Integrating learning styles and affective behavior into an intelligent environment for learning

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Abstract. It is well known that personalized tutoring helps to improve the learning process and to obtain better results. With this aim we have developed an affective behavior model to provide students with an instruction according to their affect state besides the knowledge state. Now we are developing a model including the learning styles of the students. We based our model on the Felder-Silverman Learning Styles Model. According to the student learning style, the instruction is establishing by a proposed set of rules. To prove our model we propose to use an LMS in compliance with SCORM. In this paper we present our general proposal.

Keywords: affective model, learning styles, LMS, intelligent learning environments, learning objects.

1 Introduction

Up to the present time, most of the intelligent learning environments personalize learning basically by following what the student knows and selecting the next learning object according to the student's current knowledge. This is usually implemented with a student model where his knowledge state is compared with the knowledge of an expert, teacher or instructor in the domain of the course. On the other hand, while several models of affect have been proposed, few proposals of personalization of the tutorial actions based on affective models are reported in the literature [1] and the same happens with personalization using learning styles [2].

We are developing a model including knowledge, affect and learning styles of students. Next, we describe the affective model followed by a section presenting the learning style model. In section 4, an introduction to the learning management system (LMS) Moodle is provided. In section 5, we present our integration proposal to implement intelligent tutors at IIE. Finally, conclusions are presented.

Before to proceeding, we want to clarify two terms: affect and emotion. Although literature offers several definitions of emotion, there is not an accepted definition. According to [3, 4] emotion is a reaction to events which are supposed to be important for the needs, goals, and interests of an individual. Generally, affect is use in a broader sense than emotion; as a term to comprise emotion, sentiments, feelings, moods. Consistent with [5], in this paper these terms are used interchangeably.

2 Affective Behavior Model

Emotions have been recognized as an important component in motivation and learning. There is evidence that experienced human tutors monitor and react to the emotional state of the students in order to motivate them and to improve their learning process [6]. If we want to consider the student affective state in the tutorial actions, an important problem is to identify the best tutorial action given both the students' affective and knowledge state. We have developed an affective behavior model (ABM) [1] that takes affect into account when interacting with a student by i) inferring the affective state of the student (affective student model); and ii) by establishing the optimal tutorial action based on the student's current affective and knowledge state (affective tutor model). A flow diagram of the ABM is presented in Fig. 1.

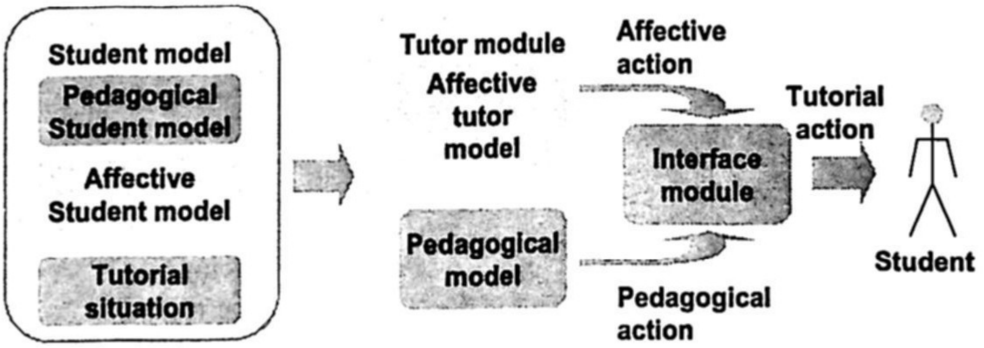

Figure. 1. General diagram of the affective behavior model. The model is composed by an affective student model and an affective tutor model. The tutor model produces an affective action considering the affective and pedagogical student models and the tutorial situation. The affective action is a component of the tutorial action to be presented to the student

To generate a tutorial action, the ABM considers the affective and knowledge state of the student (as assessed by the corresponding student models), as well as the tutorial situation. The tutorial action is viewed as consisting of two components. The first component targets mainly the student's affective state (affective component) and, the second component (pedagogical component) targets mainly the student's knowledge and consists of verbal hints. Thus selecting a tutorial action involves selecting these two components. Finally, the interface module establishes the physical realization of the tutorial action.

