Detection of primitive collective behaviors in a crowd panic simulation based on a multi-agent approach

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Abstract

We propose an approach towards multi-agent system for simulation and detection of primitive collective behaviors emerging from a crowd in panic. This paper presents various works on which our method is based, by methods of planning and decisions allowing emergence of primitive collective behaviors. We present then an implementation in a virtual environment and detection experiments of emergent collective behaviors by recognition and identification methods of the situations awareness in the domain of Data Fusion. Measurements and human evaluation of results show the utility of simulation and detection tools implemented. That would be applied to some current monitoring system, such as envisaging behavior anomalies according to specific scenarios.

Key words

Multi-agent system, collective behavior, crowd panic, simulation, detection

1 Introduction

Events of an overflow crowd can occur during social gatherings and can cause their interruptions, damages, wounded and sometimes deaths. Individuals' gatherings are increasingly frequent. And without responsibility assumption of their safety measures, such as means of collective behaviors detection to prevent the emergence of problems, which can quickly getting out of control. As the Love Parade on July 24th, 2010 at Duisburg (Germany) where twenty-one people perished at the time of a collective panic during the passage of a tunnel, in spite of a security force present and trained to control the crowd which could only reduce wrongs. In another way, the detection of collective behaviors would be an inestimable help in many real and virtual situations.

This paper is in a thorough study aiming at defining the necessary means to detect collective behaviors in monitoring application including data fusion functions. In order to limit the complexity of the study, we work in a virtual environment for the detection of collective movements. This simplification makes possible to concentrate on the main goal and the checking of techniques effectiveness suggested by comparison with a virtual environment under control.

After this introduction, section 2 presents an analysis of the simulation and the detection of collective and social behaviors through various selected techniques used by multi-agent system. Finally, section 3 discusses the implementation of the software, experiments and obtained results.

2 Background

To model a crowd panic behavior, we present a study of crowd behaviors, follow-up of multi-agents system to model the latter. The concept of agents and multi-agent system has several definitions in the literature and we used some methods which we will present in this part.

2.1 Crowd Behaviors Simulation

Before discussing the manner of generating collective movements, we were interested first of all in their origin, individual behaviors.

2.1.1 Individual formal models

For a set of no-cooperative agents such as a crowd, each agent has an individual goal and can interact with other agents to achieve this goal. But when people are in panic, their goals are the same one for all, but they only try to achieve theirs before the other people.

There are three possible behavioral modeling approaches [14]: macro-level formal models (models of society behaviors), meso-level formal models (models of groups behaviors), and micro-level formal models (models of individual behaviors). Our agents must function in *stigmergy*, i.e. execution of some behavior like consequently of effects produced in the local environment by the precedent behavior. The choice of the modeling type depends on the nature of the problem to solve and on micro-models by the modeling of individual behaviors in panic.

Fiske [6, 7] defines the human conceptual model as being intercultural frameworks in all human cultures, coordinating their social interactions by using a mixture of fundamental relational models: communal sharing, authority ranking, equality matching and market pricing. These four models are organized in a set of associated concepts and rules which are used as a generative grammar for thinking and coordinating their relations. For example, an agent in a crowd panic will tend to trust a superior authority and to follow its close relations.

Agents model must thus have a cognitive architecture and a system multi-agent seems the best indicated for a crowd behavior.

2.1.2 Crowd Behavior Models

There are two characteristics for crowd behaviors: common stimulus between crowd participants and the imitated behavior. One finds recurring models thus, like the two following models using imitation and contagion characteristics in crowd.

SCT model [8] is a model based on the theory of social comparisons [5] and applies when an agent does not know its state (lack of opinions, capacities, and means of evaluations on itself). It compares its behavior with those resembling to him and try to correct the differences there found. With this model, displacements group behaviors are more sophisticated.

With his model, Helbing [9] is interested in calculating the wished speed and real directions and forces of interactions between agents and obstacles. It takes into account:

- Individuals real information : body mass, rate of possible path in normal weather and under the effect of panic, desired direction and speed, time of adaptation between the speed shifting,…;
- Forces of interactions: a repelling power which occurs between each agent and an obstacle by a body force which fights against bodies' compression and a friction force.

We can, while basing ourselves on this model, reproduce scuffles and trampling at the time of crowd panic movements.

