Crowd Simulation Using Informed Virtual Geospatial Environments

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Abstract: - Crowd is an emergent 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 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. 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 informed virtual geospatial environments. 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.

Key-Words: - Social Agents, Virtual Humans, Informed Virtual Geospatial Environments, Social Behavior, Crowd Simulation.

1 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) [5]. Crowd phenomena take place in a spatial environment, and ignoring the characteristics of this environment would greatly decrease the quality of crowd simulations. 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 [3]. 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 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 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 [5]: 1) automatically creating an accurate geometric representation of a 3D VGE; 2) automatically integrating the geometric representation with several types of semantic information; 3) 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.

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. Section 3, introduces a new model to automatically build informed virtual geographic environments Section 3 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.

2 Related Work

2.1 Virtual Geospatial Environments

GIS data are mainly represented in two forms [1]: 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 [2] is the direct mapping of the raster format, and can also be applied to the vector format (Figure 1). The advantage of this discrete method is that multiple semantic data layers are easily merged in the same geometric representation [3]: 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. 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 [3] or large crowd simulation [2] because of the fast data access it provides.

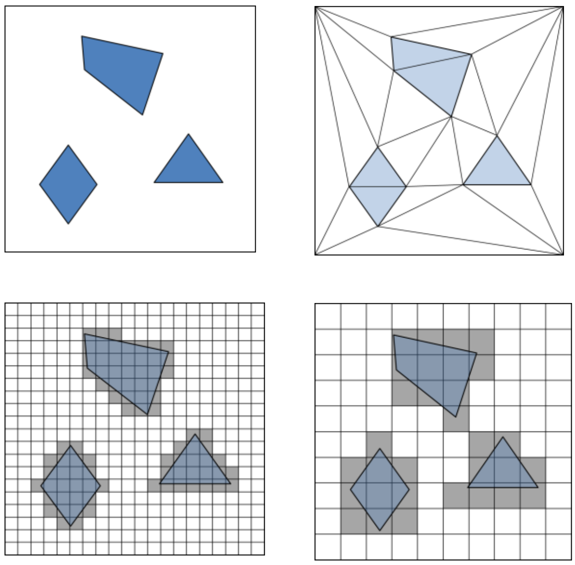

Fig 1. The two common cell decomposition techniques used to represent environments

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) [4]. 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. Another advantage is that the memory complexity of this approach only depends

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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 [4]. 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.

2.2 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. [12] 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. [21, 22] mention that usually social forces models tend to create simulations that look more like particle animation than human movement, and propose to add psychological, physiological and geometrical rules. Other approaches address some kinds of social links in a different way. Reynolds [25] proposes a set of behavioral rules to manage emergent motion phenomena between flocks of simple agents.

More recently, Lamarche et al. [16] 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 [17]. 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. [15] propose to use five psychological factors (motivation, stress, confidence, focus and emotions) to understand and assess individual behaviors in a crowd. Silverman et al. [13, 26] 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 [7] 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 [19] 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

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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 [10], and the social identity theory [23, 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 [11], where each agent has a threshold which leads him to adopt an activity when exceeded. Newell [20] 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 [18] 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) [27] claims that individuals evaluate their own opinions and desires by comparing to others. In a recent work, Kaminska and Fridman [14] 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 [22]. 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 [28], 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 [8]. The Elaborated Social Identity Model of crowds (ESIM) [9] 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. 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 [24].

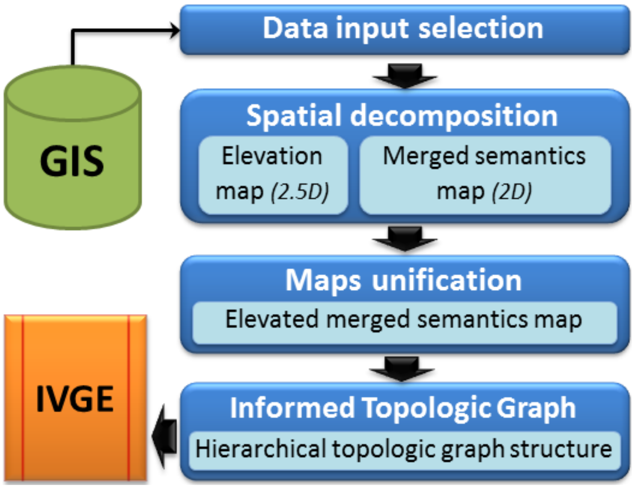

Fig 2: The four stages to generate an IVGE from GIS data.

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.

3 Generation of IVGE from GIS Data

We propose an automated approach to compute the IVGE data directly from vector GIS data [5]. This approach is based on four stages which are detailed in this section (Figure 2): input data selection, spatial decomposition, maps unification, and finally the generation of the informed topologic graph.

