Informed Virtual Geographic Environments for Knowledge Representation and Reasoning in Multiagent Geosimulations

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***Abstract*—In this paper, we propose a novel approach that extends our Informed Virtual Geographic Environment (IVGE) model in order to effectively manage knowledge about the environment and support agents' cognitive capabilities and spatial behaviours. Our approach relies on previous well established theories on human spatial behaviours and the way people apprehend the spatial characteristics of their surroundings in order to navigate and to interact with the physical world. The main contribution of our approach is to provide cognitive situated agents with: (1) knowledge about the environment represented using Conceptual Graphs (CG); (2) tools and mechanisms that allow them to acquire knowledge about the environment; and (3) capabilities to reason about this knowledge and to autonomously make decisions and to act with respect to both their own and the virtual environment's characteristics.**

***Keywords*-Informed Virtual Geographic Environments, Knowledge Management, Agent and Action Archetypes, Agentification of Geographic Features, Spatial Situation.**

INTRODUCTION

During the last decade, the Multi-Agent Geo-Simulation (MAGS) approach has attracted a growing interest from researchers and practitioners to simulate phenomena in a variety of domains including traffic simulation, crowd simulation, urban dynamics, and changes of land use and cover, to name a few [3]. Such approaches are used to study various phenomena involving a large number of simulated actors (implemented as software agents) of various kinds evolving in, and interacting with, an explicit description of the geographic environment called Virtual Geographic Environment (VGE).

A critical step towards the development of a MAGS is the creation of a VGE, using appropriate representations of the geographic space and of the objects contained in it, in order to efficiently support the agents' situated reasoning. Since a geographic environment may be complex and large scale, the creation of a VGE is difficult and needs large quantities of geometrical data that characterise the environment as well as semantic information that qualifies space.

In order to yield realistic MAGSs, a VGE must precisely represent the geometrical information which corresponds to geographic features. It must also integrate several semantic notions about various geographic features. To this end, we propose to enrich the VGE data structure with semantic information that is associated with the geographic features [13], [14], [17]. This semantic information is structured using a standard knowledge representation formalism. Finally, we leverage such a structured knowledge representation using a novel model for knowledge management to enhance the support of spatial behaviours of agents in multi-agent geo-simulations.

The rest of the paper is organized as follows: Section I provides a short survey of works on geographic environment representation as well as on agents' spatial behaviours, introduces the *affordance* concept, presents the notion of *knowledge about the environment*, and outlines its importance for spatial agents in order to let them make decisions that take into account the characteristics of the virtual geographic environment in which they evolve. Section II briefly summarises our IVGE computation model. Section III introduces the concept of *Environment Knowledge* (EK) and details the method that we propose to define it using Conceptual Graphs (CGs) [22]. It also presents the environment knowledge base along with the associated decision making process which involves an inference engine. Section IV provides a description of the proposed agent model and presents patterns of spatial behaviours. To conclude, Sections V and VI illustrate and discuss, through a case study, how environment knowledge management supports situated agents's spatial behaviours in virtual urban environments.

I. RELATED WORKS

A. Environment Representation

Virtual environments and spatial representations have been used in several application domains. For example, Thalmann *et al.* proposed a virtual scene for virtual humans representing a part of a city for graphic animation

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purposes [4]. Donikian *et al.* proposed a modelling system which is able to produce a multi-level data-base of virtual urban environments devoted to driving simulations [25]. More recently, Shao *et al.* proposed a virtual environment representing the New York City's Pennsylvania Train Station populated by autonomous virtual pedestrians in order to simulate the movement of people [21]. However, since the focus of these approaches is computer animation and virtual reality, the virtual environment usually plays the role of a simple background scene in which agents mainly deal with geometric characteristics.

Despite the multiple designs and implementations of virtual environments frameworks and systems, the creation of geometrically-accurate and semantically-enriched geographic content is still an open issue. Indeed, research has focused almost exclusively on the geometric and topologic characteristics of the virtual geographic environment. However, the structure of the virtual environment description, the optimization of this description to support large-scale and complex geographic environments, the meaning of the geographic features contained in the environment as well as the ways to interact with them have received less attention.

