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Abstract

Adaptation to learners' learning styles can help education systems improve learning efficiency and effectiveness. This research orientation has been studied by many researchers lately, but most of the existing education systems lack adaptation in which every learner is delivered the same learning content. Moreover, many researchers concluded that it is worth applying automatic identification of learning style because of its advantages in precision and time savings. In our study, we concentrate on two main technologies to implement adaptation in education systems: semantic web and intelligent agents. Using ontology with the Semantic Web services makes it faster and more convenient to query and retrieve educational materials. Intelligent agents 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 domain ontology that is suitable for adaptive e-learning environments. The ontology describes the learning objects that compose a course as well as the learners and their learning styles. We also present a multi-agent e-learning system that supports pre-defining and re-examining students' learning styles during the course for better personalization. In the system, the learning style of each learner can be identified automatically and dynamically. We used a new literature-based method that uses learners' behaviors on learning objects as indicators for this task. The evaluation showed a high precision in detecting learning styles and in delivering learning materials. Together with the mentioned benefits, this result indicates that our e-learning system is capable of wide use.

KEY WORDS: *adaptation, semantic web, ontology, personalized, multi-agent, e-learning system.*

I. Introduction

Nowadays, the combination of education and the web leads us to web-based education (WBE) that has become a very important branch of educational technology. In WBE, organization and the access to learning objects (LOs) are important matters. Several standards of LO metadata have been used such as IEEE LOM, SCORM, Dublin-Core. Metadata provides better representation and understanding of learning content, and enables people to transform, share, and reuse learning content. However, the metadata is not enough; it is lacking reasoning capability and machine processing ability (Wang, Fang, and Fan 2008).

By putting WBE in the context of semantic web, we have a new generation of WBE, or semantic web-based education (SWBE). The use of semantic web and web intelligence makes WBE more effective and more appealing to learners, teachers, and authors alike (Devedzic 2006). Ontology is considered as the key concept in semantic web. It represents domain knowledge by defining terminology, concepts, relations, and hierarchies in a machine-readable form. It also makes web-based knowledge easier in processing, sharing, and reusing. The ontological description of LOs can overcome

disadvantages when using other representations. Therefore ontology-based learning systems are becoming more common day by day.

Personalization in education is also one of the hottest research and development topics currently. In this context, each learner has his own learning style that indicates how he learns most effectively. Several well-known learning style models are proposed by Myers-Briggs, Kolb, and Felder-Silverman. Personalized e-learning systems allow students to learn by themselves so that it would improve learning effects and overcome the disadvantage of traditional classroom teaching (Min and Lei 2008). Besides ontology technology, artificial intelligent agents can be used to improve personalization in learning systems by tracking learners' activities during the course to estimate their learning style and providing them appropriate LOs.

Our research concentrates on personalized e-learning systems using both ontology technology and intelligent agents. We propose a domain ontology aimed to support personalized online learning.

The ontology describes the learning material that composes a course in terms of both learning resources and acquired knowledge, as well as the learners and their learning styles. The acquired knowledge is structured along competencies and abilities acquired, mapped to concepts and learning resources. A multi-agent e-learning system that can provide learners with appropriate learning objects according to their learning styles was developed in an attempt to assess the efficiency of the learning process.

The rest of this paper is organized as follows: Section II introduces related work including learning object and learning style. Section III presents materials and methodology. In Section IV, we discuss our results, and Section V draws on conclusions and future work.

II. Related Work

2.1. Learning object

The expression "learning object" is one of the most cited terms in 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. About this problem, McGreal (2004), in his study on LOs definitions, highlighted that there are five types of definitions most used:

i.   "anything and everything;
ii.   anything digital, whether it has an educational purpose or not;
iii.   anything that has an educational purpose;
iv.   only digital objects that have a formal educational purpose;
v.   only digital objects that are marked in a specific way for educational purpose."

Some research has been carried out with the aim of investigating the LO'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, proposed an original ontological schema as an investigative tool for learning objects description. Their results show that an LO 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 styles

2.2.1. Learning style concepts

Some authors have proposed different definitions for learning style. For example, in (Riding and Rayner 1998) 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.

