

# Dynamic User Modeling and Adaptation based on Learning Styles for Supporting Semi-Automatic Generation of IMS Learning Design

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**Abstract**— In the context of virtual learning environments, it is difficult to find proposals addressing both problems at the same time, user modeling and adaptation processes based on learning styles. In particular, for the teachers, these processes require huge amounts of time and effort in the course construction, which most of the times is not recognized by the educational institutions. The main issue discussed in this paper is the creation of a dynamic user model based on learning styles (LS) to enrich and to support the automatic generation of an adaptive IMS learning design (LD) in order to reduce the amount of time and efforts for teachers providing learners with personalized learning experiences.

**Keywords** - learning style; learning design; dynamic user modeling; adaptation process, learning environment.

## I. INTRODUCTION

Nowadays, the use of learning management systems (LMS) has become a critical issue for educational institutions because many of them offer their courses supported by these learning platforms. Since LMSs have mainly focused in the management of the learning process, one of the most important challenges in these kinds of systems is the effort in its personalization according to the learners' needs. Adaptive hypermedia systems (AHS) offer a conceptual and accepted approach for addressing the personalization problem.

There are many user features supporting the adaptation process, and one of the most frequently used is the learners' learning style. Addressing learning styles has been reported to be a good approach to support the learning process of learners [1, 2], since learners are assumed to have different preferences for different types of learning objects (LO), medias and learning activities.

However, the generation of learning designs adjusted to user features is not an easy problem, in particular for the teachers. Actually, this problem implies that teachers need to know the different instructional theories, control different user variables and they need to know how to develop standardized learning designs.

In this paper, we introduce a middleware approach to support teachers in the semi-automatic generation of a pedagogical, personalized and standardized learning design based in the dynamic inference of the users' learning styles.

The document is organized as follows: in the second section, we present a general framework for user modeling and adaptations; in the third section, the user modeling process based on learning styles is introduced; in the fourth

section, the IMS learning design generation process is detailed; and finally, in the fifth section, some conclusions and future works are introduced.

## II. OUR FRAMEWORK FOR MODELING AND ADAPTING TO LEARNING STYLES

The learning style is one of the most common user features used to support adaptation processes in adaptive hypermedia systems. In [4], we introduce a preliminary adaptation process based on learning styles. This process begins when the user is asked to fill out Felder's Index of learning Styles (ILS) questionnaire [5], then, using a classification task, the learning object types are delivered to the users in their preferred order.

The approach introduced in this paper addresses some limitations of our previous work by considering the change of the user preferences over time. A monitoring process of the user interactions in the learning management system is proposed as well as a process to supports the dynamic user modeling and adaptation.

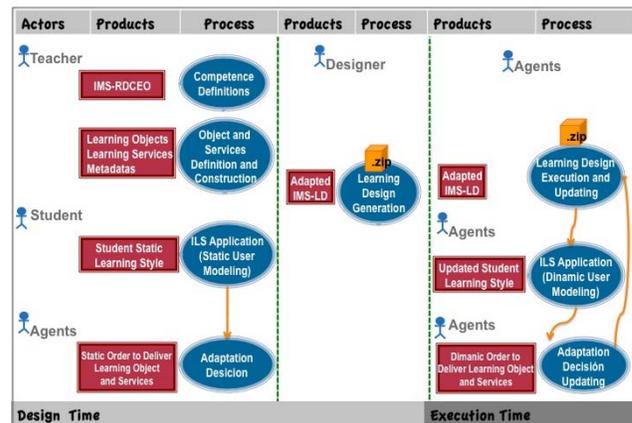


Figure 1. IMS LD Specification Elements

Figure 1 describes the main elements of our proposed framework. Ovals and rectangles in the figure represent, respectively, the processes and products developed and generated at two different proposed times: course design time (when the course is created and composed in the LMS) and course execution time (when learners are learning in the course). At the design time, the necessary information for the *Designer* (an intelligent agent who generates the course) is developed and constructed. Using different authoring tools, teachers define the course competence, and they create

learning objects, services and their metadata. On the other hand, students are asked to fill out Felder's ILS questionnaire and with this information intelligent agents infer the preferred order to present learning objects. Then, Designer uses this information in order to generate an adapted IMS-LD. At the execution time, the generated learning design is display in the LMS and the user behavior is monitored. This dynamic information is used in two ways: (1) to redefine the users' learning styles and (2) to update the learning design properties for providing users with a course based on their most recently identified learning styles (as described in more detail in Section III and IV). Both of these updating processes are triggered based on execution parameters provided by teachers or the LMS administrator. Such parameters include, for example, when the user modeling process and properties update should take place.

### III. DYNAMIC USER MODELING PROCESS BASED ON LEARNING STYLES

A static approach for detecting students' preferences according to learning styles aims at capturing the students' preferences, in particular, the preferred order of learning object types at a specific time (t) without considering any change in students' preferences at the time t+1. But our hypothesis based on [1, 2] is that the users' preferences can change due to many factors, such as the quality of the learning objects of the course, or due to the possibility that the user did not response consciously to the ILS questionnaire for personal reasons, which lead to wrong information about students' learning styles. For these reasons dynamic student modeling based on students' behaviors in a course becomes a promising and useful possibility.

