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Intelligent Virtual Laboratory and Project-Oriented Learning for Teaching Mobile Robotics*

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We have combined 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 by experimenting in a virtual laboratory and later by building a small mobile robot for a competition. The course is based on the project-oriented learning (POL) didactic strategy. Throughout the course the students design, build and program a small mobile robot to participate in student competitions. Here we present an evaluation of the virtual lab and of the tutor, and of the course in general.

INTRODUCTION

FOR INTERDISCIPLINARY fields such as robotics, it is necessary to integrate knowledge in different areas with a variety of skills in order to achieve effective learning. In this work we have combined 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 have used 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 junior/senior 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—such as line-following, maze-solving, rescuing, etc.—in order to design a robot for a competition. 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].

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The characteristics of open-learning environments often involve simulation, whereby learners can experiment with different aspects and parameters of a given phenomenon and so observe the effects of any changes. This is desirable in virtual laboratories. However, a substantial limitation of an open learning environment is its effectiveness for learning, because it strongly depends on the learner's 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 performance and exploration behavior in several experiments, in order to decide the best way to guide the student in subsequent experiments, and in order to recategorize 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. A group of students in a robotics course used the virtual lab. In this test group, some students used the virtual laboratory with the tutor, and others only used the virtual lab. The experiments show that the students who had the help of the tutor performed better than the others. We applied an additional qualitative questionnaire, in which most of the students found 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 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. First we introduce POL, then we describe the robotics course in general, including a description of the main phases in the process. The next section explains how POL is used in the course, then we present a semi-open learning environment, which is part of a general architecture for virtual laboratories that incorporates an intelligent tutor. The main component of the tutor, a probabilistic relation student model, is summarized next, followed by an evaluation of the virtual lab and the course with a group of students. The final section concludes with a summary and suggestions for future work.

PROJECT-ORIENTED LEARNING

POL is one of several active learning methods devised during the last decade as a result of research on collaborative learning in the fields of the behavioral and cognitive sciences [5]. With POL, student teams work on a single guiding thread, or project, for an entire course [6]. Students organize themselves into teams and play roles while sharing work amongst them, and delivering feedback to their team 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]. It is hard to prove that students are motivated to learn when the instructor applies POL to their classroom activities. Johnson states that "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 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 for 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.

COURSE DESCRIPTION

The robotics course is the 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). Some of the main characteristics of the course are described below.

General objectives

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., thus learning 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 attributes fostered in the course are: teamwork, honesty, leadership, self-directed learning, creativity, and the capacity to identify and solve problems.

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, the Markov decision process and reinforcement learning.

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 strengthen the basic concepts in kinematics, sensors, programming and control. During the fifth week, students form teams and select the competition in which they will participate. This first part of the course is illustrated in Fig. 1.

In the second part of the course, the students start building and programming their robot, taking advantage of the experience in the virtual lab. Advanced topics in planning, learning and reasoning are covered in the classroom. In the

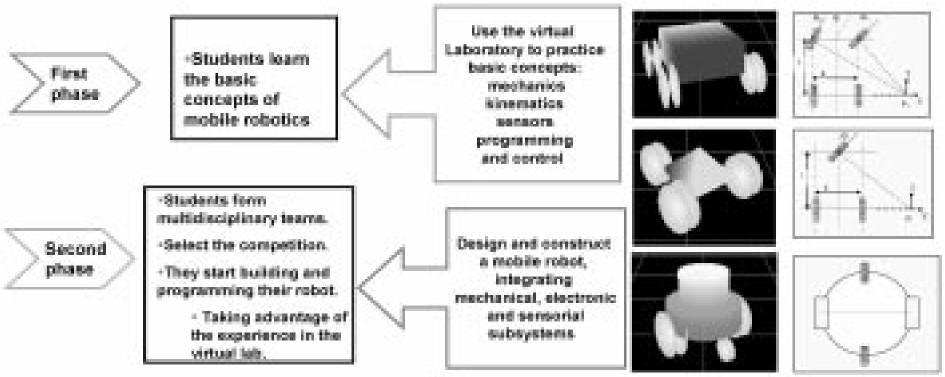

Fig. 1. First and second phases of the learning activities in the robotics course.

last stage, the students incorporate these techniques in their robot, according to the competition goals. Fig. 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, thus contributing towards overcoming flaws which may arise throughout the course.

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 an autonomous mobile robot 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.

Assessment process

For the course assessment, three milestones of the project are considered with respect to the robot development phases of the chosen competition. The total evaluation of the course comprises a variety of different aspects (shown in Table 1).

Table 1. Course assessment

Points	
25	Learning activities (virtual laboratory practice, homework, group process, etc.)
30	Advances of the project (3 milestones)
20	Mid-term and final exams
25	Final robot competitions

Twenty subjects enrolled in the last course, comprising five teams of four students each. The students chose their own competitions. In this case, the competitions selected were maze-solving and Lego beginners.

USING PROJECT-ORIENTED LEARNING TO SHOW 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 a competition.
- Each team designs (mechanics, electronics and sensors) and builds their robot (1st milestone).

