RECENT ADAPTIVE E-LEARNING CONTRIBUTIONS TOWARDS A "STANDARD READY" ARCHITECTURE

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ABSTRACT

Adaptation and personalization services of the information offered to the users in open e-learning environments are considered to be the turning point of recent research efforts. The "one-size-fits-all" approach has some important drawbacks, from the educational point of view. Adaptive Educational Hypermedia Systems in World Wide Web became a very active research field and the need of standardization arose, as the continually augmenting research efforts lacked the interoperability dimension. This paper classifies up todate research work indicating some important points that can lead to an open and unified architecture that support an Adaptive e-Learning System based on widely accepted standards.

KEYWORDS

e-learning standards, adaptive e-learning system architecture, adaptativity parameters

1. INTRODUCTION

As the Internet and World Wide Web are rapidly developed, the technologies that support the educational processes come closer to the traditional educational systems. A recent research demonstrated that both instructors and learners have very positive perceptions toward using e-learning as a teaching assisted tool. (Liaw et al., 2007) According to (Brusilovsky and Miller, 2001) Adaptive and Intelligent Web-Based Educational Systems provide an alternative to the traditional 'just-put-it-on-the-Web' approach in the development of Web-based educational courseware. In their work (Brusilovsky and Pyelo, 2003) mention that Adaptive and Intelligent Web-Based Educational Systems attempt to be more adaptive by building a model of the goals, preferences and knowledge of each individual student and using this model throughout the interaction with the system in order to be more intelligent by incorporating and performing some activities traditionally executed by a human teacher – such as coaching students or diagnosing misconceptions.

There exist a wide variety of diverse Adaptive and Intelligent Web-Based Educational Systems. The 'rules' that are used to describe the creation of such systems are not yet fully standardized, and the criteria that need to be used pedagogically effective rule-sets (i.e. adaptation parameters) are, as yet, poorly mentioned (Brown et al., 2005). Many experimental Adaptive Educational Hypermedia Systems have been created – each to their own unique specifications. As yet, however, no combined effort has been made to extract the common design paradigms from these systems.

The scope of this paper is to provide a starting point for the development of a unified architecture for the retrieval of Learning Objects (LOs) from disperse Learning Objects Repositories (LOR) to an e-learning environment. Practically, LOs acquisition is achieved by querying LOR distributed over the internet. This LO "journey" must comply with widely accepted standards. Aiming to highlight interoperability issues, a brief description of up todate research work is presented and classified according to the adaptivity strategy followed by several researchers. Furthermore, techniques and methods from the referenced work are suggested for application to the architecture's foundation to provide an open, modular and distributed solution, closely coupled to given standardizations.

The rest of the paper is structured as follows. Section 2 analyzes some widely used adaptivity parameters, which are applied in the proposed architecture. The connection of adaptivity parameters and standards is explained in Section 3. The paper closes with the description of the architecture.

2. ADAPTIVITY PARAMETERS

Cognitive style - cognitive abilities. According to (Riding and Rayner, 1998) Cognitive Style (CS) refers to an individual's method of processing information. Cognitive Abilities are mechanisms that allow humans to acquire and recognize pieces of information, to convert them into representations, then into knowledge, and finally to use them for the generation of simple to complex behaviors.

There are many different classifications of CSs as different researchers emphasize different aspects (Riding and Cheema, 1991). In (Karampiperis et al., 2006) work, authors selected two cognitive characteristics from the Cognitive Trait Model (Kinshuk and Lin, 2004), namely working memory capacity (the cognitive system that allows us to keep active a limited amount of information for a brief period of time for further) and inductive reasoning ability (the ability to figure out the rules/theories/principles from observed instances of an event). Such algorithms could be applied in this paper's proposed architecture.

Learning style. Learning Theories converge to the fact that students learn and acquire knowledge in many different ways, which has been classified as LSs. LSs' classifications have been proposed by Kolb (Kolb, 1984) and others (Honey and Mumford, 2000), (Dunn and Dunn, 1992), (Felder and Silverman, 1988). Most of the authors categorize them into groups and propose certain inventories and methodologies capable of classifying learners accordingly. In his work, Brusilovsky (Brusilovsky, 2001) noticed that several systems that attempt to adapt to LS had been developed, however it was still not clear which aspects of LS are worth modelling, and what can be done differently for users with different styles. Since then efforts have been made and a quite large number of surveys have been published that remark the benefits of adaptation to LS (Graf and Kinshuk, 2007).

(Milosevic et al., 2007) discuss about designing lesson content tailored to individual users, taking into consideration LS and how could LOs metadata be used for LO retrieval according to the specific needs of the individual learner. They suggest that every LS class should get a different course material sequencing. Another approach in LS estimation is proposed by (Botsios et al, to appear). Instead of using just a static questionnaire to estimate the learner's LS, the authors implemented the Fault Implication Avoidance Algorithm and a Probabilistic Expert System. Their system gives a "clear" LS estimation (no "grey" estimation areas), making the results of practical use in an AEHS.

