A Probabilistic Relational Student Model for Virtual Laboratories

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Abstract

We have developed an intelligent tutoring system coupled with a virtual laboratory, which constitute a semi–open learning environment. This environment provides the student with the opportunity to learn through exploration within a virtual laboratory, while achieving the expected learning objectives. The key element of this environment is a novel representation for the student model based on probabilistic relational models. This student model has several advantages: flexibility, user adaptability, high modularity and facilities for 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, to decide the best way to guide the student in following experiments, and to re-categorize the students based on the results. We have implemented a tutor for a virtual robotics laboratory, and evaluated the system with an initial group of 20 students. The results show that students who explore the virtual environment with the help of the tutor have a better academic skills, and also that the predictions of the student model are generally accurate.

1. Introduction

Student models adapt the learning experience to suit the learner's perceived needs [16]. However, the practical difficulty in building reliable student models is defining the role for student models. When we couple an intelligent tutor within a virtual laboratory, providing the student with the opportunity to learn through free exploration, but with specific performance criteria that guide the learning process, we need a novel model which takes care of the balance between the virtual laboratory capabilities versus the tutoring labor based on decisions such as when to interrupt an experiments, the student performance follow up, task planning, help needing etc. [12].

This work is focused on the student model which is the key component of such a system. Student models adapt the learning experience to suit the learner's perceived needs [16]. However, the practical difficulty in building reliable student

models is defining their role. The debate is centered on what kind of information the student model should provide. On one hand, student models provide only information about the latest student input to which the system has to react. On the other hand, student models provide a detailed description of student's knowledge and psychological makeup. Neither extreme is feasible or desirable.

In the student model, the cognitive state of a learner is inferred from two parts: the previous data about the student and the student's behavior during the interaction with the system [4]. Both involve uncertainty, so a model that considers it is required. Thus, the main objective of this work is to develop a student model representation for an intelligent tutoring system of a virtual laboratory, using probabilistic relational models.

Probabilistic relational models provide a new approach to student modeling, integrating the expressive power of Bayesian networks and the facilities of relational models. They allow the domain can be represented in terms of entities, their properties, and their relations. The dependency model is defined at the class level, allowing it to be used for any object in the class [9].

We selected, as a case study, a simulated mobile robotics laboratory. There has been much interest in achieving educational and research objectives through the use of small, low cost and configurable mobile robotics kits; so the students have to deal with integrated systems building, real world issues, teamwork, multidisciplinary information and critical thinking [8]. Using a 3-D simulator, the students can explore the first concepts in the course: mechanical design, sensors and control, before they start building the physical robot [18].

We present the development of an intelligent tutoring system coupled with a robotics virtual laboratory. There are three main contributions of this work:

1. It offers a semi-open learning environment providing the students with the opportunity to learn through exploration with different aspects and parameters for the experiments, while enabling them to achieve the expected learning objectives.

2. It incorporates a probabilistic relational student model which has several advantages: flexibility, it allows to consider different models for each student and each experiment in a common framework; adaptability, by obtaining an initial model of a new

learner from similar student models; modularity, it can be easily extended to include more students, experiments and lessons; and extensibility, it can be easily extended to other domains.

3. Based on the relational student model, we developed a system to assess the effectiveness of learner exploration behavior and experiment performance at different levels of granularity, to allow the tutor to decide the best way to guide the student during interaction and to re-categorize him to adapt the help needed by the student, and determine the complexity of the following experiments.

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2. Bayesian nets on student models

In the student model the cognitive state of a learner is inferred from two parts: the previous data about the student and student's behavior during the interaction with the system [4]. Both involve uncertainty, so a model that considers it is required. Some useful tools used to do that are Bayesian nets.

The Bayesian nets [13] provide a joint probability distribution over a set of attributes, and express this as the product of n conditional probabilities distributions (CPDs). They are directed acyclic graphs (DAGs), with one node corresponding to each attribute. Each node provides a probability distribution over the values of the attribute it represents, conditional upon the values of the attributes represented by its parents. Its whole probability is given by (1):

$$P(v_1,...v_n) = \prod_i P(v_i \mid P(v_i)) \qquad (1)$$

Where $P(v_i)$ are the parents of v_i in the graph.

