Intelligent virtual laboratory and project oriented learning for teaching mobile robotics

Julieta Noguez 1, L. Enrique Sucar 2

1 Tecnológico de Monterrey, Campus Ciudad de México, Calle del Puente 222, Col. Ejidos de Huipulco, Tlalpan 14380 México, D.F., México
jnoguez@itesm.mx
http://doc.mor.itesm.mx:8181/jnoguez

2 Tecnológico de Monterrey, Campus Cuernavaca, Paseo de la Reforma 182-A, Col. Lomas de Cuernavaca, 62589 Temixco, Morelos, México
esucar@itesm.mx
http://dns1.mor.itesm.mx/~esucar

Abstract. We are combining collaborative didactic techniques, virtual laboratories and intelligent tutors to improve the process of learning mobile robotics. The students learn the basic concepts in mobile robotics, first experimenting in a virtual laboratory, and later by building a small mobile robot for a competition. The guiding thread for the course is based on the Project Oriented Learning (POL) didactic strategy. Through out the course the students design, build and program a small mobile robot to participate in student competitions. We present an evaluation of the virtual lab and of the tutor, and of the course in general.

Keywords: robotics, intelligent tutoring system, project oriented learning, virtual laboratory, student model.
1 Introduction

For interdisciplinary fields, such as robotics, the integration of knowledge of different areas, and several skills for effective learning is required. In particular, we are combining project oriented learning, virtual laboratories and intelligent tutors in an innovative course in which the students learn the basics of mobile robots by building and programming a robot for a competition.

The Project Oriented Learning (POL) didactic technique activates learning as an educational paradigm that transforms direct experience into a tool for supporting and stimulating learning [1]. We are using POL as the main didactic strategy for an undergraduate course in mobile robotics at ITESM Campus Cuernavaca [2]. The course is for Computer Science and Electrical Engineering majors at the sophomore level. Based on POL and collaborative learning, the students learn by doing. They form interdisciplinary teams that must learn about mechanical design, kinematics, sensors, control, and artificial intelligence in order to design a robot for a competition such as line following, maze solving, rescuing, etc. To support this process, we have developed several tools, including an intelligent tutoring system coupled to a virtual laboratory, which facilitate and guide the learning process, particularly in the first stages of the course [3].

The characteristics of open learning environment often involve simulation where learners can experiment with different aspects and parameters of a given phenomenon to observe the effects of these changes. These are desirable in virtual laboratories. However, the substantial limitation of open learning environment is the effectiveness for learning, because it strongly depends on the learner ability to explore adequately. We have developed a semi-open learning environment for a virtual robotics laboratory based on simulation, to learn through free exploration, but with specific performance criteria that guide the learning process. We proposed a generic architecture for this environment, in which the tutor module combines the performance and exploration behaviour in several experiments, to decide the best way to guide the student. The most important element of this environment is a representation of the student model based on probabilistic relational models [4]. This student model has several advantages: flexibility, user adaptability, high modularity and facility of model construction for different scenarios. The model keeps track of the students’ knowledge at different levels of granularity, combining the performance and exploration behavior in several experiments, in order to decide the best way to guide the student in the subsequent experiments, and to re-categorize the students based on the results.

We present an initial evaluation of the virtual lab and of the tutor, and of the course, in general. In this test group, some students used the virtual laboratory with the tutor and others only the virtual lab. The experiments show that the students with the help of the tutor have a better performance than the others. We applied an additional qualitative questionnaire, in which most of the students consider that the virtual laboratory is useful for learning the relevant concepts, and 80% enjoyed the learning environment. For evaluating the course in general, we show the results from the students’ opinions, based on questionnaires, and the results of their participation in several national competitions.

The rest of the paper is organized as follows. Section 2 introduces POL, section 3 describes the robotics course in general, including a description of the main phases in the process, and section 4 explains how POL is used in the course. Section 5 presents the semi-open learning environment, which is part of a general architecture for virtual laboratories that incorporates an intelligent tutor, as described in section 6. The main component of the tutor, a probabilistic relation student model, is summarized in section 7. Section 8 presents the valuation of the virtual lab and the course with a group of students, and section 9 concludes with a summary and direction for future work.
2 Project oriented Learning

POL is one of several active learning methods, devised during last decade as a product of research on collaborative learning in the fields of the behavioral and cognitive sciences [5]. POL considers that student teams will work on a single guiding thread, or project, for an entire course [6].

