A Novel Spatial Behavioral Approach for Agent-Based Crowd Simulation

Mehdi Mekni

***Abstract*—** Crowd is an emergent, complex, spatially constrained phenomenon raised by the local interactions of a large number of individuals. Managing these interactions implies both low level mechanisms such as navigation and path planning in virtual geospatial environments, and high level behaviors qualified as social behaviors. Most existing simulation models deal with the navigation process, leading to the emergence of macroscopically identifiable groups. However, these models do not provide means to individuals to reason about groups, and so to take into account groups in social behaviors. Moreover, these models do not benefit from a rich and abstracted representation of the virtual environment. In this paper, we propose a novel behavioral approach to simulate high-level decision mechanisms based on social characteristics. These mechanisms enable the support of social agents evolving in and interacting with informed virtual geospatial environments. Such virtual environments are abstracted in order to support large scale geographic spaces. We show that this agent-based model allows taking into account different psychological and sociological theories in order to provide realistic and sophisticated groups management. Finally, we show the interest of our approach to crowd simulation thanks to its application to the simulation of crowd control in urban environments.

***Keywords*—** Virtual Humans, Informed Virtual Geospatial Environments, Environmental Abstraction, Social Behavior, Crowd Simulation.

I. Introduction

Understanding social behaviors such as the crowd phenomenon has reached a rapidly growing audience from a variety of disciplines, either animation for entertainment goals, or simulation for validation and safety reasons. However, most of the current approaches usually focus on physical interactions occurring between individuals in crowds. These approaches do not consider the behavioral aspects neither the interactions with the physical environment. Though, the high-level decisions of individuals are strongly influenced by their belonging to groups, be they emergent like in crowds, or set like a family. Indeed, the influence of a group can be so strong that it may imply a complete behavioral change of an individual, as it the case in panic or rioting situations.

One candidate approach to simulate crowds is Multi-Agent Geo-Simulation (MAGS). MAGS is a modeling and simulation paradigm which aims to study phenomena in a variety of domains involving a large number of heterogeneous actors (implemented as software agents) evolving in, and interacting with, a Virtual representation of the Geospatial Environment (VGE) [1]. Crowd phenomena take place in a spatial environment, and ignoring the characteristics of this environment would greatly decrease the quality of crowd simulations [2]. A critical step towards the development of an efficient crowd simulation tool is the creation of a VGE, using appropriate representations of the geographic space and of the sensors evolving in it, in order to efficiently support the agent situated reasoning. Since a geographic environment may be complex and of large scale, the creation of a VGE is difficult and needs large quantities of geometrical data originating from the environment characteristics (terrain elevation, location of objects and agents, etc.) as well as semantic information that qualifies space (trees, buildings, etc.). In order to yield realistic crowd simulations, a VGE must precisely represent the geometric 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 with semantic information that is associated with the geographic features. A number of challenges arise when creating such a semantically-enriched and geometrically-accurate representation of a VGE, among which we mention [3]: 1) automatically creating an accurate geometric representation of a 3D VGE; 2) automatically integrating the geometric representation with several types of semantic information; 3) abstracting the virtual environment in order to support large scale geographic environments; and 4) making use of this representation in "situated reasoning" algorithms. Examples of such algorithms include path planning and navigation which aims to support agent mobility within the with respect to the environment's characteristics (obstacles, land cover, terrain shape, etc.).

In this paper, we aim at gaining better insight in social behaviors as well as the modelling of virtual geospatial environment. We propose a bottom up approach of the crowd phenomenon, by making it emerge from the sum of individual behaviors and interactions between individuals or with the physical environment. We particularly focus on the high-level decision mechanisms related to groups and social considerations, by building our model on well-established sociological and psychological theories. Nevertheless, our model fits in the continuity of recent agent-based approaches by extending the agents reasoning abilities, while taking advantage of existing reactive behavioral models. The proposed model also builds on top of spatial agent capabilities to interact with virtual geospatial environments.

Mehdi Mekni is with the University of Minnesota, Crookston Campus, Crookston, MN, 56716 USA (phone: 218-281-8222; fax: 218-281-8080; e-mail: mmekni@ umn.edu).

The rest of the paper is organized as follows. Section 2 also provides an overview on the importance of virtual geospatial environments to support agent interactions with the virtual environment in which it evolves. It also presents related works on crowd simulation as well as social behaviors either from a computer science or a sociological point of view. This section also provides an overview on the process of abstraction of virtual environments. Section 3, introduces a new model to automatically build informed virtual geographic environments it also provides an overview of our social agent's behavioral model. Section 4 details the high-level decision mechanism and the social behaviors of our agents. Section 5 highlights some simulation results, and presents an illustration of the concepts introduced in this paper. Finally, Section 6 concludes with the perspectives of our work.

II. Related Work

A. Virtual Geospatial Environments

GIS data are mainly represented in two forms [4]: raster and vector formats. The raster format subdivides semantic information into regular squares or square regions representing discrete, contiguous land areas. This approach generally presents averaged quantitative data, whose precision depends on the subdivision size. The vector format exactly locates semantic information with arbitrary complex geometric shapes. This approach generally presents one qualitative object per defined shape.

The VGE exploitation of these data is generally done in two ways. First, the grid method is the direct mapping of the raster format, and can also be applied to the vector format (Fig.1) [5]. The advantage of this discrete method is that multiple semantic data layers are easily merged in the same geometric representation [6]: the locations where data can be stored are predefined by the grid cells. The main drawback of this method is the problem of localization accuracy, which makes it difficult to position information that is not aligned with the subdivision [7]. Another disadvantage of the grid approach is that its memory complexity depends on the chosen cell resolution, which makes it difficult to represent large environments with fine precision. This method is mainly used for animation [8] or large crowd simulation [9] because of the fast data access it provides.

Second, the exact geometric subdivision method consists of subdividing the environment in convex cells defined by the original vector format. The convex cells can be obtained by several algorithms, among which the most popular is the Constrained Delaunay Triangulation (CDT) [10]. The CDT produces triangles while keeping the original geometric shapes whose boundaries are named constraints. The first advantage of the exact subdivision is that it preserves the input geometry, allowing accurate visualization of the environment at different scales.

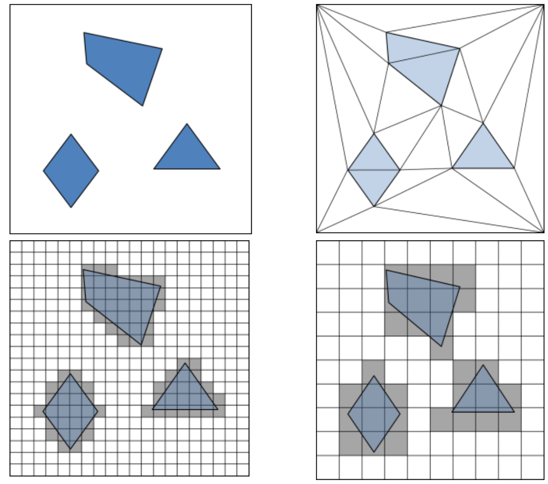


Fig 1: The two common cell decomposition techniques used to represent environments.

Another advantage is that the memory complexity of this approach only depends on the number of shapes, not on the environment's extent and subdivision as is the case for grids. The main drawback of this approach is the difficulty of merging multiple semantic data for partially overlapping shapes. This method tends to be used for crowd microscopic simulation where the motion accuracy is fundamental.

Two kinds of information can be stored in the description of a VGE. Quantitative data are stored as numerical values which are generally used to depict geometric properties (like a path's width of 2 meters) or statistical values (like a density of 2.5 persons per square meter). Qualitative data are introduced as identifiers which can be a reference to an external database or a word with arbitrary semantics, called a label. Such labels can be used to qualify an area (like a road or a building) or to interpret a quantitative value (like a narrow passage or a crowded place). An advantage of interpreting quantitative data is to reduce a potentially infinite set of inputs to a discrete set of values, which is particularly useful to condense information in successive abstraction levels to be used for reasoning purposes.