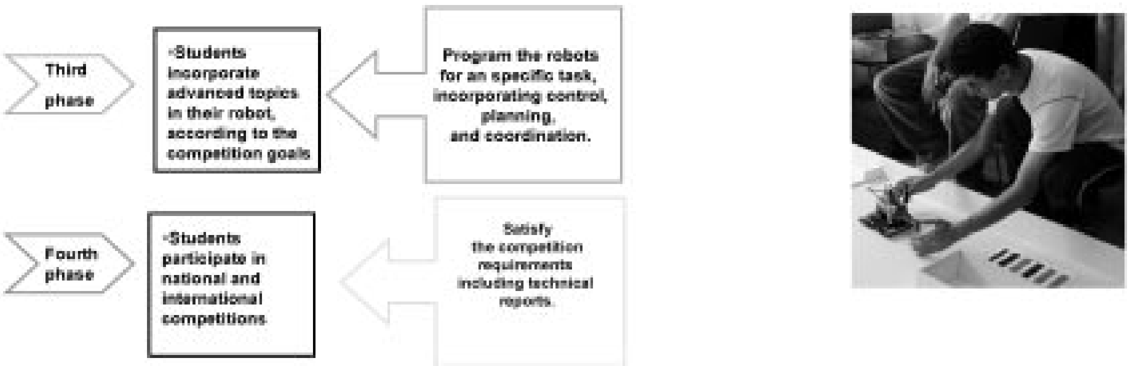

Fig. 2. Third and fourth phases of the learning activities in the robotics course.

- Students specify the software architecture and develop the basic software modules (2nd milestone).
- Teams develop 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: in the fifth week, the teams are formed and 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, on which they make individual and collaborative reflections.
5. The students must satisfy the requirements of the three milestones and give a final presentation, including technical reports which explain the progress of the project.

By reading the students' 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.

VIRTUAL LABORATORY

We have incorporated a virtual laboratory in the first phase of the course, 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 sensor 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, based on decisions such as when to interrupt an experiment, 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.

General architecture

We proposed a generic architecture (Fig. 3) to develop the semi-open learning environment, providing several advantages:

- *Flexibility*, allowing different experiments in a common framework.
- *Adaptability*, so that it can be adapted to different levels of students by using a student model.
- *Modularity*, whereby it can be easily extended to other domains, to include more students, more knowledge objects and more experiments.

The main elements in this architecture are the following:

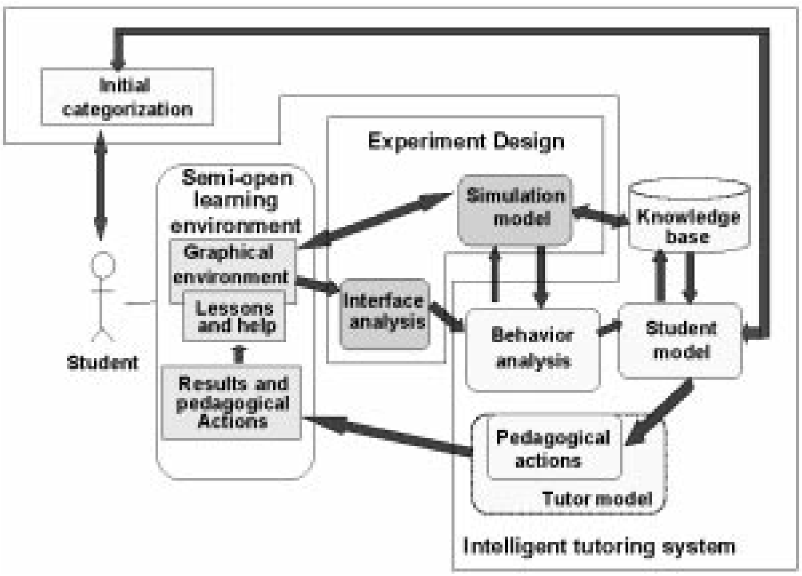

Fig. 3. Generic architecture for the virtual robotics laboratory.

- *Initial categorization*. We designed an approach that increases the possibility of the learning environment interacting in an appropriate way with the student. Following the philosophy of virtual laboratories being non-invasive, we used the academic background of the student for an initial categorization: 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 to explore different parameters to observe their effects inside the simulated lab, but each experiment has specific objectives the student needs to achieve, thus 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 are displayed 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 with 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.

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 changes they make [12]. This is a desirable characteristic in virtual laboratories. However, a substantial limitation of these systems is their effectiveness for learning, which strongly depends on the learner, on the specific features that influence the learner's ability to explore adequately, and a clear definition of what constitutes effective exploration behavior [13–14]. Several authors [15–17] have presented open learning environments. They argue that additional metacognitive skills, such as self-explanation, may improve the effectiveness of a student's exploration. However, this hypothesis needs further study 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 guiding the learning process. In the virtual robotics laboratory, we considered important aspects of open learning environments, because the student has the opportunity 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 exploration, which are combined with the simulator and experiment behavior. We defined an interface with this information. The main elements of the interface for one of the experiments (shown in Fig. 4) are:

1. *Simulator*. In this area the simulated robot and its environment are displayed graphically and updated according to the 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 the robot's 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 some basic knowledge on mechanical design, sensors, control theory and programming. The main difficulty for the tutor is how to assess several knowledge items with little student interaction. Thus, we defined a sequence of specific experi-

