Multi-scale behavioral models for urban crisis training simulation

Jérôme Comptdaer
Dr Emmanuel Chiva
Stéphane Delorme
Henri Morlaye
Jérôme Volpoët

MASA-SCI
24, bd de l'Hôpital, 75005 Paris, France
Tel: + 33 1 554 313 20 – Fax: + 33 1 554 313 49
{jerome.comptdaer, emmanuel.chiva, stephane.delorme, henri.morlaye, jerome.volpoet}@masagroup.net

Dr Olivier Balet

C-S
Rue Brindejonc des Moulinais, 31500 Toulouse, France
Tel: + 33 5 611 765 28 - Fax: + 33 5 611 765 78
olivier.balet@c-s.fr

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ABSTRACT: *The ability to react to critical events during a crisis is a crucial skill for crisis managers which can only be developed through serious trainings. The CRIMSON urban crisis simulation system creates a virtual environment responsive to the managers' actions. CRIMSON simulates populations in the city as well as low-level entities such as police and fire-fighters units. Populations are simulated through a macroscopic model for global behaviors and urban mobility while low-level entities implement a microscopic approach for behavioral modeling. These heterogeneous models interact in a multi-scale behavioral simulation providing easy control for the trainer, and impact assessment of the trainee's decisions.*

1. Population simulation: a critical issue for urban crisis training

In 2005, the United Nations (U.N., 2005) reported that around 73% of the European Union population was residing in urban areas, 66% in Japan, 81% in the United States, 68% in Eastern Europe, and 42% in developing countries. These areas have proven extremely vulnerable to all sorts of threats. Indeed, with such population concentrations (up to 35 million inhabitants in Tokyo), any natural or man-made risk can turn in a huge tragedy without proper emergency plans and procedures.

In this context, risk assessments, emergency plans, and more rarely real scale training exercises, have become accepted tools for crisis management preparation, and strongly rely on simulation to provide this capability. Simulation is therefore a critical tool to immerse command posts and crisis intervention teams in a realistic environment, in order to assess their techniques and procedures.

Re-creation of an environment as complex as a large city heavily relies on the modeling of urban terrain and unexpected events (e.g. toxic cloud propagation, flooding, bombing…). However, this terrain is not empty, and one therefore has to account for the human dimension, representing both the urban population, and the intervention forces that need to be coordinated.

Today, both military and civil security operations share a similar feature: population is no longer extraneous but becomes the key player. Therefore, the complexity of population behavior must be accounted for, and reproduced without being limited to a simple reproduction of urban traffic.

In order to immerse incident management teams in situations where they can assess their procedures, train and experiment while seeing the actual effects and impacts of their decisions on the operational theater, both population and force representation need to be reactive, adaptive and dynamic.

This article discusses how both population and force modeling issues are addressed and implemented in CRIMSON, a crisis management training system which is under development in the context of European Security Research Program. We first introduce the CRIMSON project and platform, and describe how population modeling was addressed and implemented with respect to the state-of-the-art. We then discuss the macroscopic dynamic population model, before describing doctrinal agents that animate the structured forces. The last part of the article deals with multi-scale representation, and focuses on the interaction between the various models.

All examples in the article are drawn from the CRIMSON implementation.

1.1 The CRIMSON context

CRIMSON project's aim is to at investigate, develop and validate an innovative crisis management training platform using the latest virtual reality and simulation technologies. The project is partly funded by the European Community. This system, also named CRIMSON, is designed to enable inter-agency preparation, rehearsal and management of security missions including evacuation, search and rescue operations, active agents control and remediation in response to urban crises such as terrorist attacks, seizure of hostages, CBR (Chemical, Bacteriological and Radiological) attacks, or fires.

