Evaluating Spatial Knowledge through Problem-Solving in Virtual Learning Environments

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Abstract. Modeling the cognitive processes of learners is fundamental to build educational software that are autonomous and that can provide highly tailored assistance during learning [3]. For this purpose, many student models have been developed. However to the best of the authors' knowledge there is no model for the evaluation and teaching of spatial reasoning. This paper describes how a knowledge representation model for modeling cognitive processes of learners is applied to represent the knowledge handled in a complex and demanding task, the manipulation of the robotic arm CanadarmII, and more specifically, how a training software for CanadarmII manipulations can benefit from the model to evaluate spatial mental representations and provide customized assistance.

1 Introduction

Many complex tasks involve relying on complex spatial representations. One such task is the manipulation of the CanadarmII arm on the international space station (ISS). The CanadarmII arm is a robotic arm with seven degrees of freedom (represented in figure 1). Handling it is a demanding duty since astronauts who control it have a limited view of the environment, being rendered by only three monitors. Each one show the view usually obtained from a single camera at a time among about ten cameras mounted at different locations on the ISS and on the arm. Guiding a robot via cameras requires several skills such as selecting cameras and setting views for a situation, visualizing in 3D a dynamic environment perceived in 2D and selecting efficient sequences of manipulations. Moreover, astronauts follow an extensive protocol that comprises many steps, because a single mistake (for example, neglecting to lock the arm into position) can engender catastrophic consequences. To accomplish the task, astronauts need a good ability to build spatial representations (spatial awareness) and to visualize them in a dynamic setting (situational awareness).

Our research team is working on a software program named CanadarmTutor [11] for training astronauts to the manipulation of CanadarmII in a manner similar as in the coached sessions on a lifelike simulator that astronauts attend. CanadarmTutor's interface (cf. fig. 2) reproduces part of CanadarmII's control panel. The interface's buttons and scrollwheels allow the user to associate a camera to each monitor and adjust the zoom, pan and tilt of the selected cameras. The arm is controlled via keyboard keys in inverse kinematics or joint-by-joint mode. The text field at the lower part of the window list all the actions done so far by a learner and display the current state of the simulator. The menus allow setting preferences, selecting a learning program and requesting tutoring feed-back or demonstrations.

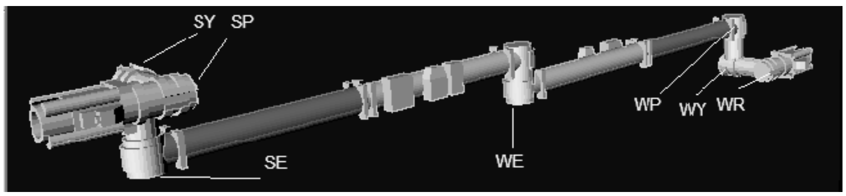

Fig. 1. A 3D model of the CanadarmII arm illustrating the 7 joints.

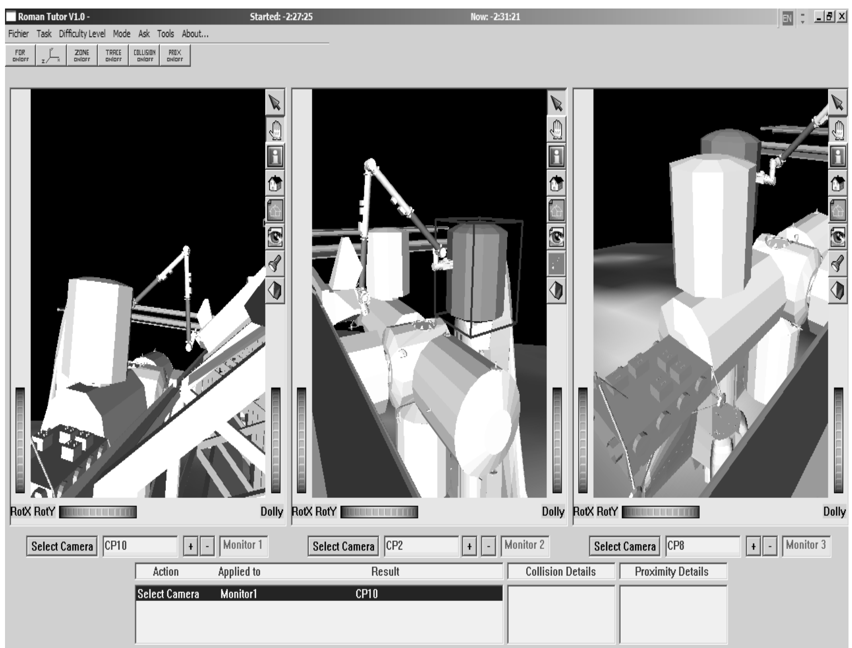

Fig. 2. The CanadarmTutor interface.