With POL, students must organize themselves into teams, and play roles while delegating work amongst themselves, and delivering feedback to their teams mates [7]. Overall success in these terms is not easily measurable. Since most of the learning process will take place outside the realm of the computer system, learning has to be assumed whenever there is evidence of its existence through visible actions [8]. Besides, it is hard to prove that students are motivated to learn when the instructor applies POL to their classroom activities. Johnson states “… changing to a cooperative style is not simple. There is a big difference between putting students into groups to learn… and structuring your teaching so students learn cooperatively…” [9].

The project oriented technique provides the following advantages [7]:

- It allows the students to learn how to solve problems using relevant knowledge independently of the discipline.
- Activities are focused on exploring and working out a practical problem with an unknown solution.
- Activities are designed in such a way that they can involve several areas of the same discipline or the interaction of different disciplines.
- Project oriented courses consider in their design the application of interdisciplinary knowledge so the students can appreciate the relationship between different disciplines in the development of a particular project.
- The project assignment promotes the search of open solutions so students are free to create new knowledge.

We designed the pedagogical aspects of the mobile robotics course based on this collaborative didactic technique.

3. Course description

The robotics course is a first course in mobile robotics for Electrical Engineering and Computer Science majors. It is an optional course usually taken at the junior or senior level (3rd or 4th year in the engineering curricula). We now describe some of the main characteristics of the course.

3.1 General objectives

The students must learn the basic concepts of mobile robotics, first by experimenting in a virtual laboratory, and later by building a small mobile robot for a competition. Throughout the course, the students design, build and program a small mobile robot to participate in a competition, such as line following, maze solving, rescue, etc.; learning on the way the basic concepts in several fields related to mobile robots: mechanical and electronic design, sensors, control, programming and artificial intelligence. They have to assimilate, integrate and apply all these concepts in multidisciplinary teams. The desired abilities to develop in the course are: team work, honesty, leadership, self directed learning, creativity, and the capacity to identify and solve problems.

3.2 Course contents
This basic robotic course covers the following topics: mechanics and electronics concepts, sensors and actuators, robot vision, robot architectures, programming, control, map building, planning, Markov decision process, reinforcement learning and human-robot interaction.

3.3. Learning Activities

In the first part of the course, the basic concepts of mobile robotics are covered in weekly lectures. During this period, the students use the virtual laboratory to practice these basic concepts in mechanics, kinematics, sensors, programming and control. During the 5th week, students form teams, and select the competition in which they will participate as shown in figure 1.

They start building and programming their robot taking advantage of the experience in the virtual lab. Concurrently, advanced topics in planning, learning and reasoning are covered in the classroom. In the last stage, the students incorporate these techniques in their robot, according to the competition goals. Figure 2 shows these phases.

The reflection process is a very important tool for students. They need to construct a portfolio for learning-by-doing management, conflict resolution, and overall synthesis of all products, derived from the team activities and their integration in a robot prototype. It also serves to point out elements that have not been completed; and, thus, contributes overcoming flaws which may appear throughout the course.
3.4 Course Project

The main focus of the course project is to design and build a robot to participate in a competition. For example, the 4th Latin American IEEE Student Contest [10] has both beginner and advanced categories. An example is the Lego [11] beginner category: a game is defined to develop solutions for autonomous mobile robotic based on the Lego platform. Two teams need to design, build and program two robots with different abilities which are placed in an arena (a robotics manipulation pharmacy), in order to produce a drug according to a prescription without any human interaction. Robots read the prescription at the beginning of the challenge.

3.5 Assessment process

For the course assessment, three milestones of the project are considered with respect to the robot development phases of the competition chosen. The total evaluation of the course is formed of different aspects, which are shown in Table 1.