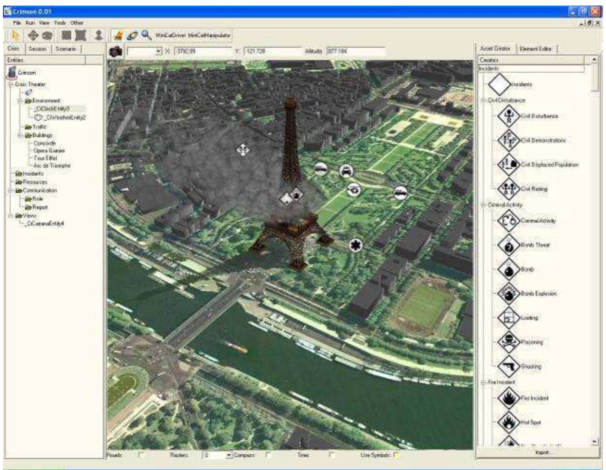

Figure 1: CRIMSON trainer screenshot with Urban database, courtesy of Infoterra.

CRIMSON assists emergency services and public administrators (such as key decision-makers, public managers, policy makers, planners, legal executives, etc.) in visually exploring crisis scenarios to better prepare for crises and reach consensus on complex environmental and security risks before disaster strikes. At the same time, it gives primary intervention teams a clear and vivid understanding of the pressing realities of crisis management procedures that cannot be grasped through normal, routine training operations.

The system proposes a module allowing massive urban databases generation, real-time rendering and animation of those environments. It allows single or collaborative training of crisis management teams. In the latter case, operators are considered as trainees and a session director controls the urban environment, the population behavior (crowd movements, panic, casualties, aggressors, etc.), and the crisis parameters (explosions, fires, toxic clouds, vehicle breakdowns, atmospheric conditions, etc.) He can also generate events, monitor and assess the behavior of each trainee and evaluate the quality and pertinence of their reactions.

The accurate restitution of population and intervention team behavior is critical to allow a realistic and seamless restitution of the real crisis effects. Such components enable immersive training sessions and avoid extensive human animation requirements, thanks to an autonomous agent behavior model.

1.2 Related works

The simulation of population behavior and flows requires to reproduce the global dynamic characteristics of a large human group while simultaneously accounting for fine-grained individual properties, while ensuring interactivity at all levels. In order to achieve this, two complementary approaches are traditionally used.

The macroscopic approach is commonly used among physicists for the modeling of natural systems and encompasses, for example, flow-based modeling (Kisko et al., 1998), fluid mechanics (Helbing, 1992), or statistical modeling methods (Batty et al., 2003; Fusco, 2004). This approach reproduces the global properties of the system, but does not account for the characteristics of its constituents.

On the contrary, the microscopic approach simulates complex phenomena such as crowd behavior as the sum of individual behaviors. It includes particle-based modeling (Bouvier et al., 1997; Helbing et al., 2000; Thompson, et al. 2003; Legion, 2004), cellular automata techniques (Benesson et al., 2004), optimization-based modeling (Still, 2000), and agent-based modeling (Bandini et al., 2004; Tecchia et al. 2001). Usually, elementary behaviors computation does not require extensive CPU time, and such bottom-up techniques can be used to model large numbers of entities forming small or medium-sized crowds. However, this approach does not scale well when simulating population in large cities with millions of dwellers.

Hybrid approaches have been developed to combine the benefits of two previous approaches. Examples in urban traffic modeling can be found in (Burghout, 2004; El Hmam et al., 2006), where the authors use a macroscopic model to simulate global traffic and apply a microscopic model on critical areas such as crossroads.

As a training simulation software, CRIMSON must be scalable compatible with real-time computation constraints.

Moreover first responders must be simulated at a microscopic level to exhibit operational procedure effects on the crisis and CRIMSON uses hybrid approach. It combines the two following heterogeneous models:

1. An original macroscopic model reproducing population behavior and urban mobility (i.e. traffic, population flows, etc.)

2. An innovative microscopic approach for specific units (Comptdaer et al., 2005) allowing the accurate restitution of their behavior.

The two following sections describe and discuss the two approaches used in CRIMSON for human behavior restitution.

