A new microscopic approach to crowd modeling applied to urban crisis management training

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ABSTRACT: Modeling human behaviors is the new challenge that current simulations are facing. In this context, the complexity of interactions between individuals is a major implementation challenge which becomes critical when addressing the modeling of large groups such as human crowds. In this paper we introduce a new generic framework called DirectIA® and explain how this new technology can be used to create fully adaptive behavioral entities which form highly realistic and interactive crowds. Especially, we present a specific implementation, in a virtual environment representing a train station. Results show how this approach can successfully model crowd reactions in various context, ranging from normal to panic situations.

1. Introduction

Human behavior is a key issue that simulations have to address. Indeed, in the last five years, synthetic environments, virtual terrains, physical engines and virtual reality technologies have tremendously improved, due to the emergence of new techniques and the dramatic increase in computing performance. Human behavior modeling has not followed the same path.

Most of human behavior simulations still rely on classical techniques; some of the most well known being finite state machines and hierarchical decision trees. It is obvious that such techniques, which are effective in simple cases, face complex issues such as combinatorial explosion when confronted with more realistic modeling requirements:

- when a large variety of situations has to be accounted for;
- when a wide diversity of individual behaviors need to be modeled.

While users level of expectation rises, new approaches must therefore be developed and validated to cope with this complexity.

This is especially true in the military simulation domain, where requirements have dramatically changed in the last ten years. Along with the emergence of asymmetrical conflicts, the modeling of civilian crowds, and non conventional or non structured forces, becomes critical, in order not only for training purposes, but also to validate new courses of action.

In modern crisis and conflicts, civilians do not obey any behavior code tacitly involving some sort of violence control. Confrontations between military forces and civilians can suddenly degenerate, above all when other parties, determined and organized, infiltrate them. This fine-grained level of detail requires, at the simulation level, that the crowd model exhibits dynamic and interactive mass movements, as well as individual initiatives. In that respect, conventional technologies fail to address the problem, hence the need for a new generation of modeling approaches. Moreover, many incidents have been documented that involve overcrowding and crushing during emergency situations (Fahy & Proulx, 1995). Such studies emphasize the importance of research on human and social behaviors during emergency evacuations (such as building emergency evacuations for instance) in order to improve safety in public places (Bryan 1997; Proulx 2001).

This paper presents a new realistic model for the simulation of groups and crowds based on adaptive decisional entities. We will emphasize how this generic behavioral model can be used to implement heterogeneous entities which interact together as a crowd in a synthetic environment.
We introduce two main novelties: (i) a new approach allowing the modeling of high-level individual behaviors in a microscopic crowd simulation; (ii) a direct link with the application, thanks to a framework that allows rapid prototyping.

The first part will introduce the DirectIA® architecture and will focus on the concept of motivational model applied to crowd modeling. The second part will show how this new approach can be used to model a crowd evolving in a train station environment.

2. **Dynamic and realistic crowd behavior emerges from adaptive heterogeneous agents**

2.1 **State of the art**

Human crowd behavior modeling is a complex issue since it requires to reproduce the global dynamic characteristics of a large human group (e.g. emerging behaviors) while simultaneously accounting for fine-grained individual properties, and at the same time ensuring interactivity at any level.

To solve this issue, two complementary approaches are traditionally used: the macroscopic approach and the microscopic approach.

The macroscopic approach is commonly used by physicists for the modeling of natural systems. In this approach, global metrics (e.g., pressure) are defined in order to describe the global behavior. The crowd can, for example be viewed as a fluid; in this case, the macroscopic approach allows modeling the fluid without accounting for all molecular interactions. The global model can also be supported by statistical laws (Batty et al., 2003). This top-down approach can optimally reproduce the global properties of the system, but does not account for the characteristics of its constituents (Still, 2003).