In this paper, we briefly illustrate our approach that is based on an exact representation whose precision allows realistic applications such as micro-simulation of crowds [10]. The resulting topological graph encompasses quantitative data as well as qualitative information from the arcs of the graph are propagated to the nodes, which allows, for example, deduction of the internal parts of the buildings or of the roads in addition to their outline.

B. Abstraction of Virtual Geographic Environments

Current virtual environment models do not support large-scale and complex geographic environments and fail to capture real world physical environments' characteristics. When dealing with large-scale and complex geographic environments, the spatial subdivision which can be either exact or approximate produces a large number of cells. The topologic approach allows representation of such a spatial subdivision using a graph structure and takes advantage of efficient algorithms provided by the graph theory. However, the graph size may still remain large when dealing with geographic environments with dense geographic features. Moreover, geographic features with curved geometries (Fig.2) produce a large number of triangles since they are initially represented by a large number of segments.

Environment abstraction is a process to improve organization of the information obtained at the time of spatial subdivision of the geographic environment. The unification process is addressed principally in two ways: (1) a pure topological unification which associates the subdivision cells according to their number of connections; (2) a more conceptual unification which introduces a semantic definition of the environment, like the IHT-graph structure [11]. Lamarche and Donikian proposed a topologic abstraction approach that assigns to each node of the graph resulting from spatial decomposition, a topological qualification according to the number of connected edges given by its arity [12]. The topologic abstraction algorithm aims to generate an abstraction tree by merging interconnected cells while trying to preserve topological properties [12]. When merging several cells into a single cell, the composition of cells is stored in a graph structure to generate the abstraction tree. The topologic abstraction proposed by Lamarche and Donikian reduces the size of the graph that represents the spatial subdivision [13]. The grouping process relies on the topological properties of the cells and the resulting graph contains fewer nodes and preserves the topologic and geometric characteristics of the geographic environment. However, the topological characteristics are not sufficient to abstract a virtual environment when dealing with a large-scale and complex environment involving areas with various qualifications (buildings, roads, parks, sidewalks, etc.).

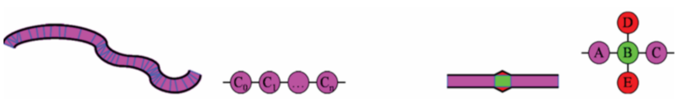


Fig 2: Cells resulting from curved geometries and alignment anomalies.

C. Crowd Simulation

Since critical situations such as escape panic and unplanned evacuations may threaten public safety, many research works have been carried out on the simulation of dense crowds. Models based on particle and fluid dynamics have been proposed to explain people's behaviors in such constrained situations, mainly for evacuations scenarii. In these models individuals' behaviors are very simple and mainly consist of reactions to surrounding forces. For example, Helbing et al. [14] introduced the Social force model for pedestrian dynamics, where individual motion is subject to so-called social forces (acceleration, attraction, repulsion) which are a measure of the internal motivation of individuals to perform certain actions or movements. Pelechano et al. [15] mention that usually social forces models tend to create simulations that look more like particle animation than human movement [16], and propose to add psychological, physiological and geometrical rules. Other approaches address some kinds of social links in a different way. Reynolds [17] proposes a set of behavioral rules to manage emergent motion phenomena between flocks of simple agents.

More recently, Lamarche et al. [18] have enhanced this principle to control crowds of people in constrained environments, with more complex behaviors. These authors also propose an open architecture for realistic navigation, where each pedestrian can perform high-level decision behaviors such as path planning [12]. However, these systems fail to explain why patterns of group movements occur because they lack references to psychological and sociological high-level behaviors of crowd members.

Other authors proposed models for individual agents that incorporate psychological factors. For example, Kenny et al. [19] propose to use five psychological factors (motivation, stress, confidence, focus and emotions) to understand and assess individual behaviors in a crowd. Silverman et al. [20] developed the PMFserv framework to model human decision-making based on emotional subjective utility constrained by stress and physiology. Other authors attempt to include cognitive appraisal models to create computational models of emotions that can be embedded in agent systems [21] and to use them to explain and simulate the reactions of people in a crowd. Most of these approaches provide models to specify the individual's characteristics (physiological, psychological and emotional) in order to model emotion appraisal and the individual's behaviors.

However, they do not provide sufficient constructs and mechanisms, whenever they provide any, to specify and simulate the interactions of individuals and groups. Hybrid systems combine particle, flocking, and reactive behaviors [29], where the intelligence level of the agents can vary from none to high. Musse and Thalmann [22] developed Vi-Crowd, a system that is composed of a hierarchy of a virtual crowd, groups and individuals. The authors developed a model that distributes the "crowd behaviors" to the groups and then to the individuals. This kind of approach allows them to simulate some aspects of the dynamics of groups in a crowd, but essentially in a kinematic way, by taking advantage of the geometric properties of agents moving in groups, such as inter-distances, orientations, or personal space. However, there is a need for more elaborated models integrating both the individual's characteristics (psychological, emotional) and social behaviors in order to explain why agents may join or dissociate from a group.

It is worth investigating the large body of literature on the sociology of crowds and on collective actions and group dynamics. Several theories have been proposed over the past fifty years such as the social contagion, the social comparison theory [23], and the social identity theory [24]. Social contagion is the spread of a behavior between individuals in a population, such as the spread of rumors and aggressive actions in riots. Computational approaches to simulate social contagion are based on threshold models [25], where each agent has a threshold which leads him to adopt an activity when exceeded. Newell [26] also introduced social contagion in his behavioral decision model, using a set of axioms. The phenomenon of contagion reminds us of the early writings on crowd done by Le Bon [27] which presented the idea that crowd participants are given to spontaneity, irrationality, loss of self-control, and a sense of anonymity. While social contagion may occur in specific extreme circumstances, in most cases individuals do not lose their individualities in order to adopt the uniform behavior of the crowd entity.

In an attempt to explain this phenomenon, the Social Comparison Theory (SCT) [28] claims that individuals evaluate their own opinions and desires by comparing to others. In a recent work, Kaminska and Fridman [24] claim that SCT may account for some characteristics of crowd behavior, in particular with respect to imitational behavior and group formation. They propose algorithms that allow agents to carry out some behaviors based on social comparison. However, they only tackle what we call the kinematics of groups, in a similar way to the Social Forces Model [15]. It is too simplistic and must be completed with other theories.

The Social Identity Theory refers to an individual's self-understanding as a member of a social category [29], and assumes that identity is multiple and constitutes a complex system rather than being unitary. Evidences to support the social identity model come from both experimental and field studies [30]. The Elaborated Social Identity Model of crowds (ESIM) [31] enhances the initial social identity model with a notion of self in social relations, along with the actions that are characteristic of a social position [32]. A typical pattern of identity change has been observed in several crowd events: moderate participants of a crowd change identity and become activists as a result of police actions perceived as being illegitimate [33].

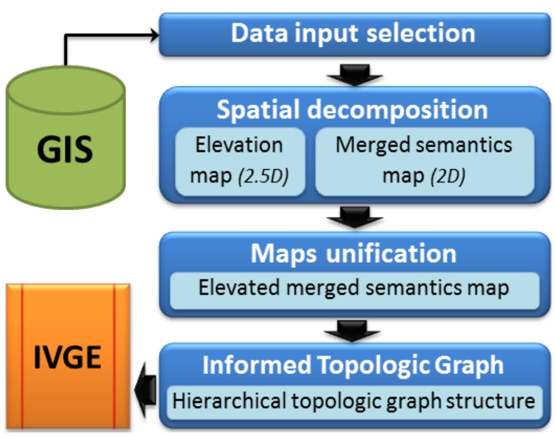


Fig 2: The four stages to generate an IVGE from GIS data.

In order to simulate and explain collective behaviors and attitude changes in crowd phenomena, we propose to extend current approaches by explicitly introducing:

- Social notions in the agent models, such as the social identity and the mechanisms that allow an agent to adopt a new identity under some conditions;
- The notion of social group to which an agent may belong, and identify to (as for example a group of agitators, a family, etc.);
- The notion of what we call a Spatio-Temporal Group (STG), which is easily recognizable in space and time such as a line of policemen or a group of friends walking side by side;
- Mechanisms that allow an agent to join a group or to leave a group.