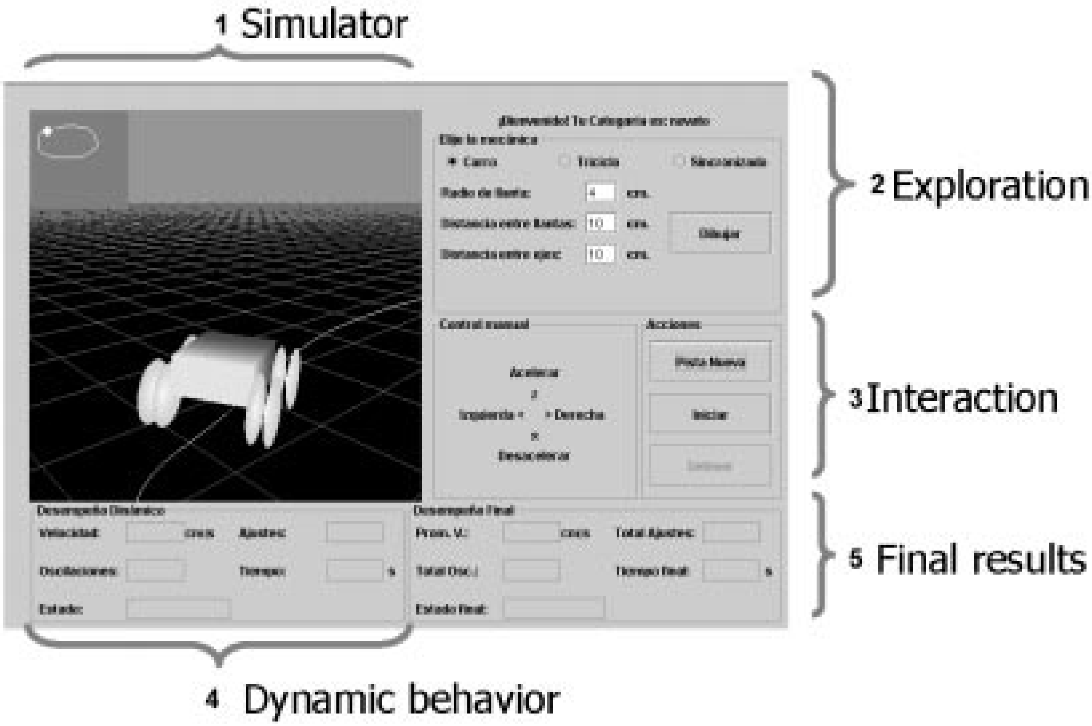

Fig. 4. The main elements of the interface for the semi-open learning environment.

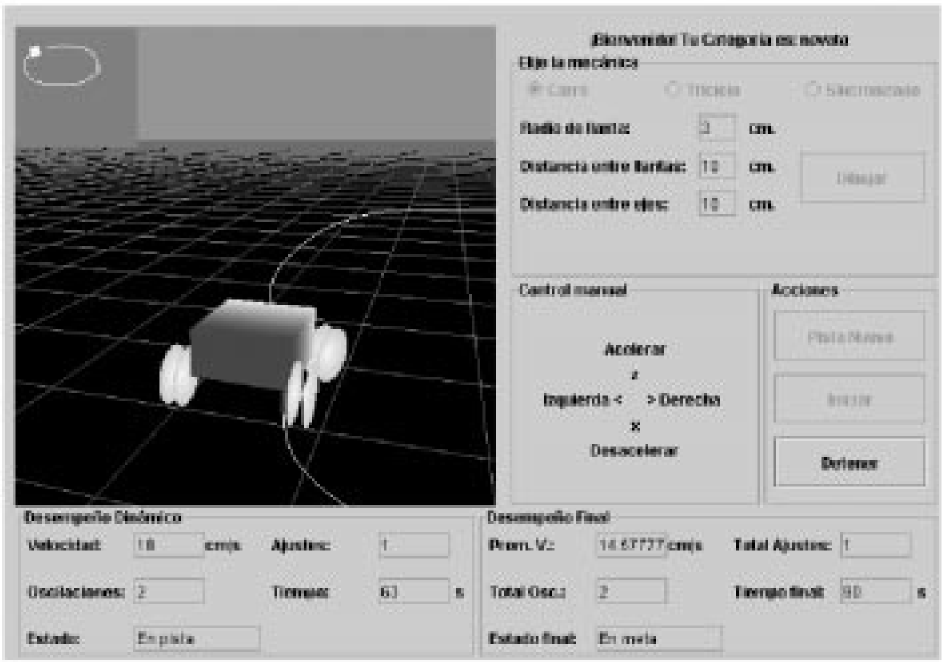

Fig. 5. Experiment 1: mechanical and kinematics can be explored.

ments to enable assessment of the knowledge items.

The first experiment involves the mechanical properties of mobile robots, as shown in Figs. 1 and 5. The educational goals are: (i) to learn mechanical aspects of mobile robotics, and (ii) to practice with different configurations and sizes using manual controls.

The second and third experiments are designed to explore the basic properties of infrared (IR) sensors (which help to change speed and direction), as shown in Fig. 6.

The fourth experiment concerns actuators and control theory. We defined a set of basic robotics instructions 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