The microscopic approach simulates crowd behavior as the sum of individual behaviors. In such simulations, a force field is applied onto elementary entities in order to influence their final behaviors (Reynolds, 1987). Such models include flocking and steering techniques. Since elementary behaviors computation does not require extensive CPU time, such bottom-up techniques are used to model large numbers of entities forming huge crowds (Bouvier et al., 1997; Helbing et al., 2000). These emergent systems (such as crowd dynamics) intend to simulate complex phenomena with the interactions of simple entities (Thompson, et al. 2003; Legion, 2004). Also, agent based systems simulate individual and social behaviors with a “perception-interpretation-action” model. These agents continuously assess the surrounding environment and make decision according to the model in a proactive fashion. The human social behaviors can then be observed as emergent phenomena. (Pan, et al., 2005; Bandini, et al., 2004).

Although such systems define a complex communication framework to provide emergent behaviors, the behavior of the simulated entities needs to remain very simple and homogeneous, to ensure maximal efficiency, which is also a major drawback when dealing with human crowd modeling.

An attempt to unify these two approaches is made by hierarchical crowd modeling techniques (Musse & Thalmann, 2001). With these techniques, the crowd is considered as a set of groups of human agents among which a behavior is distributed. Individual behaviors within a group follow the global behavior specifications. The global motion of the crowd is based on goals which are then redistributed to the sub-groups, ensuring a global hierarchical consistency (Musse, Babski et al., 1998).

This hierarchical model allows simulating visually realistic crowds. However the crowd behavior depends on the group behaviors realism and individual behaviors still remain simple. The complexity of interactions between individuals themselves and between individuals and their environment is not well simulated either.

In order to deal with this complexity and overcome those drawbacks, we introduce a new generic agent based framework on that simulates individual behaviors, interactively and dynamically. It has been called DirectIA® (standing for Direct Intelligent Adaptation).

2.2 **DirectIA® agent architecture**

This framework provides a generic decisional engine that allows implementing adaptive entities capable of taking decisions according both to their internal state and their environment. While these entities are commonly called agents, through DirectIA®, we introduce the concept of motivational agents. This approach lies within the framework of situated artificial intelligence (AI).

In the situated approach, elementary behaviors are adjusted altogether into more complex (higher-level) behaviors. As opposed to symbolic AI, situated AI models a system reactive capabilities and its adaptation to unforeseen situations.

The DirectIA® decision engine has been described previously (Chiva et al. 2003) as a three-layer architecture. Two decisional layers (the motivational graph and the behavioral graph) propagate an activation to the final actions layer which causes the agent to select the most adapted actions according to the current context (i.e., to take an appropriate decision).
DirectIA® has been developed from ethological research, and therefore borrows ideas and concepts from that field. From such a point of view, a motivation can be viewed as an internal variable that accounts for both the internal state of the entity and the stimuli it receives (McFarland & Bösser, 1993).

This motivation defines possible goals for the entity and is used to trigger behaviors. By reaching such goals, the entity tries to maintain the variable in an “acceptable” state, thus “satisfying the motivation”. In that respect, a motivational system can be viewed as a dynamic system, able to generate its own goals and to assess its own needs.

A tremendous advantage is that, using this technique, the entity is able to manage several goals simultaneously and combine competitive alternatives.

**Behavioral graph**

DirectIA® is, in fact, a hyper-connected graph (an oriented graph, without cycles). Whereas each node of the graph describes a behavioral rule dealing with its sub-goals, the leaves of the graph define final actions. Rules assessment is done layer by layer, propagating strength value to the final nodes or actions. This iterative assessment of the graph avoids the backtracking bottleneck.

**Actions selection**

Once the assessment of the behavioral graph has been completed, the agent selects the most appropriate actions according to the behaviors strength propagation (Tyrell, 1992). The elementary actions are directly bound to the agent physical effectors in order to interact with the environment.