III. Generation of IVGE from GIS Data

We propose an automated approach to compute the IVGE data directly from vector GIS data [34]. This approach is based on four stages which are detailed in this section (Fig.2): input data selection, spatial decomposition, maps unification, and finally the generation of the informed topologic graph.

A. 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. As we consider 2.5D IVGE, a given coordinate cannot have two different elevations, making it impossible to represent tunnels for example. Second, semantic layers are used to qualify various types of data in space.

B. Spatial Decomposition

The second step consists of obtaining an exact spatial decomposition using Delaunay triangulation, and can be divided into two parts in relation to the previous phase. First, an elevation map is computed, corresponding to the triangulation of the elevation layers. All the elevation points of the layers are injected into a 2D triangulation, the elevation being considered as an attribute of each node. This process produces an environment subdivision composed of connected triangles. 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 [35].

1) Merging Elevation and Semantics Layers

The third step to obtain our IVGE consists of unifying the two maps previously obtained. First, preprocessing is carried out on the merged semantics map in order to preserve the elevation precision inside the unified map. Then, a second process elevates the merged semantics map. The elevation of each merged semantics point P is computed by retrieving the corresponding triangle T inside the elevation map, i.e. the triangle whose 2D projection contains the coordinates of P. Once T is obtained, the elevation is computed by projecting P on the plane defined by T using the Z axis.

2) 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.

IV. Abstraction of IVGE

In this Section, we describe the abstraction process which optimizes the description of the IVGE. Sub-section A presents the first enhancement which is related to the qualification of terrain. We propose a novel approach of information extrapolation using a one-time spatial reasoning process based on a geometric abstraction. This approach can be used to create new qualitative data relative to elevation variations. These data are stored as additional semantics bound to the graph nodes, which can subsequently be used for spatial reasoning. Sub-section B introduces the second enhancement which optimizes the size of the informed graph structure using a topological abstraction process. This process aims at building a hierarchical topologic graph structure in order to deal with large-scale virtual geographic environments. Sub-section C details the third enhancement technique which propagates qualitative input information from the arcs of the graph to the nodes, which allows deduction of the internal parts of features such as buildings or roads in addition to their boundaries. Moreover, this technique uses Conceptual Graphs (CG) [36], a standard formalism for the representation of semantic information. Fig.2 illustrates the abstracted IVGE generation model.

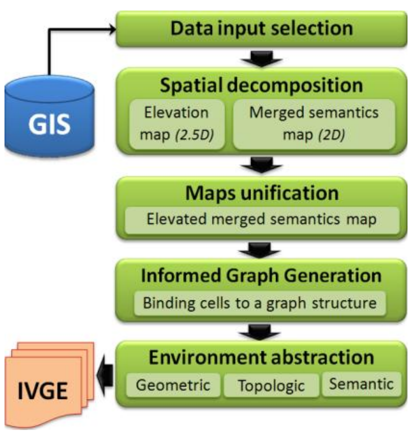


Fig 2: The IVGE global architecture of IVGE generation including the environment abstraction process.

A. *Geometric abstraction*

Spatial decomposition subdivides the environment into convex cells. Such cells encapsulate various quantitative geometric data which are suitable for precise computations. Since geographic environments are seldom at, it is important to consider the terrain's elevation and shape. While elevation data are stored in a quantitative way which is suitable for exact calculations, spatial reasoning often needs to manipulate qualitative information. Indeed, when considering a slope, it is obviously simpler and faster to qualify it using an attribute with ordinal values such as gentle and steep rather than using numerical values. However, when dealing with large scale geographic environments, handling the terrain's elevation, including its light variations, may be a complex task. To this end, we propose an abstraction process that uses geometric data to extract the average terrain's elevation information from spatial areas. The objectives of this Geometric Abstraction are threefold. First, it aims to reduce the amount of data used to describe the environment. Second, it helps for the detection of anomalies, deviations, and aberrations in elevation data. Third, the geometric abstraction enhances the environment description by integrating qualitative information characterizing the terrain shape. In this section, we fist present the algorithm which computes the geometric abstraction. Then, we describe two processes which use the geometric abstraction, namely *Filtering elevation anomalies* and *Extracting elevation semantics*.

As presented in the previous chapter, the geographic environment is subdivided into cells of different shapes and sizes. The algorithm takes advantage of the graph structure obtained from the IVGE extraction process. A cell corresponds to a node in the topological graph. A node represents a triangle generated by the CDT spatial decomposition technique. A cell is characterized by its boundaries, its neighboring cells, its surface as well as its normal vector which is a vector perpendicular to its plane. Now we introduce the notion of a group, which is a collection of adjacent cells. The grouping strategy is based on a coplanarity criterion which is assessed by computing the difference between the normal vectors of two neighboring cells or groups of cells. Since a group is basically composed of adjacent cells it is obvious to characterize a group by its boundaries, its neighboring groups, its surface, as well as its normal vector. However, the normal vector of a group must rely on an interpretation of the normal vectors of its composing cells. In order to compute the normal vector of a group, we adopt the area-weight normal vector [37] which takes into account the unit normal vectors of its composing cells as well as their respective surfaces.

Let S_c denote the surface of a cell c and N_c be its unit normal vector, the normalized area-weight normal vector N_G of a group G is computed as follows:

$$\overrightarrow{N_G} = \sum_{c\in G}\left(S_c.\overrightarrow{N_c}\right) \Big/ \sum_{c\in G} S_c \qquad (1)$$

The geometric abstraction algorithm uses two input parameters: 1) a set of starting cells which act as access points to the graph structure, and 2) a gradient parameter which corresponds to the maximal allowed difference between cells' inclinations. Indeed, two adjacent cells are considered coplanar and hence grouped, when the angle between their normal vectors is inferior or equal to the gradient.

The terrain's elevation which characterizes each group is still a quantitative data described using area-weighted normal vectors. Such quantitative data are too precise to be used by qualitative spatial reasoning. Hence, a qualification process would greatly simplify spatial reasoning mechanisms. The geometric abstraction allows improving IVGE by qualifying the terrain's elevation using semantics and integrating such semantics in the description of the geographic environment.

B. *Topological abstraction*

Our work on the generation of informed virtual geographic environments using an exact spatial decomposition scheme subdivides the environment into convex cells organized in a topological graph structure. However, inside large scale and complex geographic environments (such as a city for example), such topological graphs can become very large. The size of such a topological graph has a direct effect on paths' computation time for path-finding. In order to optimize the performance of path computation, we need to reduce the size of the topological graph representing the IVGE. The aim of the topological abstraction is to provide a compact representation of the topological graph that is suitable for situated reasoning and enables fast path planning. However, in contrast to the geometric abstraction which only enhances the description of the IVGE with terrain semantics, the topological abstraction extends the topological graph with new layers. In each layer (except for the initial layer which is called level 0), a node corresponds to a single or a group of nodes in the immediate lower level (Fig.5). The topological abstraction simplifies the IVGE description by combining cells (triangles) in order to obtain convex groups of cells. Such a hierarchical structure evolves the concept of Hierarchical Topologic Graph in which cells are fused into groups and edges are abstracted in boundaries. To do so, convex hulls are computed for every node of the topological graph. Then, the coverage ratio of the convex hull is evaluated as the surface of the hull divided by the actual surface of the node. The topological abstraction finally performs groupings of a set of connected nodes if and only if the group ratio is equal or close to one depending on the problem domain. Let C be the convexity rate and CH(gr) be the convex hull of the polygon corresponding to gr. C is computed as follows:

$$C(G) = \frac{\text{Surface}(G)}{\text{Surface}(CH(G))} \quad \text{and} \quad 0 < C(G) \leq 1 \qquad (2)$$

Indeed, the convex property of groups needs to be preserved after the topological abstraction. This ensures that an entity can move freely inside a given cell (or group of cells), and that there exists a straight path linking edges belonging to the same cell (or group of cells).