<table>
<thead>
<tr>
<th>Points</th>
<th>COURSE ASSESSMENT</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>Learning activities (virtual laboratory practices, homework, group process, etc)</td>
</tr>
<tr>
<td>30</td>
<td>Advances of the project (3 milestones)</td>
</tr>
<tr>
<td>20</td>
<td>Midterm and final exams</td>
</tr>
<tr>
<td>25</td>
<td>Final robot competitions</td>
</tr>
</tbody>
</table>

The last course had 20 subjects enrolled, with five teams of 4 students each. The students chose on their own, the desired competitions. In this case, the competitions selected were maze solving and Lego beginners.

4. Using Project Oriented Learning to evidence learning

During this course, the students build a small mobile robot, and the associated technical documentation, based on the POL didactic strategy. The project has the following phases:

- The students constitute teams; they make contractual agreements, and choose the competition.
- Each team designs (mechanics, electronics and sensors) and builds their robot (1st milestone).
- Students specify the software architecture and develop the basic software modules (2nd milestone).
- Teams develop the high-level programming modules, integrating all in a functional robot (3rd milestone).
- Teams participate in the competition.

The group process to develop the project consists of establishing the following steps:

1. At the beginning of the course, we ask the students to reflect on their expectations of the course, their actual knowledge level concerning the course, and their commitment to contributing to the success of the course.
2. Each team is formed according to each member’s strengths and weaknesses.
3. Commitment contract. At the fifth week the teams will be formed, and will start their team project. At this point, they make and sign a formal contract specifying the roles of each participant. Each team includes four members, and during each phase of the semester the leading role can be changed.
4. The teams are asked to present weekly reports on the advances of the robotics project, in which they make individual and collaborative reflections.
5. The students must satisfy the requirements of the three milestones, and a final presentation, including technical reports which explain the progress of the project.
By reading the reflections and assessing skills and learning goals, the instructor uses this information to supervise the progress of each team. We combine team reflections of self-perception with teacher assessments based on the technical goals delivered.

5. Virtual laboratory

In the first phase of the course, we have incorporated a virtual laboratory so that the students can explore the aspects related to the design of the robot: mechanical configuration, kinematics and sensors. The students can easily explore different mechanical and sensors configurations before they start building their robot. The laboratory also includes facilities for practicing basic control programming. The virtual laboratory is designed as a semi-open learning environment and incorporates an intelligent tutor. This environment provides the student with the opportunity to learn through free exploration, but with specific performance criteria that guide the learning process. The model takes care of the balance between the virtual laboratory capabilities versus the tutoring labor based on decisions such as when to interrupt an experiment, the student performance follow up, task planning, and the best pedagogical actions. The semi-open learning environment is designed as a general architecture for virtual laboratories that incorporate intelligent tutors, so it can be easily extended to other domains. Next we describe this architecture.

3.1 General architecture

We proposed a generic architecture to develop the semi-open learning environment, providing several advantages: flexibility, it allows to consider different experiments in a common framework, adaptability, it can be adapted to different levels of students by using a student model, and modularity, it can be easily extended to other domains, to include more students, more knowledge objects and more experiments. This generic architecture is depicted in figure 3.

![Figure 3. Generic architecture for the virtual robotics laboratory.](image)

The main elements in this architecture are the following:

- **Initial categorization.** We designed an approach that increases the possibilities of the learning environment to interact in an appropriate way with the student. Following the philosophy of virtual laboratories of being non invasive, we used the academic background of the student for an initial categori-
zation as: novice, medium or expert. This categorization is based on a probabilistic model that links previous courses with the different knowledge concepts relevant for the experiments in the laboratory. An initial category is obtained for each student, and this is updated after each experiment based on the student model that will be described later. This category is used to define the exercise complexity for each experiment and the different types of help given to the student.

- **Semi-open learning environment.** We considered aspects of open learning environments, because the student needs explore different parameters to observe their effects inside the simulated lab, but each experiment has specific objectives the student needs to achieve, enabling an effective assessment of the exploration behavior and learning goals.

- **Simulator.** This module contains a set of experiments based on kinematics models of different configurations of mobile robots. The robot and its environment and displayed in a graphically, so the student can interact with the robot (via direct commands or a program) and visualize the experiment. It includes the student interaction analysis, the experiment performance, and exploration behavior results.