2.2 Multi-Agent Systems

Agents [1] are provided with perception capacities of their environment, means of action and rules of decision, allowing selecting some aspects of their current behavior according to internal and external variables which are accessible for them.

For the model, hybrid agents with BDI architecture (Belief Desire Intention) [2, 12] correspond to the best manner of being able to generate various types of behaviors:

- Reactive for fast decision-making possible: the reflex behaviors at the time of risk situations that it will produce in direct response with some stimuli;
- Cognitive for a long-term plan.

The general idea is that the agent tilts between those two types of behavior according to the requirements, for better reflect the human behavior.

[3] and [10] proved the importance of an organization structure in order to improve the required effectiveness of a MAS. For our study, we choose an organization structure of coalition since one seeks to model a individuals group with behaviors generated by decisions beat on their perceptions of the environment and other individuals (the more numerous they are and the more they have information).

A source of inspiration for the creation of MAS is the bio-inspired systems. Within the model framework, the two approaches bio-inspired following were used for the emergence of collective behaviors.

2.2.1 Bio-inspired systems

Introduced into [13], *Flocking* consists of the swarm creation, similar to the movements of birds group. In such an organization each agent decides, in an autonomous manner, its behavior starting from local observations. The basic model consists in following rules:

- Separation: agents attempt to avoid collisions with nearby agents;
- Alignment: agents attempt to match direction with nearby agents;
- Cohesion: agents attempt to stay close to nearby agents.

Thanks to these three rules which locally coordinate the agents in the environment, a decentralized approach, it is possible to manage one very a large number of agents in time actual. And it is robust with regard to the failure of some agents, which is the crowd behavior characteristic having a common objective.

In system based pheromones, inspired in the way in which the ants organize themselves, agents are strongly connected with the environment. They communicate only indirect way by the deposit of pheromones in the environment. For that the agent has a simple memory of the already visited and perceived zones, pheromones can be deposited with a quasi not existing evaporation and dispersion.

Having agents perceiving the environment locally allows having situation awareness, however what can one detect in the behaviors to be automatic situation awareness.

2.2.2 Behaviors Detection

The behavior detection is part of the field of the activity recognition. The use of a multi-agent system gives us behaviors indications of each agent towards the remainder of the environment. It remains with knowledge what is interesting to detect.

Crowd panic characteristics:

- Movements of group;
- Recurrent displacements and the possibility of anticipating them;
- Physical shocks;

For that, we choose works on the HMM (Hidden Markov Model) to learn and find the same behaviors, and behaviors where individual vital space decreases in a crowd. We presented them in experiments.

3 Our model

This section is divided into two parts. The first allows simulating panic crowd behavior. It is necessary to perform the detection. The second part explains the heart of our problem, i.e. to present a form of behavior detection which can allow the creation of new tools for crowd safety.

3.1 Modeling agents for crowd simulator

Our crowd model is based on some equations and behaviors from the state of the art. Agents have one mean of communication, a partial observability of their environment, for a reproduction close to reality. Agents do also decide in real time, implying low complexity algorithms. Moreover, lack of communication limit the perception of their environment, it prevents any communication protocol to share their knowledge.

Each agent decides to choose an action according to its possible movements, desires and intentions:

- near dangers, agents try to move away in direction to the shelter;
- agents will have a tendency to explore the environment while following other individuals while they are not inside a shelter or near to a danger.

The cognitive architecture of agents which we produced can be defined as follows:

- its perceptions: other agents, obstacles, dangers, shelters, as long as they are in its view field;
- its rules of decision: a BDI architecture where the choice of the next travel of an agent results from the best increased reward of the sum of the rewards to move away from dangers (negative weight), to join a shelter (positive weight), to move in group (positive weight), to have a behavior minimal of browsing (negative weight in presence of pheromones) and do attention to no be stopped (positive weight).
- its set of action: a possible speed and a direction according to the model of Helbing [9].

Algorithm 1: Decision direction for an agent.
Input: $D \leftarrow \{\ldots\}$ // all its possible direction: eight directions and on the spot which can be reduced by his near-by environment (obstacles, dangers, agents).
$P \leftarrow \{\ldots\}$ // all its perception (other agents, obstacles, dangers, shelters, pheromones).
Output: Direction taken by the agent.

valueBest $\leftarrow -\infty$ // the best value of direction
directionBest $\leftarrow$ the current direction

```
foreach d in D do
    value ← 0
    foreach p in P do
        if the distance between agent and p decreases when one takes d then
            value ← value + (the weight of the type p) / (distance × number of the type d)
        end
    end
    if value > valueBest then
        valueBest ← value
        directionBest ← d
    end
end
```

Initially, agents know their positions. Therefore they have knowledge of obstacles, but not of dangers. Once dangers appear, their partial perceptions obtained from their travels allow them to update their own knowledge (positions of obstacles, individuals, dangers, shelters).