**A framework ideally suited to crowd behavior modeling**

With the DirectIA® architecture, behaviors can be easily added or modified, and existing behaviors and elementary actions can be reused. What makes it ideal in the context of crowd modeling is that DirectIA® agents are able to exhibit complex and adaptive emergent behaviors. This architecture therefore can be viewed as a fine-grained modeling system (since the level of detail can go down to the individual level) which complexity can be mastered, in order to avoid combinatorial explosion.

DirectIA® is currently used in a variety of simulations, both in the military domain (Cantot & Chiva, 2004; Chiva et al. 2005) in the context of training and OR, and in the industry (PLM, professional training, videogame middleware). Since the DirectIA® framework has already been extensively used and validated, we will not focus on its functioning but rather on its use to create a new realistic crowd model accounting for individual stress behaviors, in the context of a simplified train station synthetic environment.

**2.3 Crowd modeling**

**The crowd theoretical phenomenon**

The crowd phenomenon appears when hundreds to thousands of people are gathered together in the same place, without any specific reason. Each individual wants to satisfy his own motivations, but this simultaneity causes particular effects. The seminal work “Psychologie des foules” written by Gustave Le Bon in 1895 (Le Bon, 1895), explains that a crowd cannot be considered as the sum of each individual's mind, but rather as motivated by primary passions and instincts. McPhail defines a gathering as "a patchwork quilt of multiple and diverse sequences of individual and collective behaviors." (McPhail, 1991). Individuals engage in several behaviors, some with just a few nearby people and others collectively with the larger gathering. In fact, within a crowd, individuals lose their individuality.

To account for this phenomenon, each agent of the simulated crowd inherits from a common DirectIA® behavioral model. However, each entity is individually instantiated, which allows implementing heterogeneous behaviors and personalities.

During the behavioral assessment (i.e., each time the DirectIA® architecture is activated), each agent takes care of its local environment. By local, we mean a small area that depends on the state of the agent. An important
component that influences this internal state is the stress level.

As we will show in the following, the model focuses on crowd behaviors modeling during critical situations. In such situations, physiological and psychological responses, including stress modulation and panic, as defined by the literature, are taken into account in the model.

**Stress definition**

Stress is a very confusing concept, often misunderstood. H. Selye first introduced the theory of general adaptation syndrome by defining stress (Selye, 1956) as a normal bio-physiological and psychological defensive reaction of the human body against all kind of threats or aggressions. It is an immediate reaction that triggers an adaptive behavior.

This reaction is traditionally divided in three stages. First, an alarm phase wakes up all body defenses. Second, an adaptation mechanism keeps the alert active. Finally, the defenses break down if the situation remains unchanged: this is called the exhaustion phase. However this model does not account for the complexity of individual reactions. In 1999, Crocq extends Selye's theory (Crocq, 1999). The stress is defined as having three direct effects in modulating the decision: (i) it focuses attention on the danger or critical situation, (ii) it mobilizes decisional capabilities and (iii) it triggers actions (Crocq, 1999).

To take into account this mechanism is therefore of critical importance when modeling emergent behaviors within crowds. In the model, the stress is the result of a mix between external stimulations (also called stressors by Selye) and internal properties. According to the origin of stimulation, we will use specific terms to refer to stress such as anxiety, edginess, fear, annoyance, etc.

The model uses several key variables to represent the stress concept. In our model, an agent is sensitive to four different stress stimuli: dangerous and annoying objects, crowd density and schedule. They directly impact three internal state variables: “need to flee”, “edginess level”, “rush level”. Thus each variable can trigger different behaviors according to a specific situation and combine them into a adaptive and complex reaction. In order to simulate the stress effects defined above, an emotional transfer function is applied to the stimulations strengths. It defines a surprise factor reinforcing the first behavioral decision and a habituation factor attenuating the first stimulation strength. These factors reflect attention or awareness of the agent to its environment. A situation with a normal stress level triggers adaptive reactions. But the more an agent is stressed, the closer it monitors its environment.