- **Intelligent tutoring system.** We coupled an intelligent tutoring system to the virtual laboratory. The tutor follows the exploration and performance of the student in the lab, updates its model, gives the appropriate help if required, and defines the next experiments. When a student performs an experiment in the virtual lab, the student model propagates the evidence from the experiments’ evaluation to the knowledge objects in the knowledge base. Based on this evidence and the accumulated evidence from previous experiments, the behavior and performance module updates the student model. After each experiment, the results are used by the tutor module to decide the best pedagogical action. The main component of this tutor is a novel student model based on probabilistic relational models [3].

In the next section we describe in more detail the semi-open learning environment, and then the student model.

### 6. Semi-open learning environment

Open learning environments often involve simulations where learners can experiment with different aspects and parameters of a given phenomenon to observe the effects of these changes [12]. This is a desirable characteristic in virtual laboratories. However, a substantial limitation of these systems is their effectiveness for learning. It strongly depends on the learner, on the specific features that influence the learner ability to explore adequately, and a clear definition of what constitutes effective exploration behavior [13-14]. There are several authors [15-17] which present open learning environments. They argue that additional meta-cognitive skills such as self explanation should improve the effectiveness of a student’s exploration. However, this hypothesis needs further studies before drawing stronger conclusions.

We propose a semi–open learning environment which provides the student with the opportunity to learn through free exploration but with specific performance criteria that guide the learning process.

In the virtual robotics laboratory, we considered important aspects of open learning environments, because the student has liberty to explore different parameters to observe their effects inside the virtual lab, but each experiment has specific objectives that the student needs to achieve. Some questionnaires and interviews were applied to students and professors in order to define the main desired characteristics for free explorations and combining them with the simulator and experiment behavior. We defined an interface with this information. The main elements of the interface for one of the experiments are shown in figure 3:

1. **Simulator.** In this area the simulated robot and its environment are displayed graphically, and updated according to dynamic behavior of the robot.
2. **Exploration.** This area allows for different aspects to be explored by students for each experiment. For example, the first experiment involves mechanical design concepts, so the students can change the type of robot, the diameter of the wheels, and the size of the robot.
3. **Interaction.** In this area, the options for the students’ interaction with the robot are specified. For instance, in the first experiments they can change robot direction and increase or decrease its speed.
4. **Dynamic behavior.** The interface shows the dynamic behavior of the mobile robot according to the experiment, including several performance parameters.
5. Final results. When the experiment is finished, this section displays the final results.

The same framework is used for all the experiments.

To define the experiments, we initially consider a line following competition, which requires some basic knowledge on mechanical design, sensors, control theory and programming from the students. The main difficulty of for the tutor is how to assess several knowledge items with little student interaction. Thus, we defined a sequence of specific experiments to enable the assessment of the knowledge items, step by step.

- The first experiment involves mechanical properties of mobile robots, as shown in figures 1 and 4. The educational goals are: (i) to learn mechanical aspects of mobile robotics, and (ii) to practice with different configurations and sizes using manual control.

- The second and third experiments are designed to explore basic properties of infrared (IR) sensors (which help to change speed and direction) as shown in figure 5.

**Figure 3.** Main elements of the interface for the semi-open learning environment.

**Figure 4.** Experiment 1: mechanical and kinematics aspects can be explored.
・The fourth experiment is related with actuators and control theory. We defined a set of basic robotics instruction for controlling the simulated mobile robot, which are similar to the libraries used for programming the real robots used in the second part of the course. We constructed an interpreter this language. The student needs to write his/her control program previously, taking care of the mechanical and sensor aspects which were explored in experiments 1, 2 and 3. To use the virtual laboratory, the students need to load his/her control program. The system verifies its syntax, if there are no errors, they can select the execute button and the system shows the robot movements based on the control program.

When a student uses the virtual lab, the intelligent tutor follows the experiments and gives personalized help. This tutor, and its main element, the student model, are described in the next section.