2. CRIMSON population model: population behavior and urban mobility

Simulation of huge population involving millions of people (at city scale or larger) is a critical algorithmic issue both in term of scalability due to the number of individuals, and in terms of representation complexity of urban environment for crowd modeling. As opposed to simple urban traffic simulations, population simulation in a crisis context cannot be implemented using coarse and simple behavioral models (such as simple traffic simulation) as the population must exhibit adapted and, above all, realistic behaviors against unforeseen or unusual simulated events. For instance some people may try to retrieve their children at school during crisis which is a traditional phenomenon that is not taken into account in crisis plans.

To address this issue, our solution lies in a macroscopic approach of the population modeling that also integrates relevant properties of microscopic modeling. The simulated population is capable of exhibiting high-level behaviors according to the current situation and the environmental stimulations. Keeping the classical flow propagation paradigm, this implementation introduces goal-oriented behaviors and a situated representation of individuals. While being part of a global flow, each simulated individual can still be tracked down in terms of position and behavior. CRIMSON is based on a Geographical Information System (GIS) which provides the road graph with mobility properties. The population model uses this static information and builds its own dynamic representation of the environment.

2.1 The population behavior modeling framework

At a given time, the population is modeled as a distribution of individuals over three dimensions: location, profile, activity. The distribution evolves over time according to specific rules.

Time

CRIMSON is time-step based. The usual time step is 10 seconds. Experience showed this time step is suitable for typical training sessions. It is possible to fast-forward in time or to jump to a specific date. Special dates such as week-ends or holidays can be taken into account.

Location

A city in CRIMSON is modeled as a directed graph representing a simplified version of the road network. Nodes represent road intersections. Arcs represent segments of roads. A set of *containers* is attached to each arc. Information regarding the population distribution is stored in these containers as a <*profile, activity*> matrix describing a group of individuals. Each kind of container corresponds to a type of location. Currently the following types are taken in account: road, pavement, house, office, shop. Other types of spaces can be added.

Profile

A *profile* corresponds to the socio-cultural group to which an individual belongs. Individuals having the same profile behave the same with respect to the date and the time of the day. Thus, the main behavior of each individual belonging to a given profile needs to be computed only once by the profile itself. The socio-cultural group takes only one decision which is then implemented by every member, simplifying both the modeling of the population and the algorithmic complexity of the decision process.

A profile implements a DirectIA behavioral model as described in (Comptdaer et al., 2005) which allows an intuitive modeling focused on environmental stimuli, concurrent motivations and triggered behaviors and actions. Such profiles are easy to model as shown in (Chiva et al., 2003, 2004, 2005) and provide advanced reactive capabilities such as trade off and opportunism in front of unexpected events.

A DirectIA implemented profile triggers actions or activities with a computed strength according to the profile definition, the current time and eventual local point of interests. Once activities are selected, individuals belonging to the assessed profile are spread over each activity of each container according to the current profile and the computed activity strength.

```
∀ p ∈ Profiles
  DirectIA.EvaluateProfile(p)

∀ edge ∈ Graph
  ∀ p∈ Profiles
    ∀ c ∈ Containers(edge)
      distribution <- DirectIA.GetLocalEvaluation(p, c)
      c[p]<-SpreadOver(c[p], distribution, p)
```

Figure 2: Profile distribution algorithm. c[p] represents the container vector of individuals belonging to the profile p. SpreadOver function distributes individuals belonging to a specific profile in the current container according to the computed distribution with respect to density.

Activity

While the profile defines a socio-cultural group, the activity of the group describes its behavior at a specific time. A profile is defined by a sequence of overlapping activities over time. Moreover, at a given time, individuals belonging to different profiles share the same activity. The activity practiced by an individual defines how he will perceive his environment and be stimulated by it.

The activities are selected by the profile's decisional process. When a new activity is triggered by the profile, involved individuals will gradually switch to the new activity. The transition can be linear with time or follow a predefined progression.