The conditional probabilities can be stored in tabular form (matrix) or through a functional representation. The net also represents the conditional independencies of a variable. Probabilistic reasoning or probabilistic propagation consists in the propagation of the evidence of known variables through the net to know the posteriori probabilities of the unknown variables.

3. Related work: Probabilistic student models

Student models based on Bayesian networks (BN) have been used to allow important simplifications in diagnosis, the task to infer the cognitive state of the student from observable data [5, 7, 11, 19]. However, the effort required to define the network structure, the difficulty to obtain the parameters and the computational complexity of the inference algorithms, have to be considered to implement these types of models.

Other difficulties for using Bayesian nets for student modeling have been detected. The human expert should define the network structure, the conditional dependencies, and also the initial parameters to feed the model. This task is hard because he/she needs to find a general model for several

students, but each student has different knowledge, abilities, preferences and academic antecedents.

Some authors decided to simplify the problem using nodes representing student's abilities and nodes which represent binary knowledge questions. They grouped different level questions according to five categories [14]. But this kind of system can only diagnose the abilities one by one with binary questions using a tree structured BN.

Other systems, like OLAE [11], generate the Bayesian net parameters for each resolved problem using student behavior during the solution process. It considers four node types, including rules, rules application, facts and actions. Off line, the system obtains it and propagates the evidence across the net. This makes it difficult to apply it in virtual laboratories and other web based systems, which work on line. Additionally, the solution process does not give enough information to obtain the student model. Other difficulties for using Bayesian nets for student modeling have been detected [14]. For example, it is hard to assess the effective exploration and define which learning objectives were reached using the same general model for several students.

We proposed the use of Probabilistic Relational Models (PRM) [9] to represent the student model, allowing the domain to be represented in terms of entities, their properties, and the relations between them.

4. The probabilistic relational models

Koller states in [9] "…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 $X_1,...,X_n$. 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. Also, PRM's explicitly use the relational structure of the model, an attribute of an object to depend also on attributes of related objects. A PRM specifies the probability distribution using the same underlying principles used in specifying 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 probabilistic parameters.

Probabilistic relational models allow each attending student in the same model to be represented. Each attribute, x.a, of the individual student x, is directly influenced by only a few other parameters related with this student. Each class represents the set of parameters of several students, like in databases, but the model also includes the probabilistic dependencies between classes for each student.

PRM's allow a compact and natural representation of student models for virtual laboratories. The initial values can be obtained from data of previous student interaction using statistical techniques. The basic idea is to obtain an initial model of the student from other student models with similar

characteristics; and then to improve the model with data from learner interaction with the virtual laboratory.

5. Relational student model

In order to apply PRM's to student model we have to define the main objects involved in the domain. As shown in figure 1, the main classes, related with students and experiments, were set of 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, allowing it to be used for any object in the class.
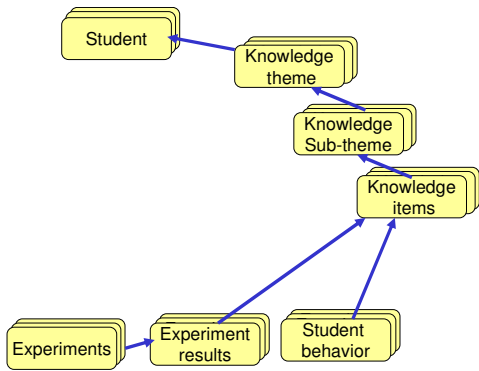
Figure 1. Conditional probabilistic dependencies between some classes related with experiments.

Some attributes in this model represent probabilistic values. This means than an attribute represents a random variable that is related to other attributes in the same class or in other classes as in a Bayesian network, as is shown in figure 2. A PRM specifies the probability distribution using the same underlying principles used in specifying Bayesian networks. In general, we expect that each of the random variables in a PRM is directly influenced by only a few others.
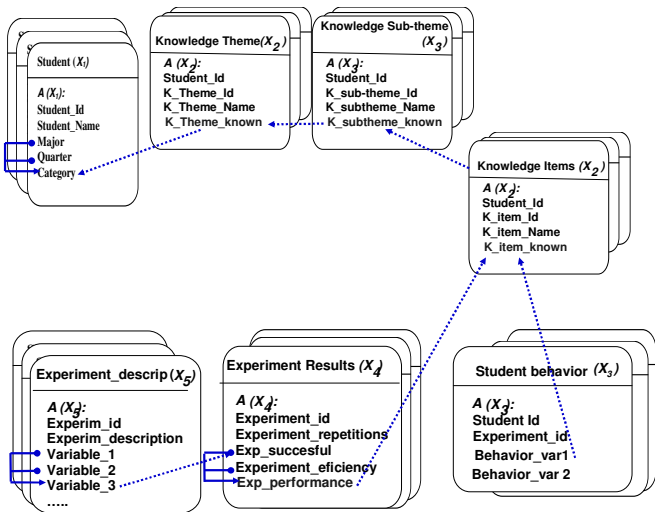