7. Intelligent tutor

As most Intelligent Tutoring Systems (ITS), the virtual laboratory has 3 main parts: (i) the knowledge base, (ii) the tutor, and (iii) the student model. One of the main differences with other ITS, is that in this case there is not a direct evaluation of the student with questions or problems. The students are evaluated indirectly based on the results of the experiments and the exploration behavior. With this information, the tutor has to deduce the state of the student, and decide the best pedagogical action. Given the uncertainty inherent in this task, we have developed a probabilistic relational student model for the virtual laboratory.

Many tutors use student models based on Bayesian networks (BN), which are useful for diagnosis, the task of inferring the cognitive state of the student from observable data [18-21]. However, the effort required to define the network structure, the difficulty to obtain the parameters and the computational complexity of the inference algorithms, difficult the application of these types of models, in particular in real time situations such as virtual laboratories. An additional complication is to find a general model for several students, given that each student has different knowledge, abilities, preferences and academic antecedents. In order to solve these problems, we proposed the use of Probabilistic Relational Models (PRM) to represent the student model, allowing the domain to be represented in terms of entities, their properties, and the relations between them. Next we give a brief introduction to PRMs, and then we discuss their application to student modeling.

7.1 Probabilistic relational models

Koller [23] states: “…The basic entities in a probabilistic relational model are objects or domain entities. Objects in the domain are partitioned into a set of disjoint classes X₁,...,Xₚ. Each class is associated with a set of attributes A(Xᵢ). Each attribute Aᵢ ∈ A(Xᵢ) takes on values in some fixed domain of values V(Aᵢ)”. The dependency model is defined at the class level, allowing it to be used for any object in the class. For
each class, its dependency relations with other classes are defined. Later, the specific dependencies between the attributes of an object are defined based on attributes of related objects.

This representation allows for two types of attributes in each class: (i) information variables, (ii) random variables. The random variables are the ones that are linked in a kind of Bayesian network that is called an skeleton. From this skeleton, different Bayesian networks can be generated, according to other variables in the model. For example, in the student model we describe below, we define a general skeleton for an experiment, from which particular instances for each experiment is generated. This gives the model a greater flexibility and generality, facilitating knowledge acquisition. It also makes inference more efficient, because only part of the model is used in each particular case.

A PRM specifies the probability distribution of the skeletons using the same underlying principles used for Bayesian networks. The assumption is that each of the random variables in a PRM, in this case the attributes \( x.a \) of the individual objects \( x \), is directly influenced only by a few others. A PRM therefore defines for each attribute \( x.a \), a set of parents, which are the directed influences on it, and a local probabilistic model that specifies the probabilistic parameters. Once an specific network is generated from an skeleton, the inference mechanism is the same as for Bayesian networks.

PRM’s allow a compact and natural representation of student models for virtual laboratories which is detailed next.

### 7.2. Probabilistic relational student model

In order to apply PRM’s to student modeling, we have to define the main objects involved in the domain. As shown in figure 6, the main classes related with students and experiments, were defined. For each class, a number of attributes (information variables and random variables) is defined. For example, the class \( X_k \), Experiment results, is formed by attributes such as id, number of repetitions, success, efficiency, performance. The dependency model is defined at the class level, allowing it to be used for any object in the class. Figure 7 shows the model in more detail, with some of the attribute for each class, and the dependencies between these classes.

![Figure 6](image.png)

**Figure 6.** A general student PRM for virtual laboratories. The model specifies the main classes of objects and their dependencies. For instance, the class Knowledge items represents the knowledge of the student for the particular concepts for an experiment, which are related to the experiments results and student behavior; and influences the knowledge of the student at higher levels (sub-themes and themes).

Once the model is specified at the class level, including the attributes and their dependencies, we can extract a skeleton, that is a general Bayesian network model for a fragment of the model. For instance, a skeleton obtained from the model in figure 7 is depicted in figure 8. This network includes the dependencies between the student knowledge at different levels of granularity, and the results of the experiments in terms of performance and exploration results.
Figure 7. A detailed view of the model in figure 6. It shows some of the attributes for each class in the model.