3.2 Modeling the crowd behavior detection

The simulation of panic crowd makes it possible to obtain data for Collective Behaviors Patterns (CBP) domain. Analyze and predict the CBP is required in the Activity Recognition domain. Instead of analyzing complex behaviors arbitrarily, we use a set of primitive behaviors to summarize and to analyze this specific MAS.

Let us consider an agent in MAS provided with interactions capacities. We base our behavior model detection on approach explained in [4]. The use of local interactions makes emerge a perceived organization and it is the representation of a collective behavior.

The idea was then to show that one can make use of his data to detect ways in the crowd which pose problem for their safety: prediction of crowd displacements and repetitive places of scuffles. In the model, agents generating individual behaviors are all pedestrians. And we applied to the machine learning a travel probability distribution for each state (each possible position of an agent). This enables us the evidence recurrent behaviors of crowd travels.

For this, we used a HMM (Hidden Markov Model) [11] define as a 3-uplet $\langle A,B,\Pi \rangle$:
- $A = \{ a_{ij} \}$ transition probabilities where $a_{ij} = Pr(s_{t+1} = q_j \mid s_t = q_i)$ the transition probability that the state of the HMM at time t+1 will be q_j if at time t it was q_i (where $q_i = (x_i,y_i)$ are coordinates on the map);
- $B = \{ b_j \}$ emission probabilities where $b_j(V) = Pr(V \mid s_t = q_j) = 1$ the emission probability that the observation is V if at the time t it was q_i and where the observation vector is $V = \{ v_0, \ldots, v_T \}$ where v_t is the visible observation at time t (here, it's always 1 because we know the states by the simulation);
- $\Pi = \{ \pi_i \}$ initial probabilities where $\pi_i = \Pr(s_t = q_i)$ the probability to be initially in the state q_i;

These discrete processes check the Markov assumption to the order k which consists in telling that transition probabilities depend only on n previous states. We obtain from it a Markovian chain of the first order with states not directly observable (internal to the agents) on which one can carry out predictions of future positions of agents (see 4.2.1 for results).

4 Simulation and Experiments

In this part, we present the software implementation with experiments results for each idea.

4.1 Software

A crowd panic allows observing collective behaviors emerging, since individuals have behaviors of moving under the panic action. This kind of system is entirely configurable over the environment and individuals. This is not possible in reality: implying real individuals in such scenario could be unsafe.

In our model, each individual is an agent. The environment in which agents evolve is observed by a graphic interface. The complete system programming was made under Java language.

4.1.1 Illustrations

We present illustrations on the behavior obtained by agents. In the following figures, we use the following representations:

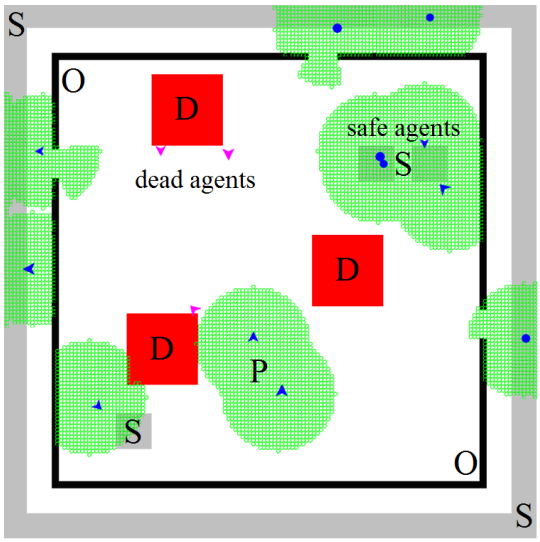

Figure 1: Initial situation

- *Agents* by a blue circle when they don't move, by an blue arrow which indicates the *direction* of their current path or by a magenta arrow when they *died* (caused by the proximity of a danger or underwent a trampling);

- *Obstacles* by black zones;
- *Dangers* by red zones;
- *Shelters* by grey areas;

- their current *Perceptions* by green zones (reduced by smoke on the following illustration, if not they would see all that can be perceived and green limits would not appear);

In this situation, some agents are found dead with three zones of dangers (on fire for example) and three zones of shelters (interior), but they are found safe from leaving the place. They are disseminated here through the environment. This situation can be a large room where three zones undergo a fire.