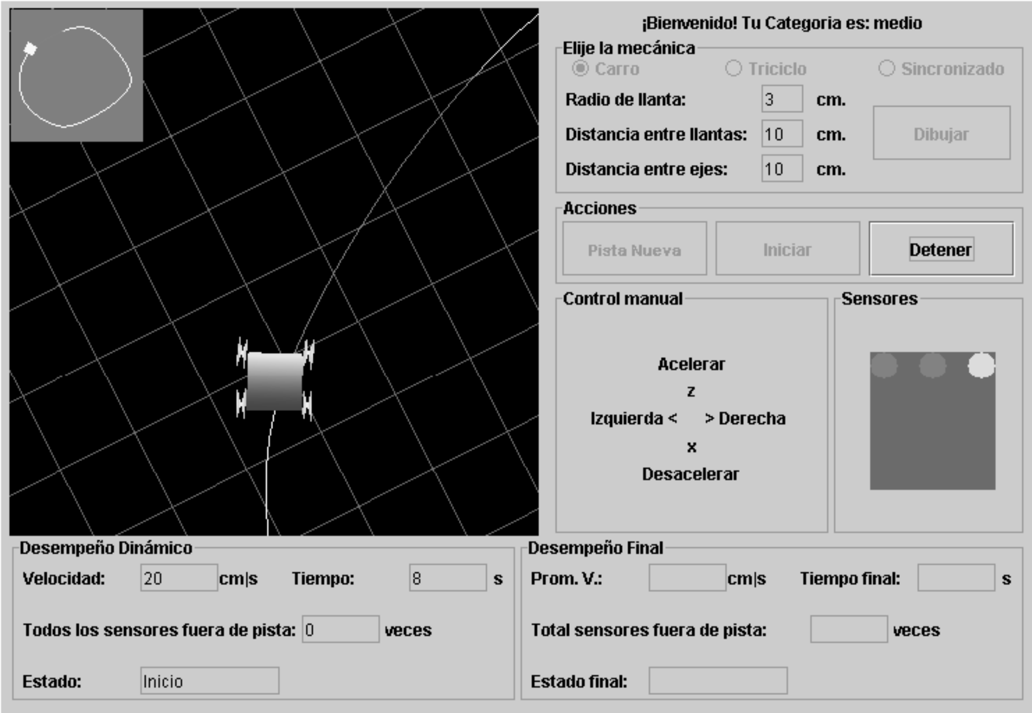

Fig. 6. Experiment 2: use of infrared sensors.

for this language. The student needs to have written 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 student needs to load his/her control program. The system verifies its syntax and, 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.

INTELLIGENT TUTOR

As for most intelligent tutoring systems (ITS), the ITS for the virtual laboratory has three main parts: (i) the knowledge base, (ii) the tutor, and (iii) the student model. One of the main differences with other ITSs 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 assess the cognitive state of the student and decide the best pedagogical action. Given the uncertainty inherent in this task, we have developed [3] 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 of obtaining the parameters and the computational complexity of the inference algorithms, makes the application of these types of models difficult, particularly in real-time situations such as virtual laboratories. An additional complication is finding 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) [22] 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.

Probabilistic relational models

Koller [23] states that "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 $X_1, \ldots, X_n$. Each class is associated with a set of attributes $A(X_i)$. Each attribute $A_j \in A(X_i)$ takes on values in some fixed domain of values $V(A_j)$." 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 the attributes of related objects.

This representation allows for two types of attributes in each class: (i) information variables and (ii) random variables. The random variables are the ones that are linked in a kind of Bayesian network that is called a *skeleton*. From this skeleton, different Bayesian networks can be generated, according to other variables in the model. For example, in the student model described below we define a general skeleton for an experiment, from which particular instances for each experiment are 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 specific case.

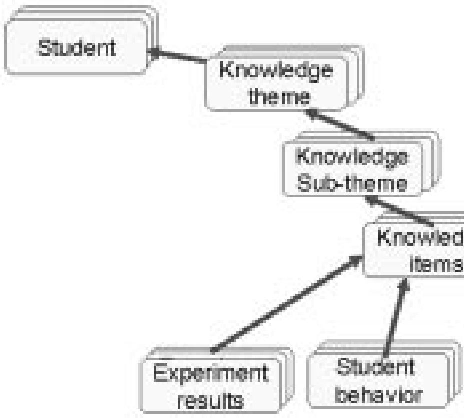

Fig. 7. A general student PRM for virtual laboratories. The model specifies the main classes of objects and their dependencies. For instance, the class *knowledge items* represents the knowledge of the student for the particular concepts for an experiment, which are related to the experiment's results and student behavior, and which influence the knowledge of the student at higher levels (sub-themes and themes).

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 by just 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 a specific network is generated from a skeleton, the inference mechanism is the same as for Bayesian networks.

PRMs allow a compact and natural representation of student models for virtual laboratories. Next we describe briefly a novel student model based on probabilistic relational models [3].

Probabilistic relational student model

In order to apply PRMs to student modeling, it is necessary to define the main objects involved in the domain. As shown in Fig. 7, the main classes related with students and experiments were defined. For each class, a number of attributes (information variables and random variables) are defined. For example, the class X_4, *experiment results,* is formed by attributes such as *id, number of repetitions, success, efficiency, performance*. The dependency model is defined at the class level,

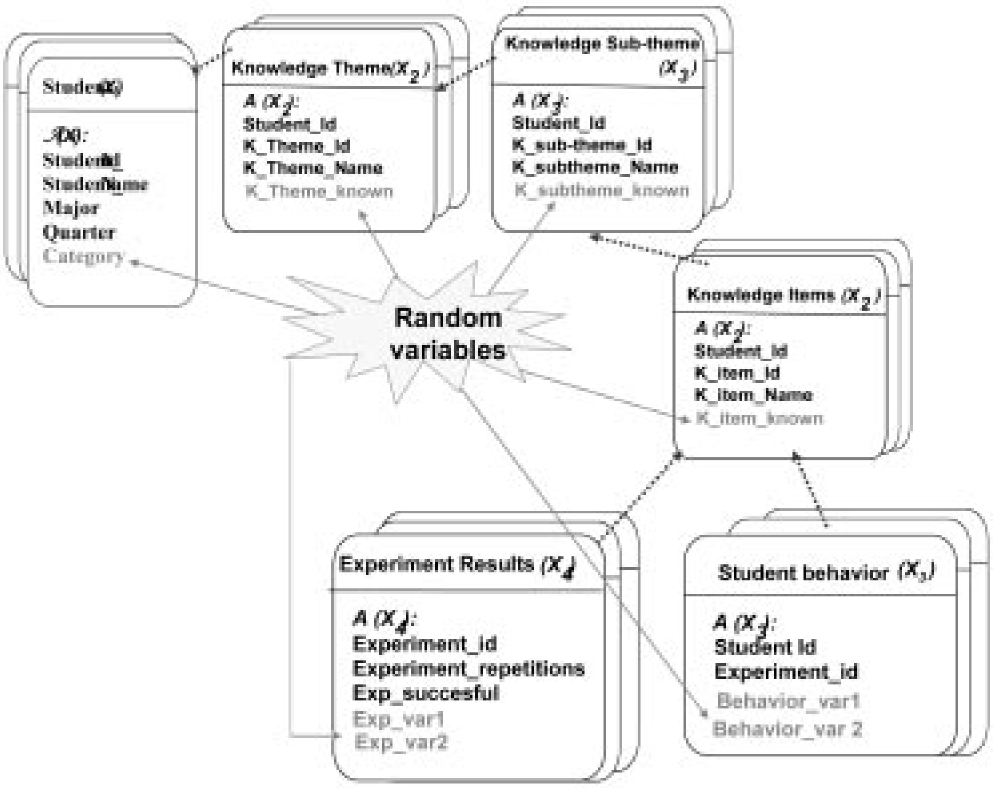

Fig. 8. A detailed view of the model in Fig. 6, showing information and random variables (attributes) for each class in the model and the dependencies between classes.