Learning behavior - motivation. With the term Learning Behavior (LB) we address the easily changeable psychological-emotional state of the learner, while interacting with an e-learning system. Boredom, frustration, motivation, concentration, tiredness are emotional conditions that, among others, are considered important for the effectiveness of the learning process.

Tracing LB in real time is a quite challenging task. (Conati, 2002) and (Gutl et al., 2005) presented approaches to modeling user affect designed to assess a variety of emotional states during interactions, using special sensors (following the Ortony, Clore and Collins cognitive theory of emotions). In (Chen et al., 2005) work, authors propose a Dynamic Fuzzy Petri Net inference engine that monitors "browsing time" and "browsing count" of users' interaction with their system. According to them, whenever the learner spends too much time on a specific section, he/she is very interested in it or confused by it. (Milosevic et al., 2007) examined the users' motivation as a factor of learning efficiency. According to the authors, motivation is a pivotal concept in most theories of learning. It is closely related to arousal, attention, anxiety and feedback. Increasing learner's motivation during online course is one of the key factors to achieve a certain goal. Such approaches could be applied in this paper's proposed architecture.

Competence level - personal goals - course material difficulty. Some researchers emphasized that personalization in e-learning systems should take under consideration different levels of learner/user knowledge and goals. As was pointed out in (Brusilovsky, 1996), Adaptive Educational Hypermedia Systems can be useful in any application area where a hypermedia system is expected to be used by people with different goals and knowledge, who may be interested in different pieces of information presented on hypermedia page and may use different links for navigation.

(Chen et al., 2006) proposed a system based on modified Item Response Theory which provides learning paths that can be adapted to various levels of difficulty of course materials and various abilities of learners. Meanwhile, the concept continuity of learning pathways is also integrated by analyzing concept relation degrees for all database courseware while applying personalized curriculum sequencing. To prevent the learner from becoming lost in course materials, the system provides personalized learning guidance, filters out unsuitable course materials to reduce unnecessary cognitive loading, and provides a fine learning guidance based on individual user profile. A technique like the one previously mentioned could be applied in this paper's proposed schema.

3. STANDARDS AND ADAPTIVITY PARAMETERS

E-Learning broad applications over the Internet have led to a common demand for reusable and sharable LOs, communication functions (between LOs and LMSs) and User metada. Groups such as SCORM (Shareable Content Object Reference Model), IEEE LTSC (IEEE Learning Technology Standards Committee), IMS (Instructional Management Systems) and AICC (Aviation Industry CBT Committee) have undertaken significant work.

In Table 1 research efforts that seek to connect adaptivity parameters and standards are presented. The adaptivity parameter, type and assessment method is displayed in the second column and the standardization reference in the third column. The given solutions will underlie the proposed architecture, which is briefly described in the next section.

Table 1. Adaptivity parameters and standards

paper	**adaptivity parameter – adaptivity type – assessment method**	**reference to SCORM standardization (LOM)**
Milosevic et al (2007)	learning style - adaptive navigation - Kolb Learning Style Inventory	<LearningResourceType> <NavigationRules>
	motivation - adaptive presentation - pre-, post- tests	<educational> <semantic density>
Watson et al (2007)	knowledge level - adaptive content retrieval - SCO performance assess.	SCORM interaction elements
Karampiperis et al (2006)	cognitive style - adaptive content retrieval - monitoring navigation steps	<general><structure><aggregation_Level></general> <educational><InteractivityType><InteractivityLevel> <SemanticDensity><Difficulty><typicallearningtime> <learningresourcetype></educational>
Chen et al (2006)	knowledge level - adaptive content retrieval - Iem Response Theory	<general><Description><Keyword></general> <educational><Difficulty></educational>
Chen et al (2005)	learning behavior - adaptive content retrieval - Dynamic Fuzzy Petri Net	<Organization> SCORM Rollup Rules

4. ARCHITECTURE – A FIRST APPROACH

In this section a brief description of the proposed unified architecture is given. The proposed architecture consists of many common parts that can be found in related architectures (Samson et al., 2002) and describes a scenario of LOs retrieval from disperse LORs.

The numbered list which follows, describes the most important aspects of the architecture's module (figure 1). The "x" symbol in the corner of some boxes implies that the "x"-marked module is optional. Disabling some, or all, of these modules, the system becomes less parametric or less "intelligent".

1. LMS. The beginning and the end of the e-learning experience. The LMS captures user interactions and forwards them to next modules. Also, the LMS is responsible to receive and display the returned LOs. Of course, both captured user interactions and received LOs must be standardized.

2. According to visited LOs (in figure 1: current state) and user interactions –information that is send from the LMS- the relevance estimation engine is responsible to create the appropriate query to "ask" LOR for "relevant" LOs. Algorithms proposed by Chen et al (Chen et al., 2005), Chen et al (Chen et al., 2006) and Watson et al (Watson et al., 2007) could be applied to provide a taxonomy of "relevant" LOs. Taking under consideration user interactions and LOs metadata, these algorithms are inference engines that provide selection rules to filter LOs from disperse and vast LORs.