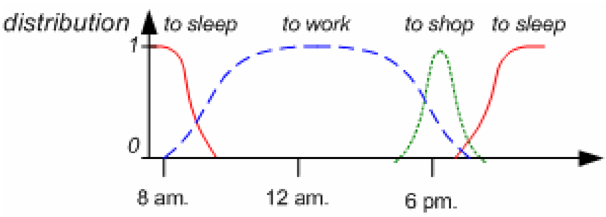

Figure 3: A profile is a set of activity distributions over time. In this example, most people tend to work from 9AM to 5AM and sleep from 10PM to 9AM.

An activity is bound to container types. When an activity is triggered, individuals in the currently evaluated edge move toward the other more appropriate containers of the same edge. Thus, individuals are spread over the edge containers according to the current activity strength.

```
∀ a ∈ Activities
  ∀ c_type ∈ ContainerTypes(a)
    influence[a][c_type] <- CustomDistribution(a, c_type)

∀ edge ∈ Graph
  ∀ a ∈ Activities
    ∀ c ∈ Containers(edge)
      people <- Σ_profiles c[p][a]
    ∀ c ∈ Containers(edge)
      c[a] <- SpreadOver(c[a], a, influence[a][c], people)
```

Figure 4: Activity distribution pseudo-algorithm. c[a] represents the container vector of individuals exhibiting the activity a. SpreadOver function distributes individuals exhibiting a specific activity in the current container with respect to density.

While an individual receives its activity from its profile (it is the profile which defines a global decision for the whole socio-cultural group), it is important it remains reactive to local events impacting only the surrounding individuals. Thus, environmental stimuli can only impact a local zone. These stimuli situated in the environment are perceived by the profile's DirectIA decisional engine and trigger specific activities applied only by the individuals in the impacted zone. These activities can take precedence over the global activity, for example a "working" individual facing a fire will receive from its profile a new "escape" activity. The implemented dynamics of these event-triggered activities is left to the modeling stage of the population. An activity has a specified duration (i.e. it remains active while individuals are exposed in the zone), or is terminated when a particular event occurs. For example, an individual will seek for help when injured. This activity may disappear when the individual has spent enough time in a hospital.

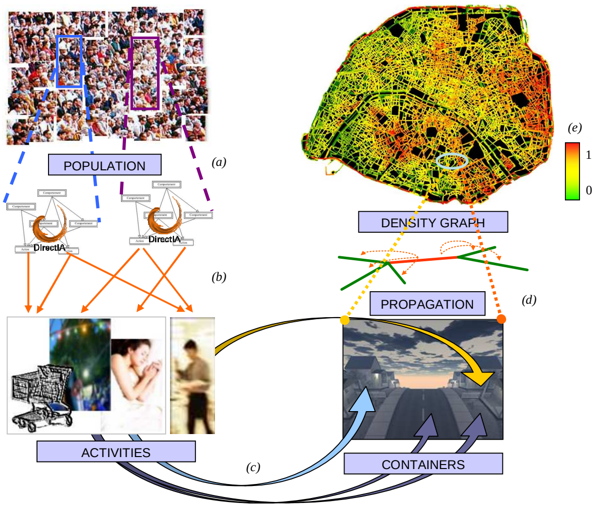

Figure 5: Population model overview.

Local events can trigger local behaviors, even though the decisional engine operates at a macroscopic level and solves the decisional process of all individuals facing a common situation. This factorizing feature is essential in order to satisfy the real-time constraints of the simulation especially when dealing with large populations.

2.2 An active environment based on potential fields driving population behaviors and mobility

A major goal of the population model is to allow urban mobility to emerge from the behavioral modeling. The geographical repartition of socio-cultural groups' residences is implemented by creating neighborhoods featuring different proportions of each profile.

The individual propagation phenomena are described by attractive or repulsive areas taken into account by individuals exhibiting a specific activity according to the current events, localization or time. The environment behaves as a set of potential fields, influencing individuals already "polarized" by their current activity.

The model is based on a combination of different potential fields directly bound to intuitive urban phenomena. For instance, the business district of the city is an attractive area for workers from 8am to 6pm during the week. Such kind of modeling process allows the direct definition of simulation parameters from main geographical and sociological features.