The task of interest in this paper is moving the arm from one configuration to another, according to the security protocol. The aim of the work presented here is to describe the relevant cognitive processes of learners that interact with CanadarmTutor so that the integrated virtual tutor can precisely follow their reasoning and grant a tailored assistance. The remainder of the article is organized as follows. First, a literature review on spatial cognition is given. Then, the next sections describe a cognitive model and its extension. We then present the first results obtained from its application in CanadarmTutor. Finally, the last section announces further work and present conclusion.

2 Spatial Cognition

Since more than fifty years, many researchers have been interested in the mental representations involved in spatial reasoning. The concept of cognitive maps was initially proposed by Tollman [18], following the observation of rats behavior in mazes. He postulated that rats build and use mental maps of the environment to take spatial decisions. O' Keefe & Nadel [16] gathered neurological evidences for cognitive maps. They observed that some nerve cells of rats (called place cells) are activated similarly when a rat is in a same spatial location; this is observed regardless of what the rat is doing. These results and the results of other studies allowed O' Keefe & Nadel to formulate the assumption that humans not only use egocentric space representations (which encode the space from the person's perspective), but also resort to allocentric cognitive maps (independent of any point of view). According to O'Keefe & Nadel [16], an egocentric representation describes a route to follow to go from one place to another, and it is composed of an ordered set of stimuli/response associations. Usually, this knowledge is gained through experience, but it can also be acquired directly from descriptions (for instance, from textual route instructions). Route navigation is very inflexible and leaves little room for deviation. Indeed, choosing correct directions with landmarks strongly depends on the relative position of a person to landmarks. Consequently, a path deviation can easily disturb the achievement of the whole navigation task. An incorrect encoding or recall can also compromise seriously the attainment of the goal. According to Tversky [20], egocentric representations may be sufficient to travel through an environment, but they are inadequate to perform complex reasoning. For reasoning that requires inference, humans build cognitive maps that do not preserve measurements but keep the main relationships between elements. These representations do not encode any perspective but makes it possible to adopt several perspectives. Cognitive maps are also prone to encoding or recall errors. But it is generally easier to recover from an error, when relying on cognitive maps than on an egocentric representation. Recently, place cells have also been discovered in the human hippocampus [6]. In the light of this result and other researches carried out during the last decades in neuroscience, experimental psychology and other disciplines, there is no doubt that humans use allocentric and egocentric space representations [14].

Cognitive models of spatial cognition have been proposed. However, they are usually specialized in some particular phenomena of spatial cognition such as visual perception and motion recognition [5], navigation in 3D environments [10, 13] and mental imagery and inference from spatial descriptions [4]. Models that attempt to give a more general explanation of spatial cognition have no computational implementation (for example, [7]). Moreover, to the best of the authors' knowledge there is no model for the evaluation and teaching of spatial reasoning and spatial representations.

Cognitive models of spatial cognition can generally be viewed as proposing structures for modelling cognitive processes at either a symbolic level or at a neural level (for example [13]). Symbolic models that rely on allocentric representations [4, 5, 8] usually represent –with some particularities– spatial relationships as relations of type “a r b” where “r” is a spatial relationship such as “is at the left of” or “is on top of” and where “a” and “b” are mental representations of objects. Unlike allocentric representations, egocentric representations are typically represented as sets of relationships between the self and objects. This representation is in accordance with researchers in psychology such as Tversky [20] that suggest that cognitive maps are encoded as sets of spatial relationships in semantic memory. Since cognitive maps are key to complex spatial reasoning, tutoring software that diagnose and teach complex spatial reasoning requires the capacity to evaluate semantic knowledge.

3 The Theoretical Model

Our model for describing cognitive processes in tutoring systems [7] is inspired by the ACT-R [1] and Miace [12] cognitive theories, which attempt to model the human process of knowledge acquisition. It is a symbolic model that organizes knowledge as (1) semantic knowledge [15], (2) procedural knowledge [1] and (3) episodic knowledge [19]. This paper does not explain the episodic memory part of our model since it is not central to the discussion, here.