Keefe (1979) 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) define learning style as the "complex manner in which, and conditions under which, learners most efficiently and most effectively perceive, process, store, a n d 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 "individual's characteristic way of processing information, feeling, and behaving in learning situations" (p. 176) (James et al. 1998).

2.2.2. Felder-Silverman learning style model

Several well-known learning style models were proposed. In our research, we concentrate on the Felder-Silverman model (Felder 1988) because the authors provide the questionnaire and a completed guide to use it. Moreover, this model has been proven to be effective in many adaptive learning systems (Hong and Kinshuk; Peña, Marzo, and de la Rosa 2005; Zywno).

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

Their model permits classification of students into 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 into understanding (Soloman and Felder).

The ILS instrument is composed of 44 questions, 11 for each of the four dimensions previously described. This questionnaire can be easily completed through the web (Soloman and Felder) and provide 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 probably has immense difficulty in learning in an environment that does not support that preference.

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

III. Materials and Methodology

3.1. Ontology design

The representation of learning objects using metadata is not good enough because of the lack of machine processing ability and reasoning capability. With the development of semantic web and ontology, all these problems can be overcome because ontology is good at reasoning and is machine-readable. The use of ontology to represent learning objects enable different education applications to share and reuse the same educational contents. Furthermore, the machine-readable ability of ontology enhances the speed of query processes and the accuracy of the responded results. Hence, learners can have the learning objects they need quickly and they can be more reliable.

José M. Gascueña, Antonio Fernández-Caballero, and Pascual González (2006) proposed a domain ontology for personalized e-learning in education systems. They considered two characteristics that describe each educational resource which are: (1) the most appropriate learning style and (2) the most satisfactory hardware and software features of the used device. Starting from the ontology proposed by Gascuena, Fernandez-Caballero, and Gonzalez (2006), our work concentrates on developing an e-learning system that works well on PCs with a web browser, not on limited memory and screen size devices such as PDAs.

3.2. Learning objects labeling

Each learning object is labeled with one subtype of any element in the set of 16 types of combinations from four categories mentioned in Section 2.2.3. For example, learning object 1 is labeled as ActiveSensingVisualSequential, while learning object 2's label is Visual only.

Based on the theoretical descriptions about learning style characteristics of Felder–Soloman, and on the practical research of Graf, Kinshuk, and Liu (2008), Hong and Kinshuk, and Popescu, Trigano, and Badica (2008), 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

3.3. Learning styles estimation

Completing the Felder-Silverman questionnaire when first logging in to the system is an optional choice for each learner. If he takes that entry test at that time, the system can deliver learning materials adaptively for him immediately. 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 $\text{Time}_{\text{expected\_stay}}$ of a ReflectiveSensing learning object is 30 ms, then $\text{Time}_{\text{expected\_stay}}$ 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 $\text{Time}_{\text{spent}}$ for each of all the eight learning style elements of the learner is calculated. Then we find out eight respective ratios:

$$RT_{LS\_element} = \frac{\sum \text{Time}_{\text{spent}}}{\sum \text{Time}_{\text{expected\_stay}}}$$

We use the same manner to find out the ratios $RV_{\text{LS\_element}}$ which are concerned with 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 in the calculation.

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

Finally, we calculate the average ratios:

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

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

R_{avg}	LS preference
0–0.3	Weak
0.3–0.7	Moderate
0.7–1	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 elements of one dimension are less than 0.3. At the current round of adaptation, we no longer consider this dimension because it is not needed 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 Table 2.

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.

3.4. Learning objects 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

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learner in the previous example, he will receive only learning objects, whose learning style labels consist of Active, or Reflective, or Visual.

IV. Results and Discussion

4.1. The ontology

In our ontology, we consider only the learning style characteristic, we have added some classes and properties, and we have modified some relationships to make it more reasonable for real courses. Figure 1 shows the layout of the domain ontology that we developed.