allowing it to be used for any object in the class. Fig. 8 shows the model in more detail, with information and random variables for each class, and the dependencies between classes.

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 Fig. 8 is depicted in Fig. 9. 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.

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 Fig. 9, we can define particular instances for each experiment. As shown in Fig. 10, a generic skeleton

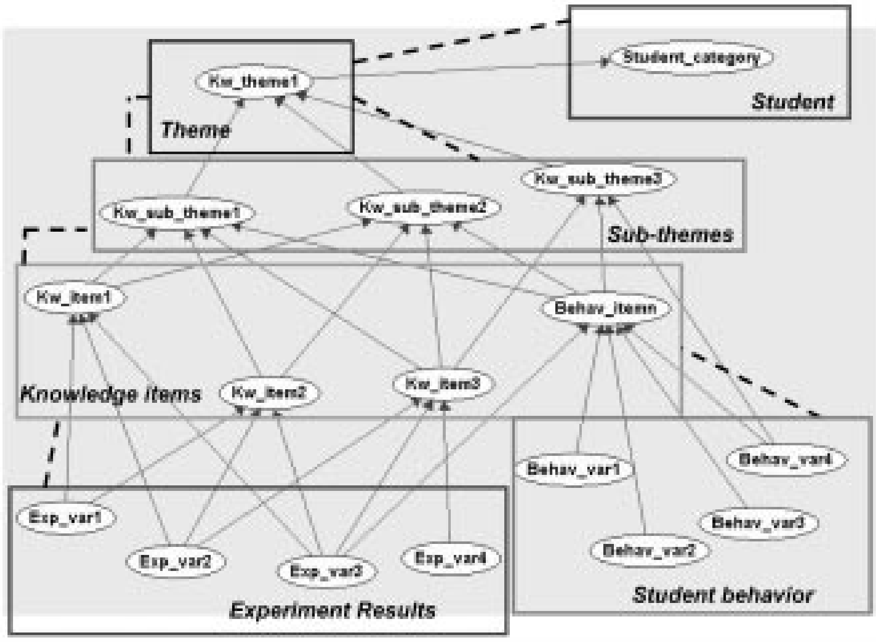

Fig. 9. A general skeleton obtained from the PRM in Fig. 8, specifying the dependencies between the random variables (attributes) of each class related to other classes.

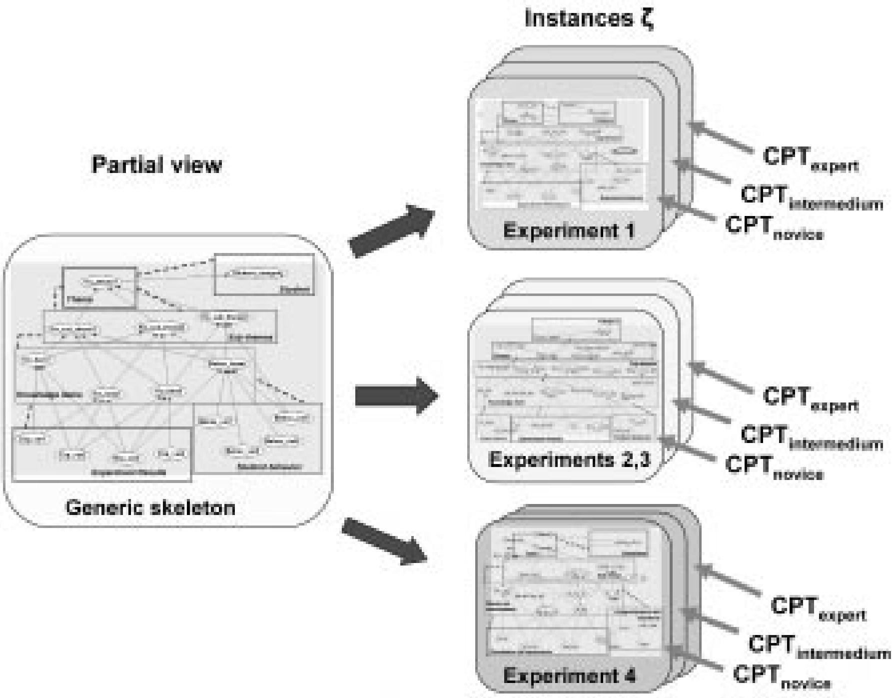

Fig. 10. Obtaining different instances from a generic skeleton of the experiments in the student model. From one skeleton, several instances are obtained according to the experiment and student level.