The semantic memory contains descriptive knowledge. Our model regards semantic knowledge as concepts taken in the broad sense. According to recent researches [9], humans consider up to four concept instances simultaneously (four dimensions) in the achievement of a task. However, the human cognitive architecture is able to group several of them to handle them as one, in the form of a vector of concepts [9]. We call described concepts these syntactically decomposable concepts, in contrast with primitive concepts that are syntactically indecomposable. For example, whereas the expression “PMA03 isConnectedToTheBottomOf Lab02” is a decomposable representation, the symbol “PMA03”, “isConnectedToTheBottomOf” and “Lab02” are undividable representations. The concept “PMA03 isConnectedToTheBottomOf Lab02” represents the knowledge that the “PMA03” ISS module is connected at the bottom of the “Lab02” ISS module on the ISS (assuming the ISSACS coordinate system). In this way, the semantic of a described concept is given by the semantics of its components. While concepts are stored in the semantic memory, concept instances occur in working memory, and are characterized by their mental and temporal context [12]. Thus, each occurrence of a symbol such as “Lab02” is treated as a distinct instance of the same concept.

The procedural memory encodes the knowledge of how to attain goals automatically by manipulating semantic knowledge. It is composed of procedures which fires one at a time according to the current state of the cognitive architecture [1]. Contrary to semantic knowledge, the activation of a procedure does not require attention. For example, when someone evaluate automatically “PMA03 isConnectedToTheBottomOf Lab02” to obtain the value “true”, the person does not recall the knowledge explicitly. It is a procedure acquired following the repeated recall of the “PMA03 isConnectedToTheBottomOf Lab02” semantic knowledge from memory. As Mayers et al., [12], we differentiate primitive procedures and complex procedures. Whereas primitive procedures are seen as atomic actions, the activation of a complex procedure instantiates a set of goals, to be achieved either by a complex procedure or a primitive procedure. We consider goals as a special type of semantic knowledge. Goals are intentions that humans have, such as the goal to solve a mathematical equation, to draw a triangle or to add two numbers [12]. At every moment, the cognitive architecture has one goal, a semantic knowledge that represents an intention. Our model is based on the proposal of many researchers that goals obey the same constraints as semantic knowledge. i.e. they are competing to become the activated goal, they can be forgotten and their activation vary according to the context [2]. In our model, this assumption means that cognitive steps may not always need to be achieved in a sequential order. Goals are realized by means of procedural knowledge execution. There can be many correct and incorrect ways (procedures) to achieve a goal. Our model represents goals as a special type of described concepts. A goal has zero or more components, which are concept instances. These instances are the object of the goal. For example, the concept instance “Cupola01” could be component of an instance of the goal “GoalSelectCamerasForViewingModule”, which represents the intention to select the best camera for viewing the “Cupola01” ISS module. The components of a goal are determined by the complex procedure that instantiated the goal.

4 The Computational Model

Our model describes knowledge entities (concepts, procedures and goals) according to sets of slots. A slot associates values to knowledge entities. Each value can be a pointer to another knowledge entity, or arbitrary data such as character strings or integers.

Concepts are encoded according to seven slots. The “Identifier” slot is a character string used as a unique reference to the concept. The “Metadata” slot provides general metadata about the concept (for example, authors’ names and a textual description). The “DLReference” slot describes the concept with a logical formalism. This logical description allow inferring logical relationships between concepts such as “is-a” relationships. These relationships between concepts should be seen as a feature to facilitate the task of knowledge authors, by allowing them to define goals, procedures and described concepts that can be applied to concepts that satisfy a concept’s logical description. This originality of our model is described in details in [7]. The “Goals” slot contains a goals prototypes list; it provides information about goals that students could have and which use the concept. “Constructors” specifies the identifier of procedures that can create an instance of this concept. “Components” is only significant for described concepts. It indicates, for each concept component, its concept type. Finally, “Teaching” points to some didactic resources that generic teaching strategies of a tutoring system can employ to teach the concept.

Goals have six slots. "Skill" specifies as a string the necessary skill to accomplish the goal, “Identifier” is a unique name for the goal, “Metadata” describes the goal metadata, "Parameters" indicates the types of the goal parameters, "Procedures" contains a set of procedures that can be used to achieve the goal, and “Didactic-Strategies" suggests strategies to teach how to achieve that goal.