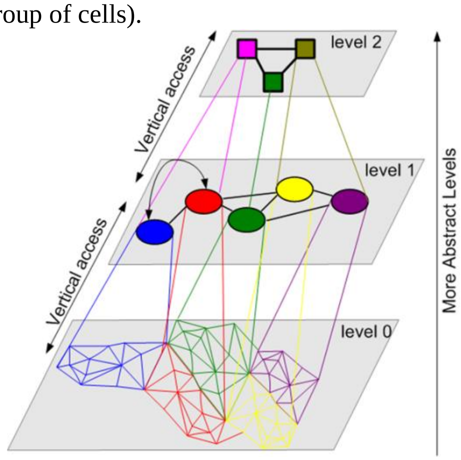
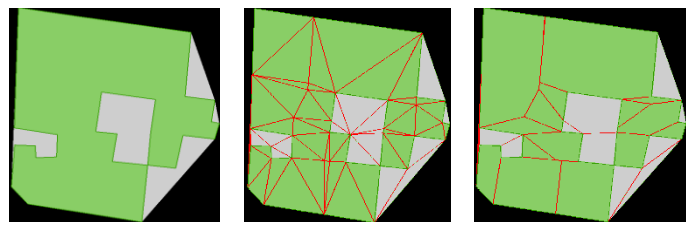


Fig 5: The topological graph extraction from space decomposition and extension into different levels using the topological abstraction.

Fig.5 illustrates an example of the topological abstraction process and the way it reduces the number of cells representing the environment. In Fig. 5(a), we present the initial vector format GIS data of a complex building. Fig. 5(b) depicts the initial exact spatial decomposition which yields 63 triangular cells. Fig. 5(c) presents 28 convex polygons generated by the topological abstraction algorithm. The optimization rate of the number of cells representing the environment is around 55%.

To conclude, we proposed in this section two approaches aiming at enhancing the description of the IVGE. The first approach permits to qualify the terrain’s elevation using semantic elevation which is in-tegrated in the IVGE. The second approach aims at simplifying large informed graphs corresponding to large scale and complex geographic environments. This approach reduces the number of convex cells by overlaying the informed graph with a topologically abstracted graph produced by a topological abstraction. The resulting IVGE is hence based on a hierarchical graph whose lowest level corresponds to the informed graph initially produced by the spatial decomposition. In the following section, we show how we use a well-known knowledge representation formalism to represent the semantic information in order to further enhance the IVGE description with respect to agents’ and environments’ characteristics.



(a) (b) (c)

Fig 6: Illustration of the topological abstraction process with a strict convex property (C(gr) = 1); (a) the GIS data of a complex building; (b) the exact space decomposition using CDT techniques (63 triangular cells) ; (c) the topological abstraction (28 convex polygons).

C. *Semantic Abstraction*

Two kinds of information can be stored in the description of an IVGE. Quantitative data are stored as numerical values which are generally used to depict geometric properties (like a path's width of 2 meters) or statistical values (like a density of 2.5 persons per square meter). Qualitative data are introduced as identifiers which can range from a word with a given semantics, called a label, to a reference to an external database or to a specific knowledge representation. Such semantic information can be used to qualify an area (like a road or a building) or to interpret a quantitative value (like a narrow passage or a crowded place). An advantage of interpreting quantitative data is to reduce a potentially in finite set of inputs to a discrete set of values, which is particularly useful to condense information in successive abstraction levels to be used for reasoning purposes. Furthermore, the semantic information enhances the description of the IVGE, which in turn extends the agents' knowledge about their environment. However, the integration of the semantic information raises the issue of its representation. Therefore, we need a standard formalism that allows for precisely representing the semantic information which qualifies space and which is computationally tractable in order to be used by spatial reasoning algorithms used by agents.

Several knowledge representation techniques can be used to structure semantic information and to represent knowledge in general such as frames [38], rules [39] (also called If-Then rules), tagging [40], and semantic networks [41] which have originated from theories of human information processing. Since knowledge is used to achieve intelligent behavior, the fundamental goal of knowledge representation is to represent knowledge in a manner that facilitates inference (i.e. drawing conclusions) from knowledge. In order to select a knowledge representation (and a knowledge representation system to logically interpret sentences in order to derive inferences from them), we have to consider the expressivity of the knowledge representation. The more expressive a knowledge representation technique is, the easier (and more compact) we can describe and qualify geographic features which characterize IVGE. Various artificial languages and notations have been proposed to represent knowledge. They are typically based on logic and mathematics, and can be easily parsed for machine processing. However, Sowas's Conceptual Graphs [36] are widely considered an advanced standard logical notation for logic based on existential graphs proposed by Charles Sanders Peirce and on semantic networks.

Syntactically, a conceptual graph is a network of concept nodes linked by relation nodes. Concept nodes are represented by the notation [Concept Type: Concept instance] and relation nodes by (Relationship-Name). A concept instance can be either a value, a set of values or even a CG. The formalism can be represented in either graphical or character-based notations. In the graphical notation, concepts are represented by rectangles, relations by circles and the links between concept nodes and relation nodes by arrows. The most abstract concept type is called the universal type (or simply Universal) denoted by the symbol $\perp$.

Fig. 7: Illustration of the action, agent and location concepts using a concept type lattice.

Crowd simulation usually involves a large number of situated agents of different types (human, animal, static, mobile, etc.) performing various actions (moving, perceiving, etc.) in virtual geographic spaces of various extents. Using CGs greatly simplifies the representation of complex situated interactions occurring at different locations and involving various agents of different types. In order to create models for MAGS we consider three fundamental abstract concepts: 1) agents; 2) actions; and 3) locations. Taking advantage of the abstraction capabilities of the CGs formalism (through the Concept Type Lattice (CTL)) instead of representing different situated interactions of various agents in distinct locations, we are able to represent abstract actions performed by agent archetypes in abstract locations. Moreover, we first need to specify and characterize each of the abstract concepts. The concept type lattice enables us to specify each abstract concept in order to represent situated behaviors such as path planning of agents in space. Fig.7 presents the first level of the concept type lattice refining the agent, action, and location concepts. Figures 8(a), 8(b), and 8(c) present the expansion of the concept type lattice presented in Fig.7. Fig.8(a) illustrates some situated actions that can be performed by agents in the IVGE such as sailing for maritime vehicles, rolling for terrestrial vehicles, walking for humans, and accessing for humans to enter or exit buildings (we assume that buildings are not navigable locations from the perspective of outdoor navigation). Fig.8(b) depicts how the location concept may be specialized into *Navigable* and *Not Navigable* concepts. The *Navigable* concept may also be specialized into *Terrestrial Vehicle Navigable*, *Pedestrian Navigable*, *Marine Vehicle Navigable*, and *Bike Navigable* which are dedicated navigable areas with respect to agent archetypes and environmental characteristics as specified by the elementary semantics. Fig.8(c) illustrates a few agent archetypes that are relevant to our geo-simulation including pedestrians, cars, trucks, and bikes.

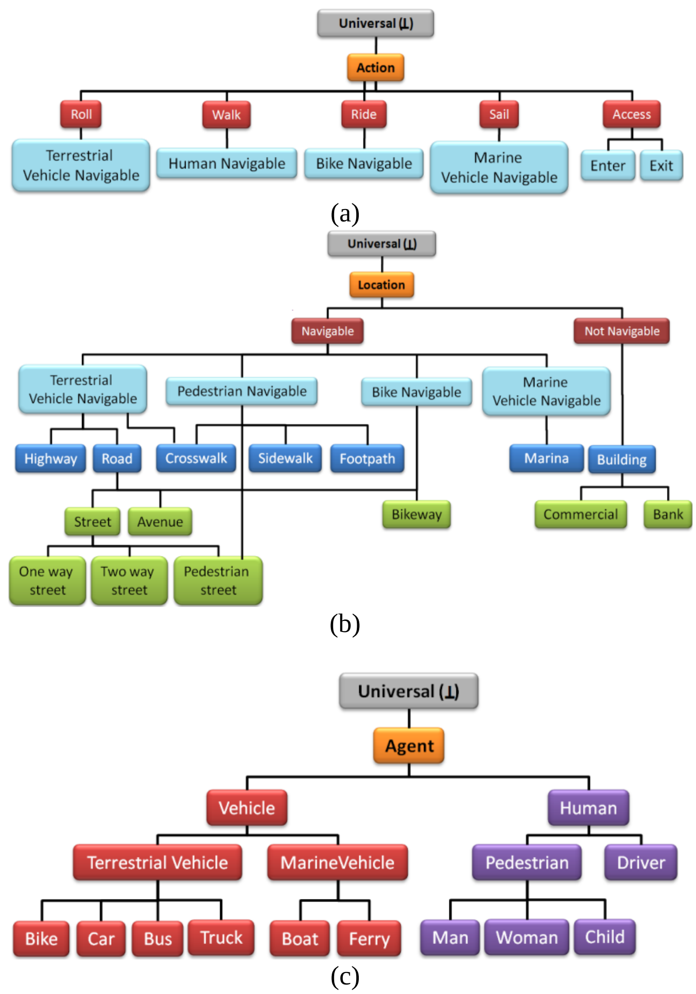


Fig. 9: an example of a conceptual description of agents' archetypes (a), actions performed (b), and locations situated in a geographic environment (c).