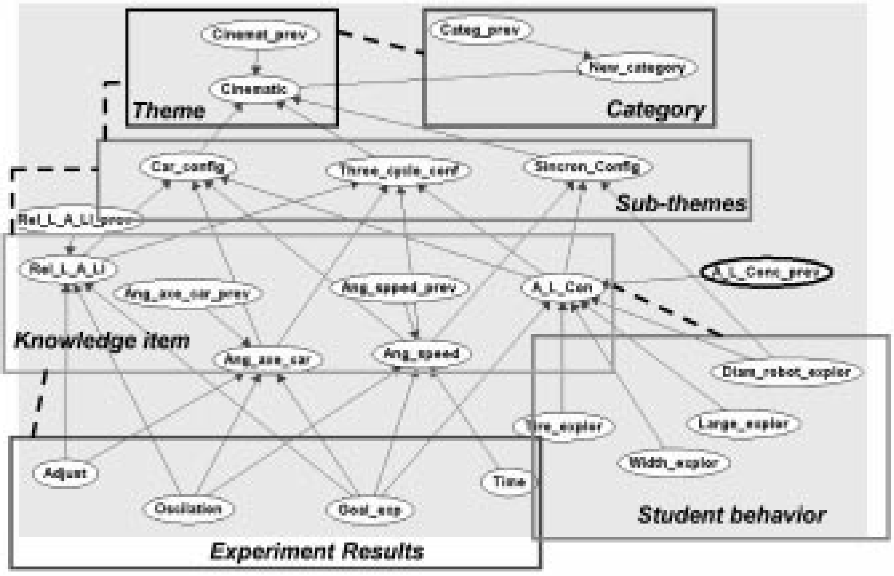

Fig. 11. Instance $\tau 1$ corresponding to experiment 1, obtained from the skeleton in Fig. 9.

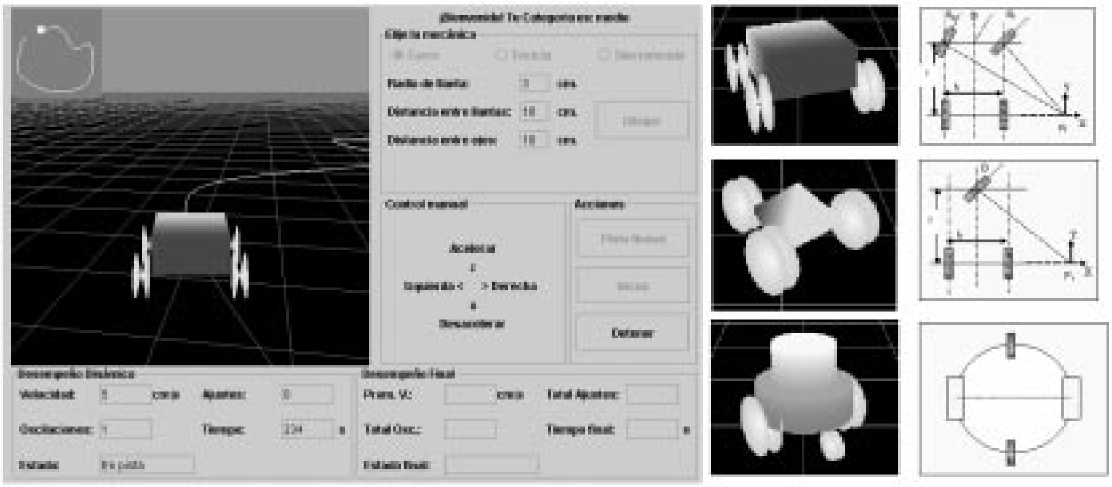

Fig. 12. Experiment 1: kinematics and mechanical aspects of mobile robots are explored by students in this experiment. The left side shows the virtual lab interface, and the right shows the three types of configuration that can be explored.

is used to obtain several instances of the probabilistic relational model to infer the knowledge gain of a student for different experiments.

As in Bayesian networks, the parameters of the model consist of the conditional probability table (CPT) of each variable (attribute), given its parents, which are defined for the skeleton of the relational schema. This model allows different conditional probability tables for each instance, according to the categorization of the student as novice, intermediate or expert. This is because the relationship between performance and the knowledge items changes according to the level of the student. An example τ_1 for experiment 1, obtained from the skeleton in Fig. 9, is shown in Fig. 11. The random variables associated to this instance now have specific values according to the performance, exploration and concepts associated with experiment 1.

An example: experiment 1

As mentioned above, the first experiment involves the mechanical properties of mobile robots. The educational goals are: (i) to learn the mechanical aspects of mobile robotics, and (ii) to practice with kinematical models using manual control. The interface is shown in Fig. 5. Different aspects should be explored by the students for this experiment. The exploration characteristics are related to the experiment goals. Students are able to explore three different kinematics models and several parameters for each model, as shown in Fig. 12.

The learners' knowledge of the objects targeted by the virtual laboratory in experiment 1 are: angle speed, the large–wide relation, axels relation, and robot dimensions. Then the results of each experiment, in terms of exploration and performance, are considered in the relational student model. When a

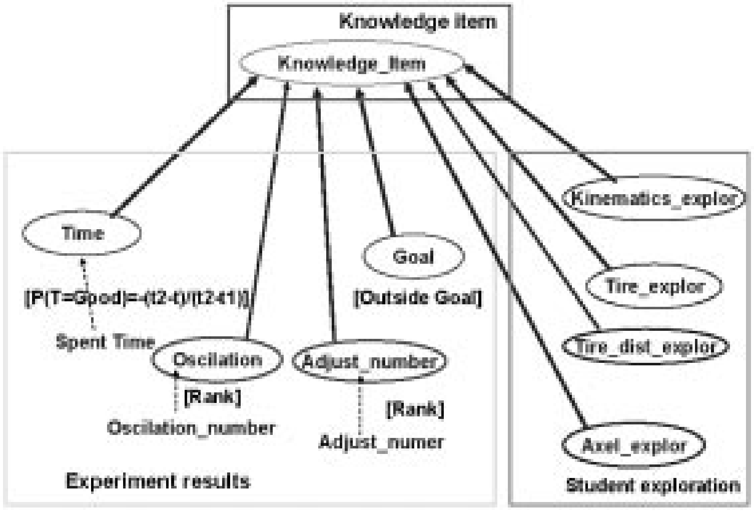

Fig. 13. Taking evidence from experiment results: the exploration and performance (results) parameters are mapped to the knowledge items (one item is shown in the figure for simplicity, but this item represents several concepts or variables).