Ten slots describe procedures. The “Metadata” and “Identifier” slots are the same as for concepts/goals. “Goal” indicates the goal for which the procedure was defined. “Parameters” specifies the concepts type of the arguments. For primitive procedures, “Method” points to a Java method that executes an atomic action. For complex procedures, “Script” indicates a set of goals to be achieved. “Validity” is a pair of Boolean values. Whereas the first indicates if the procedure is valid and so it always gives the expected result, the second indicates if it always terminate. “Diagnosis-Solution” contains a list of pairs “[diagnosis, strategy]” that indicate for each diagnosis, the suitable teaching strategy to be adopted. Finally, “Didactic-Resources” points to additional resources (examples, exercises, etc.) to teach the procedure.
A graphical tool has been built to ease knowledge authoring.

The model was used to represent the cognitive processes of learners that utilize a Boolean reduction rules tutoring system [7]. Although the model was successfully employed to offer tailored assistance, the model lays the emphasis on procedural knowledge learning and offers less support for semantic knowledge learning. The reason is that there is no structure for modeling the retrieval of knowledge from semantic memory, a key feature of many cognitive theories. As a consequence, it is impossible to specify, for instance, that to achieve a goal, one must be able to recall correctly the described concept “CameraCP5 AttachedTo S1” (the camera CP5 is attached to the ISS module named S1) to use it in a procedure thereafter. Evaluating semantic general knowledge is essential for diagnosing and teaching spatial reasoning, if we take the view that cognitive maps are encoded as semantic knowledge.

6 The Extended Model

To address this issue we extended our model. The extension adds a - pedagogical – distinction between “general” and "contextual” semantic knowledge. We define general knowledge as the semantic knowledge (memorized or acquired through experience) that is true in all situations of a curriculum. For instance, such knowledge is that the approximate length of the end effector of CanadarmII is one meter. To be used properly, general knowledge must (1) be properly acquired beforehand, (2) be recalled correctly and (3) be handled by valid procedures. A general knowledge is a described concept, because to be useful it must represent a relation.

Contextual knowledge is the opposite of general knowledge. It is the knowledge obtained from the interpretation of a situation. It is composed of concepts instances. For example, the information that the rotation value of the joint “WY” of CanadarmII arm is currently 42° is a contextual knowledge obtained by reading the display. Authors do not need to define contextual knowledge, since it is dynamically instantiated by the execution of procedures that represent each learner’s cognitive activity. We added three slots to described concepts. The “General” slot indicates whether the concept is general or not. The “Valid” slot specifies the validity of the concept (true or false), and optionally the identifier of an equivalent valid concept. In addition, the “RetrievalComponents” slot specifies a set of concepts to be instantiated to create the concept components when the concept is instantiated. Table 1 presents a concept encoding the knowledge that the spatial module “MPLM” is connected below the module “NODE2” on the ISS (according to the ISSACS coordinate system). The “Valid” slot indicates that it is an erroneous knowledge and that the valid equivalent knowledge is the concept “MPLM_TopOf_Node2” (cf. table 2). The “DLReference” slot content that is not presented in these tables allow the system to infer that these two concepts are subconcepts of the “SpatialRelationshipBetweenModules" concept that is the concept of spatial relationship between two ISS modules.

Table 1. Partial definition of the concept “MPLM_Below_MPLM2“ concept.

SLOT	VALUE
Identifier	MPLM_Below_Node2
Metadata	Author: Philippe Fournier-Viger, Date : 2007
DLReference	…
Type	GoalRecallCameraForGlobalView
Components	Module, Module
RetrievalComponents	MPLM, Node2
General	True
Valid	False

We added a retrieval mechanism to connect procedures to the general knowledge in order to model the recall process. It works as the retrieval mechanism of ACT-R, one of the most acknowledged unified theory of cognition. We choosed ACT-R, because our model is already based on that theory. A slot named “Retrieval-request” is added to procedures, to express a retrieval request for a concept in semantic memory, by means of patterns. A pattern specifies the identifier of a concept to be retrieved and zero or more restrictions on the value of its components. Table 3 shows the procedure “ProcedureRecallCameraForGlobalView”. The execution of this procedure will request the knowledge of the camera on the ISS that give the best global view of a location taken as parameter by the procedure. The “Retrieval-request” slot states that a concept of type “ConceptRelationshipCameraGlobalView” (a relation that state that a camera gives a global view of a place) or one of its subconcepts is needed, and that its first component should be a place whose concept type match the type of the procedure parameter, and the second component need to be of type “ConceptCamera” (a camera). A correct recall following the execution of this procedure will result in the creation of an instance of “ConceptRelationshipCameraGlobalView” that will be deposited in a temporary buffer with a capacity of one concept instance and made available to the next procedures to be executed.