Figure 2. Relational student model showing conditional probabilistic dependencies between some attributes and classes related with the experiments.

Some of the main advantages of PRM's can be extended to a relational student model. First, from a PRM model we can define several Bayesian nets with different conditional probabilistic values. Second, it is easy to organize the classes by levels to improve the understanding of the model. Third, it allows organization by several structures of levels facilitating the model construction.

From model of figure 2, we can obtain a hierarchical Bayesian net, as shown in figure 3. We partitioned the experiment class, according to our object of interest, creating two subclasses: experiment performance and experiment behavior, which constitutes the lowest level in the hierarchy. The intermediate level represents the different knowledge–items (concepts) associated to each experiment. These items are linked to the highest level which groups the items in sub-themes and themes, and finally into the students' general category.

In this environment it is necessary to register student data and background, before students use the virtual lab to obtain an initial model of a new learner from similar student models. We defined three categories of students: novice, intermediate and expert. Each category has the same Bayesian net structure, obtained from the relational student model, but different CPTs are used.
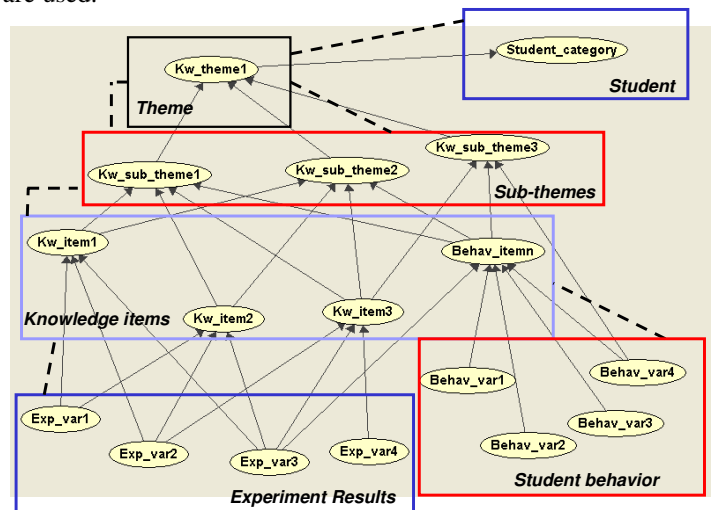

Figure 3. A bayesian net derived from relational student model.

When a student performs an experiment in the virtual lab, the relational student uses the inference mechanism for each category, and it is used to propagate evidence from the experiments' evaluation to the knowledge items, and then to the knowledge sub-themes and to the knowledge themes. Based on this evidence and the accumulated evidence from previous experiments, the system decides to re–categorize the student. After each experiment, the knowledge level at the different level of granularity –items, sub-themes and themes, is used by the tutor to decide if it should provide help to the student, and at what level of granularity.

We selected, as a case study, a simulated mobile robotics laboratory. Using a 3-D simulator, the students can explore the first concepts in the course: mechanical design, sensors and control, before they start building the physical robot [18]. We

present the development of an intelligent tutoring system coupled to a robotics virtual laboratory.

6. System architecture

The basic architecture of the robotics virtual laboratory is depicted in figure 4. The main elements are: initial categorization module, learning environment, experiment design and the intelligent tutoring system.
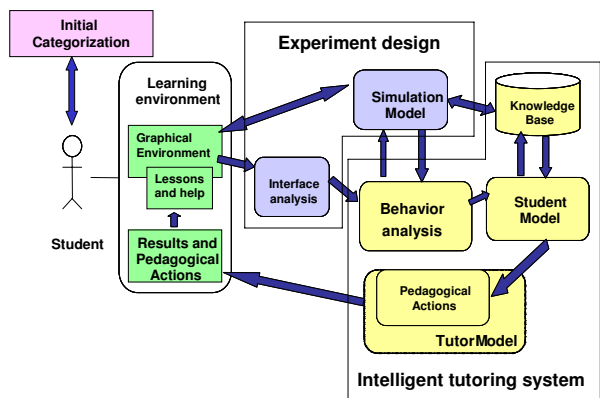
Figure 4. Basic architecture of the robotic virtual laboratory.