Our affective student model uses the OCC model [4] to provide a causal assessment of student's emotions based on contextual information. The OCC model defines emotional state as the outcome of the cognitive appraisal of the current situation with respect to one's goals. The student model consists of a dynamic

Bayesian network (DBN) that probabilistically relates student personality, goals and interaction events with student's affective states, based on the theory defined by the OCC model. Fig. 2 shows a high level representation of the model, where each node in the network is actually a set of nodes in the actual model. The model is based on the proposal by [7, 8].

The DBN models the dynamic nature of the student's emotions. To infer the affective state at t_n, it considers the student's knowledge, personality, and the tutorial situation at that time, as well as the student affective state at t_{n-1}. The tutorial situation is defined based on the results of the student actions.

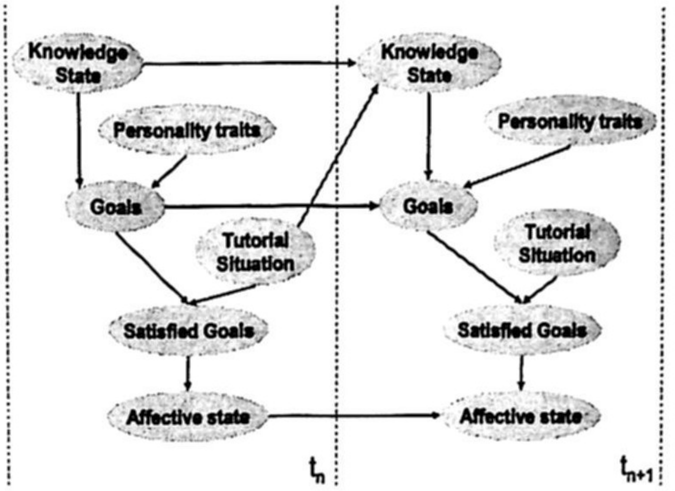

Figure 2. *High level DBN for the affective student model. We include two time slice to represent the dynamic behavior of affect and its impact in the next state.*

The student's appraisal of the current situation given her goal is represented by the relation between the goals and tutorial situation nodes through the satisfied goals node. The influence of the appraisal process on the student's affect is represented by the link between the satisfied goals node and the affective state node. From the complete set of emotions proposed by the OCC model, the affective model only includes six emotions: joy, distress, pride, shame, admiration and reproach.

According to the OCC model, one's the goals are fundamental to determine one's affective state, but asking the students to express these goals during game playing would be too intrusive. Consequently, the goals in our network are inferred from indirect sources of evidence. We use personality traits as a predictor of the student's goals, but we also include the student's factorization knowledge.

The personality traits we included in the model are based on the five-factor model [9], which considers 5 dimensions for personality: openness, conscientiousness, extraversion, agreeableness, and neuroticism. We include only 2 factors, conscientiousness and neuroticism, to establish goals, because these are the ones for which a stronger relationship was found with learning [10]. The information on the student's knowledge state and tutorial situation nodes comes from the model of student's knowledge and from the outcome of student's actions.

The dependency relations in the DBN have been established based on the literature [8, 9] and on insights from teachers.

Once the affective student state has been determined, the tutor has to respond accordingly. To do that, the tutor needs a model which establishes parameters that enable a mapping from the affective and knowledge student state to tutorial actions. The tutorial actions are composed by an affective and a pedagogical component.

Because we want that tutorial actions both help students learn and foster a good affective state, we use decision theory to achieve the best balance between these two objectives. The decision process is represented as a dynamic decision network (DDN), shown in Fig. 3. The DBN included in the DDN model is used to predict how the available tutorial actions influence a student's knowledge and affect given her current state. This prediction is used to establish the utility of each tutorial action for the current state.