**Panic phenomenon**

The panic can hit a single person, a group, or a crowd indiscriminately. After an alert signal stimulation, the individual will flee straight ahead, suspending all current activities. This panic escape behavior is a contagious phenomenon. If people are too stressed, they will compulsively imitate each other's reactions. This explain why and how general panics can wake up and propagate. The group under panic loses its structure, hierarchy and task dispatching (Crocq, 1999). This is why we currently focus our simulation on crisis situations and not hierarchical relationship.

**Motivations and priorities**

Gathered in a dense crowd, people do not care for others. In an extreme case, they only want to satisfy their own motivations, without helping injured people or people on the ground. They only have very low-level social relationships, and transmission of emotions from people to people is fast (Anzieux, 1968).

To account for such mechanism, our model defines several kind of motivations. In normal situation, people try to satisfy their main motivations. However, during a panic situation, life-saving behaviors supersede these motivations.
**Low level motion**

Once a moving action is selected, a pathfinding algorithm (we use the A* algorithm) computes the most fitted path to the endpoint the agent has to reach. The agent will then try to follow as close as possible the computed path, with the help of a steering algorithm. This algorithm helps avoiding dynamical obstacles along the path, such as other agents. Moreover, this algorithm is also influenced by the agent motivations, such as reaching crowded areas (in order to avoid staying alone) during stressful situations.

**Conclusion**

We have introduced a generic model of life-saving behaviors, according to stress definitions and panic phenomenon. This model will be integrated into a more complex behavioral model in order to deal with the everyday life of a train station simulation.

3. **Case study: A train station simulation**

This new macroscopic approach models the crowd behaviors using adaptive agents. A crowd simulation system (called COHUE, a French acronym for “Comportements HUmain Emergents”, standing for Emergent Human Behaviors) demonstrates the advantages of the modeling approach presented above. The current scenario takes place in a small train station. Trains run in opposite directions (toward the city or the suburbs). Several ticket offices or vending machines are located in the station. The station has two entrance doors. Agents enter into the station, coming from trains or the outside, then, at each instant, try to satisfy their own motivations.

3.1 **Definition of behaviors**

Each agent is defined using the general motivations and behaviors (such as life-saving motivations and behaviors), defined above, depending on stress-related state variables. A new environment brings in new possibilities of interaction, e.g., with new objects. New motivations and behaviors have to be taken into account in this new environment, in our case, to model the everyday life of a train station. Thanks to DirectIA®, which enables to define each behavior independently, we avoid the exhaustive definition of all decisional rules corresponding to each specific situation, which would otherwise require a huge decisional tree.

We have chosen three new motivations for agents evolving in the train station environment:

- **Buying tickets and queuing.** If an agent wants to buy a ticket and decides to do this by moving towards a vending machine or a human-run ticket office, he must wait in the corresponding queue. The queue selection decision is computed by evaluating the following variables: the queue length (the waiting time depends on the ticket office type), the proximity of the ticket office, and the agent's own time schedule. When he is close enough to the selected queue, he gets registered to it, and follows the others registered agents waiting for a ticket.

- **Exit selection.** Before exiting the station, agents select the closest station entrance and try to reach it. Then, they compute the most fitted path. Normal situation has no direct influence on the selection process. However, during a panic, the exit selection process is influenced by crowd density. As observed in real panic situations, the agent will have a tendency to move towards crowded areas and eventually decide to switch his selection to a door further away.

- **Taking a train.** The decision to take a train comes from the motivation to reach special key points, corresponding to train doors, on one of the two train platforms. These motivations also depend on the train schedule and the agent's own schedule.

3.2 **Scenario**

**Description**

Both everyday life in the train station and highly stressful situations (such as an explosion or a terrorist attack) can be simulated with our system. In the current scenario, trains arrive and leave the station at specific times, ticket offices also have specific opening time. These objects activation can be considered as stimuli that will trigger changes in agents motivations. Each agent has several features: initial values of state
variables, the relative weight of motivations defining the agent goals, and emotional parameters defining the agent sensitivity to stimuli coming from the environment.