4.1.2 Experiment 0: The movements

The three dangers areas appear instantaneously (Figure 2), killing some agents which are close for them. A few seconds later, agents scattered as a preliminary, gathered in several groups, there was emergence of coalitions.

We see several formed groups where agents keep a distance between walls and hazardous areas, and move towards internal outputs or shelters. We can see that agents in end of tail are not informed of reasons of travels carried out by the head of the group. This looks like a collective panic behavior where individuals follow the sway in the crowd.

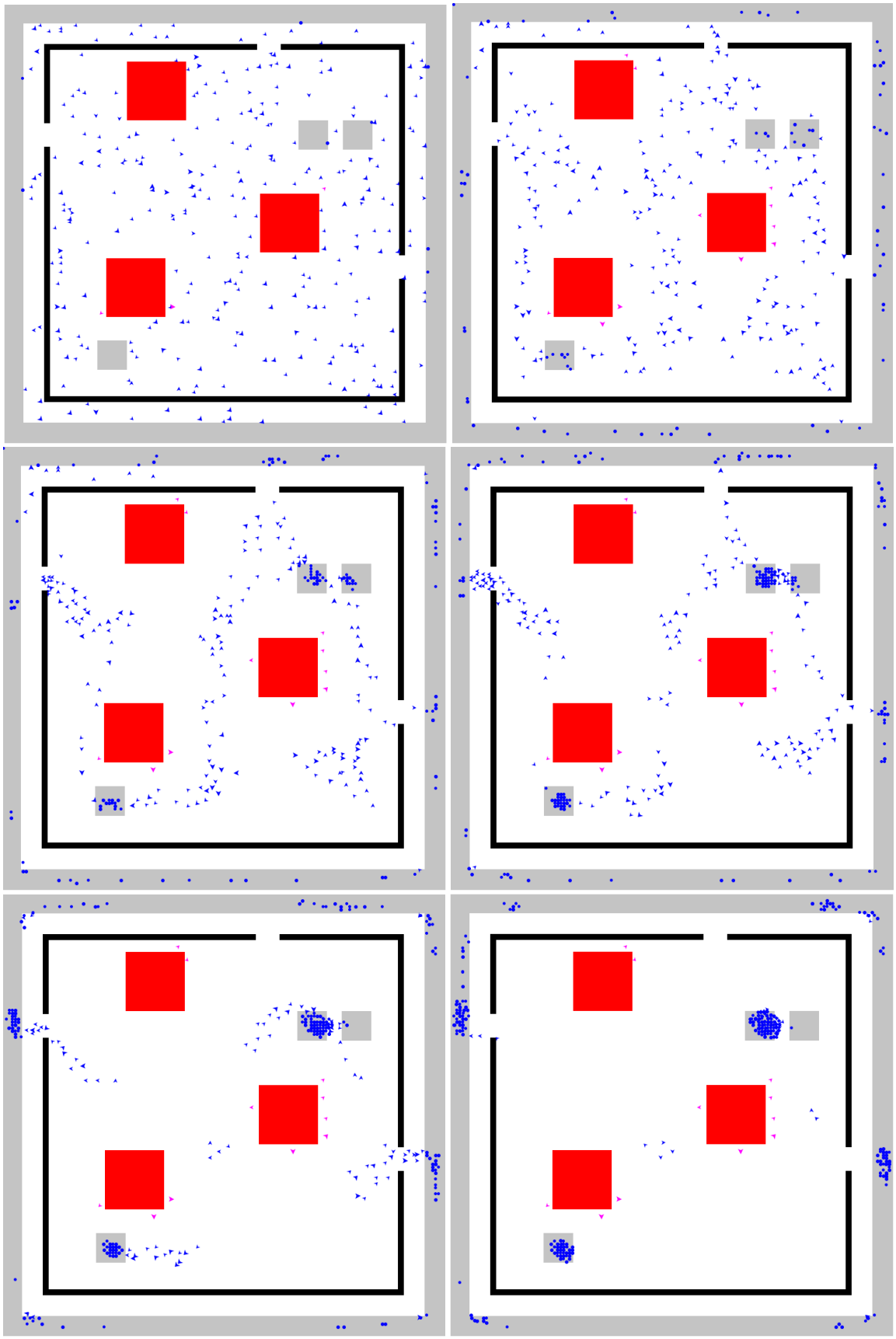

Figure 2: Example of unfolding (at t = 0, 5, 10, 15, 20, 25 seconds)

One can see in the last illustration, a group of four individuals in the middle of two dangers having only the knowledge of dangers and the dead ones which approached some. Not seeing shelters and

outputs, therefore it remains on the spot under the panic blow, by their weak perception.