In order to show how powerful such a representation may be, let us consider the following example. We want to simulate the navigation of three human agents (a man, a woman, and a child), two bike riders (a man and a woman), and three vehicles (a car, a bus, and a boat) in a coastal city. The navigation behaviors of these different agent archetypes must respect the following constraints (or rules): 1) pedestrian agents can only move on sidewalks, on pedestrian streets, and eventually on crosswalks if needed; 2) vehicles can move on roads and highways; 3) boats sail on the river and stop at the harbor port; and 4) bikes move on bikeways, roads, and streets but not on pedestrian streets. Using standard programming languages, it might be difficult to represent or develop the functions related to such simple navigation rules which take into account both the agents' and the locations' characteristics. However, the representation of these navigation rules becomes an easy task when using CGs and our defined concept type lattice. Here are their expressions in CGs:

[PEDESTRIAN:*p] ← (agnt) → [WALK:*w1] ← (loc) → [PEDESTRIAN NAVIGABLE:*pn]

[VEHICLE:*v] ← (agnt) → [ROLL:*r1] ← (loc) → [TERRESTRIAL NAVIGABLE:tn]

The arrows indicate the expected direction for reading the graph. For instance, the first example may be read: an agent *p which is a "*pedestrian*" walks on a location *pn which is "*pedestrian navigable*". Since this expression involves the concepts Pedestrian, Walk and Pedestrian Navigable, this rule remains valid for every sub-type of these concepts. Therefore, thanks to CGs and the concept type lattice, there is no need to specify the navigation rules for men, women, and children if they act as pedestrians in locations such as pedestrian streets, sidewalks, or crosswalk. Indeed, these agent archetypes are subtypes of the Pedestrian concept and pedestrian streets, sidewalks, and crosswalks are subtypes of the Pedestrian Navigable concept. To conclude, CGs offer a powerful formalism to easily describe different concepts involved in crowd simulation including agents, actions, and environments.

V. SOCIAL AGENT BEHAVIORAL MODELS

A. *Behaviors Description*

We propose two ways to specify the behaviors of our autonomous agents. These agent's behaviors are automatically triggered during the simulation at a chosen frequency. We can first describe behaviors by using rules. This easy description can only be used for relatively simple and independent behaviors, because of the lack of interdependency management of this kind of formalism. Each rule is composed of a Boolean expression which must be validated in order to evaluate the body of the rule, composed of agent's elementary actions. We use rules for most of the agent's reactive behaviors, such as the management of navigation or perception.

The second way to describe behaviors is based on hierarchical concurrent state machines. This formalism is more suited to specify cognitive behaviors because it allows to simply describing potentially complex behavioral plans, with the introduction of contextual evaluation. Moreover, the competition between behaviors is managed thanks to resources. A resource symbolises a behavioral requirement for the agent, with a limitation notion. For example, the agent's ability to move is represented by a resource, allowing a single behavior to control the agent's displacement at a given time. In order to separate the competitive behaviors for a resource, each state of the automaton which declares the need for at least one resource must specify a priority. This priority symbolises the relative importance of the state with respect to the others which need the same resource. Then, the state with the highest priority gets the resource and hence the ability to execute, whereas other states are paused until their priority becomes high enough. One can notice that the priority is dynamically evaluated at each simulation step, and so that an active state can temporarily loose a resource at the benefit of another state.

B. *Behavioral Model Overview*

We propose to structure the agent's behaviors with a cognitive approach similar to A. Newell's behavioral pyramid [15] (Fig.3(b)). Our model is organised in three successive behavioral categories (Fig.3(a)).

Individual behaviors are common to all simulated agents. They represent the standard behaviors of a human being such as moving and perceiving. Because of their generic aspect, these behaviors only address short term decision making. Thus, this category only represents the lowest layers of the pyramid, with physiological, reactive, and some cognitive behaviors. We will not detail the behaviors of these layers because they are out of the scope of this paper, and we will consider that the common abilities of a human being are fulfilled. Moreover, one can notice that this behavioral category is predefined for all agents, and will not change during the simulation.

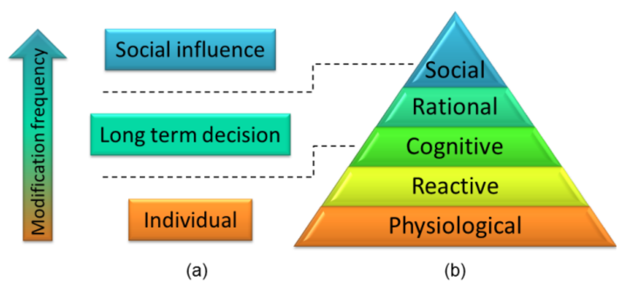


Fig 3: Comparison between our approach (a) and A. Newell's behavioral pyramid (b). The arrow on the left illustrates the variation potential of the agent's behavioral layers, while the dashed lines indicate their repartition inside the pyramid.

Long term decision behaviors are specific to different kinds of people. We will detail these behaviors in the next section, but for now we can consider that this category is in charge of the long term behavioral planning of the social agent. Indeed, the behaviors associated with this category represent the role of a human being in the society, either on his own like a working man or a teenager, or in relation to a social group like a father in a family. Moreover, this behavioral category manages the target goals of the social agent, and selects the appropriate sub-goals and actions needed to reach these goals.

In contrast to the individual behaviors, this category can be modified during the simulation under certain conditions, but with a low variation potential. Social influence does not directly control the lower behavioral layers. Instead, these behaviors may only alter the agent's characteristics. We will also detail this category in the next section, but for now we can consider that it represents the influence of the agent's surrounding social environment on its state, and thus on its way to behave. Moreover, this category is optional, i.e. it is only raised in some circumstances depending on the agent's social identity and environment. Additionally, the behaviors of this category are the agent's most volatile ones, and can change with a relatively high frequency, up to one time per minute.

VI. High Level Decision and Social Behaviors

In our approach, we propose to strongly link the high-level decision processes of the agent, corresponding to goal-oriented behaviors, with the social behaviors. In this way, we are able to implicitly manage the social influence on the ongoing behaviors, as we will see with the social identity and role. Moreover, we also explicitly manage short term social influences on the agent states, and so on its behaviors, which will be illustrated with the spatio-temporal groups and their influence.

A. *Social Identity*

The social identity represents an individual's self-understanding as a member of a social category. Examples of social identities can either be general like a worker or an unemployed person, or more specific like a demonstrator or a journalist. This behavioral component defines the long term goals of the individual with respect to his social position. Moreover, the associated behavioral graph indicates the individual's know how specific of his social identity. We propose to manage the social identity as a composed behavioral component, divided into two parts (Fig.4). An agent has one fundamental social identity and may choose one adopted social identity among a set of available ones. The fundamental social identity is an unchanging behavioral graph of the agent. This state machine is a controller which defines the dynamics of social identity changes, while keeping a link to the original behaviors that socially characterise the agent. Indeed, this graph can be compared to a controller because it does not directly produce any perceptible action of the agent, but only selects the currently adopted social identity.

