A NEW FRAMEWORK FOR THE CONTROL OF LMS IN ITS

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Abstract: Intelligent Tutoring Systems (ITS) offer an automatically personalized environment guiding the student and allows him to put his knowledge and skills in a more effective way than with traditional lessons. Besides, this learning methodology gives study location and time freedom to the student thanks to Internet facilities. Moreover the Learning Management System (LMS) or plat-form which holds the ITS, gathers the course materials and student information making them available and reusable for other control courses. In this paper, we propose a new approach to LMS in ITS, applying data mining techniques.

1 INTRODUCTION

European syllabus reform for the new university degrees implies a drastic change in the studies organization. This reform considers the personal time study as teaching hours.

One solution to put this reform into practice is, for example, thanks to internet-based education. But we must tutor the student in order to enhance his learning process. Human tutoring is extremely laborious and expensive; however ITS are computer systems for custom-made learning, that don't need human tutor intervention.

This paper shows a new framework for ITS applied to Control Systems and Automatic Engineering studies.

2 MODEL

The ITS architecture (Fig. 1a) is organized in three submodels based on three types of knowledge (Ong and Ramachandran, 2003): Student model, Tutor model and Domain model.

Making a comparison with control theory, the process to be controlled in an ITS is the student learning process.

The student shows a learning style and some previous knowledge that are going to be dynamically modified by the student interaction with the course.

The sensor system consists of information extraction and storage in a database. Subsequently this information is analyzed by data mining techniques.

Data mining feedbacks the ITS controller. It adapts the course's LMS models. The teacher supervises the process and he defines the course contents according to the course curriculum.

Apart from this first control loop that has just been described (Figure 1a), it exists another slower external loop in the model proposed (Figure 1b). It verifies how well the ITS works and it controls how fine it fits the student needs by comparing the students results with the initial course objectives.

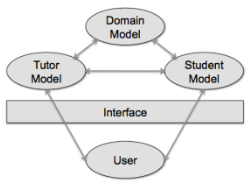

Figure 1a: ITS components.

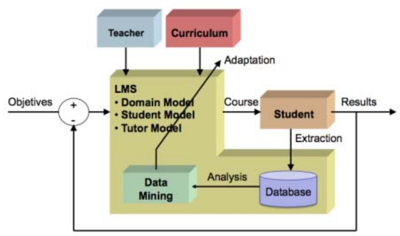

Figure 1b: ITS model architecture.

The LMS model suggested (Figure 2) is made up at the same time of student model, tutor model and domain model. It also considers the relationships or

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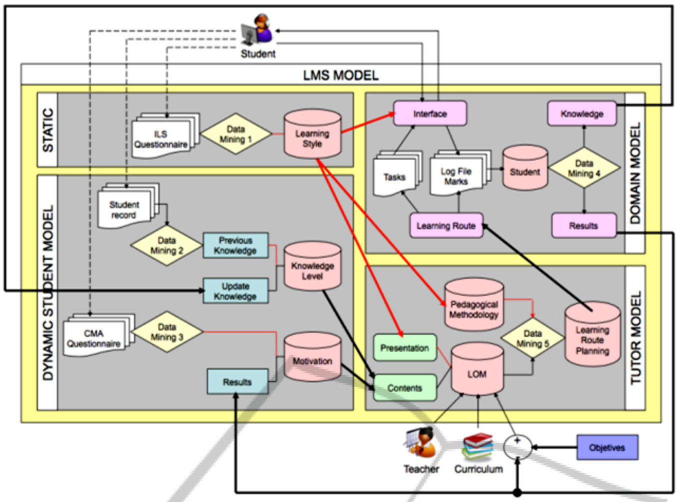

Figure 2: Integration of the three models (Student, Tutor and Domain) inside the LMS.

information flows among them. The arrows symbolize these relationships: red (system's initialization), black (direct feedback or information update) and dashed line (initial student data taking from surveys).

- Student Model: The first block models the static features that don't change in the course of time (cognitive characteristics and learning preferences). The other one gathers the dynamic features (student knowledge and motivation state). This block is in continuous updating because it depends on students interaction with the LMS course.