6.1. Initial categorization

Using a relational probabilistic model, we designed an approach to increase the possibilities of the learning environment to interact in an appropriate way with student. Following the idea that virtual laboratories are non invasive, we used the previous student information based on the academic background. In figure 5 is shown the initial categorization model, based on PRM's.

When academic background of each student is introduced to the system, the relational model propagates evidence of approved courses to obtain an initial categorization
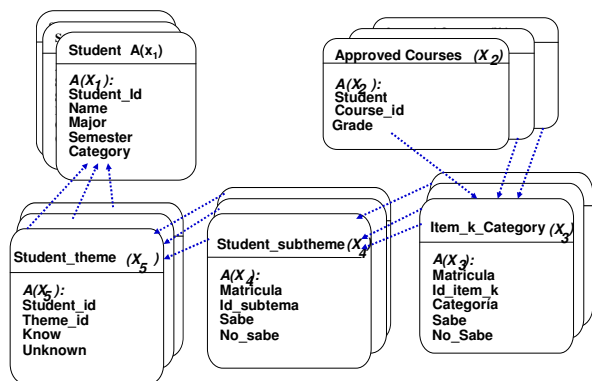
Figure 5. Initial categorization model.

For example, if a student has approved the courses Physics 2, Mathematics III, and a Topic of Robotics, this student has a major probability to know the knowledge item *angle speed*. The specific Bayesian net is shown in figure 6.
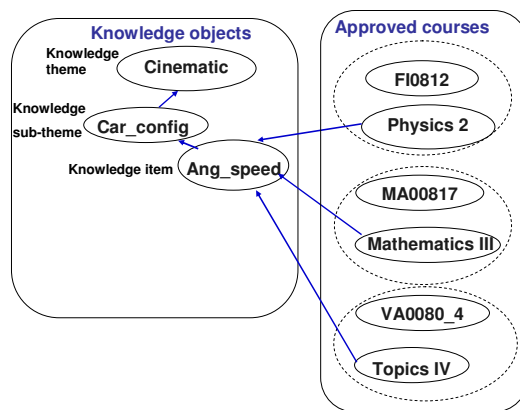
Figure 6. Fragment of the Bayesian net to define initial student categorization.

In table 1 are shown the results for novice and intermediate category for four knowledge items, obtained from the background of two typical students.

Table 1. Examples of the initial categorization for different knowledge items, for novice and intermediate students.

Knowledge item	Novice category P(K-item=Know)	Intermediate category P(K-item=Know)
Angle speed	0.3229	0.8891
Large-wide relation	0.3148	0.8689
Axes relation	0.44.21	0.8845
Robot-dimensions	0.2712	0.8872

The evidence from previous approved courses is propagated to each knowledge item of the defined experiments. Then these results are propagated to sub-themes and themes, to finally define an initial category. A fragment of this Bayesian net structure is shown in figure 7.
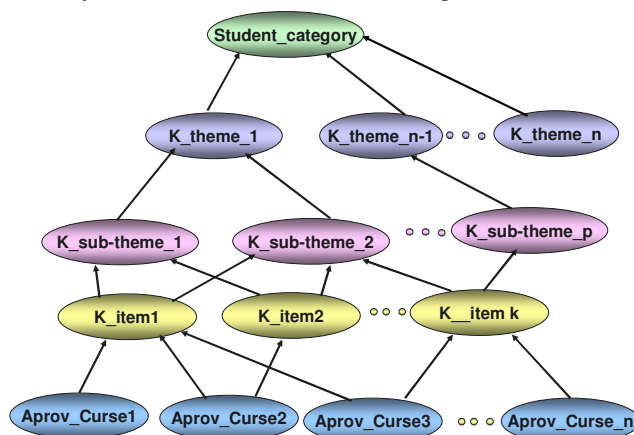
Figure 7. Fragment of the Bayesian net to define initial student categorization.