Other coalitions show well their bringing together with shelters, their distance with dangers, but few outputs of the area. This proves some capability to prefer internal shelters rather than external shelters which would oblige to pass by an exiguous exit.

This experience illustrates a swarm behavior. This simulation is sufficient to regard it as the result of an observation obtained by sensors, and could be used for our detection system.

4.2 Detection of the collective behaviors

In emergency and evacuation situations, a manual interpretation of complex behavioral situations is often impossible (lack of personnel and time for understanding the situation). And the static infrastructure (a system of cameras and communications) can't function correctly or be deployed in probably unforeseen critical zones.

4.2.1 Experiment 1: Recurrent movements

On Figure 3a, they are repeated travels of about fifty agents with a normal perception, and on Figure 3b, when there is a reduced perception (for example by the smoke). With this experimentation, more agents have a reduced perception and more their travels are slow, random and brought closer with the other agents thus a behavior to browsing with regard to the presence of dangers.

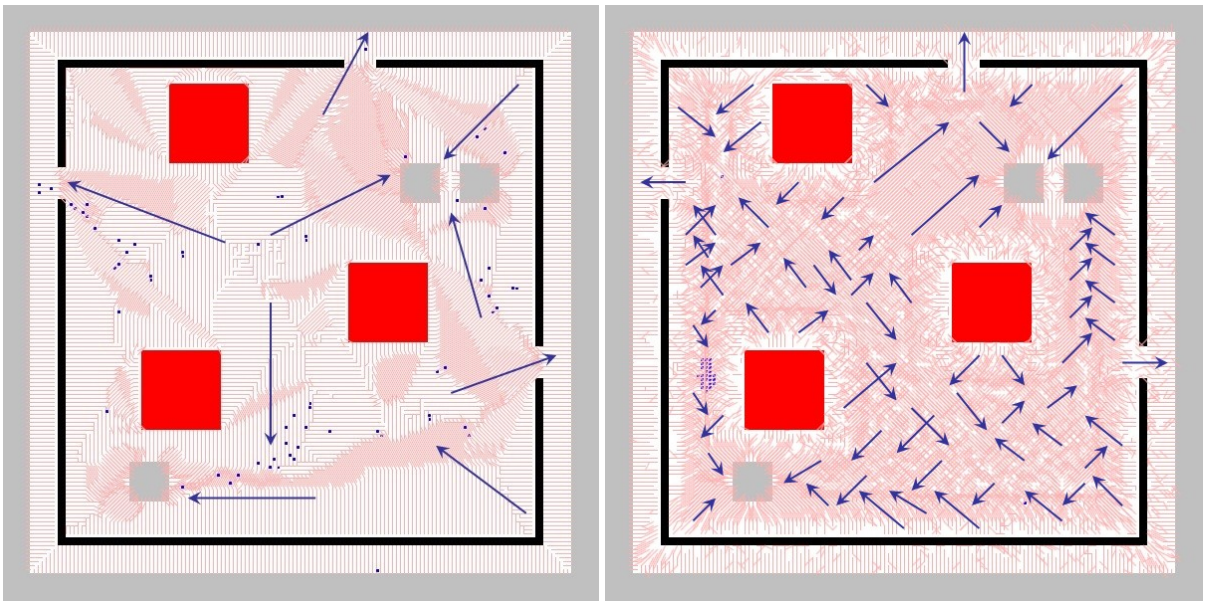

Figure 3: (a) Direction displayed of repeated travels of agents with a normal perception and (b) With a limited perception

Figure 4 and 5 are there to help to understand Figure 3: one displays a red line corresponding to the movement with the greatest probability for each state $q_{x,y}$ (for recall, 9 actions are possible: 8 directions and to remain on the spot). The result is obtained after *m* observations in *n* iterations of experiment 0.