B. Spatial Behaviours and Knowledge Management

Research on spatial behaviours investigates the processes that take place when spatial agents representing people or other dynamic actors orient themselves and navigate through complex and large-scale virtual geographic environments [18]. In order to build agents that exhibit plausible spatial behaviours with respect to their capabilities and to the virtual environment characteristics in which they evolve, we need to analyse humans' spatial behaviours in the physical world [29]. We also need to determine how spatial agents can make decisions using knowledge provided by the virtual environment. In this section, we present several works related to *spatial behaviours* and *affordances* and outline the importance of *knowledge about the environment* for the support of agents' spatial behaviours.

Several theories in the field of *human spatial behaviours* have been proposed in order to explain how people navigate in the physical world, what people need to find their ways, and how people's visual abilities influence their decisions [5]. Actually, these theories point out the use of various spatial and cognitive abilities to apprehend the physical world in which people evolve and with which they interact [7]. Weisman identified four classes of environmental variables that influence spatial behaviours in physical worlds: *visual access*; *architectural differentiation*; *signs to provide identification or directional information*; and *plan configuration* [26]. Seidel's study at the Dallas/Fort Worth Airport showed that the spatial structure of the physical environment has a strong influence on people's spatial behaviours [20]. Arthur and Passini introduced the term *environmental communication*, arguing that the built environment and its parts should function as a communication device [1]. Information about the geographic environment along with the spatial and cognitive capabilities are fundamental inputs to the spatial decision-making process [7]. This knowledge include information collected using perception capabilities, memorised information resulting from past experiences, and information provided by the environment it self [8].

Knowledge is an important asset for agents because it allows them to reason about it and to autonomously make informed decisions [28]. By its very nature, knowledge is *disparate* and *heterogeneous* and can be represented in various ways (qualitatively and quantitatively), and can be either structured or unstructured. Knowledge usually includes information about the agent's characteristics, as well as about the description of the geographic environment in which it is situated. Thus, spatial agents require knowledge about their environment in order to reason about it, to infer facts, and to draw conclusions which will guide them to make decisions and to act. A number of challenges arise when creating knowledge about the environment for spatial agents' decision-making, among which we mention: 1) to represent knowledge using a standard formalism; 2) to provide agents with tools and mechanisms to allow them acquire knowledge about the environment; and 3) to infer and to draw conclusions and facts using premises that characterise the geographic environment. The main reason why virtual environments have received less interest from practitioners is that geographic environments may be *complex*, *large-scale*, and *densely* populated with a variety of *geographic features*. As a consequence, formally representing knowledge about geographic environments is usually complex and time consuming [27]. Another issue which needs to be addressed is the way to allow spatial agents to acquire this knowledge in order to autonomously make decisions. There is a need for a *knowledge management* approach: (1) to represent knowledge about geographic environments using a standard formalism; (2) to allow spatial agents to acquire knowledge about the environment; (3) to allow agents to reason using knowledge about geographic environments.

II. Computation of IVGE

In this section, we briefly present our automated approach to compute the IVGE data using vector GIS data. This approach is based on four stages: *input data selection*, *spatial decomposition*, *maps unification*, and finally the generation of the *informed topologic graph* [14]. A detailed description of the spatial decomposition and layers integration techniques is provided in [12], [13], [17].

GIS Input Data Selection: The first step of our approach consists of selecting the different vector data sets which are used to build the IVGE. The input data can be organized into two categories. First, *elevation layers* contain geographical marks indicating absolute terrain elevations [14]. Second, *semantic layers* are used to qualify various types of data in space. Each layer indicates the physical or virtual limits of a given set of features with identical semantics in the geographic environment, such as roads or buildings.

Spatial Decomposition: The second step consists of obtaining an exact spatial decomposition of the input data into cells. First, an elevation map is computed using the Constrained Delaunay Triangulation (CDT) technique. All the elevation points of the layers are injected into a 2D triangulation, the elevation being considered as an attribute of each node. Second, a merged semantics map is computed, corresponding to a constrained triangulation of the semantic layers. Indeed, each segment of a semantic layer is injected as a constraint which keeps track of the original semantic data by using an additional attribute for each semantic layer.