A dynamic user model should take into account the changes of students' preferences over time, responding to these changes at a time (t+1).

In [6] Graf et al. define three steps that should be analyzed in order to propose a dynamic user model based on learning styles. First one is the definition of the dynamic model itself; the second one is to compare the stored learning style with the current inferred learning style to identify deviations or possible changes; and the third step is to take a decision about whether a user's learning style should be changed according to the previous analysis.

We propose to build a dynamic user model based on studies by Graf et al. [1, 6] Popescu et al. [2], and Garcia et al. [7], which relate behaviors of students in a learning system with their Felder's learning styles. We have analyzed different types of possible user interactions (criteria to detect users' learning styles) and we have identified several significant and agreed relations with the Felder's learning style dimensions. Table I shows the identified user interaction variables we are considering for the dynamic user modeling process.

The positive and negative symbols indicate the positive or negative relationships between learning styles and the user interaction type, where a positive sign indicates a relationship to a sensing, active, sequential, or visual learning style.

Since different studies [8, 9] suggest that the student behaviors in a specific variable fit to a normal distribution, we propose to develop a standard deviation analysis in order to infer changes in the users' learning styles, taking into account the described interaction variables.

TABLE I: INTERACTION VARIABLES VS FELDER'S DIMENSIONS

Perception (Sensitive/Intuitive)	Processing (Active/Reflective)	Understanding (Sequential/Global)	Entry (Visual/Verbal)
content visit (-)	content visit (-)	outline visit (-)	content visit (-)
content stay (-)	content stay (-)	outline stay (-)	ques_graphics (+)
Content Type	outline stay (-)	ques detail (+)	ques text (-)
t Fundamental (Intuitive) (+)	example stay (-)	ques overview (-)	forum visits (-)
t Definition (Intuitive) (+)	selfass visit (+)	ques interpret (-)	forum stay (-)
h Definition (Intuitive) (+)	selfass stay (-)	ques develop (-)	forum post (-)
concrete type (+)	selfass twice wrong (+)	navigation skip (-)	Content Media
example visit (+)	exercise visit (+)	navigation overview visit (-)	t Image (+)
example stay (+)	exercise stay (+)	navigation overview stay (-)	t Image + t Video (+)
selfass visit (+)	quiz stay results (-)	n nextButton (+)	h Image (+)
selfass stay (+)	forum visit (-)	t AdditionalInfo (Global) (+)	h Image + h Video (+)
exercise visit (+)	forum post (+)	n_returns_LO (Global) (+)	t Text (verbal) (+)
ques detail (+)	Forums student not participate (reflexive) (+)	t Exercise (+)	t Example (+)
ques facts (+)	Forums - student reads the message posted by others (forums) (reflexive) (+)	exams results while she jumping over the contents (Global) (+)	
ques concepts (-)	n chat msg (+)		
ques develop (-)	t chat (Listen) (+)		
quiz revision (+)	Chat not participation (-)		
quiz stay results (+)	t Interactivity (+)		
time to finish an exam and deliver it (+)	h Interactivity (+)		
answer changes (+)	mail systems use (+)		
Content Media	mail systems no use (reflexive) (+)		
t Image (+)	Number of Collaborative Activities (+)		

We estimate the behavior standard deviation ( $\sigma$ ) for a particular student with respect to the mean ( $\mu$ ) and we locate the student in the Felder's Scale according to table II in an 11-item scale, as is used in the ILS questionnaire.

TABLE II: STANDARD DEVIATION VS FELDER'S SCALE VALUES

Possible value of the Student Behaviour	Corresponded Felder's Value
$\mu$	6
$\mu + 1\sigma$	7-8
$\mu + 2\sigma$	9-10
$\geq (\mu + 3\sigma)$	11
$\mu - 1\sigma$	5-4
$\mu - 2\sigma$	3-2
$\leq (\mu - 3\sigma)$	1

Equation 1 is used to calculate values for each Felder dimension, consolidating the interaction variables associated to each dimension.

$$\text{DimSide}_j = \frac{\sum_{i=1}^N C_{ij}}{N}, \quad (\text{Equation 1})$$

Where,  $C_{ij}$  is the behavior value for the variable  $i$  applied for the student  $j$ ;  $N$  is the number of analyzed variables for each particular Felder dimension. DimSide is calculated for each Felder dimension. In this way the sum of all values, expressed on an 11-item scale [1-11], describe the tendency of the student in each particular dimension.

The result of the user modeling process is the redefinition of the result of ILS questionnaire based on the analysis of the user interactions.

The teacher takes the decision about when the user modeling process takes place. He/she can indicate, for example, whether the recalculation should take place every day, week, month or semester.

We propose a semiautomatic approach for the learning style change decision, where teachers are notified by the system if any change in a student's learning style has been detected. Then, the teacher can reflect about whether the user modeling process is adequate for his/her student and decides if the change in the user's learning style should be done. Such a change in the learning style of a student causes the redefinition of some IMS Learning Design properties as well as the classification rules for learning objects delivering.