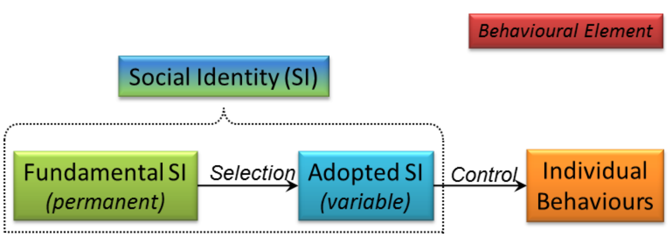


Fig 4: The social identity (SI) behavioral management. The fundamental SI can change the adopted SI at any time, while this one controls the individual behaviors resulting in successive elementary actions.

This second behavioral graph is independent from the first one, and defines the actions path to reach the goals of the social identity. Indeed, this is the adopted social identity which controls the individual behaviors of the agent in order to produce the perceptible interactions with the environment. For example, this behavior can select the destination and speed of the agent, or make it interact with some equipment, or even manage its communication with other agents. Moreover, this behavior can be composed of several concurrent goals and sub-goals, which are managed locally thanks to resources needs inside the hierarchical parallel state machines.

B. *Social Group*

A social group defines the social interrelationships between a group of people who know each other. This kind of group does not define geometric links between the members, but just reflects their social relations. Hence, a social group cannot be directly perceived by someone who does not belong to the group. However, all the members of a social group know each other, i.e. know who they are and what their role within the group is. We propose to manage a social group thanks to data structures in our architecture (Fig.3).

A social group is an abstract notion (i.e. it is not a situated component) composed of a list of social roles. Each social role is also an abstract notion, which is related to an identified social group. A social role is defined by a social identity, corresponding to the behaviors associated with all the agents playing this role inside the group. These agents are referenced by the role allowing them to freely access the group structure, including the different roles and agents inside the group, and eventually to take the group into account in their behaviors.

The social identity associated with a role is defined exactly in the same way as previously, with a fundamental and an adopted part. However, the fundamental social identity can only choose an adopted social identity among the potential roles in the group. Indeed, it is not possible for someone to play a role that is not explicitly linked to his original social group. Additionally, agents have the ability to leave a social group, and so to abandon their role, even if it is a really rare case.

Let us notice that an agent can belong to any number of social groups, from none to many. For example, someone can play the role of the father in a family social group, as well as being the boss in a company social group. Additionally, as it was said in the previous section, each agent has an elementary social identity defining its general role in the society. So, finally an agent may have many concurrent social identities in competition to decide about its short to long term goals and actions. In the same way as previously, this competition is directly managed by the resources needs declared by the concurrent behaviors.

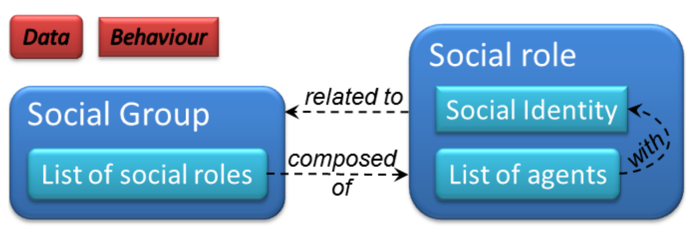


Fig 3: The social group architecture. A social group contains a list of applicable social roles, which each contains a list of the agents playing that role by adopting an associated social identity.

C. *Spatio-Temporal Group*

A spatio-temporal group (STG) manages spatial relationships between close people. On the contrary to a social group, the members of a STG do not necessarily know each other. However, the group structure is perceivable from outside, making its members identifiable in terms of location, and potentially attitudes. In a similar way as for the social group, we propose a data structure to handle a STG (Fig. 4).

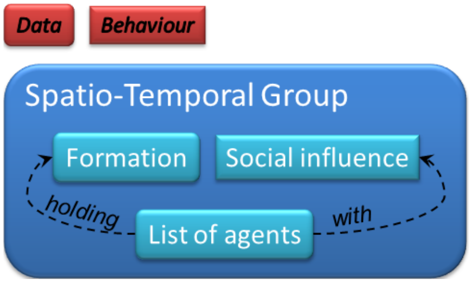


Fig 4: The spatio-temporal group (STG) architecture. A STG contains a list of the participating agents, as well as the geometrical formation they have to maintain and the social influence behavior they adopt.

An STG is a situated notion containing the list of member agents. All of these members adopt an optional social influence behavior, which cannot directly produce actions but can influence the other agent's behaviors. Additionally, the members must maintain a given formation in order to belong to a STG. This formation defines the spatial organisation that the agents must comply with in order to be part of the STG. A formation can be very strict, like a line formation for military forces, or quite unconstrained, like a loose formation for demonstrators which is only defined by a bounding circle. A formation is defined relatively to the STG hot spot, which defines the position of the entire group in the environment. This hot spot can be static, like for a waiting queue formation, or dynamic, like for a group of friends walking together. In this last case, the dynamic hot spot can be hold by an agent, moving along with him, or can be computed by a third party mechanism. The behavior in charge of maintaining the formation is defined in the individual behaviors, and thus is provided for any agent. This behavior controls the agent's navigation ability, represented by a resource, and so is in competition with any other behavior that would select a destination. One can notice that an agent can only belong to one STG at a given time. This limitation is due to the strong impact of the STG on the agent's location, because of the formation constraint, making it impossible for the agent to maintain two formations at the same time. However, an agent can belong to an STG as well as to one or several social groups. This possibility is very useful to represent spatially organised social groups, by combining both notions. For example, to represent family members walking together, we can use: first, a social group defining all the roles of a family (father, mother, and children); second, a STG containing all the family members, configured with a loose formation and a hot spot linked to the agent playing the father social role.

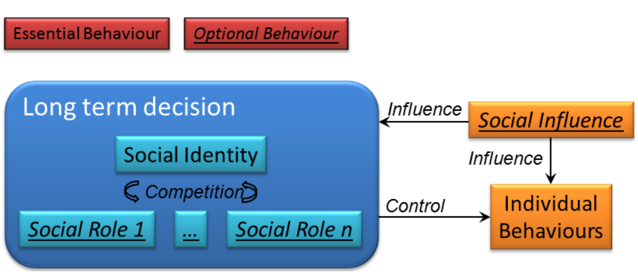


Fig 5: Social agent behavioral model synthesis.

The individual low level behaviors are controlled by the high level decision mechanisms, which are composed of a social identity and optional social roles. Both of these categories can be influenced by a social behavior given by an STG.

D. *Synthesis*

To conclude with the social agent's behavioral models, let us look at the overall mechanism. As shown in Fig. 5, all the three behavioral categories of the agent are linked. An optional social behavior can be adopted if the agent belongs to an STG. This behavior only influences the individual behaviors and the long term decision. This long term decision is in charge of selecting the immediate actions by controlling the individual behaviors. While being the rational centre of the agent, the long term decision is heavily linked to social considerations. Indeed, this category is composed of the agent's social identity, and of all of its optional social roles. All these behavioral graphs are independently described, but are re solved competitively by the agent. Then, the competition for the control of the low-level actions of the agent is simply managed thanks to the resource needs of the behaviors.

VII. Results

The application of our social behavior models in the simulation of crowds provides useful tools to a variety of application domains. Examples of such domains include the entertainment industry (games and movies), security planning and crowd management (planning events involving large crowds such as demonstrations at World Summits, popular celebrations such as soccer games and religious celebrations), and military operations in urban settings involving civilian crowds. In the context of a crowd control research project conducted in collaboration with Defence Research and Development {blind}, we propose to simulate crowd control in conflict situations involving control forces and the use of non-lethal weapons. This research project aims to provide decision makers with new ways to analyse such situations and to assess the efficiency of different intervention strategies.

In order to validate the novel approach that we propose, we simulate a demonstration event held in an urban environment. The simulation involves a large number of geo-referenced individual social agents immersed in an informed virtual environment. Both the crowd and the control forces are represented by social agents who are endowed with individual capabilities such as perception, navigation, and memory. Thus, the agents can perceive and react to their evolving virtual environment with a plausible level of behavioral realism. The scenario that we propose aims to put forward the ability of our social agents to autonomously switch roles inside their social groups. Such social role dynamics are based on the agents' situation assessment and directed by the presented behavior models. For simplification purposes, this scenario will focus on the control forces. It involves a small squad of control forces which is deployed to protect a governmental building (A governmental building is presented in Fig. 6).