Figure 8. A general skeleton obtained from the PRM in figure 7. It specifies the dependencies between the random variables of each class related to other classes.

From the skeleton, it is possible to define different instances according to the values of specific variables in the model. For example, from the general skeleton for experiments of figure 8, we can define particular instances for each experiment. As it is shown in figure 9, a generic skeleton is used to obtain several instances of the probabilistic relational model to infer the knowledge gain of a student for different experiments. This model allows different CPT’s for each instance, according to the categorization of the student as novice, intermediate or expert. This is because the relations between performance and the knowledge items change according to the level of the student.
Figure 9. Obtaining different instances from a generic skeleton of the experiments of student model.

An instance $\tau_1$ for experiment 1, obtained from the skeleton in figure 8 is shown in figure 10. The random variables associated to this instance have know specific values according to the performance, exploration and concepts associated to experiment 1.

![Diagram](image)

Figura 10. Instancia $\tau_1$ que corresponde al experimento 1, basado en el esqueleto del modelo relacional probabilista del esquema experimento. Las relaciones de dependencia entre clases se han definido ahora a nivel de variables aleatorias específicas.

The PRM model is also used for the initial categorization of the students based on their academic background [3].

Next we present the evaluation of the course and the virtual laboratory that incorporates the intelligent tutor and student model.

8. Evaluation process

We present, firstly, an evaluation of the virtual lab and of the tutor, and, secondly, of the course in general.
I. Virtual laboratory evaluation.

We have concluded a user study with the semi–open learning environment. In particular, we evaluated the tutor and the student model, using the virtual robotics laboratory. By analyzing the learners’ explorations, as they used the system, we have some insight on the general effectiveness of experiment performance. We obtained quantitative and qualitative results that give some measure of the prediction capabilities of the proposed student model, and of the utility of the tutor in a semi–open learning environment.

- **Participants.** The subjects were EE and CS undergraduate students at the sophomore and senior levels. A total of 20 subjects, enrolled in a robotics basic course participated in the study. Although there were few students, we decided to divide them into a control and an experimental group to test the VL issues with ITS and without ITS.

- **Experiment design.** In the experiment, all subjects used the virtual laboratory, described in the semi-open learning environment section. We introduced the academic background of each student to the system. The system, using the probabilistic model, applied the pre-categorization process for each student. Both, control and experimental group students were divided in two categories: novice and intermediate. We, then, applied the pre-test after a 60 minutes lecture on basic robotics concepts. The pre-test is paper and pencil test designed to evaluate the learners’ knowledge of the objects target by the virtual laboratory. It consisted of 25 questions organized in the same way as the knowledge objects of the student model. Both, control and experimental groups participated in a session (30 to 60 minutes), performing experiments with the virtual laboratory. The experimental group had the support of the tutor during the experiments, while the control group explored the virtual lab without tutor.

- **The post-phase.** The post-test consisted of a test analogous to the pre-test, with 25 questions organized in a same way as the knowledge objects of the student model, and of a ten item questionnaire targeted at students’ opinions about their virtual laboratory experience. In addition, the system produced log files that capture the sessions at the level of basic exploration actions and experiment performance results.

II. Results

Figures 11 and 12 show the initial categorization results versus the pre-test for the first knowledge objects targeted by experiments 1 and 2 (the graphs show the averages of the 20 students). The knowledge values for the pre-categorization model were defined based only on academic background. For the students categorized at the intermediate level (figure 5), the predictions of the model are very good for almost all the knowledge objects. For the novice student, we found that, in general, the predictions are below the test results. However, a lecture was given just before the pre-test was applied, so we think that this affected the results in particular for the novices.

Figures 13 and 14 summarize the results after experiments 1, 2, 3 and 4, for the control and experimental groups. The graphs of tutor and without tutor represent the knowledge objects (items, sub-themes and themes) assessed inside of the virtual laboratory for the control and experimental groups.
The graphs of pre-test represent the knowledge objects assessed by a paper and pencil test, before students complete the experiments using the virtual laboratory. The results for novice students (according to the initial categorization) are shown in figure 6, and those for intermediate students are shown in figure 7. The results show that the students that explore the virtual environment with the help of the tutor have the better performance. As shown in these figures, students with intelligent support improved their knowledge level of the targeted knowledge objects significantly.
Additionally, based on a questionnaire, most of the students consider that the virtual laboratory is useful in learning the relevant concepts, and 80% enjoyed the learning environment.