The conditional probabilities tables (CPTs) between the experiments' parameters and the items, and then between items and sub-themes, and sub-themes and themes, are all represented using Noisy-OR models [6]. This simplifies knowledge acquisition, as only one parameter is required for

each parent of each variable in the graphical model. The CPTs for each category are stored to be used across each student experiment. For example, the category defines the complexity of the path to be followed by a mobile robot.

6.2 Learning environment

Open learning environments often involve simulation where learners can experiment with different aspects and parameters of a given phenomenon to observe the effects of these changes [17]. 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, in the specific features that influence the learner ability to explore adequately, and the lack of a clear definition of what constitutes effective exploration behavior [2, 4].

There are several authors [1, 3, 10] which present open learner models. 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.
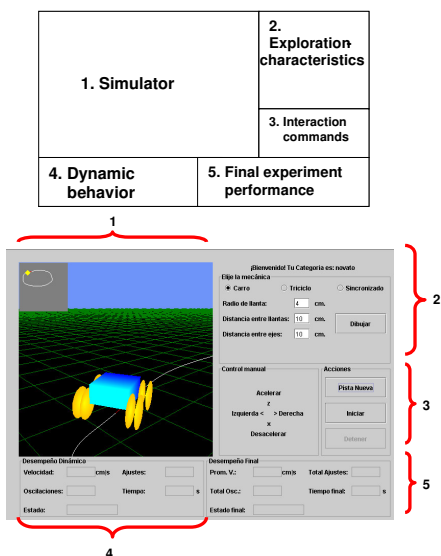

Figure 8. Main elements of the virtual laboratory interface.

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 are shown in figure 8.
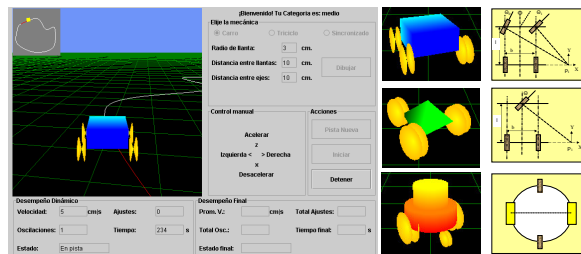

Figure 9. Mechanical and kinematical aspects can be explored.

An example of the mechanical and kinematical characteristics for explorations is shown in figure 9.

6.3. Experiment design.

We initially consider a line following experiment, which requires some basic knowledge in mechanical design, sensors, control theory and programming from the students. For the first experiment, it is assumed that the mechanical and sensor configurations of the robot were previously defined. The main difficulty of this experiment 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 robotics design concepts, as shown in figure 9. The educational goals are: (i) to learn mechanical aspects of mobile robotics, and (ii) to practice with kinematical models using manual control. The interface is shown in figure 8.
- 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 10.
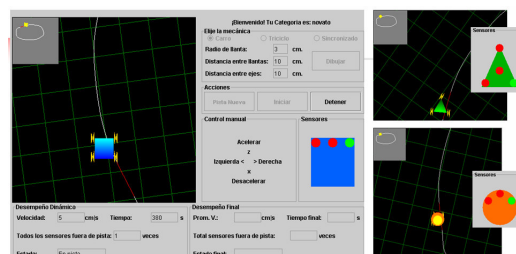

Figure 10. Experiment with infrared sensor.

- The fourth experiment is related with actuators and control theory. We defined a set of basic robotics instruction for control a mobile robot. We constructed an interpreter to simulate automatic control program. The student needs to write his/her control program previously, taking care of the mechanical and sensor positions defined in the experiments 2 and 3. To use the virtual laboratory the students need to load his/her control program and the

system verifies the syntax of the program. If there are no errors, they can select the execute button and the system shows the robot movements based on the control program.

The results of each experiment, in terms of exploration and performance, are considered in the relational student model for each defined category. When the student selects another experiment, he/she is re-categorized considering the previous results and the new knowledge items related with this new experiment.