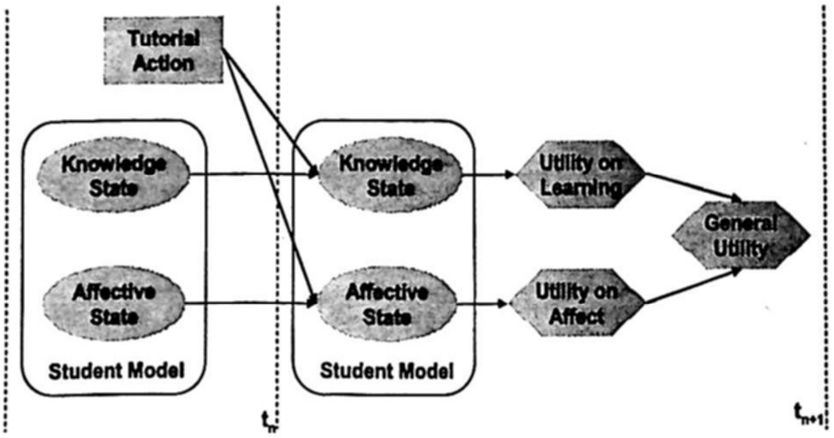

Figure 3. *High level DDN for the affective tutor model. This network is used to establish the tutorial action to be presented to the student.*

Our model uses multi-attribute utility theory to define the necessary utilities [12]. That is, the DDN establishes the tutorial action considering two utility measures, one on learning and one on affect, which are combined to obtain the global utility by a weighted linear combination. These utility functions are the means that allow educators adopting the system to express their preferences towards learning and affect.

After the student performs an action, i.e. after the student model is updated (time t_n), a new time slice is added (time t_{n+1}). At time t_n we have the current student state and the possible tutorial actions; at time t_{n+1} we have the prediction of how the tutor action influences the student's affect and knowledge, from which we estimate the individual and global utilities. The influence of each tutorial action on student's knowledge and affect, and the corresponding utility, are based on the teachers' expertise.

The utility for learning is measured in terms of how much the student's knowledge is improved by the tutorial action given her current knowledge. Similarly, the utility for affect is measured in terms of how much the student affect improves as a result of the action. Finally, the overall utility is computed as a weighted sum of these two utilities Thus, the tutor calculates the utility for each tutorial action considering the current state, and it selects the tutorial action with the maximum expected utility.

When the tutorial action has been selected, the decision network has finished its work and the time slice t_{n+1} is discharged. This is because the tutorial action is not used to update the student model but only to predict the impact of the tutorial action. At this point, the tutor delivers the selected action to the student and then uses the resulting student's response to update the student models. This cycle is repeated for each student action.

This model have been evaluated in two domains with good and encouraging results; the evaluations of the affective model can be found in [1, 13].

3 Learning Styles Model

To incorporate learning styles in the adaptation logic of tutorial systems it is required an approach to identify the best tutorial action given the students' learning style. First, we present the Felder-Silverman Index of Learning Styles model [2, 14, 15], a well-known and used learning styles theory and model is presented. Then the model is used in a rule-based proposal to incorporate learning styles in intelligent tutors. We use rules since they are conceptually easy to implement and integrate into adaptive tutors.

The Felder-Silverman categorizations of learning styles are: Sensing-intuitive, Visual-verbal, Active-reflective, Sequential-global.

Active and Reflective Learners. The Active style learner understands information best by doing something with it and likes group work. The Reflective style learner understand information best by thinking about it quietly first and prefers to work alone.

Sensing and Intuitive Learners. The Sensing learner likes learning facts and solves problems by well-established methods and dislike complications. The Intuitive learner prefers discovering possibilities and relationships and likes innovation and dislikes repetition.

Visual and Verbal Learners. The Visual remembers best what they see—pictures, diagrams, flow charts, time lines, films, and demonstrations. The Verbal gets more out of words—written and spoken explanations

Sequential and Global Learners. The sequential gains understanding in linear steps and follows logical stepwise paths in finding solutions. The Global learns in large jumps and solves complex problems quickly once they have grasped the big picture.

To identify the learning style of a person, the Felder-Silverman assessment instrument is used, which is a Soloman and Felder questionnaire, consisting of 44 questions [16].

The rule-base is a collection of rules and each rule proposes a set of teaching instructions for one learning style. Table 1 shows the rules.

Rules are conceptually easy to implement in tutorial systems. However, to apply these rules, every lesson of a course has to be converted into 8 different lessons according to the teaching instructions. This effort is justified if there are many potential students classified in each of the learning styles so that they can benefit of the personalized learning objects. As opposed to the Affective Behavior Model, the learning style of a person is assessed once at the beginning of the course.