Each course has its objectives including competence, knowledge, and abilities. There is a competence per objective. For example, after taking the Artificial Intelligence (AI) course, learners are able to solve complex problems in AI. There are several pieces of knowledge (concepts) and abilities that will contribute to the achievement of a given competence. Here knowledge, of course, means theoretical angle, and abilities correspond to practical skills. Class Ability was added because of this reason.
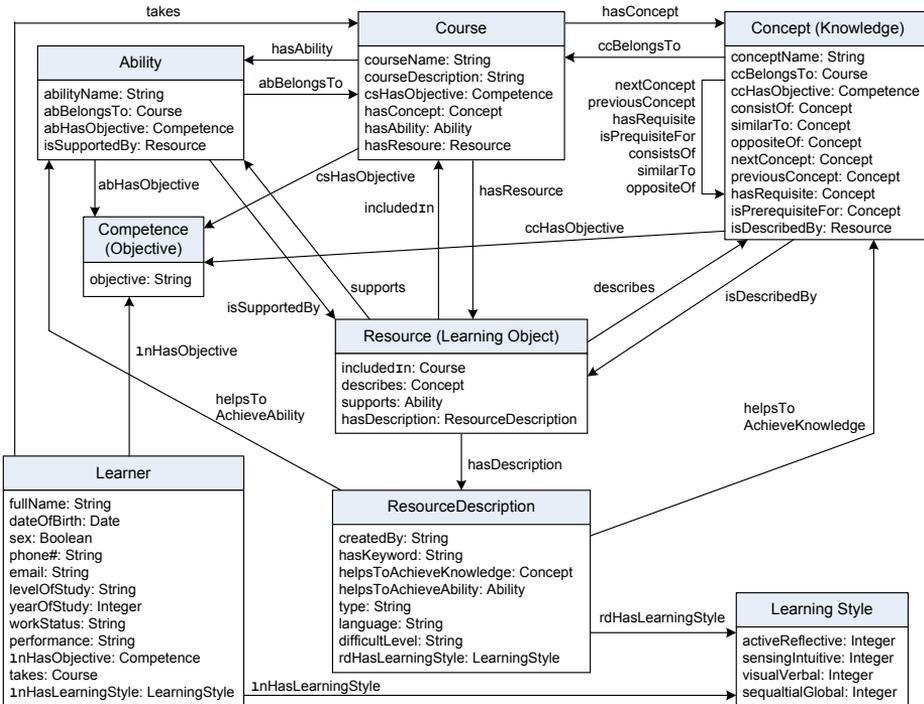

Figure 1. General layout of domain ontology

Like class Concept, class Ability contains abHasObjective property, and isSupportedBy (supports is its inverse) pointing to the set of resources (learning objects) that support the ability.

A resource, or a learning object, can be included in several courses; it can reference several concepts; and it can support several abilities. Class ResourceDescription describes a learning object more clearly. Some added properties are:

(1) helpsToAchieveKnowledge and helpsToAchieveAbility respectively point to the knowledge and the ability that it helps to achieve.

(2) type—a learning object can be: one to several PowerPoint slides, one animation that illustrates the concept, one picture or several pictures, one multiple choice exercise, one input text exercise, one programming exercise, one http address, one article, etc.

We first use Felder-Silverman Learning Style Model to identify learners' learning styles for our e-learning system. We assign rdHasLearningStyle property for learning objects so that they can be adaptively delivered to learners.

Class Learner was added because learner is the most important factor of adaptive learning systems. As one can observe, each learner (a) has his name (fullName); (b) has a date of birth (dateOfBirth); (c) is male or female (sex); (d) has a phone number (phone#); (e) has an email (email); (f) is a graduate student or an undergraduate student (levelOfStudy); (g) is in which year of study (yearOfStudy); (h) studies on-campus or off-campus (workStatus); (i) has his performance (performance) that can be excellent, good, average, bad, terrible; (j) has his learning objective (lnHasObjective); (k) has a list of courses that he has to take (takes); and (l) has a learning style (lnHasLearningStyle). This last property together with the same property of the learning object, of course, helps to implement personalization in the learning system.