Map Unification: The third step to obtain our IVGE consists of unifying the two maps previously obtained. This phase can be depicted as mapping the $2D$ merged semantic map onto the $2.5D$ elevation map in order to obtain the final $2.5D$ elevated merged semantics map. First, preprocessing is carried out on the merged semantics map in order to preserve the elevation precision inside the unified map. Indeed, all the points of the elevation map are injected into the merged semantics triangulation, creating new triangles. Then, a second process elevates the merged semantics map.

Informed Topologic Graph: The resulting unified map now contains all the semantic information of the input layers, along with the elevation information. This map can be used as an *Informed Topologic Graph* (ITG), where each node corresponds to the map's triangles, and each arc corresponds to the adjacency relations between these triangles. Then, common graph algorithms can be applied to this topological graph, and graph traversal algorithms in particular [13].

III. From Semantic Information to Environment Knowledge

In [15], we proposed a novel model along with a complete methodology for the automated generation of informed VGEs. Then, we presented our abstraction approach which enriches and structures the description of the IVGE, using geometric, topologic and semantic characteristics of the geographic environment. In order to represent semantic information which characterises our informed virtual environment model, we also proposed to use Conceptual Graphs (CGs) [22]. Our aim now is to evolve the semantic information to the level of *knowledge* and hence to build a knowledge-oriented virtual geographic environment in which spatial agents autonomously make informed decisions.

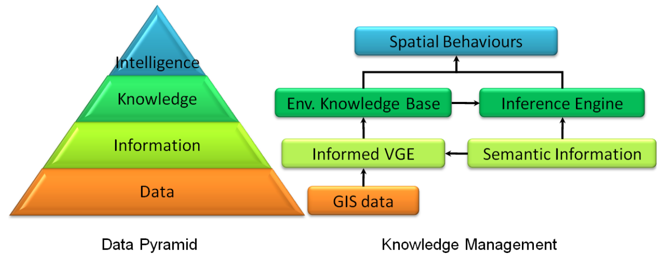

Figure 1: The proposed knowledge management approach; on the left hand side, the pyramid data [11]; on the right hand side, the knowledge management approach relying on our IVGE model and involving a knowledge base coupled with an inference engine to support agents' spatial behaviours.

The process of making an informed decision has been modelled as a pyramid built on data [11] as shown on the left hand side of *Figure 1*. *Data* corresponds to the transactional, incremental physical records [11]. In our IVGE model, this data corresponds to the geometric and geographic data provided by GIS. In and of itself this data is not sufficient to support spatial agents' decision-making. This data must be organized into information in order to be useful. *Information* is data that has been contextualized, categorized, often calculated (from initial data), corrected, and usually condensed [19]. In our IVGE model, information corresponds to the description of the IVGE resulting from the exact spatial decomposition of the geographic environment and enhanced with semantic information. Information often contains patterns within it and is sometimes useful for simple spatial behaviours such as motion planning. However, the context of these spatial behaviours can only be formed using some *knowledge*. *Knowledge* provides the next step of data organisation. For information to become knowledge, the context of the information needs to include predictive capabilities. Using predictive capabilities of knowledge, spatial agents can autonomously make informed decisions. The more complex and voluminous the underlying data sets are, the more effort is required to progressively organise it so that it becomes knowledge useful to the agents' decision-making. However, since our IVGE description is structured as a hierarchical topologic graph resulting from the geometric, topologic, and semantic abstraction processes, and since the semantic information is expressed using conceptual graphs, we are able to build knowledge about the environment to support agents' spatial behaviours.

A. Environment Knowledge

We define the notion of *Environment Knowledge* (EK) as a specification of a conceptualization of the environment characteristics: the objects, agents, and other entities that

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are assumed to exist in the informed virtual geographic environment and the relationships that hold among them. Hence, EK is a description (like a formal specification of a program) of the spatial *concepts* (geographic features) and *relationships* (topologic, semantic) that may exist in a geographic environment. This description is provided by users in order to enrich the qualification of the geographic features which characterise the environment. It is expressed using a standard formalism which is close to natural language and computer tractable.

