours on learning objects as indicators for estimating students' learning styles during an online course conducted in our POLCA learning management system. The evaluation of learning style estimation and adaptation from our experiment show a high precision. Together with the mentioned benefits of learning style adaptation, this result indicates that our method is capable for wide use.

Categories and Subject Descriptors

K.3.2 [**Computing Milieux**]: Computer and Information Science Education – *Computer science education*

General Terms

Algorithms, Management, Performance, Design, Verification.

Keywords:

Adaptation, Personalization, Learning style detection, Learning management system.

1. INTRODUCTION

The combination of education and the web led us to web-based education that has become a very important branch of educational technology. Adaptation in education is one of the hottest research and development nowadays. In this context, each learner has his own learning style which indicates how he learns most effectively. Several well-known learning style models are proposed by Myers-Briggs, Kolb and Felder-Silverman. Adaptive e-learning systems allow students learn by themselves so that it would improve learning effect and overcome the disadvantage of traditional class teaching [4].

To implement adaptation or personalization in such learning management systems (LMSs), students' learning styles need to be identified first. Beside the static approach that uses a questionnaire for identifying learning styles, there are two approaches that automatically detect learning styles: data-driven and literature-based. The literature-based approach is the newest and it is still studied by few researchers. It investigates learners' behaviours in their interactions with LMSs. It does not require learners to waste their time on completing a questionnaire. 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 [17].

In our study, we concentrate on the literature-based approach with respect to Felder-Silverman Learning Style Model (FSLSM). We promote a new method to estimate each student's learning styles based on the number of visits and the time that he spent on learning objects. The method was experimented in our own web-based LMS called POLCA. Our initial results in discovering learning styles and matching learning objects with suitable learners are promising.

In the next section, we introduce related work including learning object and learning style definitions, Felder-Silverman Learning Style Model, and two approaches for automatically identifying learning styles. In Section 3 we present the material and methodology that contain the problems of system design, learning object labelling, learning style estimation, and learning object delivery. Section 4 shows our results and discussion, while Section 5 draws on our conclusions and future work.

2. RELATED WORK

2.1. Learning object definitions

The expression "learning object" is one of the most cited terms in the e-learning literature. However, this term is not cited within relevant terminological reference sources, such as the Oxford English Dictionary, the Merriam-Webster Dictionary, or the WordReference website.

The Learning Technology Standards Committee choose the LOM's (Learning Object Metadata) definition in which Learning Objects are defined as "any entity, digital or non-digital, which can be used, re-used or referenced during technology supported learning". Examples of technology-supported learning include computer-based training systems, interactive learning environments, intelligent computer-aided instruction systems,

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distance learning systems, and collaborative learning environments. Examples of Learning Objects include multimedia content, instructional content, learning objectives, instructional software and software tools, and persons, organizations, or events referenced during technology supported learning [9]. However, this definition is extremely broad, and upon examination fails to exclude any person, place, thing, or idea that has existed at any time in the history of the universe, since any of these could be "referenced during technology supported learning."

D.A. Wiley (2000) defined a learning object as "any digital resource that can be reused to support learning." This definition includes anything that can be delivered across the network on demand, be it large or small. Examples of smaller reusable digital resources include digital images or photos, live data feeds (like stock tickers), live or prerecorded video or audio snippets, small bits of text, animations, and smaller web-delivered applications, like a Java calculator. Examples of larger reusable digital resources include entire web pages that combine text, images and other media or applications to deliver complete experiences, such as a complete instructional event. This definition is based on the IEEE LTSC's (Learning Technology Standards Committee) definition and it is sufficiently narrow to define a reasonably homogeneous set of things: reusable digital resources [3].

Beside previous work, some research has been carried out with the aim of investigating the learning object's domain from a formal ontological perspective, for example the study conducted by Sicilia et al. (2005), starting from the previously cited research of McGreal's, proposed an original ontological schema as an investigating tool for learning objects description. Their results show that a learning object can be ontologically defined as "any physical object which is purposively designed and developed in order to support someone to reach at least one learning objective".