6.4. The intelligent tutoring system

We defined the elements of this module working in the following way: when a student performs an experiment in the virtual lab, the experiment results and student exploration behavior, are mapped to probabilistic values of experiment results. In figure 11 it is shown a fragment of the model used to convert evidence from the results of the first experiment.
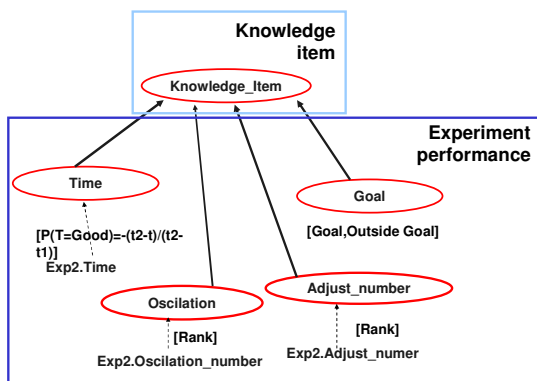

Figure 11. Taking evidence from experiment results.

In the following step, the system converts the experiment results toward probabilistic values.
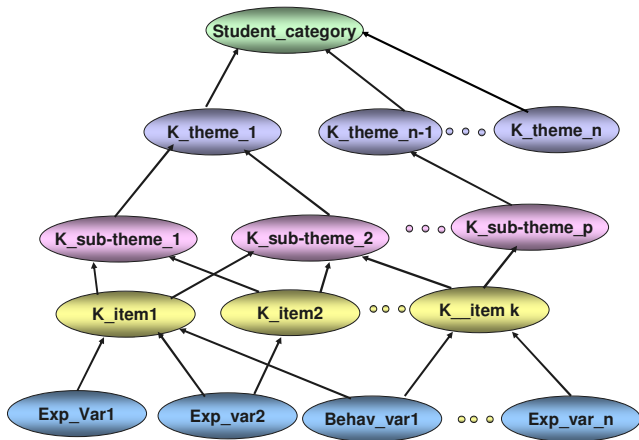

Figure 12. The Bayesian net used to infer evidence from experiment results.

Then, these probabilistic values are used to propagate evidence from the experiments' evaluation to the knowledge objects of the knowledge base. The student's knowledge base

changes at the different levels of granularity in the same way as the initial categorization of figure 7, while the learner explores the relevant exploration parameters, and as they reach goals related with the experiment performance. It is shown in figure 12.

We included also a dynamic model to add, based on previous experiments, the accumulated evidence from previous interaction for the same experiment. This can be represented in a dynamic model as shown in figure 13.

After each experiment is finished by a student, the results are used by the tutor module to decide the best way to guide the student. If the experiment goals are below the expected value, the tutor applies then an influence diagram [15] to decide the best pedagogical action, such help or lessons.
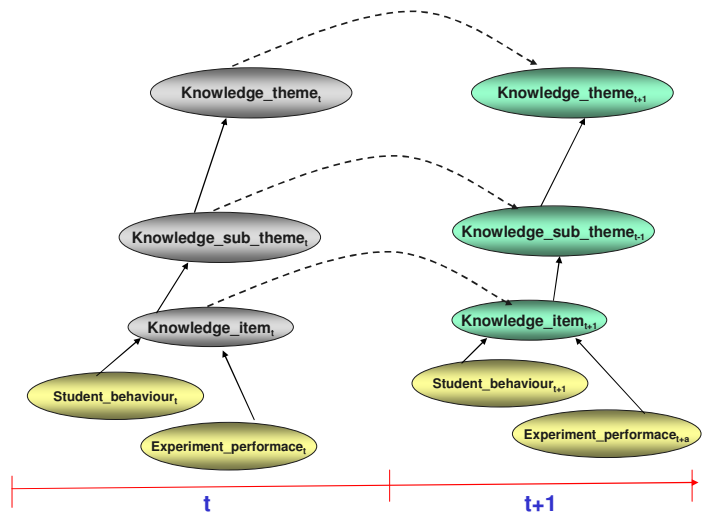

Figure 13. Fragment of dynamic Bayesian net to propagate experiment results toward a new student categorization.

The relational student model is integrated within a data base and an authoring tool that facilitates the construction of the model for different experiments and domains. The instructor can specify the relevant exploration and performance parameters for each knowledge item, and then the relationships between items, sub-themes and themes.

7. 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. The intelligent tutor analyzes the learners' explorations, as they used the system. 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.

7.1. Virtual laboratory evaluation.

Participants. The subjects were Electronic Engineers and Computer Sciences 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, chosen randomly, to test the Virtual Lab issues with intelligent tutor and without it.

Experiment design. In the experiment, all subjects used the virtual laboratory. 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.