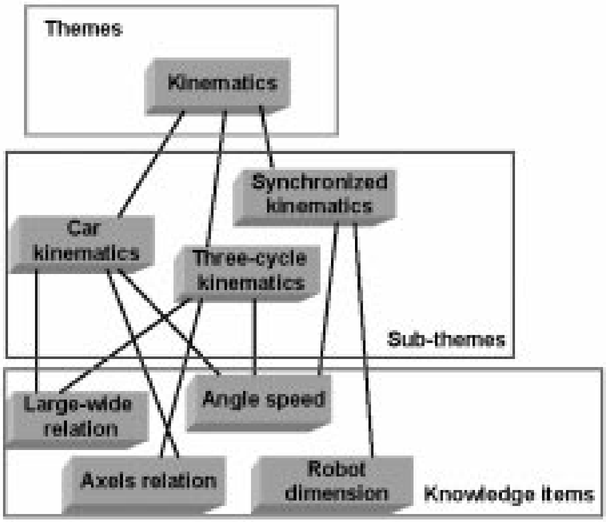

Fig. 14. The student's knowledge has different levels of granularity. It is organized in a hierarchical structure, from themes to sub-themes, and from sub-themes to knowledge items. The figure shows the concepts related to experiment 1.

student performs an experiment in the virtual lab, the experiment results and student exploration behavior are mapped to different *knowledge items* relevant to the experiment. Fig. 13 shows a fragment of the model used to convert evidence from the results and exploration.

The evidence from the experiment results is propagated first to the basic concepts (knowledge items) related to this experiment, and then to the sub-themes and themes according to a hierarchical knowledge structure for the course. This propagation is done using standard probability propagation techniques [24, 25] applying the Bayesian network for experiment 1 (see Fig. 11), derived from the PRM student model. In the case of a PRM, we can take advantage of the flexibility of the model to simplify probability propagation, so inference is done over an instantiation (skeleton) of the model. The student's knowledge base changes at the different levels of granularity according to a hierarchical structure previously defined. The knowledge items, sub-themes and themes related to experiment 1 are shown Fig. 14.

After each experiment, the results are used by the *tutor module* to decide the best pedagogical action. If the experiment's goals are below the expected value, the tutor decides the best pedagogical action, such as help or lessons. The PRM model is also used for 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.

EVALUATION PROCESS

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

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 gained some insight into the general effectiveness of the experiment's 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 basic robotics 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 the control and experimental group students were divided into two categories: novice and intermediate. We then applied the pre-test after a 60-minute lecture on basic robotics concepts. The pre-test is a paper-and-pencil test designed to evaluate the learners' knowledge of the objects targeted by the virtual laboratory. It consisted of 25 questions organized in the same way as the knowledge objects of the student model. Both the 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 a tutor.
- *The post-phase*. The post-test consisted of a test analogous to the pre-test, with 25 questions organized in the same way as the knowledge objects of the student model, and of a ten-item questionnaire seeking 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.

Results

Figs. 15 and 16 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 (Fig. 16), the predictions of the model are very good for almost all the knowledge items. 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.

Figs. 17 and 18 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 the virtual laboratory for the control and experimental groups.

The graphs of the *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 Fig. 17, and those for intermediate students are shown in Fig. 18. The results show that the students that explored the virtual environment with the help of the tutor performed better. As shown in these figures, students with intelligent

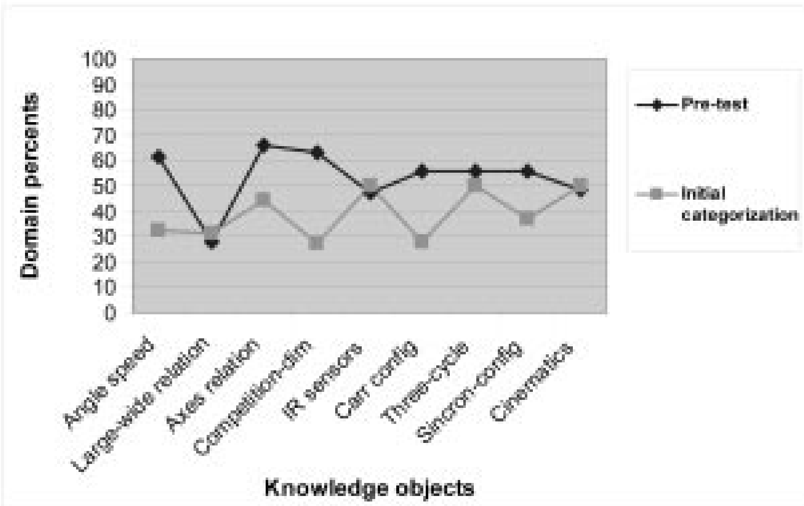

Fig. 15. Initial categorization versus pre-test for novices.