2.2. Learning style

2.2.1. Learning style definitions

Many authors proposed different definitions for learning style. For example, in [15] learning style is described as "an expression of individuality, including qualities, activities, or behavior sustained over a period of time". In educational psychology, style has been identified and recognized as a key construct for describing individual differences in the context of learning. According to [15], key elements in this construct consist of one's affect (mood, feelings), behavior (doing things, activity), and cognition (thinking and knowing). This author reinforces that each person's personal style is the way in which that individual systematically and habitually responds to and works on a learning task.

Keefe [7] defines learning styles as "cognitive characteristics, affective and psychological behaviors that serve as relatively stable indicators of how learners perceive, interact with and respond to the learning environment."

James and Gardner (1995) [8] 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) [10].

2.2.2. The Felder-Silverman Learning Style Model

Several 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) [14] 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] [5] [11].

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].

• **Sensory/Intuitive**

- Sensing learners tend to like learning facts; intuitive learners often prefer discovering possibilities and relationships.
- Sensors often like solving problems by well-established methods and dislike complications and surprises; intuitors like innovation and dislike repetition. Sensors are more likely than intuitors to resent being tested on material that has not been explicitly covered in class.
- Sensors tend to be patient with details and good at memorizing facts and doing hands-on (laboratory) work; intuitors may be better at grasping new concepts and are often more comfortable than sensors with abstractions and mathematical formulations.
- Sensors tend to be more practical and careful than intuitors; intuitors tend to work faster and to be more innovative than sensors.
- Sensors don't like courses that have no apparent connection to the real world; intuitors don't like "plug-and-chug" courses that involve a lot of memorization and routine calculations.

• **Visual/Verbal**

Visual learners remember best what they see - pictures, diagrams, flow charts, time lines, films, and demonstrations. Verbal learners get more out of words - written and spoken explanations. Everyone learns more when information is presented both visually and verbally.

• **Active/Reflective**

- Active learners tend to retain and understand information best by doing something active with it - discussing or applying it or explaining it to others. Reflective learners prefer to think about it quietly first.
- "Let's try it out and see how it works" is an active learner's phrase; "Let's think it through first" is the reflective learner's response.
- Active learners tend to like group work more than reflective learners, who prefer working alone.
- Sitting through lectures without getting to do anything physical but take notes is hard for both learning types, but particularly hard for active learners.

• **Sequential/Global**

– Sequential learners tend to gain understanding in linear steps, with each step following logically from the previous one. Global learners tend to learn in large jumps, absorbing material almost randomly without seeing connections, and then suddenly "getting it."
– Sequential learners tend to follow logical stepwise paths in finding solutions; global learners may be able to solve complex problems quickly or put things together in novel ways once they have grasped the big picture, but they may have difficulty explaining how they did it.

The ILS instrument comprises 44 questions, 11 for each of the four previously described dimensions. This questionnaire can be easily done on the web [12] 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.

2.3. 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. Figure 1 (Graf, 2007) points out the difference between the data-driven approach and the literature-based approach in terms of their relationship to FSLSM. While the data-driven approach is based on the ILS questionnaire and aims at imitating it, the literature-based approach is directly based on the FSLSM, using the information from literature as basis.

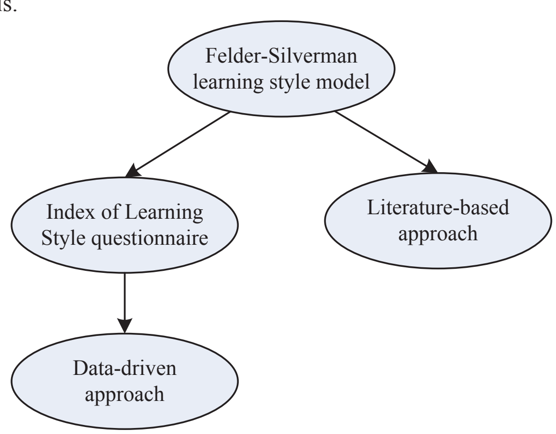

Figure 1. Relationship between Felder-Silverman learning style model and the two approaches

2.3.1. 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 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. [13] 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 communication tools.