7.2. Results

Figures 14 and 15 show the initial categorization results (predicted) versus the pre-test for the first knowledge objects targeted by experiment 1 (the graphs show the averages of the 20 students). The knowledge values for the pre-categorization model were defined based only on academic background.
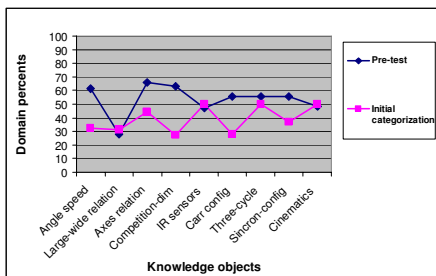
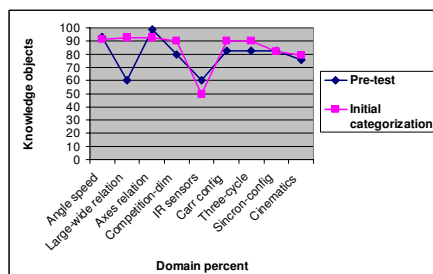**Figure 14.** Initial categorization vs pre-test for novices.

Figure 15. Student categorization vs pre-test for intermediate.

For the students categorized at the intermediate level (figure 15), 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.

Figures 16 and 17 summarize the results after experiments 1, 2, 3 and 4, for the control and experimental groups (according to the initial categorization). 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.
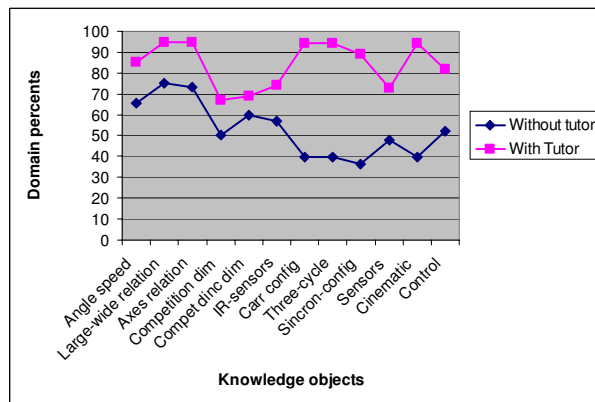
Figure 16. Results for novice students after performing experiments 1, 2, 3, and 4.

The results show that the students who explore the virtual environment with the help of the intelligent tutor have the better performance. As shown in these figures, students with intelligent support improved their knowledge level of the targeted knowledge objects significantly.
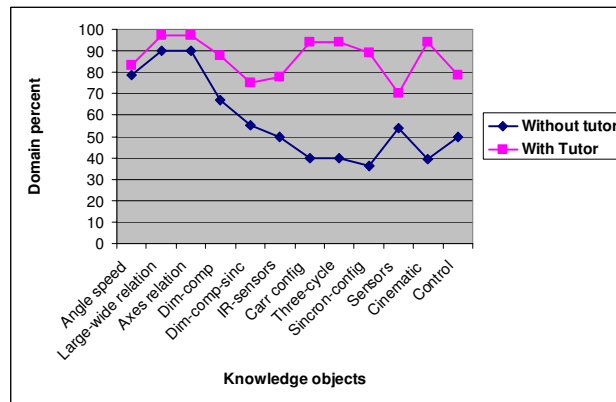
Figure 17. Results for intermediate students after performing experiments 1, 2, 3, and 4.

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.

8. Conclusions and future work

We have developed an intelligent tutoring system coupled with a virtual laboratory, which constitute a semi–open learning environment. We presented a relational student model. It takes care of the balance between the virtual laboratory capabilities versus the tutoring labor based on the best decisions of pedagogical actions.

Using relational student model, it is easy to organize the classes by levels to improve understanding the model and facilitate the inference process. It allows organization by several structures of levels facilitating the model construction.

This model 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 others domains.

The model keeps track of the students' knowledge at different levels of granularity, combining the performance and exploration behavior in several experiments, to decide the best way to guide and to re-categorize the student.

We have evaluated the system with an initial group of students. The results show that students who explore the virtual environment with the help of the tutor improved significantly their knowledge of the target knowledge objects.

We are currently extending our evaluation of the tutor with more experiments. We are designing also a model to integrate an affective behavior to the intelligent tutoring system in order to provide students with a suitable response from a pedagogical and affective point of view.

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