Let us emphasize that enhancing a multi-agent geosimulation with EK, allows spatial agents to reason about the characteristics of the virtual geographic environment. Practically, EK is composed of *spatial concepts* (i.e., ask queries and make assertions) and spatial relationships (i.e., describe actions and behaviours). Our aim is to improve the perception-decision-action loop on which rely most agent models. Considering Newell's pyramid [16] which comprises the reactive, cognitive, rational and social levels of agent behaviours, we mainly focus on the knowledge acquisition process in order to support the decision-making capabilities of spatial agents. *Figure 2* illustrates two elements: (1) the knowledge acquisition process, and (2) the action archetype process, that we introduced in order to extend Newell's initial pyramid.

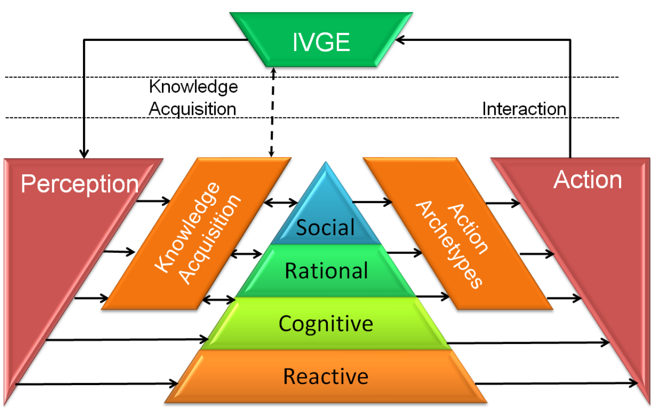

Figure 2: The enhanced perception-decision-action loop.

The management of the environment knowledge is composed of two main parts: (1) an *Environment Knowledge Base* (EKB) which relies on spatial semantics represented using the CG formalism; and (2) an *Inference Engine* (IE) which allows to manipulate and to acquire environment knowledge in order to provide spatial agents with the capability of reasoning about it.

Conceptual graphs are widely used to represent knowledge [22], [23]. Actually, CGs enable us to formally represent spatial semantics characterizing our IVGE model and allow us to build a structured *Environment Knowledge Base* (EKB) based on a finite bipartite graph [24]. The EKB allows MAGS users to represent, using a standard formalism, the information characterizing the virtual environment as well as the objects and agents it contains. Moreover, the EKB enables us to explicitly specify *affordances* [6] in order to support the agents spatial interactions with the informed virtual geographic environment in which they evolve. The environment knowledge base, which is part of this process relies on the notion of *spatial semantics*. *Spatial Semantics* (SS) consists of a structured, conceptualised, and organised representation of geographic features, agents, and objects that an informed virtual geographic environment may contain. Spatial semantics relies on two types of nodes: *semantic concepts* and *semantic relations*. Semantic concepts represent entities such as agents, objects and zones as well as attributes, states and events. Semantic relations represent the relationships that hold among semantic concepts.

The environment knowledge can be constructed by assembling percepts. In the process of assembly, semantic relations specify the role that each percept plays and semantic concepts represent the percepts themselves. Semantic concepts involve two types of functions; *referent* and *type*. The function *referent* maps semantic concepts to generic markers denoted by names starting with an asterisk * or individual markers usually denoted by numbers. For example, if the referent is just an asterisk, as in $[HOUSE : *]$, the concept is called a generic semantic concept, which may be read as *a house* or *some house*. The function *type* maps concepts to a set of type labels. A semantic concept s_c with type (s_c)= t and reference (s_c)= f is displayed as $[t{:}f]$. The function type can also be applied to relations. For example, if the referent is a number [HOUSE:#80972], the field to the left of the colon contains the type label HOUSE, the field to the right of the colon contains the referent #80972 which designates a particular house.

To sum up, the EKB contains knowledge about the informed virtual geographic environment that an agent may use. This knowledge is provided basically by users to enrich the qualification of the geographic features which characterise the IVGE. Finally, this knowledge is structured using semantic concepts and relations expressed using conceptual graphs.

B. Inference Engine

Now that we have defined the environment knowledge base as a structure which contains explicit descriptions of geographic features using CGs, let us describe the Inference Engine (IE) which is part of our knowledge management approach. The IE is a computer program that derives answers from our environment knowledge base. Therefore, the IE must be able to logically manipulate symbolic CGs using formulas in the first-order predicate calculus. In order to

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acquire knowledge about the virtual environment, agents use the IE and formulate queries using a semantic specification that is compatible with CGs. Agents interpret the answers provided by the IE and act on the environment. They can also enrich the EKB by adding new facts that result from their observation of the virtual environment (*Figure 3*).