- Domain Model: One course is organized in didactic units. At the same time, these units are formed by learning objects defined with metadata (LOM: activities, workshops, tasks, multimedia resources, laboratory experiences, etc.) LOM choice and sequence for a learning route is made in the Tutor model based on the course curriculum. Student's interaction with the course activities or resources produces a series of reports or records (log files). The system stores the log files together with the student marks (they are got by expert and student response comparison). By analyzing this information the system sets the student progress. The progress can be split in achievement or success that will affect the student motivation and knowledge level acquired to date.

- Tutor Model: At the beginning, it chooses from the student model data (learning style) the appropriate pedagogical methodology. The learning style also establishes which kind of multimedia materials the student prefers, which together with the contents that should be learnt in the course (knowledge level to be achieved) enable the LOM choice that better fits the student's needs. These two blocks are suitable for planning the learning route. A temporal LOM sequence for a lesson or didactical unit is what we know as learning route.

- ITS Control Loop: The ITS model is formed by the LMS model plus a control loop with the objectives and results feedback (Figure 2).

3 DATA MINING

Now, we are going to describe the different sources or tools from where we get the student data. This data will need an analysis by means of data mining techniques to extract useful information.

The Index of Learning Styles (ILS) questionnaire is an on-line instrument used to assess preferences on four dimensions of a learning style model (Felder and Silverman, 1988). The ITS clusters the questionnaire (data mining 1 in Fig. 1B) in order to establish how strong the dimension is shown in the student.

Knowledge level is based on Bloom taxonomy (Blom, 1956) mixed with the collaborative competence (Baldiris et al., 2008) that classifies the students into different levels. There are several studies about student's academic aims and their influence on motivation (González et al., 1996).

Deciding factors to deduce motivational guidance are: social recognition that determines extrinsic motivation, educational that determines intrinsic motivation and Interpersonal that affects student collaborative competence.

The Teenagers Goals Questionnaire (CMA in Spanish) evaluates these 3 factors (Martín-Albo et al., 2007). In the extrinsic case, we should determine as well, the student confidence in his studies (self-esteem). This factor has an influence on the higher difficulty level that the student is able to reach without fail in his motivation.

The Rosenberg self-esteem scale (RSES) evaluates the self-esteem in the university context (Wolpers et al., 2007). Web-based educational systems can record student's system access in log files.

Theses files provide a basic Internet student tracking. An open code specification based in attentionXML, is called Contextualized Metadata Attention, CAM (Perkins, 1995). It captures user's observations (browser information use, Web sites, news feeds, blogs, etc.)

The system clusters Student's dataset (data mining 4) to extract the different types of students according to their knowledge level and learning preferences. In this step, the system also looks for anomalous values that correspond with learninghandicaps or misunderstandings.

There are different pedagogical methodologies suggested by several authors. Each of them has a series of characteristics as regards to the type of resources, student's level of participation, student's learning involvement, etc. This choice entails a specific learning route that can be associated (data mining 5 in Fig. 1b and 2) with a unique student's profile.

The Tutor model organizes the units following an established plan designed by the teacher who bases his opinion on curriculum's guidelines. Materials chosen for each learning route will change according to their success (voting), student difficulty level and student pedagogical methodology. LMS control system assessment and satisfaction is carried out making a comparison between the student's average results during the LMS course and those of the previous year, without the LMS platform.

On the other hand, a reduction in the subject desertion rate also denotes the smooth running of the system.

Finally, if the LMS course is implemented in all subjects of the Engineering Grade, we can use the University's efficiency rate. It is defined as the proportion between the total number of credits of the grade syllabus and the total number of credits enrolled by the student.

4 CASE STUDY

To date, it has been implemented the first part of the Model proposed. It covers the static student model analysis, applying data mining techniques, which provide the type of students.

The initial surveys are facilitated to the students thanks to open source application called LimeSurvey. Student's data is clustered by Fuzzy k-prototypes algorithm (Ng and Wong, 2002) for numerical and symbolic data developed in Matlab.

The result of the data mining process is the types of students' clusters. Once the clusters are made, by means of a fuzzy rules algorithm (Nguyen and Walker, 2000), we can associate each of them to the pedagogical methodologies and resources' difficulty level. With these two factors, we can form the adaptive and personal unit content sequence called learning route for each student.

5 CONCLUSIONS

This work has focused on developing a new model for ITS. The future work will finish the ITS model implementation in a platform or LMS.

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