#### IV. SEMI-AUTOMATIC IMS LEARNING DESIGN GENERATION BASED ON HTN PLANNING

##### A. Learning Design Specification

A well-accepted definition for an instructional design process is the following: the process that should be followed by teachers in order to plan and to prepare the instruction [10]. IMS-LD Specification [11] suggests a standardized language to represent and execute Personalized Units of Learning (UoL) in the context of a virtual environment.

Adaptation based on learning styles implies for us to organize the learning objects and activities in a particular course in the preferred order of a student with respect to his/her learning styles. We have addressed this problem by the automatic creation of different Activity Structures for each particular learning style. How this process is done using HTN Planning is explained in the next section.

##### B. HTN problem to generate personalized UoL based on the Users Learning Styles

In [12], the problem of generating a particular IMS-LD (level B) based on competences and using planning techniques was addressed. The planning problem included the definitions of the competences to be achieved for the students. In the planning domain some methods were created in order to generate a sequence of activity structures to be delivered according to the students' level of competences.

In order to generate an IMS-LD that could be adapted to users learning styles, the planning problem has been extended. In particular, the method called GetPreferences has been introduced in the planning domain for obtaining the information about which types of learning objects are recommended for each learning style. Also, a set of methods has been added to the domain with the purpose to include this knowledge in the state of the world. These methods permit to establish the relation between each resource and the learning style in terms of the preferred order, using the information available in the metadata.

With this information, an activity structure in the plan for each different learning style that exists in the state of the world is created. These activity structures sequence the

instruction according to the level of user competences and learning styles.

#### V. CONCLUSIONS AND FUTURE WORK

In this paper, we deal with the problem to relieve teachers' design work when they create personalized and standardized courses. Our approach proposes a semi-automatic course generation based on a dynamic user modeling process considering learning styles and using HTN Planning for providing dynamic adaptation.

Based on feedback from teachers at Girona University, the proposed approach has potential to be of high usefulness, especially for the possibility to easily create an IMS-LD and also for the possibility of providing learning paths adapted to the students' learning styles, which could increase the students' autonomy.

Future works are oriented to take into account other user features such as special needs and teachers' preferences about pedagogical methodologies for LD generation as well as the use of other techniques for the LD generation. Layered evaluation is currently under development.

#### REFERENCES

- [1] S. Graf and Kinshuk: Providing Adaptive Courses in Learning Management Systems with Respect to Learning Styles, in G. Richards, ed., Proceedings of the World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education (e-Learn), AACE Press, Chesapeake, VA, 2007, pp. 2576-2583.
- [2] E. Popescu: Dynamic adaptive hypermedia systems for e-learning, PhD Thesis, Universit  de Craiova, Romania, 2008.
- [3] R. M. Felder., L. K. Silverman: Learning and Teaching Styles In Engineering Education. Engr. Education, 78(7), 674-681 (1988) – Preface: Felder R. M., June 2002.
- [4] C. Mej a, S. Baldiris, S. G mez, and R. Fabregat: Adaptation process to deliver content based on user learning styles, International Conference of Education, Research and Innovation (ISBN: 978-84-612-5091-2), 2008, International Association of Technology, Education and Development, Madrid (Spain), 2008.
- [5] R.M. Felder and B.A. Soloman: Index of Learning Styles, 2008.
- [6] S. Graf, Kinshuk, L. Tzu-Chien: Identifying Learning Styles in Learning Management Systems by Using Indications from Students' Behaviour. Eighth IEEE International Conference on Advanced Learning Technologies (ICALT '08). 2008.
- [7] P. Garcia, A. Amandi, S. Schiaffino: Evaluating Bayesian networks precision for detecting students learning styles, Computers & Education, vol. 49, 2007, p. 794-808.
- [8] E. Alfonso, R.M. Carro, E. Mart n, A. Ortigosa, and P. Paredes: The Impact of Learning Styles on Student Grouping for Collaborative Learning: A Case Study, User Modeling and User-Adapted Interaction, vol. 16, Number, p. 2006.
- [9] S. Baldiris, G. Moreno, R. Fabregat, I. Guarin, R. Llamosa, and J. Garcia: Extensiones en SHABOO: Sistema Hipermedia Adaptativo para la Ense anza de la Programaci n Orientada a Objetos Colombia, Enlace Inform tico, vol. 6, 2007, pp. 31 - 40.
- [10] C. Reigeluth: Instructional Design Theories and Models, a new paradigm of instructional theory. Indiana University. Laurence Erlbaum Associates, publishers. 1999.
- [11] IMS Learning Design. Version 1.0 Final Specification, 2003.
- [12] J. Hern ndez, S. Baldiris, O. Santos, D. Huerva, R. Fabregat, J.G. Boticario: Conditional IMS LD Generation using user modeling and planning techniques. Proceedings of the 8th IEEE International Conference on Advanced Learning Technologies. Riga. 14-18. July 2009.