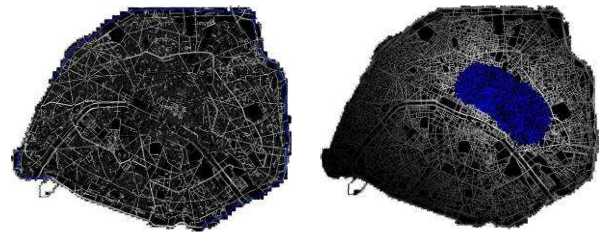

Figure 6: A model of Paris, France, with static potential fields on the left and active point of interest on the right (the patch of blue). The lighter the lines, the more they are attractive.

Several factors influencing potential fields are assessed and implemented in CRIMSON:

- The simulated road network characteristics (e.g. road width, max speed);
- Points of interest. These specific geographical features can be mobile. They attract or repulse individuals practicing specific activities during a given duration. Points of interest can either be defined at the initialization phase when the environment is defined or created during the simulation at run-time.

For each graph's edge, people are transferred to the neighbor edges according to the next edge attraction field, the container speed, and the container fluidity. The more attractive the edge, the more people transferred to this edge.

As points of interest can be either attractive or repulsive, this implementation is already adapted to crisis modeling. Indeed, specific and geolocalized events such as explosions, floods, fires, or looting, can be represented by specific points of interest which will be avoided or appreciated depending on both their nature and the population model.

Figure 7: Repulsive area.

2.3 Benefits of the approach

Thanks to this approach, the exercise supervisor can *stimulate* the crisis and leave the animation of the environment to the behavioral simulation module. The modeling phase and scenario creation stage both benefit from the intuitive nature of the modeling formalism. Moreover, the lack of quantitative population data on some cities can be bypassed through a simple modeling of neighborhoods and socio-cultural groups which is sufficient for crisis exercises.

3. Microscopic model: actors / leaders behaviors

This section describes the lowest abstraction level of the training simulation (i.e. the finest-grained behavioral entities). This level provides an interaction interface for trainees and trainers (e.g. allowing sending orders to emergency teams). It is important that entities at this level interact and behave realistically in the eye of trainees and trainers (e.g. through operational orders and reports).

3.1 Entities Representation

Entity level definition

At the microscopic level, the definition of the lowest level entities is critical as it conditions the behavioral granularity of the system. According to the final effects that are sought, the methodology relies on empirical questioning such as:

- What are the most representative entities for the trainee? It is unnecessary to represent low levels that are too far from the trainee preoccupations and that have no interaction with him.

- What are the relevant behaviors with respect to the selected entities?

- Is there enough data available to validate the behavioral model?

Usually when the trainees are in a hierarchy, entities are simulated two levels below the trainee. For example: in the SCIPIO training system (Chiva et al. 2005), trainee level is brigade commander and entities are simulated at company and platoon leader levels. In CRIMSON, the group leader is the lowest entity level.

Behavior representation

In the classical artificial intelligence domain, there are two main different ways to achieve this representation:

(i) Reactive approaches (Reynolds, 1987): using simple rules the entities react as the environment changes. This technique is very efficient since entities always exhibit a response; however behavior complexity is often sacrificed.

(ii) Descriptive approaches such as rule-based systems (Bonatti et al., 2004) or finite state machines. With these techniques it is easy to represent predefined complex behaviors. However the number of rules exponentially increases with the number of situations.

The DirectIA approach used in CRIMSON combines a free flow hierarchy (Rosenblatt and Payton, 1989) with user-defined procedures, yielding behavioral graphs. In this implementation, agents remain reactive to the environment, while exhibiting behaviors consistent with the doctrine (techniques, tactics and procedures). Advantages and drawbacks of this approach have been already discussed in (Chiva et al., 2004) and (MASA-SCI, 2006).

3.2 Interactions

Three interaction modes are implemented: communication between entities, hierarchical relationships and interaction with trainees.