In this sub-section, we first present how CGs allow us to map knowledge about the environment into first-order logic formulas. Then, we provide a short survey of existing tools that support the manipulation of CGs. We also discuss the capabilities of these tools to provide a programming language with CGs, related operations, and inference engine. Finally, we present the Amine platform [9], a platform to manipulate CGs using an inference engine embedded in PROLOG+CG language.

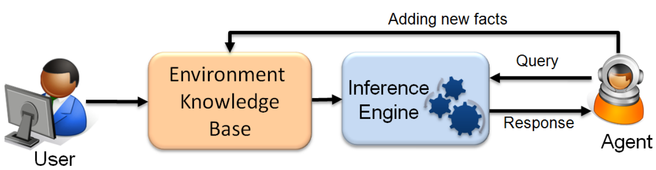

Figure 3: The inference engine uses the EKB for the purpose to answer queries formulated by agents.

Conceptual graphs offer the opportunity to map knowledge about the environment into formulas in the first-order predicate calculus.

Using formulas in the first-order predicate calculus, it is possible to build tools that allow spatial agents to manipulate knowledge about virtual environments represented using CGs. Moreover, it is possible to build tools that allow for logic and symbolic manipulations of environment knowledge and provide the opportunity to infer and to predict facts or assumptions about virtual environments. Several tools can be used to manipulate CGs (Amine, CGWorld, CoGITaNT, CPE, Notio, WebKB). These tools can be classified under at least 8 categories of tools: CG editors, executable CG tools, algebraic tools (tools that provides CG operations), KB/ontology tools, ontology server tools, CG-based programming languages, IDE tools for CG applications and, agents/MAS tools. The category "‘*CG-based programming language*"' concerns any CG tool that provides a programming language with CG, related operations, and inference engine. Only Amine belongs to this category, with its programming language: *Prolog+CG*. Therefore, we propose to use the Amine platform and Prolog+CG in order to logically manipulate symbolic CGs and to provide spatial agents with an inference engine that allows them to query the environment knowledge, to acquire environment knowledge and reason about it.

Using Amine platform, users can build an environment knowledge base (EKB) using CGs and query the Amine's inference engine (IE) to derive new knowledge from the content of the EKB using queries. The Amine platform provides a graphic user interface to support the manipulation of the EKB. Agents are able to send queries, during the simulation process, in order to acquire the knowledge they need to make a decision, using the Prolog+CG language which is provided by the Amine platform. These queries are processed by the IE which interrogates the EKB and sends back the response to agents.

In order to illustrate such a querying process, let us consider the following simple environment knowledge, composed of a set of two facts which provide an idea of the use of conceptual structures as a Prolog+CG data structure:
cg([Man:Mehdi]←agnt-[Study]-loc→[University]).
cg([Man:Mehdi]←agnt-[Play]-obj→[Soccer]).

And the following request: "‘*Which actions are done by Man Mehdi ?*"'
?- cg([Man:Mehdi]←agnt-[x]).

The answer provided by the Amine platform using its Prolog+CG inference engine is:
x = Study;
x = Play;

Now that we introduced the main parts of our environment knowledge management approach, namely EKB and IE, we detail in the following section the notions of agent and action archetypes and the way we use them to build spatial behaviours.

IV. From Environment Knowledge to Spatial Behaviours

When dealing with MAGS involving a large number of spatial agents of various kinds, the specification of their attributes and associated spatial behaviours might be complex and time and effort consuming. In order to characterise our spatial agents, we propose to specify: (1) the agent archetype, its super-types and sub-types according to the semantic type hierarchy; (2) the agent category (such as actor, object, and spatial area); and (3) the agent spatial behavioural capabilities, including moving within the IVGE content, perception of the IVGE and of other spatial agents. In the following subsections we discuss these elements.