4 Learning Management System

The use of programs to manage the activities around training and education is rapidly growing; universities and other institutions are using them to support the education/training programs. The simplest definition of learning management system (LMS) is software application for the administration, documentation, tracking, and reporting of training/education programs for e-learning and b-learning; however, an LMS is also concerned with centralize and automate administration, provide self-service and self-guided services, assemble and deliver learning content rapidly, consolidate training initiatives on a scalable web-based platform, support portability and standards and personalize content and enable knowledge reuse [17]. The functions of an LMS vary from systems for managing training and educational records, to software for distributing courses over the WWW with features for online collaboration.

An LMS should provide the following elements: The syllabus for the course, administrative information, a notice board for up-to-date course information, student registration and tracking facilities, basic teaching materials (These may be the complete content of the course, or copies of visual aids used in lectures), additional resources (including reading materials, and links to outside resources in libraries and on the Internet), self-assessment quizzes which can be scored automatically, formal assessment procedures, electronic communication support including e-mail, threaded discussions and a chat room, with or without a moderator, differential access rights for instructors and students, production of documentation and statistics on the course, easy authoring tools for creating the necessary documents including the insertion of hyperlinks [17].

Table 1. Rules of teaching instructions for each learning style for Felder-Silverman model.

Learning style	Teaching instructions
Active	Show exercises at the beginning of the chapter because they like challenges and problem solving Show less examples. They are not interested in the way others have done something, because they want to solve a problem by themselves
Reflective	Show exercises at the end of a chapter Show examples after explanation content, but before exercises Show less exercises, because they learn better by thinking about a topic instead of solving problems actively.
Sensing	Show examples at the beginning of a chapter (before explanation content) because they like concrete content. Show exercises after explanation content, because they solve problems by already learned approaches

Intuitive	Show less examples, because they like to discover topic application by themselves Show examples after explanation content, because they like abstract content more than concrete Show exercises before explanation content, because they like challenges Show less exercises with a similar teaching goal because they don't like repetition
Visual	If possible, show resources as a picture or a video
Verbal	Show resources as a text or an audio
Sequential	Show learning content in a standard sequence – explanation content, examples, exercises and summary, because they like linear approach
Global	They are less interested in details, because they need to create a global picture of the topic. Therefore, add an overview of each chapter at the beginning of the lesson Show summary before examples and exercises, because summary helps you to create a global picture

In addition, the LMS should be capable of supporting numerous courses, so that students and instructors in a given institution experience a consistent interface when moving from one course to another [18]. An important feature of LMS is the adherence to standards, such as SCORM [17], it means that the LMS can share content complying with standards regardless of the authoring system that produced it.

There are many commercial and open source LMS. Some of popular commercial LMS are: Blackboard [19], WebCT [20] and the leading open source LMS is Moodle [21]. For our proposal we decided to use Moodle.

Moodle is a software package for producing Internet-based courses and web sites. It is a global development project designed to support a social constructionist framework of education. The word Moodle was originally an acronym for Modular Object-Oriented Dynamic Learning Environment. Moodle allows providing documents, graded assignments, quizzes, discussion forums, etc. to students with an easy to learn and use interface. We are assembling a Moodle site to develop our proposal for the Institute for Electrical Research (Instituto de Investigaciones Eléctricas) at México.

To develop dynamic courses or intelligent tutors that are SCORM compliant, a method to obtain a SCORM activity tree from a graph (AND/OR graph or a tree) that represents a tutor plan is presented in [22]. This will allow running SCORM compliant intelligent tutors in Moodle.

5 Integration Approach

An integration approach is proposed that allows building intelligent tutors that are adaptive in response to the knowledge state, the affective state and the learning style of the students.

At the beginning of a course, the learning style assessment instrument (Felder-Silverman) is applied to the student. Using the rules from Table 1, the learning style determines the type of explanations to be presented to the student when taking the course. Additionally, during the course, the tutor monitors and reacts to the knowledge and emotional states of the student, using tutorial actions as described above in section 2, in order to motivate and improve the learning process of the student.

6 Conclusions and Future Work

In this paper we presented two models that will allow us to integrate affective behavior and learning styles of the students into intelligent environments to complement the current approach in intelligent tutors that only follow what the student knows using a model that tracks the knowledge state of the student. The affective behavior and learning styles models increase the degree of personalization of the intelligent environments.

In the future, we plan: to incorporate the affective and learning styles models in dynamic courses for power generation and electric distribution operators and evaluate the effectiveness of these models.

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