We have modelled the knowledge for the task of moving a load from one position to another with CanadarmII. To achieve this, we discretized the 3D space into 3D sub spaces named elementary spaces (ES). The spatial knowledge is encoded as described concepts that stand for relations as (1) a camera can see an ES or an ISS module, (2) an ES comprise an ISS module, (3) an ES is next to another ES, (4) an ISS module is at the side of another ISS module or (5) a camera is attached to an ISS module. Moving the arm from one position to another is modelled as a loop where the learner must recall a set of cameras for viewing the ESs containing the arm, select the cameras, adjust their parameters (zoom, pan, tilt), retrieves a sequence of ESs to go from the current ES to the goal, and then move to the next ES. CanadarmTutor detects all the actions like camera changes and entering/leaving an ES. Each of these actions is then considered as a primitive procedure execution. The model does not go into finer details like how to choose the right joint to move to go from an ES to another. This will be part of future improvements.

Table 2. Partial definition of the concept "MPLM_TopOf_NODE2 " concept.

SLOT	VALUE
Identifier	MPLM_TopOf_Node2
Metadata	Author: Philippe Fournier-Viger, Date : 2007
DLReference	…
Components	Module, Module
RetrievalComponents	MPLM, Node2
General	True
Valid	True

Table 3. Partial definition of the procedure "RecallCameraForGlobalView".

SLOT	VALUE
Identifier	RGlobalView
Metadata	Author: Philippe Fournier-Viger, Date : 2007
Goal	GoalRecallCameraForGlobalView
Parameters	(ConceptPlace: p)
Retrieval-request	ID: ConceptRelationshipCameraGlobalView A1: ConceptPlace: p A2: ConceptCamera

7 Evaluating the Knowledge

The model provides mechanisms for evaluating semantic and procedural knowledge. Evaluating procedural knowledge is achieved by comparing a learner's actions to the task description. We consider two types of procedural errors: (1) the learner makes a mistake or (2) doesn't react within a time limit. In the first case, we consider an error as the result of the learner applying an incorrect procedure for its current goal. For instance, a learner could forget to adjust a camera zoom/pan/tilt before moving the arm. In the second case, we consider that the learner either doesn't know any correct procedure for the present goal or doesn't recognize their preconditions. Because our model links goals to procedures that can accomplish them, the tutor has knowledge of all the correct ways to achieve the current goal in both of these situations. For complex procedures that specify sub-goals, the tutor can easily conceive an ordered sequence of valid procedures that allows accomplishing correctly any goal.

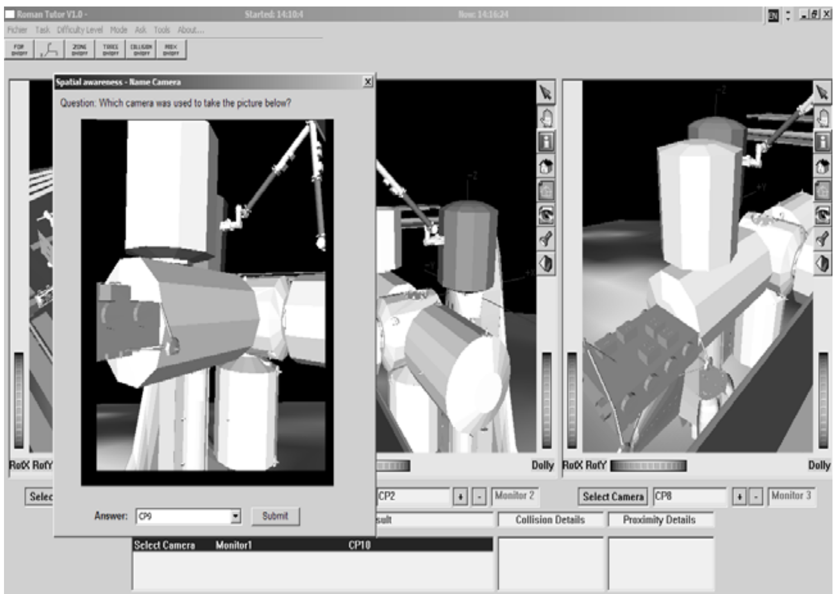

Fig. 3. A camera identification exercise.