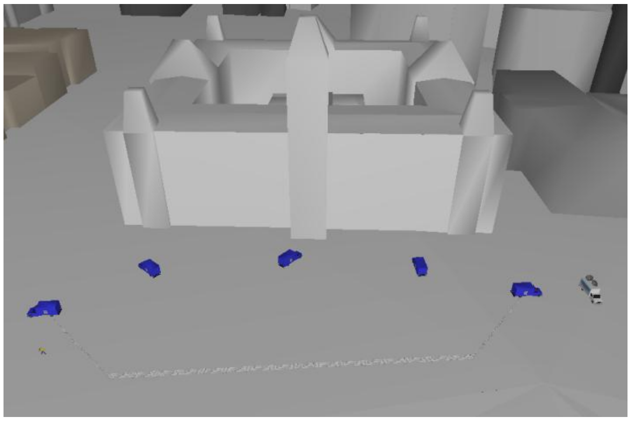


Fig 6: 3D visualization of the simulation environment showing the parliament of {blind} protected by fences and several police trucks for control forces deployment.

A squad of control forces is basically a social group composed of the following social roles: Squad Leader, Deputy-leader, and Squad Member. These three roles are managed thanks to three fundamental social identities (Fig. 7): both leader and member social identities are very simple, only selecting the associated adopted social identity; the deputy-leader fundamental social identity manages dynamic changes between the leader and member adopted social identities (in this case there is no specific deputy-leader adopted social identity). The following graphical conventions will be used in the demonstration screen shots (Fig.8): the characters' main color identifies their fundamental social identity (leader in red, deputy-leader in yellow, and member in blue); the icons on top of the characters identifies their currently adopted social identity (star for leader, echelon for member, and no icon if the agent has left the group).

The storyboard of the demonstration scenario illustrates a basic manoeuvre of a squad of control forces. A squad is initially composed of a leader, a deputy-leader, and five members. At first, the squad gets out of a police truck (Fig.9(a)). The leader creates a STG and binds its hotspot to his position. The deputy-leader (who initially has the adopted social identity of a member) as well as the squad members join the STG, and automatically maintain its formation. Then, the leader moves towards the fences while carrying the STG hotspot with him. As a result, the other squad members follow the leader while maintaining the STG formation. As soon as the leader reaches the fences, the squad can be considered to be deployed (Fig.9(b)).

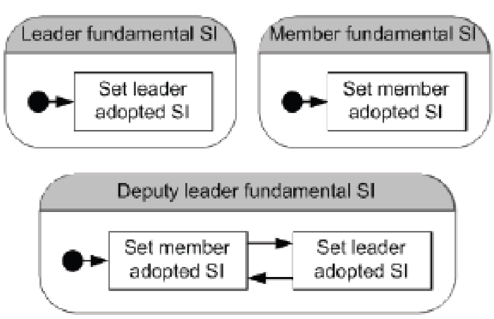


Fig 7: The leader, member, and deputy-leader fundamental social identities.

Fig 8: Graphical convention to identify the squad roles.

In order to illustrate the social role dynamics, we arbitrarily make the leader leave the group (Fig.9(c)). As a result, the deputy-leader's fundamental social identity (Fig.7) switches from the member to the leader adopted social identity. Now that the deputy leader has become the new squad leader, the hotspot of the STG is linked to his position. This leads to an automatic reorganisation of the squad members in order to maintain the formation, and finally produces a new deployment of the squad (Fig.9(d)).

Finally, the deputy-leader's adopted social identity makes him leave the place by moving back to a police truck (Fig.9(e)). In the same way as before, the members follow the new leader while maintaining the formation.

Let us notice that this example is voluntarily simplified for demonstration purposes. Indeed, we are working on a much more complex scenario exhibiting more elaborated actions for the control forces, such as the use of non-lethal weapons or crowd monitoring. Moreover, we also provide more complicated social identities for crowd members who have greater social dynamics.

VIII. Conclusion and Future Work

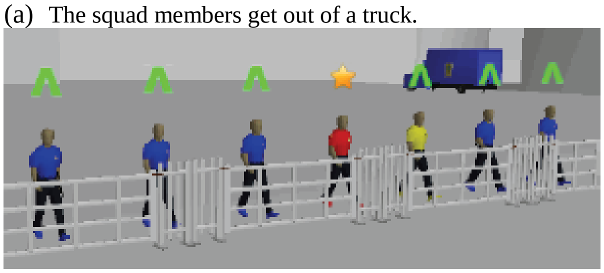
In this paper, we discussed some shortcomings of current research works which deal with social behaviors and crowd simulation in virtual geospatial environments.

First, we presented an original approach to extract an IVGE from GIS data. This approach goes beyond grid based visualization by combining the semantic information merging and the vector based representations accuracy. Indeed, as shown on Fig.7, the proposed method combines all the advantages of grids and vector layers, cutting out their drawbacks. Moreover, this data extraction method is completely automated, being able to directly process GIS vector data. Finally, we have shown the suitability of this method for GIS visualization thanks to an application which allows two visualization modes: 3D for immersion purpose, and 2D to facilitate data analysis. All of these characteristics allow anticipating several applications of this work, mainly thanks to the topological graph exploitation of the representation.

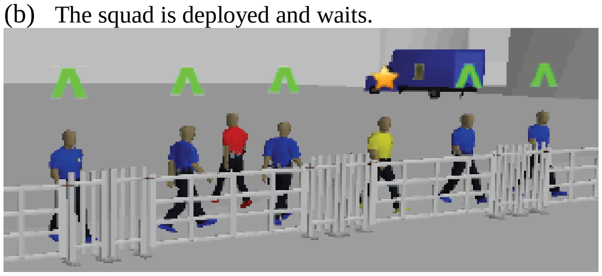
Second, we proposed a novel approach which aims at gaining better insight in crowds' social behaviors by analysing the social interaction mechanisms between individuals. Besides, our approach is related to crowd microscopic simulation because it allows describing individual attitude changes which are typically observed in crowd phenomena. The proposed agent's model combines individual and long term decision behaviors in a multi-layered architecture. Moreover, this model takes into account the social influence which represents the impact of the agent's surrounding social environment on its characteristics. Finally, emergent collective social behaviors are observed at a macro level (groups, crowd), resulting of individuals behaviors and interactions at a micro level.

The proposed behavioral models have been implemented and validated in the scope of an on-going crowd control research project.

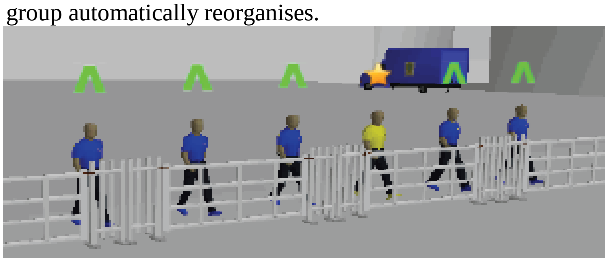
(a) The squad members get out of a truck.



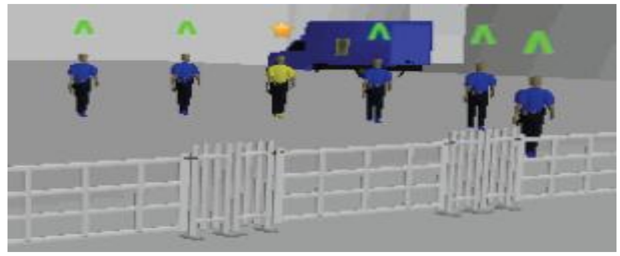
(b) The squad is deployed and waits.



(c) For an arbitrary reason, the leader leaves the social group. T deputy-leader becomes the new leader, and the group automatically reorganises.



(d) The squad is now reorganised and waits.



(e) Finally, the deputy-leader gets out, taking with him the other members because they continue to follow the STG's formation.

Fig 9 Illustration scenario of the proposed models: social group, roles dynamics, and spatio-temporal group management [42].