2.3.2. 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. [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

3.1. System architecture design

We developed an architecture for multi-agent adaptive learning systems (Figure 2). The e-learning system we are developing is a multi-agent one, human and artificial agents work together to achieve the personalization and learning tasks. There are two agents that are responsible for personalizing in the system: the learning style monitoring agent and the adaptive content agent. During the courses each learner takes, the first agent monitors his learning activities in order to re-estimate his learning style and give him an advice if it is different from his recorded one by a test. The second agent, adaptive content agent, decides which learning objects should be delivered to each learner according to his learning style.

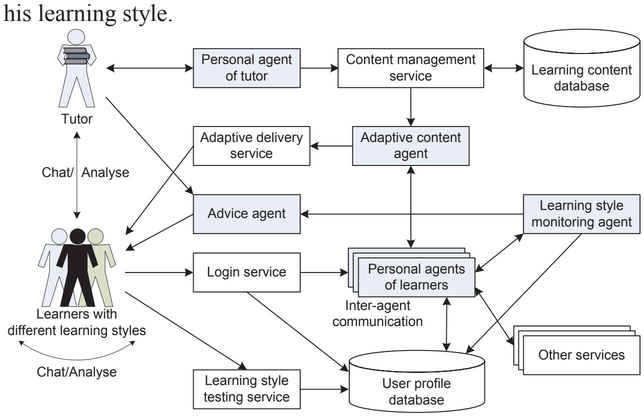

Figure 2. Architecture of adaptive learning style e-learning system based on intelligent agents and services

As depicted in Figure 2, the system architecture contains the following services and agents:

- Learning style testing service: The responsibility of this service is to hold a test for each learner at the beginning of the course to identify his/her learning style, and then to add that information in the user profile database for later uses.
- Login service: this service is responsible for user login. Once a learner login to the system, the service will search the user profile database and communicate with the learner's personal agent.
- Personal agents of learners: These agents perform the following functions:
  - Retrieve/store users' information from/to the user profile database.
  - Communicate with and exchange information with the adaptive content agent in order to help it decide to deliver the right adaptive materials to each kind of user.
  - Communicate with the learning style monitoring agent during the course to help it check if the learners' learning styles are most suitable or not.
  - Perform other tasks such as searching for information, doing tests, etc. with the help of appropriate services.
- Learning style monitoring agent: is responsible for monitoring each learner's behavior during the course to estimate his learning style, and then compare with his learning style identified via the test before. If they are not the same, the agent sends its advice to the advice agent. The agent can also update the learners' learning styles to the user profile database.
- Advice agent: receives advices from the tutor or from the learning style monitoring agent, and then send them to corresponding learners.
- Adaptive content agent: is responsible for determining what kind of learning materials should be delivered to each learner based on his learning style.
- Adaptive delivery service: delivers adaptive learning units decided by the adaptive content agent to learners.
- Personal agent of tutor: is responsible for updating the learning content database through the content management service.
- Content management service plays two roles:
  - Update learning content database from the tutor's personal agent
  - Retrieve filtered learning units from the database and provide them to appropriate learners via the adaptive content agent and the delivery service.