4.2. POLCA, an adaptive multi-agent e-learning system

4.2.1. System architecture

The e-learning system we have been 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 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 shows the architecture of the system.
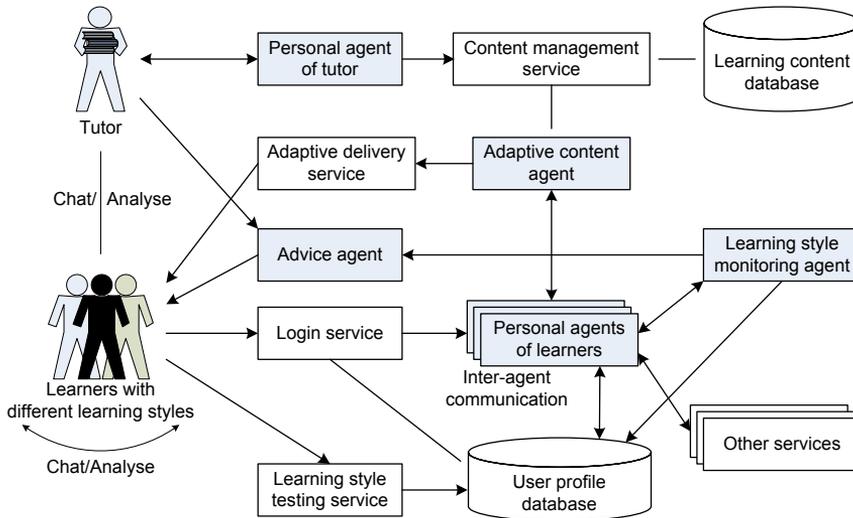
Figure 2. Architecture of adaptive learning style e-learning system
based on intelligent agents and services

4.2.2. System operation

Based on the architecture, a multi-agent e-learning system has been conducted to evaluate the adaptation method mentioned above. Members that can participate in the systems are administrators, teachers, and learners. The learning process starts when a teacher updates his course's learning units, i.e. learning objects.

After being activated by the administrator, a learner can sign in to the system and apply for a new course or navigate through learning units of permitted courses. The learner can choose the way that presents learning units: (1) normal way—all learning units will be shown; (2) adaptive way—only learning units matching his learning styles will be shown.

Student's learning style discovered at the moment is compared with his 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 (Figure 3).

Figure 3. A screen shot from POLCA to which a teacher adds a learning object
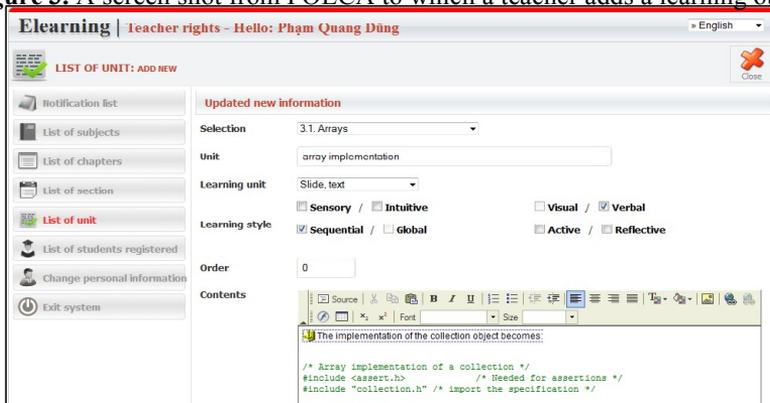
We chose an Artificial Intelligence (AI) course to evaluate our method. The duration for the experiment was nine weeks; that is enough for studying nine sections with 204 learning objects included. The learning objects are sufficient as described above. The parameter P was set to four weeks. Forty-four undergraduate students in the field of Computer Science from Politehnica University of Bucharest participated in the study. They were finally asked to fill the ILS questionnaire and to give feedback about system adaptation. The comparison of learning style detection between our method and the ILS questionnaire is (72.73%, 70.15%, 79.54%, and 65.91%) corresponding to four learning style dimensions Act/Ref, Sen/Int, Vis/Vrb, and Seq/Glo. Regarding the adaptation process, 91% of participating students evaluated that the system dynamic adaptation is good and very good.

V. Conclusions and Future Work

In this paper, we have presented a domain ontology that is suitable for the system mentioned above. The objective and the components of a course are fully described. Students' learning styles are included in the descriptions of both learners and learning objects. This helps adaptive implementation more accurately.

We have also proposed an architecture for building a personalized multi-agent e-learning system. Such a system has been developed. The system uses intelligent agents to re-estimate learners' learning styles and to deliver learning objects fit for each student. One of our future goals is t o implement the system using discussed ontology. Extensive testing is also required in order to firmly validate the proposed system and the efficiency of the approach.

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