Communication between entities

This communication type enables entities to cooperate in order to achieve common goals. Entities can communicate either by modifying their environment or directly by exchanging messages. The communication system enables entities to exchange complex information such as goals or knowledge. For example, in the CRIMSON system, a "police car" entity witnessing a riot can communicate this knowledge to some "fire fighters truck" entities.

Hierarchical relations and communication with the trainees

Hierarchical links between entities are implemented through the communication system. Entities exchange orders and reports as special messages with shared meaning. The messages use the real operational language specified both by methodology (when available) and operational experts.

This feature also allows natural interaction between trainees and the simulation. This method has been validated in the military domain ("train as you fight" paradigm) and is here successfully applied to urban crisis management training.

3.3 Illustrated example

Figure 8 features an example of all possible interactions of an entity at the microscopic level in the CRIMSON training simulation.

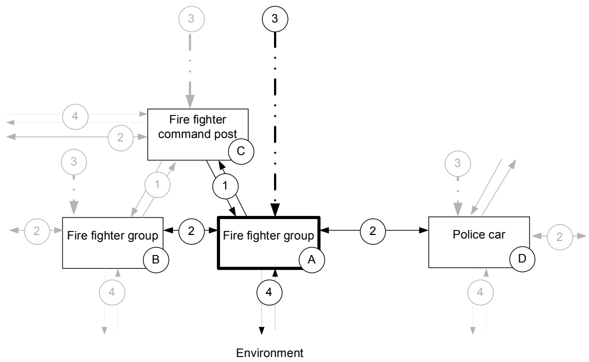

Figure 8: Entity interactions at microscopic level. Firefighter groups B and A communicate directly through inter-entities communication (2) and interact with the environment (4) while firefighter group A and command post C use hierarchical channel 1. Missions can be injected through external messages (3).

3.4 Conclusion

While classical large-scale simulations usually do not use such a detailed microscopic modeling scheme, it allows the implementation of simulated entities able to exhibit behaviors consistent with operational requirements.

This feature is helpful in introducing a natural interaction with the trainees, who can in theory use their usual tools and systems without being directly confronted with the simulation.

4. Interactions between models

As seen before, macroscopic population autonomously evolves according to predefined parameters, and reacts to environmental influences. Microscopic operational units are able to manage high level orders directly issued by animators and execute them according to a doctrine and the environment. Moreover these units can issue the appropriate orders to their subordinates relieving operators from micro-management.

Implementation of a global, consistent simulation requires these two models to be tightly coupled. This section shows how this interaction is performed in CRIMSON.

4.1 Influence of low-level entities on populations

Low-level entities interact with population through dynamic points of interest. Decisional agents have two main behavioral actions available to influence populations:

(i) Forcing individuals to change their activities within range of the created dynamic point of interest.

(ii) Influencing individuals exhibiting specific activities.

The decisional units play with these actions in order to make population behave as wished in the context of the mission they received.

4.2 Population acts on low-level entities

Populations influence the low-level entities in the following ways:

(i) low-level entities take into account potential traffic jams as they move. As the population propagates in the road network, it changes road and pavement densities, eventually influencing units' movement.

(ii) low-level entities can respond to specific behavior of the population such as rioting, looting, or sustain damage.

4.3 Case study: Demonstration and riots

The following describes how a demonstration can be modeled in CRIMSON.

A typical demonstration starts with a meeting point where demonstrating people and leaders gather. The demonstration normally proceeds according to a planned path. It gathers at the final point where it eventually disperses. Sometimes the demonstration tension exceeds a certain level, turning into violent riots and potential lootings.

In order to reproduce this sequence of events, a low-level entity representing demonstration leaders is created on a particular location. The operator then issues a demonstration mission to the leader. The leader will then attract concerned population by creating an attractive point of interest for potential demonstrators. As a consequence a portion of the population will adopt a demonstration behavior.

Figure 9: riot mission issued to leader

After a specified delay, the leader starts to move. It either follows a predefined or computed path to reach the destination. As the leader moves, it leaves a trace of point of interests. It also decreases the influence of older points of interest. This results in the population density of demonstrators to follow the leader.