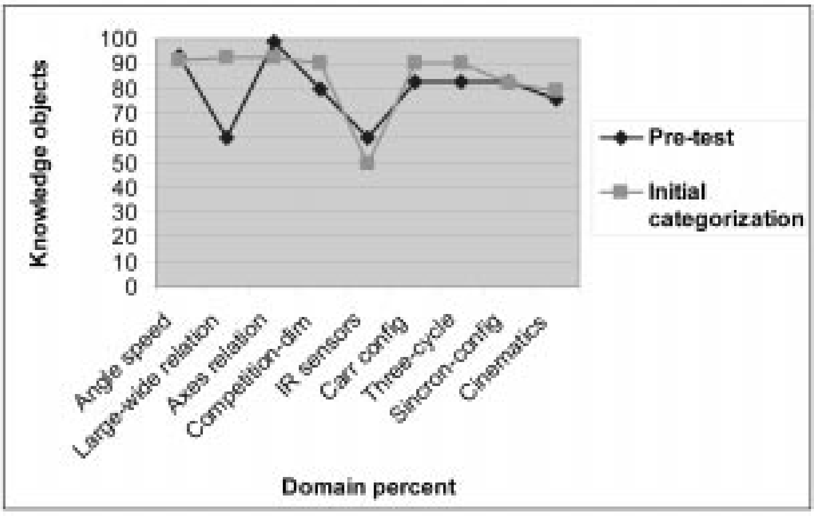

Fig. 16. Student categorization versus pre-test for intermediate students.

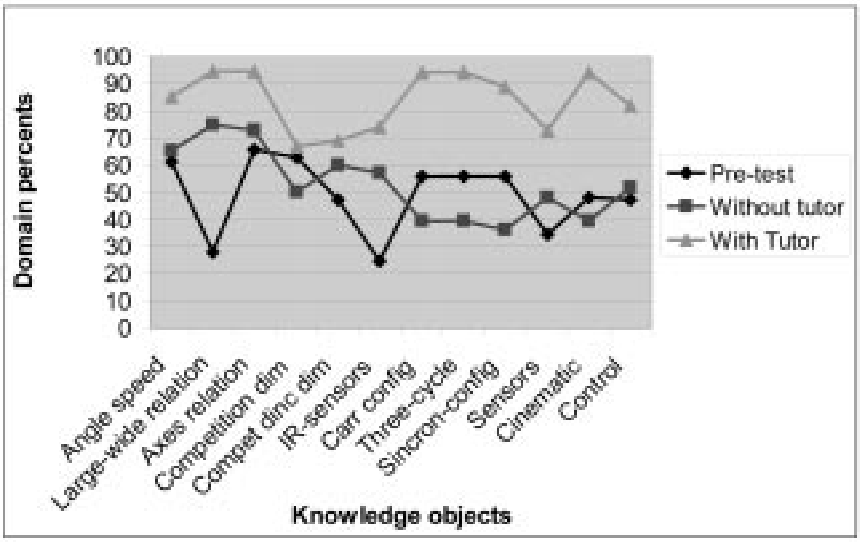

Fig. 17. Results for novice students after performing experiments 1, 2, 3 and 4.

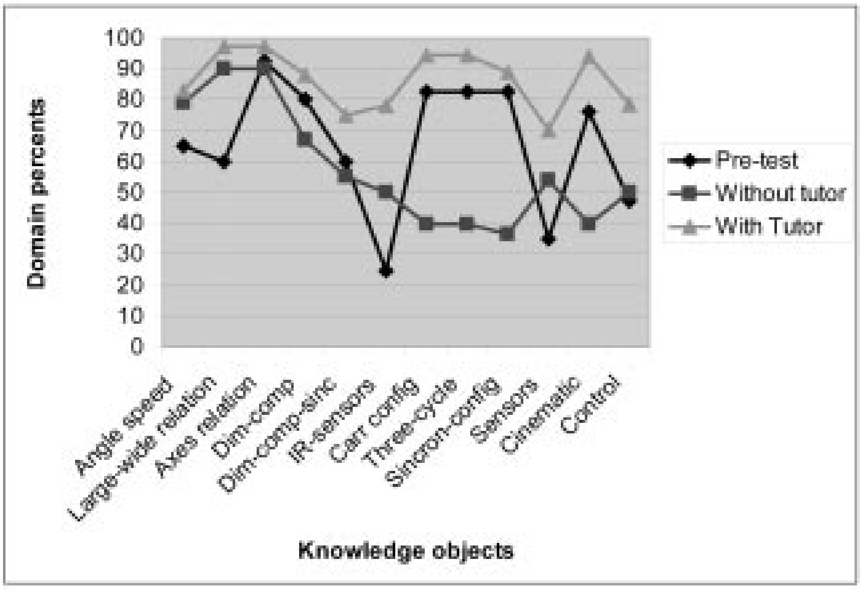

Fig. 18. Results for intermediate students after performing experiments 1, 2, 3 and 4.

support significantly improved their knowledge level of the targeted knowledge objects.

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.

Course evaluation

We evaluated the course in general using students' opinions, based on institutional questionnaires. These questionnaires have 28 specific questions related to teacher skills, the skills developed, the 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 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; they were also competing for the first time.

CONCLUSIONS AND FUTURE WORK

We have developed a course for teaching basic robotics at undergraduate level with several didactical and technical enhancements, helping the students lo learn in a more effective way. The first part of the course uses an intelligent tutoring system coupled with a virtual laboratory for mobile robots. This semi-open learning environment[1] provides the student with the opportunity to learn through free exploration, but with specific performance criteria that guide the learning process. In virtual laboratories, the student has the liberty to explore different parameters to observe their effects inside the virtual laboratory.

The semi-open learning environment also has several advantages: *flexibility*, which allows different models to be considered for each student in a common framework; *adaptability*, whereby an initial model of a new learner is obtained by considering similar student models; and *modularity*, allowing it to be easily extended to include more students, 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 processes. We have evaluated the system with an initial group of students. The results show that students who used the semi-open virtual environment with the help of a tutor performed better, and students with intelligent support significantly improved 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 methods for the tutor. We are integrating an affective behavior model with the intelligent tutoring system in order to provide students with a suitable response from a pedagogical and affective point of view [26]. We are also adding collaborative capabilities for student interaction in the semi-open virtual laboratory. Finally, we are introducing new domains to the generic architecture, in basic education and in medicine.

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