3.1 GIS Input Data Selection

The first step of our approach consists of selecting the different vector data sets which are used to build

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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.

3.2 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 [6].

3.3 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.

3.4 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.

4 Social agent behavioral models

4.1 Behaviors Description

We propose two ways to specify the behaviors of our autonomous agents [1]. 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.

4.2 Behavioral Model Overview

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

Individual behaviors are common to all simulated agents. They represent the standard behaviors of a

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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.

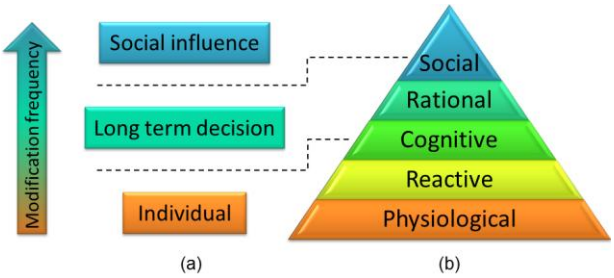

Fig 3: Comparison between our approach (a) and A. Newell's behavioral pyramid (b). The arrow on the left illustrates the variation potential of the agent's behavioral layers, while the dashed lines indicate their repartition inside the pyramid.

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.

5 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.

5.1 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 (Figure 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.

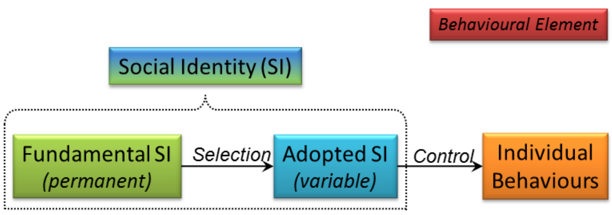

Fig 4: The social identity (SI) behavioral management. The fundamental SI can change the adopted SI at any time, while this one controls the individual behaviors resulting in successive elementary actions.

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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.

5.2 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 (Figure 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.

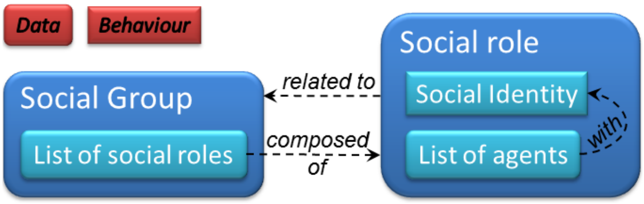

Fig 3: The social group architecture. A social group contains a list of applicable social roles, which each contains a list of the agents playing that role by adopting an associated social identity.

5.3 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 (Figure 4).

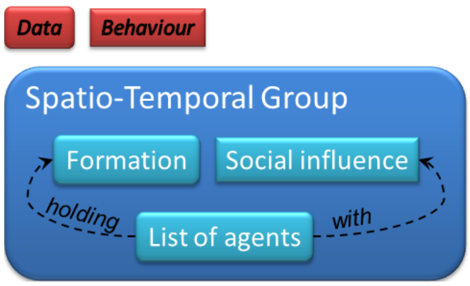

Fig 4: The spatio-temporal group (STG) architecture. A STG contains a list of the participating agents, as well as the geometrical formation they have to maintain and the social influence behavior they adopt.

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

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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.

5.4 Synthesis

To conclude with the social agent's behavioral models, let us look at the overall mechanism. As shown in Figure 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.

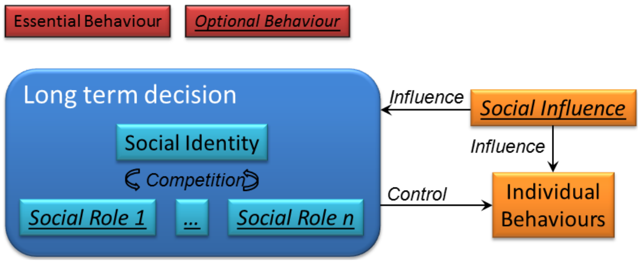

Fig 5: Social agent behavioral model synthesis. The individual low level behaviors are controlled by the high level decision mechanisms, which are composed of a social identity and optional social roles. Both of these categories can be influenced by a social behavior given by an STG.

6 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 which reproduces The Summit of the Americas held in {blind}. The simulation involves a large number of geo-referenced individual social agents immersed in an informed virtual environment representing {blind} city. 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

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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 Figure 6).