A. Agent Archetypes

In our environment knowledge management approach, the description of agents as well as objects and geographic features (spatial areas and zones) is enriched with semantic information. This means that these spatial agents belong to a semantic type hierarchy. Using the semantic type hierarchy allows us to take advantage of *inheritance* mechanisms. Hence, when modelling a MAGS involving a large number of agents, we only need to specify the attributes that are associated with the highest-level types of agents that we call agent archetypes rather than repeatedly specifying them for each lower-level agents. Let us define the Prolog+CG rule used to build a semantic type-hierarchy as follows: *Supertype* > *Subtype1*, *Subtype2*, ..., *SubtypeN*.

Below is an example of a portion of semantic type-lattice expressed in Prolog+CG whose graphical representation is provided in *Figure 4*. Note how each line conforms to the rule given above: *Entity* > *Physical*, *Abstract*.
Physical > *Object*, *Process*, *Property*.
Object > *Animate*, *Inanimate*.
Animate > *Human*, *Animal*, *Plant*.
We now explain this example. The example starts at the top of the lattice with Entity. This super-type is then declared to have two immediate sub-types: *Physical*, and *Abstract*. The *Abstract* node is not associated with any subtype, and so remains a leaf node. The *Physical* node is given three immediate subtypes: *Object*, *Process*, *Property*, each of them being associated with subtypes. These subtypes may also have subtypes, and so on down the lattice.

Another important characteristic of agent archetypes is the *multi-inheritance* property which allows an agent type to belong to two (or several) different agent archetypes and hence to inherit from their characteristics. Let us consider the following example:
Adult > *Woman*, *Man*.
Young > *Girl*, *Boy*.
Female > *Woman*, *Girl*.
Male > *Man*, *Boy*.

Let us notice that *Woman* occurs at several places. This is allowed, as long as there is no circularity (i.e., as long as a type is not specified to be a subtype of itself) whether immediately or indirectly.

There is a fundamental difference between an *archetype* on the one hand, and *instances* of that type on the other hand. For example, while *SchoolBus* is an archetype, *SchoolBus1* and *SchoolBus2* are instances of that archetype. Instances are members of the group of entities which is named by the archetype. The archetype is the name of the group.

In Prolog+CG, we have two ways of saying that a type has an instance: (1) we can simply declare it as an individual in the referent of some CG; (2) we can declare it at the top of the program in a catalog of individuals. A catalog of individuals for a given type is written as follows:
Archeype = *Instance1*, *Instance2*, ..., *InstanceN*.

B. Action Archetypes

Since our research addresses the simulation of spatial behaviours, it has been influenced by some basic tenets of

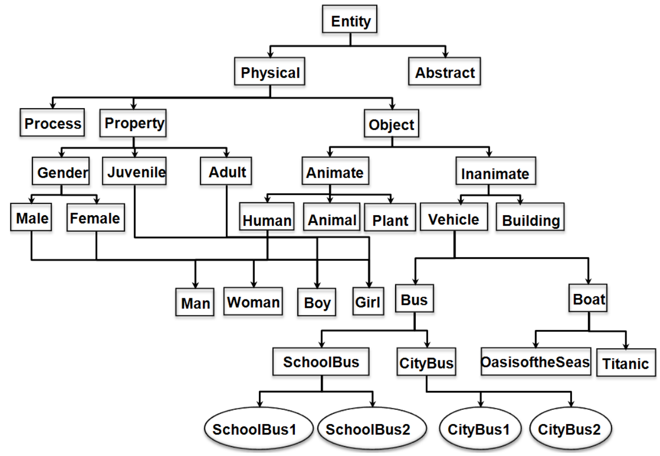

Figure 4: A graph of *Semantic Type Lattice* with instances attached to agents archetypes (circle shapes).

activity theory [2]. In particular, our approach to manage environment knowledge rests on the commitments in activity theory that: (1) activities are directed toward objects, zones, or actors [10]; (2) activities are hierarchically structured; and (3) activities capture some context-dependence of the meaning of information [2];

Theoretically, the common philosophy between our approach and activity theory is a view of the environment from the perspective of an agent interacting with it. Practically, we borrowed from activity theory two main ideas: (1) the semantics of activities and objects are inseparable [10]; and (2) activities, objects as well as agents are hierarchically structured [2].

We define an action archetype as a pattern of activities which are associated with agent archetypes. Hence, an action archetype describes a situation which involves one or several agent archetypes. We define an action archetype as a lattice of actions.