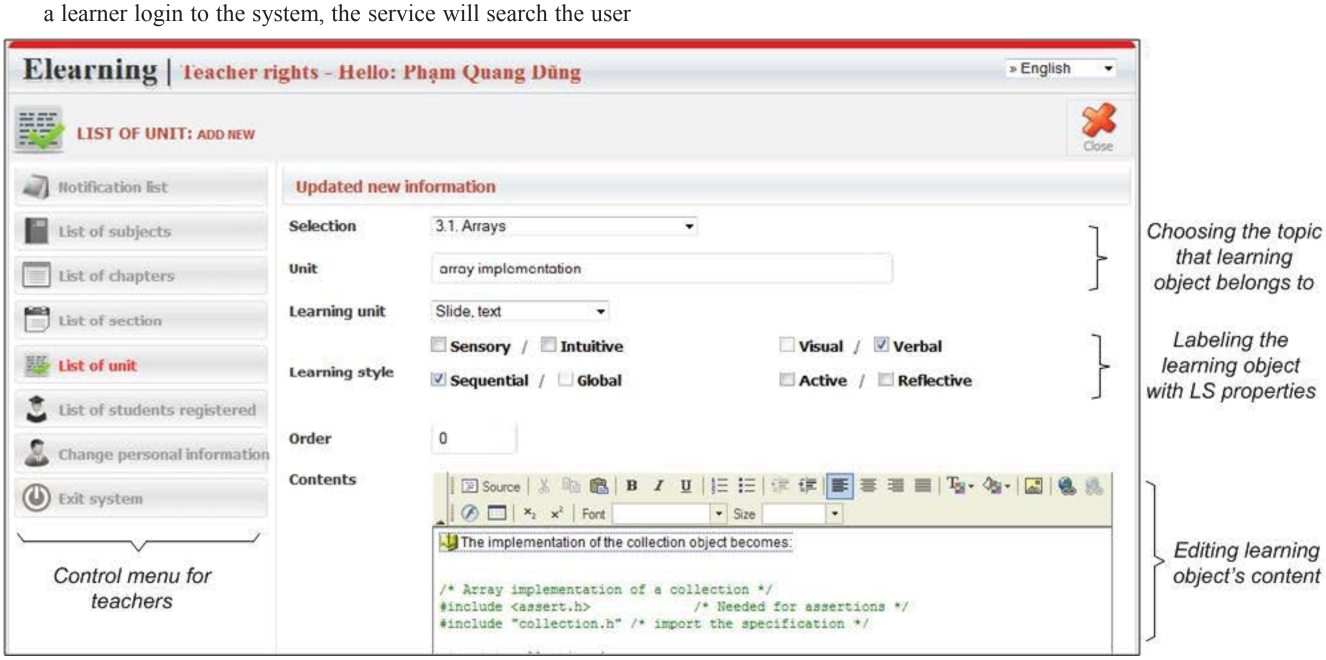

Figure 3. A screen shot from POLCA to which a teacher adds a learning object

We implemented the LMS POLCA (Figure 3) 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: 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.

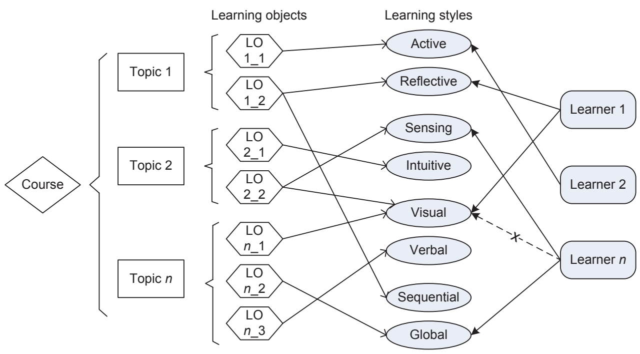

Figure 4. The adaptation in the system

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 4. The removed dashed-arrow derived from Learner *n* means that his learning style can be re-identified.

3.2. Learning object labeling

Each learning object is labeled with one subtype of any element in the set of following 16 types of learning styles combined from 4 bipolar categories mentioned in the section 2.2.2.

- 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

For example, learning object 1 is labeled as `ActiveSensingVisualSequential`, while learning object 2's label is `ReflectiveGlobal`.

Based on the theoretical descriptions about leaning styles' characteristics of Felder-Silverman [1] mentioned in the section 2.2.2, and on the practical research of S. Graf et al. [16], Hong H. and Kinshuk [5], and E. Popescu et al. [4], the learning objects in the POLCA system are label as described in Table 1.

Table 1. Labels of learning objects in LMS 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

3.3. Learning styles estimation

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 by the tutor who is responsible for the course. This time can be qualitatively identified as the maximum time used by a moderate student to finish studying the learning object. It can also be quantitatively determined in case the learning object is a video or an audio file. The time that a learner actually stays on each learning object, $\mathtt{Time}_{\mathtt{spent}}$, is recorded by the system. 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 15 second, then $\mathtt{Time}_{\mathtt{expected\_stay}}$ assigned for `Reflective`, as well as for `Sensing` is 15 second. After a period `P`, which is passed as a system parameter (for example, four 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 of time (RT):