In addition to this procedural knowledge evaluation mechanism, the extension of this model provides two ways for evaluating general semantic knowledge. Whereas primitive procedures are detectable, it is only possible to detect the recall of knowledge from semantic memory indirectly. First, the tutoring system can test general knowledge directly with questions. For example, CanadarmTutor may verify the mastery of the described concept "CameraCP9 GivesGlobalViewOf JEM" by showing the learner a view of the JEM module and asking him to identify which camera was used (cf. fig. 3). Other types of questions are also implemented such as to ask to name the closest modules to a given module, or to ask to select the best cameras for viewing one or more modules. Second, general knowledge can be evaluated through problem-solving exercises. Initially, the system assumes that recalls are done correctly. Then, as the training progresses, a better evaluation is achieved.

The result of each procedure makes it possible to infer through backward reasoning if a general knowledge was recalled (the result of the procedure allow deducing the retrieval buffer content). If the learner uses procedures to retrieve a valid knowledge several times, the system increases its confidence that the learner can recall that knowledge. In the case of the likely recall of an erroneous knowledge, the system heightens the probability of a recall error with that knowledge and will decrease its confidence that the learner masters the valid concept(s).

After many exercises and/or questions, the system acquires a detailed knowledge of the strengths and weaknesses of a learner regarding the procedural and semantic knowledge. It uses this information to generate exercises, questions and demonstrations tailored to the learner that will involve the knowledge to be trained for. For instance, if the system infers that a learner possesses the erroneous knowledge that camera "CP10" is a good camera to view the JEM module, it will likely generate direct questions about the corresponding valid knowledge or exercises that involve its recall.

The integrated pedagogical module currently takes pedagogical decisions based on some very simple rules. To teach general knowledge or procedures, the tutor extracts the didactic knowledge –consisting mostly of text hints or explanations –encoded in concepts' or procedures' didactic slots. The tutor also utilizes the spatial relations encoded in the general described concepts to generate dynamic questions. Figure 4 shows such a question that was presented to a learner to test his knowledge of the location of the S1P1TrussRight module. The virtual tutor randomly picked three erroneous question choices based on the spatial relationships. It selected one module that look similar to S1P1TrussRight (S1P1TrussLeft) and two modules that are close to S1P1TrussRight (PVARight01 and S34P34TrussRight01) based on the spatial relationships "lookSimilarTo" and "isConnectedTo".

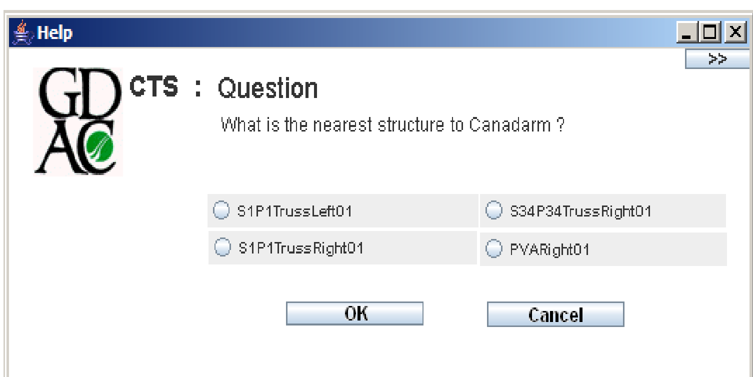

Fig. 4. A contextual question generated by the virtual tutor.

Evaluating semantic knowledge through problem-solving exercise is an interesting alternative to the automatic techniques that require doing it separately from the evaluation of procedural knowledge. For instance, Taricani & Clariana [17] offer an automatic algorithm for the scoring of concepts maps drawn by learners. A concept maps is basically a graph where each node is a concept or concept instance and each link represents a relationship. The main information contained in a concept map can be encoded as general knowledge within our framework and be evaluated according to the process described above.

8 Conclusion and further work

We have presented an original extension of our model for describing domain knowledge in virtual learning environments. The extension offers a solution for evaluating and teaching general semantic knowledge that learners should possesses. Because the model connects semantic knowledge retrieval to procedural knowledge, evaluation of the general semantic knowledge can be achieved directly through questions or indirectly through observation of problem-solving tasks.

Moreover, virtual tutors based on our model should be able to generate better feedback, because they can know how the semantic knowledge recalled is connected to procedures. Furthermore, this paper has showed how this extension can be used to support spatial reasoning. A first work on modeling the knowledge handled in CanadarmTutor has been presented. Conceiving a more elaborate version of the tutor and verifying its effectiveness is part of our ongoing research.

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