3. SCORM compliant LOR receive a query and return a number of "relevant" LOs.

4. The User Model is responsible to store (keep personal user data, preferences data and history related data) and forward user interactions to adaptivity parameters modules (see 5, 6, 7 and 8), receive their assessments and export a final filtered taxonomy of the LOs it have received from 3.

5. Learning Behavior. This module is dedicated to LB diagnosis. A suggestion for estimating learning behavior from user's interaction is proposed by Chen et al (Chen et al., 2005) (see table 1).

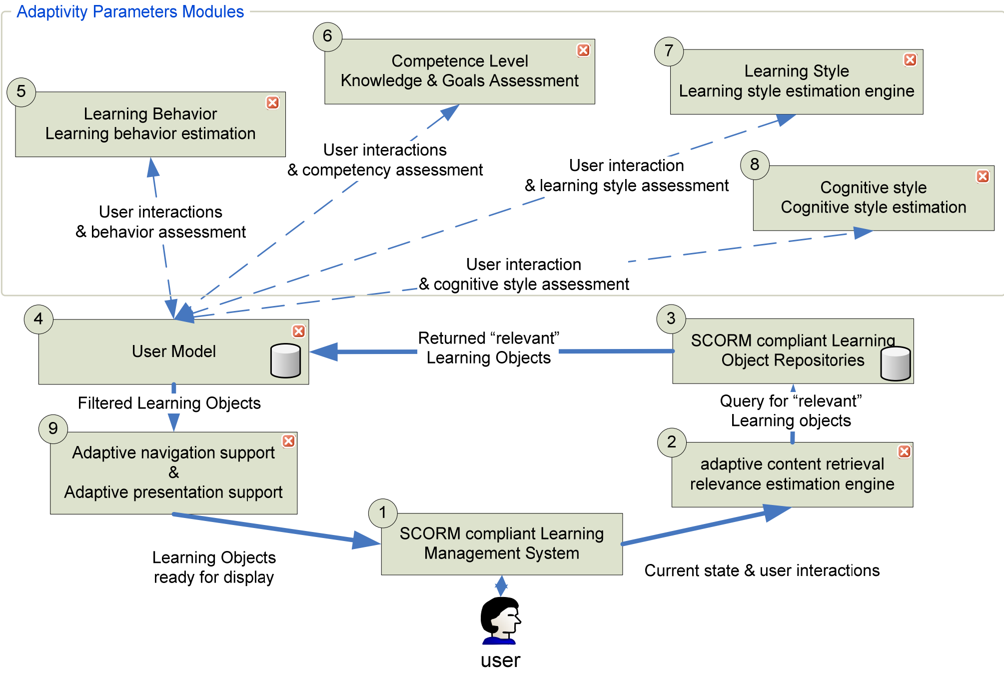

Figure 1. First approach of the architecture.

6. Competence Level. This module supports the assessment of user's knowledge and goals. The modified Item response theory from Chen et al (Chen et al., 2006) and SCO performance assessment from Watson et al (Watson et al., 2007) are two alternatives for this purpose (see table 1).

7. Learning Style. Similarly to 5 and 6, this module produces results for user's LS. Milosevic et al (Milosevic et al., 2007) developed a solution that "connects" user's learning style to specific learning objects metadata (see table 1).

8. Cognitive Style. This module is dedicated to estimate the user's CS. The module receives user interaction related data and exports an assessment. An example application is the Karampiperis et al (Karampiperis et al., 2006) work. Data about user navigation is used to export LOs metadata values (see table 1).

9. All the algorithms to provide adaptive navigation and adaptive presentation services are the last stage of this architecture. This module receives the filtered taxonomy of LOs, applies the appropriate algorithms and forwards the data to be displayed in the interface of the LMS.

5. CONCLUSION

There exist a wide variety of diverse Adaptive and Intelligent Web-Based Educational Systems. The 'rules' that are used to describe the creation of such systems are not yet fully standardized, and the criteria that need to be used pedagogically effective rule-sets (i.e. adaptation parameters) are, as yet, poorly mentioned (Brown et al., 2005). Whit this paper we provide a starting point for the development of a unified architecture for the retrieval of LOs from disperse LOR to an e-learning environment. This LO "journey" must comply with widely accepted standards. The model is based on a distributed architecture. Interoperability, information sharing, scalability and dynamic integration of heterogeneous expert fields are considered as the major advantages of the proposed model. a. Interoperability: support for available standards, technology and platform independent. b. Information Sharing: user information, learning objects, services and assessment tools. c. Scalability: continuous update of each module's functionality (Learning Objects, monitoring tools, cognition and learning style theories, sequencing and navigation algorithms). d. Integration of heterogeneous expert field: independent module development and dynamic adaptation to the latest criteria.

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