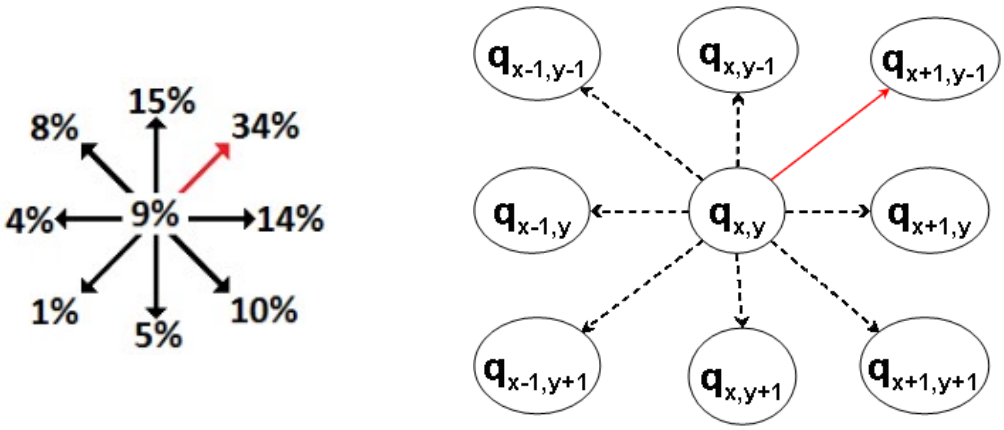

Figure 4: Example of next action probabilities for a state $q_{x,y}$.

						0%	0%	0%	0%	0%	0%							
						12%	11%	41%	4%	9%	29%							
						4%	6%	26%	1%	9%	57%							
			10%	24%	44%							1%	1%	2%	1%	1%	1%	
		Etat initial :	4%	8%	10%							1%	9%	73%	1%	31%	15%	
			0%	0%	0%							1%	2%	10%	1%	13%	36%	
																		6% 7% 0%
															Etat final :			5% 78% 0%
																		2% 2% 0%

Figure 5: Example of states transition probability after *m* observations in *n* iterations of experiment 0

We can thus parameterize a virtual environment based on a real environment. We can place dangers and obtain estimates on panic crowd behaviors. Moreover, with this probability distribution of travels obtained, one can use it on a real time system of crowd panic travel predictions (Figure 6).

To be able to predict crowd travels behaviors facing dangers appearance is an excellent tool. But the first problem is to avoid trampled and hustled persons (Figure 7).

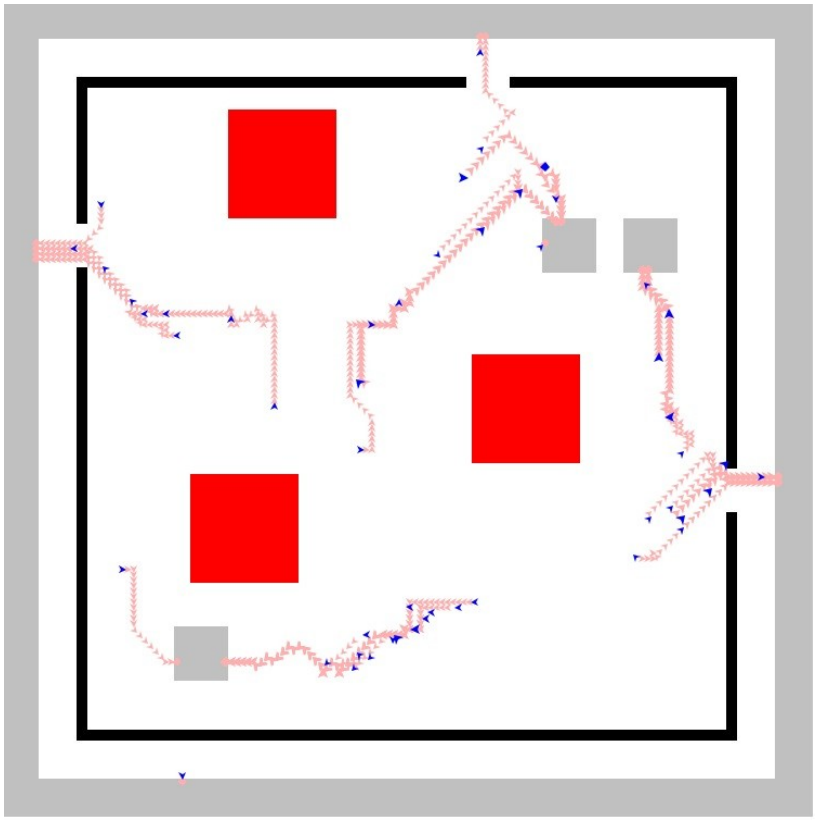

Figure 6: Illustration of future travels forecast of agents in panic

This illustration shows collective behaviors of awaited panic path.