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

To calculate the number_of_visits' ratios, $\mathtt{RV}_{\mathtt{LS\_element}}$, number of learning objects visited and total of learning objects with respect to each learning style element are counted. Those data are then used in the following formula:

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

Obviously, with a right attitude of teachers and learners, the obtained values of RTs and RVs are between 0 and 1. The average of RT and RV for each of eight learning style element, R_{avg}, is then used to estimate learners' learning styles using 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. As an obviously instance, 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 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}	0.6	0.5	0.75	0.9	0.8	0.15	0.2	0.1

Applying the rule, we define that the learning style of the learner is moderate Active/Reflective, and strong Visual. In this situation, the pair SNS/INT is rejected, and the pair SEQ/GLO can be ignored.

3.4. Learning object delivery

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.

4. RESULTS AND DISCUSSION

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 at the end of Section 3.1. The parameter P was set to six 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.

To assess the precision of our method, we use the following measure proposed by García et al. [13], 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 of learning style detection between our method and the ILS questionnaire is 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%. Compared with some data-driven studies, this result is more sufficient and is a bit higher than the outcome found out by García et al. [13], which is 58%, 77%, 63% for Act/Ref, Sen/Int, Seq/Glo dimensions, respectively, when using Bayesian networks. In another study, Cha et al. use Decision Trees and Hidden Markov Models to estimate learning styles. Their results were promising but the method has some limitation in using data. Only data from the ILS questionnaire indicating a strong or moderate preference on a specific learning style dimension were considered and data indicating a balanced learning style were eliminated. Moreover, these studies aim at identifying learning styles in a specific LMS rather than in LMSs in general.

In a comparison with a literature-based method conducted by S. Grab [16], which the precision is (79.33%, 77.33%, 76.67%, 73.33%) for the respective dimensions, our result can be considered as approximate.

Regarding to the adaptation process, 91% of participating students gave the feedback that the system's dynamic adaptation is good and very good.

Having literature-based approach's characteristics, our method is depended 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 might be used to find out learning styles in LMSs in general.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we presented a new literature-based method that uses tracked data of students' behaviour on learning objects to estimate their learning styles. The proposed method has some advantages including time saving, automatic and dynamic learning style detection, and system architecture free. It also refers to all of four dimensions of FSLSM, as well as to their preference levels. Moreover, the good experimental result makes the method become promising and capable for wide use.

We also presented an architecture suitable for adaptive learning systems and an adaptive LMS with respect to FSLSM. Experiment on learning style identification and adaptation with intelligent agents in the system also had 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.

6. ACKNOWLEDGMENTS

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7. REFERENCES

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

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

[3] D. A. Wiley. 2000. Connecting learning objects to instructional design theory: A definition, a metaphor, and a taxonomy. Available: http://wesrac.usc.edu/wired/bldg-7_file/wiley.pdf

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

[5] Hong H. & Kinshuk. 2004. *Adaptation to student learning styles in web based educational systems*. In Proceedings of ED-MEDIA 2004, World Conference on Educational Multimedia, Hypermedia & Telecommunications, pp. 491-496.

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

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

[8] James, W. B. & Gardner, D. L. (1995). *Learning styles: Implications for distance learning*. ERIC Document Reproduction Service No. EJ 514 356.

[9] LOM 2002. IEEE 1484.12.1-2002. *Draft Standard for Learning Object Metadata v.1*. Available: http://ltsc.ieee.org/wg12/files/LOM_1484_12_1_v1_Final_Draft.pdf

[10] Merriam, S. B., and Caffarella, R. S. 1991. *Learning in Adulthood*. San Francisco, CA: Jossey-Bass.

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

[12] N. Capuano, M. Gaeta, A. Micarelli, and E. Sangineto. 2005. *Automatic student personalization in preferred learning categories*. In Proceedings of the 3rd International Conference on Universal Access in Human-Computer Interaction (UAHCI 2005), July 22-27, 2005, Las Vegas, Nevada, USA, MIRA Digital Publishing, 2005,

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

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

[15] R. Riding and S. Rayner. 1998. *Cognitive Styles and Learning Strategies: Understanding style differences in learning and behavior*. David Fulton Publishers Ltd., London.

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

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