V. Case Study: Human agents taking buses

In this section, we present a case study that illustrates how the IVGE model and the proposed knowledge management approach are used in practice. This case study aims to illustrate how spatial agents representing humans leverage the environment knowledge management approach that we propose. In order to acquire knowledge about the environment and to reason about it, spatial agents apprehend the virtual environment and make decisions according to their types and capabilities and taking into account its characteristics. In this example, a few human agents representing students and workers interact with the IVGE and our EKB in order to plan their path using a bus to get to their final destinations (university and office). This case study also involves a few agents representing bus stations.

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Figure 5: The IVGE representing a part of Quebec city where the spatial behaviour simulation takes place with five geo-referenced locations.

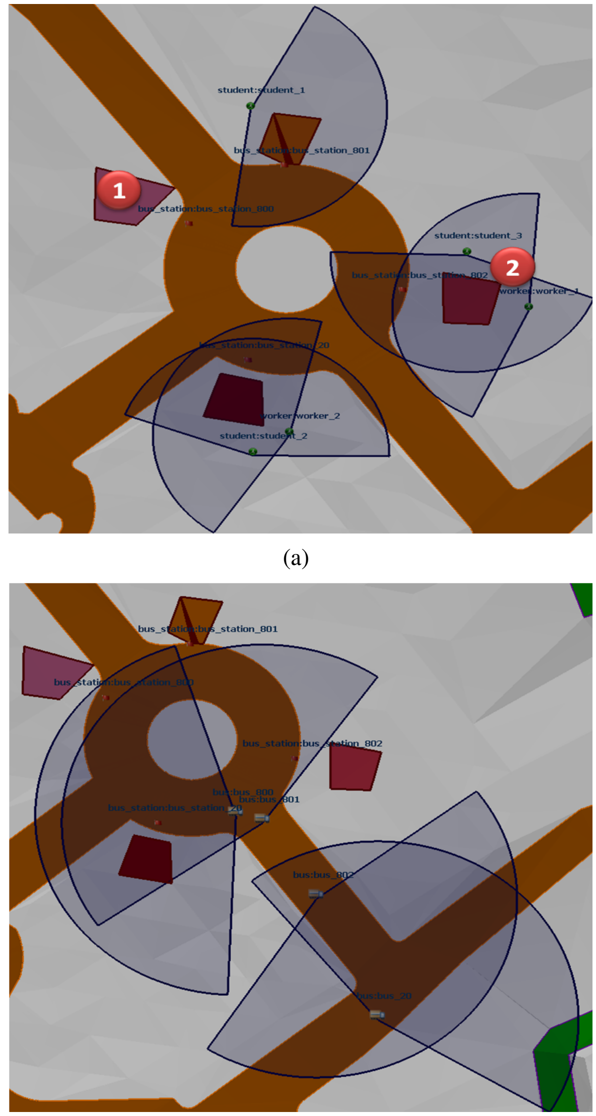
Let us consider three agent archetypes: *Bus*, *Student*, and *Worker* and several action archetypes including *STOP*, *GO*, *GETIN*, *WALK* and *ROLL*. The Bus archetype represents the different kinds of buses including city buses, school buses, etc. The Student archetype includes schoolchildness, pupils, students, etc. The Worker archetype represents working persons. This case study involves an informed virtual geographic environment representing a part of Quebec City (*Figure 5*). An environment knowledge base (EKB) is created using the Amine platform. In this EKB, we first specified the different semantic information that qualify our virtual urban environment. Second, we specified the above introduced agent archetypes namely, *BUS*, *STUDENT*, and *WORKER*. Two IVGE instances are specified: (1) *HUMANNAV* representing a view of the IVGE including the different geographic zones on which an agent of type human can move;(2) *VEHICLENAV* representing a view of the IVGE including the different geographic zones on which an agent of type vehicle can move. Besides, we specify the following facts: students and workers use buses to respectively reach universities and work places; humans walk on human navigable zones; vehicles roll on vehicle navigable zones; buses stop at stations.