Once arrived at destination, the leader can disperse the demonstrators by removing interest points. It can also raise the level of tension by setting a specific point of interest so that portions of the population start rioting.

This kind of interaction scheme is reproduced in most other operational missions. For example, low-level entities organizing a shelter will also create a point of interest with specific properties before activating it and attracting injured individuals. Area evacuation or road blocking can also be simulated in a similar way.

5. Conclusion and perspectives

5.1 Preliminary results

The behavioral model successfully implemented in CRIMSON addresses the two main challenges of urban simulation to enable crisis exercises:

(i) The simulation of urban population with credible and adaptive behaviors.

(ii) The integration of two heterogeneous models allowing intervention teams with doctrinal behaviors to directly interact with population.

CRIMSON is under active development and a early version has been reviewed by the user group composed of: the Estonian Rescue Board, the Department of Public Order and Safety of the City of Amsterdam, the Crisis Research Center of Leiden and Municipal Police of The Hague. The first qualitative results provided by the reviewers underline that the system satisfies initial requirements of a crisis management training tool. Indeed population behaviors and simulated units generate enough information to credibly stimulate training sessions.

5.2 Further developments

Future developments include investigating how to support a level of detail in the simulation of the population as to locally generate microscopic simulation from the macroscopic level. Indeed, while crisis can be managed from a global prospect, specific critical situations require local management. For example, a bomb has been identified on the third floor of a building gathering thousands of people. How will individuals react? How to organise building evacuation? This critical local problem has impact on the global crisis management plan, since it requires resources that otherwise could be mobilized to deal with other management issues. To master this complexity, one has therefore to "zoom" inside the crisis and holistically look at each problem at its own level. This microscopic approach enables an immersive visualization which, in turns, allows better analysis of the current situation. Thus the transition from a global urban situation theatre to specific local infrastructure level is a major issue that has to be addressed in order to better manage the crisis.

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7. Author Biographies

OLIVIER BALET is a senior engineer with a PhD in computer science, and the R&D manager of the CS' Virtual Reality Department. His main areas of expertise include 3D interaction and animation, Virtual Reality, multi-modal computer-human interfaces, cooperative working, physical simulation, virtual prototyping. Prior to his current position, he has conducted research on 3D interaction at the Toulouse III University, and on virtual human simulation at the ENSICA high school where he was Assistant Professor. He is also accredited expert to the European Commission, Virtual Reality professor at both the Toulouse III University and ENSICA, and the author of more than 25 papers published in international journals and conference proceedings.

EMMANUEL CHIVA is Executive Vice-President, and manages the SCI (simulation) branch of MASA. Emmanuel Chiva has a post-graduate degree from the Ecole Normale Superieure, in Paris. A biologist, he received his Ph.D. in Biocomputing in the field of dynamic complex systems modeling. He joined MASA at its inception, helped develop the Biomethodes subsidiary, and played a key role in MASA business development, before taking the operational responsibility of the SCI branch. He is a member of several industrial associations, and an expert for the European Community in the field of complexity sciences.

JEROME COMPTDAER has been working at MASA since 2003 as research and development engineer. His first job was to develop behavioral models for military simulations. He received a Computer Science Engineering degree, with a major in Cognitive Science, in 2003. He has a special interest in human and crowd behavior simulations and has been supervising the development of the population and agents modules in CRIMSON.

STEPHANE DELORME joined MASA in 2002. He first served as Modeling & Simulation supervisor before being appointed manager of a major simulation project in the field of Army Command Post training. He now holds the position of product development manager. He received an Engineering degree with a major in applied mathematics from Ecole Centrale Paris.

HENRI MORLAYE received an Engineering degree with a major in Artificial Intelligence. He has been working at MASA since 2005 as research and development engineer.

JEROME VOLPOET is the R&D manager of MASA. He received a Computer Science Engineering degree, with a major in Cognitive Science.