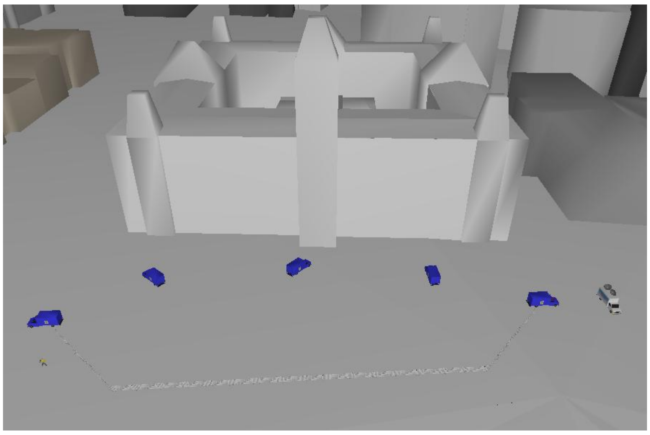


Figure 6: A 3D visualization of the simulation environment showing the parliament of {blind} protected by fences and several police trucks for control forces deployment.

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 (Figure 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 (Figure 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 (Figure 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 (Figure 9(b)).

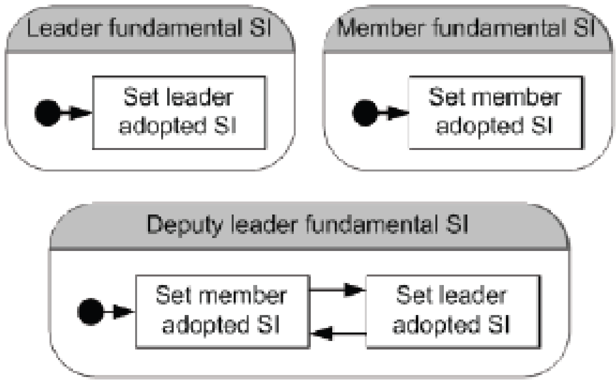


Fig 7: The leader, member, and deputy-leader fundamental social identities.

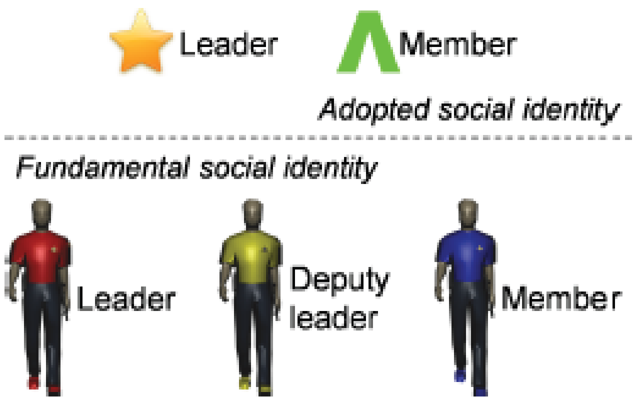


Fig 8: Graphical convention to identify the squad roles.

In order to illustrate the social role dynamics, we arbitrarily make the leader leave the group (Figure 9(c)). As a result, the deputy-leader's fundamental social identity (Figure 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 (Figure 9(d)).

Finally, the deputy-leader's adopted social identity makes him leave the place by moving back to a police truck (Figure 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.

7 Conclusion and future work

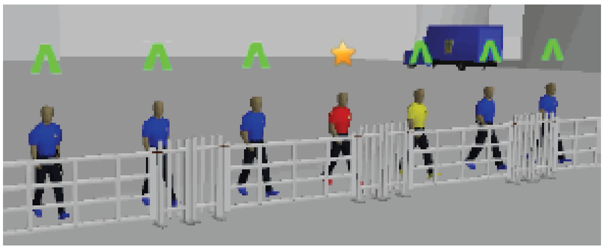
In this paper, we discussed some shortcomings of current research works which deal with social behaviors and crowd simulation in virtual geospatial environments.

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 figure 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.

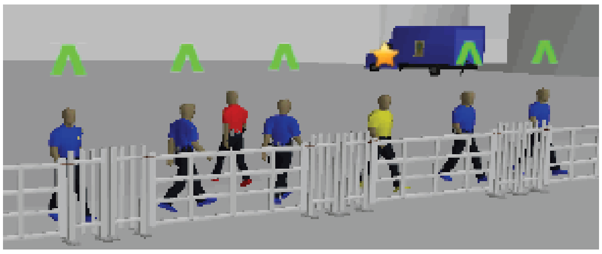
Second, we proposed a novel approach which aims at gaining better insight in crowds' social behaviors by analysing the social interaction mechanisms between individuals. Besides, our approach is related to crowd microscopic simulation because it allows describing individual attitude changes which are 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.

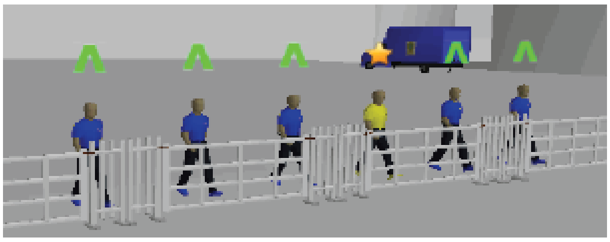
(a) The squad members get out of a truck.



(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.

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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.

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