Figure 3: The train station model, with agents trying to satisfy their motivations. The agents' colors represent the value of a specific state variable, with a shading from blue to red. For example, the agent motivation is satisfied for agents in blue, not satisfied for agents in red.

Unexpected events

Our scenario defines events that occur at specific times, and thus activate interactive objects in the scene. These objects trigger stimuli, and the agents react to them through an emotional transfer function. For example, when a ticket office opens, this stimulus calms down the people waiting in the queue, by changing their “edginess” state variable.

Depending on the object, the triggered stimulus can be spread over time, and also distance. As a result, it can have an immediate and strong influence on agents close to the object and a delayed and weakened influence on agents further away. These parameters, the strength of the stimulus, and the impacted area, are specified within the scenario. These stimuli have an influence on the crowd motivations, thus triggering new reactions from agents.

Figure 4: This sequence of images shows the activation of an object, thus propagating a stimulus of danger through the train station. This demonstrates the escape phenomenon of the agents in reaction to this unexpected event.

Results

The current performances of our simulation system allow to simulate roughly 500 people simultaneously in the train station, with a 30Hz physical engine refresh rate, and a 5Hz decisional engine refresh rate. Thus, our simple crisis simulation example enables the measurement of various indicators. Purposefully, we have chosen two different metrics in order to illustrate the range of problems that can be addressed using such a system. First, we were interested in measuring a Quality of Service (QoS) indicator concerning the train station in a normal situation. Second, we were interested in evaluating the consequences of a crisis in terms of casualties.

First, the QoS of the station itself is measured. Given that individuals arrive to the station with the same amount of time to catch a particular train, how many of them manage to do so? It could be interesting to compare these results before and after modifying particular station
equipment, such as a larger passageway, another bridge crossing the rails, etc.

The effect of a crisis in terms of casualties is evaluated by measuring the compression factor (CF), i.e., the maximum density of people around an individual, across time. If we consider that an individual is wounded for a CF between 1.5 and 3.0, and killed when its CF is above 3.0, we can estimate the number and the type of casualties caused by crowd compression during the panic following a terrorist attack. Not surprisingly, in a normal situation, no one is wounded or killed. However, the picture is far grimmer after a major crisis occurred in the station.

Since our model is not validated, we can extract specific patterns from the train station simulation. During normal situation, we can observe that individuals will uniformly feel the train platforms, trying to satisfy their “edginess” internal state by changing position (according to the density level). An other interesting arch-like pattern, well defined by Helbing (Helbing et al., 2000), is observed at the exit doors, during a panic situation. Hence, our model remains compatible with empirical observations.

As a conclusion, using our simple train station example, we have been able to compute several indicators that could be very useful for evaluating normal or crisis situations. This emphasizes the advantages of our situated AI technology for providing significant help to decision making.

4. Conclusion and Future Work

We have successfully implemented a crowd simulation prototype that demonstrates a new approach for realistic crowd behavior simulations. This prototype is based on a new framework called DirectIA® which allows achieving a realistic crowd representation including accurate individual models. A very large variety of scenarios can be built, matching the complexity of current urban crisis. This new approach intends to achieve the growing needs of urban crisis management training.

The validation of the simulated crowd behaviors will be a priority of the future work. Moreover, we intend to extend this prototype in order to handle more complex crowd behaviors. First, we would like to simulate groups of individuals, for example a sport team taking the train, and also communication between individuals in a structured group, such as hierarchical relationships. These extra features will allow us to simulate more complex crowd behaviors occurring during unexpected events which will highly increase the realism of synthetic and virtual environments.

Beyond crisis management training and military simulation, we expect this approach to be useful in a variety of applications: such as infrastructure design and optimization, virtual factory animation and PLM (Product Life cycle Management), and even entertainment (gaming, special effects in motion pictures, ...).

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6. References


7. Author Biographies

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