If agents group moves away from there, there is abnormal behavior.

Moreover, time progressively, each new iteration and their observations are integrated into the HMM and reinforce predictions.

For example, prediction of each next movement of 50 agents:

Iterations	Precisions
1	27,29%
2	52,62%
10	67,89%
100	84,15%
5000	86,54%

4.2.2 Experiment 2: The physical interactions

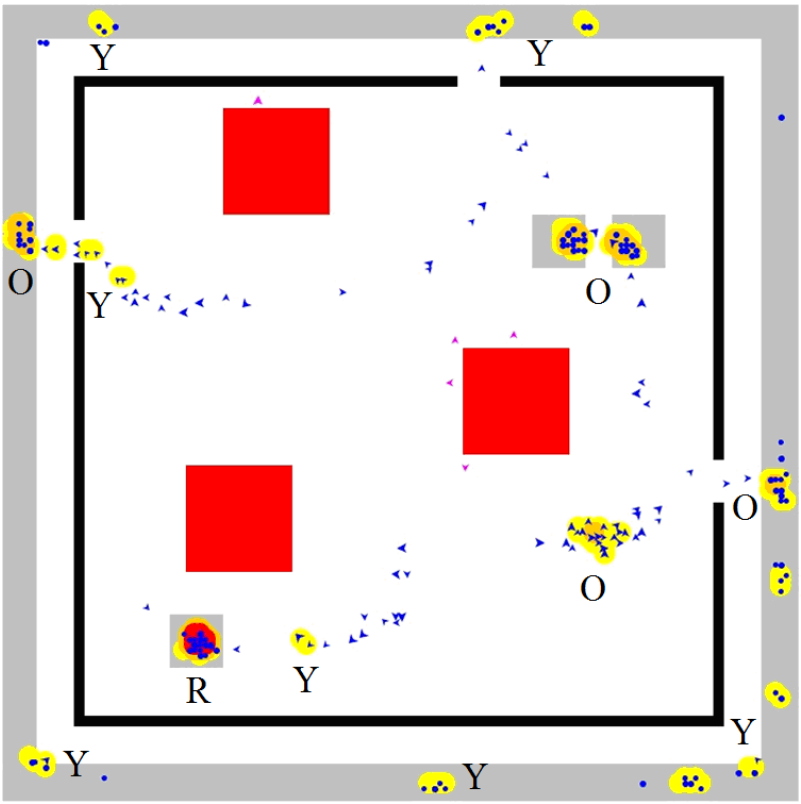

Figure 7: Illustration of scuffles and trampling

When surface per person, movements are :

> 2.3 m² :
Without problem.

> 0.9 m² :
Inconvenient, scuffles occur (*Yellow*).

> 0.5 m² :
Blocked, the capacity minimum of vital space is reached and uncontrollable movements of panic are occurred by individuals (*Orange*).

≤ 0.5 m² :
Trampling and choking some people (*Red*).

A study for the Office of Critical Infrastructure Protection and Emergency Preparedness of Canada concerns requirements of surface available per person (Burd, 2007). This study shows that slowing down and dispersing the crowd with non-blocking obstacles is a good solution to avoid scuffles and general panic. These obstacles are, for example, benches to create corridors and pillars in front of exits to oblige crowd to separate itself.

Experiments have thus enabled us to check that when agents have a reduced perception of their environment, they behave less dangerously (disappearance of trampled and hustled persons). This is not the case with a normal visibility (behavior of "first come first served").

5 Conclusion

This paper presents two fields for the analysis and the study of simulation and detection of collective behaviors while basing ourselves on a multi-agents approach.

With the literature and the produced model, possibilities of detecting some forms of collective behaviors were presented. This system could be useful to avoid risks for people during social gatherings.

In a near future, we will adapt this system to a simulation implementation using serious games, on the subject of behavior detection through semantically networked multi-agent models.

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