In addition, two instances of buses, two instances of stations, and two instances of destinations are defined: Bus1, Bus2, Station1, Station2, w, and u . Bus1 which stops at station1 goes to the workplace w. Bus2 which stops at station2 goes to the university u.

cg([BUS: Bus1]←agnt-[GO]-loc→[WORKPLACE:w]).
cg([BUS: Bus2]←agnt-[GO]-loc→[UNIVERSITY: u]).
cg([BUS: Bus1]←agnt-[Stop]-loc→[STATION: Station1]).
cg([BUS: Bus2]←agnt-[Stop]-loc→[STATION: Station2]).

Now that the agent archetypes are specified, and the facts which characterise their instances are defined, we carry out the simulation in which two agents of type *student* and three agents of type *worker* interact with the IVGE in which they evolve in order to localise the appropriate station from which they can catch the right bus to reach their final destinations. For simplification purposes, agents of type bus follow a pre-defined computed paths (*Figure 6(b)*). Agents of type student and worker start by identifying their own locations within the IVGE. Next, they interrogate the EKB in order to know which bus they should take in order to reach their final destinations (*Figure 6(a)*). The student agent asks the following query: *which bus goes to the university?*

?- cg([?]←agnt-[GO]-loc→[UNIVERSITY]).



(a)

(b)

Figure 6: Stations, student and worker passengers, and buses: (a) 3 students and 2 workers agents (green icon); (b) 4 agents of type *Bus* approaching the stations. Agents either students, workers, or buses are associated with their respective perception fields which are highlighted in blue.

The answer provided by the Amine platform is: x = *Bus2;*

Then, the student agent asks the following query: *where does Bus2 stop at?*

?- cg([BUS: Bus2]←agnt-[STOP]-loc→[?]).

The answer provided by the Amine platform is: x = *Station2;*

Once the answer is provided by the Amine platform, agents plan paths using this semantic description. Agents move towards the appropriate bus station, then wait for the bus (*Figure 6(b)*). Since our agents are endowed with perception capabilities, they are able to detect when a bus arrives at the station. The agent bus is also endowed with the same spatial capabilities and waits at the station until all the agents get in it.

VI. Conclusion and Discussion

In this paper, we presented a knowledge management approach which aims to provide spatial agents with knowledge about the environment in order to support their autonomous decision making process. Our approach is influenced by some basic tenets of *activity theory* [2] as well as by the notion of affordance [6]. It is based on our IVGE model to represent complex and large-scale geographic environments. It uses the *Conceptual Graphs* formalism to represent knowledge about the environment(*Environment Knowledge*) structured as an Environment Knowledge Base (EKB). This approach also includes an inference engine which uses the Prolog+GC language to interrogate, infer and make deductions based on facts, cases, situations, and rules stored within the EKB.

Our environment knowledge management approach is original in various aspects. First, a multi-agent geo-simulation model which integrates an informed virtual geographic environment populated with spatial agents capable of acquiring and reasoning about environment knowledge did not exist. Second, a formal representation of knowledge about the environment using CGs which leverages a semantically-enriched description of the virtual geographic environment has not yet been proposed. Third, providing agents with the capability to reason about a contextualised description of their virtual environment during the simulation is also an innovation that characterises our approach.

Nevertheless, some limits which characterise our environment knowledge management approach still need to be addressed. This approach, in its current version, is a proof of concept which demonstrates the capability of our IVGE model to : 1) integrate knowledge about the environment; 2) to allow agents to reason about it using an inference engine. Although the provided scenario is simplified, it illustrates the advantages of extending our IVGE model by: 1) using a standard knowledge representation formalism (Conceptual Graphs) and; 2) integrating an inference engine such as the Amine platform.

When the agent is acting, it uses the environment knowledge base, its observations of the virtual environment, and its goals and abilities to choose what to do and to update its own knowledge. Hence, the environment knowledge base corresponds to the agent's long-term memory, where it keeps the knowledge that is needed to act in the future. This knowledge comes from prior knowledge (provided by MAGS users) and is combined with what is learned from data and past experiences. The beliefs, intentions and desires of the agent correspond to its short-term memory. Although a clear distinction does not always exist between long-term memory and short-term memory, this issue might be addressed as part of the extension of our knowledge management approach. Moreover, there is feedback from the inference engine to the environment knowledge base, because observing and acting in the world provide more data from which the agents can learn. Evolving and allowing the agent model to learn from such data is another challenging task.

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