There are several ways in which we may improve and extend our work. First, we plan to create a data base of commonly used social identities and social groups, first for crowd control, and then for less specific situations. These behaviors will be specified thanks to the models presented in this work, and validated by experts of the related domains (police members, or sociologists). Then, thanks to the modularity of our solution, we will be able to directly use already existing social identities, or easily extend them. A second perspective of our work concerns animation. Indeed, thanks to the easy implementation of our model, we can quickly design simple social identities and spatio-temporal groups to fast populate a virtual world. Nevertheless, a deeper analysis of our model performances is required in order to check the acceptable degree of complexity of the behaviors that allows the animation of a reasonable number of agents in real time.

ACKNOWLEDGMENT

This research was supported in part by the Grant in Aid provided by the University of Minnesota and by the Research Stimulus Dollars Award offered by the University of Minnesota Crookston. The author would like to thank the reviewers for their valuable comments.

REFERENCES

[1] M. Mekni and H. Haddad, "A Knowledge-Based Multi-agent Geo-simulation Framework: Application to Intelligent Sensor Web Deployment," 2010.

[2] N. Sahli, M. Mekni and B. Moulin, "A Multi-Agent Geo-Simulation Approach for the Identification of Risky Areas for Trains," 2008.

[3] M. Mekni, Automated Generation of Geometrically-Precise and Semantically-Informed Virtual Geographic Environments Populated with Spatially-Reasoning Agents, vol. 1, Dissertation, Ed., Dissertation.com, 2010, p. 234.

[4] *GDAL: Geospatial Data Abstraction Library.*

[5] "Virtual Geographic Environments," 2009.

[6] J. Zhang, J. Gong, H. Lin, G. Wang, J. Huang, J. Zhu, B. Xu and J. Teng, "Design and development of Distributed Virtual Geographic Environment system based on web services," *Inf. Sci.*, vol. 177, no. 19, pp. 3968-3980, 2007.

[7] W. Yang, J. Gong, C. Hu and W. Wang, "Collaborative 3D Modeling of Large-Scale Virtual Geographic Environment," *Technologies for E-Learning and Digital Entertainment*, pp. 829-839, 2006.

[8] J. Gong and L. Hui, "Virtual Geographical Environments: Concept, Design, and Applications," 1999.

[9] J. Zhu, J. Gong, H. Lin, W. Li, J. Zhang and X. Wu, "Spatial analysis services in virtual geographic environment based on grid technologies," *MIPPR 2005: Geospatial Information, Data Mining, and Applications,* vol. 6045, no. 1, pp. 604-615, 2005.

[10] M. Kallmann, H. Bieri and D. Thalmann, "Fully Dynamic Constrained Delaunay Triangulations," *Geometric Modelling for Scientific Visualization,* 2003.

[11] F. Lamarche and S. Donikian, "Crowds of Virtual Humans: a New Approach for Real Time Navigation in Complex and Structured Environments," *Computer Graphics Forum, Eurographics'04,* 2004.

[12] F. Lamarche, "Humanoïdes virtuels, réaction et cognition : une architecture pour leur autonomie," 2003.

[13] S. Paris, S. Donikian and N. Bonvalet, "Environmental Abstraction and Path Planning Techniques for Realistic Crowd Simulation," *Computer Animation and Virtual Worlds,* vol. 17, pp. 325-335, 2006.

[14] D. Helbing, I. Farkas and T. Vicsek, "Simulating Dynamical Features of Escape Panic," *Nature,* vol. 407, p. 487, 2000.

[15] N. Pelechano and N. Badler, "Modeling Crowd and Trained Leader Behavior during Building Evacuation," *Computer Graphics and Applications, IEEE,* vol. 26, no. 6, pp. 80-86, 2006.

[16] N. Pelechano, J. M. Allbeck and N. I. Badler, "Controlling individual agents in high-density crowd simulation," 2007.

[17] C. Reynolds, "Flocks, Herds, and Schools: A Distributed Behavioral Model," 1987.

[18] F. Lamarche and S. Donikian, "Automatic Orchestration of Behaviours through the Management of Resources and Priority Levels," 2002.

[19] J. M. Kenny, C. McPhail, P. Waddington, S. Heal, S. james, D. N. Farrer and D. Odenthal, "Crowd Behavior, Crowd Control,and the Use of Non-Lethal Weapons," 2001.

[20] B. G. Silverman, M. Johns, J. Cornwell and K. O'Brien, "Human behavior models for agents in simulators and games: part I: enabling science with PMFserv," *Presence: Teleoper. Virtual Environ.,* vol. 15, no. 2, pp. 139-162, 2006.

[21] J. Broekens and D. DeGroot, "Scalable and flexible appraisal models for virtual agents," 2004.

[22] R. Musse and D. Thalmann, "A {M}odel of {H}uman {C}rowd {B}ehavior," 1997.

[23] L. Festinger, A Theory of Social Comparison Processes, Bobbs-Merrill, 1954.

[24] N. Fridman and G. Kaminka, "Modeling pedestrian crowd behavior based on a cognitive model of social comparison theory," *Computational and Mathematical Organization Theory,* vol. 16, no. 4, pp. 348-372, 2010.

[25] M. Granovetter, "Threshold Models of Collective Behavior," *American Journal of Sociology,* vol. 83, no. 6, pp. 1420-1443, 1978.

[26] A. Newell, Unified theories of cognition, Harvard University Press, 1990.

[27] G. Bon, The Crowd: A Study of the Popular Mind, Macmillan, 1896.

[28] J. E. Suls and L. E. Wheeler, Handbook of social comparison: Theory and research., Kluwer Academic Publishers, 2000.

[29] H. Tajfel, Differentiation between social groups: studies in the social psychology of intergroup relations, Published in cooperation with European Association of Experimental Social Psychology by Academic Press, 1978.

[30] M. Billig, Social psychology and intergroup relations, Published in cooperation with the European Association of Experimental Social Psychology by Academic Press, 1976.

[31] J. Drury and S. Reicher, "Collective action and psychological change: The emergence of new social identities," *British Journal of Social Psychology,* vol. 39, no. 4, pp. 579-604, 2000.

[32] J. Drury and S. Reicher, "The intergroup dynamics of collective empowerment: Substantiating the social identity model of crowd behavior," *Group Processes \& Intergroup Relations,* vol. 2, no. 4, pp. 381-402, 1999.

[33] J. Lengyel, M. Reichert, B. R. Donald and D. P. Greenberg, "Real-time robot motion planning using rasterizing computer graphics hardware," 1990.

[34] S. Paris, M. Mekni and B. Moulin, "Informed Virtual Geographic Environments: an Accurate Topological Approach," 2009.

[35] M. Mekni, B. Moulin and S. Paris, "Semantically-Enhanced Virtual Geographic Environments for Multi-Agent Geo-Simulation," *Advanced Geo-Simulation Models, Danielle Marceau, Itzhak Benenson, Bentham,* pp. 66-91, 2011.

[36] J. Sowa, Encyclopedia of Artificial Intelligence, S. Shapiro, Ed., Wiley, 1987.

[37] S.-G. Chen and J.-Y. Wu, "A geometric interpretation of weighted normal vectors and its improvements," 2005.

[38] M. Minsky, A Framework for Representing Knowledge, P. Winston, Ed., MIT-AI Laboratory, 1974.

[39] J. Lewis, P. Skarek and L. Varga, "A Rule-Based Consultant for Accelerator Beam Scheduling used in the {CERNPS} Complex," 1995.

[40] S. E. Varlan, "Knowledge Representation in the Context of E-business Applications," *BRAND. Broad Research in Accounting, Negotiation, and Distribution,* vol. 1, no. 1, pp. 1-4, 2010.

[41] J. Sowa, Knowledge Representation: Logical,

Philosophical, and Computational Foundations, Course Technology, 1999.

[42] M. Mekni, "Crowd Simulation Using Informed Virtual Geospatial Environments," 2013.

Dr. Mehdi Mekni received his B.Eng. (2000) degree from the department of information sciences at the University of Tunis (Tunisia), and his Ph.D. (2010) and M.Sc. (2006) degrees from the department of computer science and software engineer at Laval University (Quebec City, Qc, Canada).

He is now an assistant-professor at the University of Minnesota, Crookston campus in the department of math, science and technology. His main interests include multi-agent systems, agent-based geo-simulation, and application of artificial intelligence techniques on modeling and simulation of software agents.