III. Course evaluation

For evaluating the course in general, we obtained the results from students’ opinions, based on institutional questionnaires. These questionnaires have 28 specific questions related to teacher skills, skills developed, teacher-student relationship, and academic quality. The assessment range is from 1 to 7, where 1 is excellent and 7 is worst. The average assessment in the last term was 1.33.

The results of the team participation in several national competitions during the last three years were good, in general. For instance, they obtained second and third places in line maze competitions in 2003 and 2004, and a second place in obstacle avoidance in 2002. These are good results, considering that our students were competing with experienced participants and graduate students, while our students were enrolled in their first robotic course; and additionally they were competing for the first time.
9 Conclusions and future work

We have developed a course for teaching basic robotics at the undergraduate level with several didactical and technical contributions, helping the students learn in a more effective way. The first part of the course uses an intelligent tutoring system coupled to a virtual laboratory for mobile robots, which constitute a semi-open learning environment. The virtual laboratory can be visited at:

http://doc.mor.itesm.mx:8181/robotica

Send an e-mail to the authors for an account.

We have developed an intelligent tutoring system coupled to a virtual laboratory, which constitute a semi-open learning environment. It provides the student with the opportunity to learn through free exploration, but with specific performance criteria that guide the learning process. In virtual laboratories, we considered important aspects of open learning environments, because the student has the liberty to explore different parameters to observe their effects inside the virtual laboratory.

The semi-open learning environment has also several advantages: flexibility, it allows to consider different models for each student in a common framework, adaptability, by obtaining an initial model of a new learner from similar student models, and modularity, it can be easily extended to include more students, and more experiments and other domains.

The intelligent tutoring system keeps track of the students’ knowledge at different levels of granularity, combining the performance and exploration behavior in several experiments, in order to decide the best pedagogical actions. We have evaluated the system with an initial group of students. The results show that the students who explore the semi-open virtual environment with the help of the tutor have a better performance, and students with intelligent support improved significantly their knowledge level of the targeted knowledge objects.

We are currently extending our evaluation of the tutor with more experiments and validating the best pedagogical actions of the tutor. We are integrating an affective behavior model to the intelligent tutoring system in order to provide students with a suitable response from a pedagogical and affective point of view [24]. We are adding also collaborative capabilities for student interaction in the semi-open virtual laboratory. Finally, we are starting with new domains for the generic architecture in basic education and in medicine.

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BRIEF BIOGRAPHICAL SKETCH

Julieta Noguez is a Professor of Computer Science at the Tecnológico de Monterrey, Campus Ciudad de México, Mexico. Julieta Noguez has a M.Sc. in Computer Science from Tecnológico de Monterrey and she is a Ph.D. candidate in Computing Science from Tecnológico de Monterrey, Campus Cuernavaca. She has more than 20 publications in journals and conference proceedings, and has supervised 2 M.Sc. thesis. She is member of the Mexican AI Society, and served as reviewer for FIE2005. She received the Best Professor Award in 2000 at the Tecnológico de Monterrey, Campus Ciudad de México. Her main research interests are collaborative learning, probabilistic reasoning, virtual laboratories, and intelligent tutors.
L. Enrique Sucar is a Professor of Computer Science at the Tecnológico de Monterrey, Campus Cuernavaca, México. Dr. Sucar has a M.Sc. in Electrical Engineering from Stanford University and a Ph.D. in Computing from Imperial College. He has more than 100 publications in journals and conference proceedings, and has supervised 7 Ph.D. and 22 M.Sc. thesis. He is member of the National Research System in Mexico, has been president of the Mexican AI Society, and served on the Advisory Committee for IJCAI. He received the Best Paper Award at IEA/AIE-95 and Iberamia-2004. His main research interests are in probabilistic reasoning, computer vision, mobile robots and intelligent tutors.

REFERENCES