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Integration of emotion in evacuation simulation

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Abstract. Computer simulation is a powerful tool for planning real evacuation scenarios during a crisis. In such context, emotion is a major factor that influences human decision making process and behavior. In this paper, we present our multi-agent simulation through the mathematical formalization of its main components: emotion and its dynamics, an heuristics for evasive actions of agents, the scenarios for tests and the results of these tests. We show that on one hand, emotions increase the chaos of simulation which leads to an increase of collisions between agents, and on the other hand the evacuation time decreases because agents are more hurry to leave the place of the crisis.

1 Introduction

Simulations of crisis scenarios are very important tools for an optimal evacuation process of people during a real crisis in a public place. Crisis are difficult to model because many factors affect the results (large number of people, chaos, obstacles, *etc.*). In this article, we propose to take into account emotions felt by agents during a crisis because a lot of works have shown that they have an impact on decision making and behavior of people [17, 11, p. 2]. In particular, catastrophic situations often trigger fear¹. One of the emotions often cited in case of crisis is panic but in fact, panic does not appear in real situations [5, 6].² Thus, our simulation is based on the emotion of fear³ that is more realistic in such situations [15].

Emotion in computer sciences often relies on the model of Ortony, Clore, and Collins (OCC model for short) [12]. In previous works we have already formalized

¹ As in [12, pp. 112–118], we use fear, fright, scare, *etc.* as synonyms because they all refer to the same type of emotion in the sense of [12, pp. 15–17].

² Panic would *just* be an individual psychiatric disorder that does not spread among a crowd during a crisis situation... except in disaster movies.

³ Certainly, we feel several emotions in crisis situations. Here, we only manage fear for several reasons: i) it is certainly the most predominant emotion in crisis situations; ii) every emotion influences both the behavior of an agent and its other emotions and thus, it becomes hard both to model such complex interactions and to analyze the results of the simulation; iii) some secondary emotions could be added later in the simulation (there is no technical barrier).

a lot of the emotions defined in the OCC model [1]. We focus here on fear and we use these finely grained results to model its properties. Moreover, emotion can be spread in crowds [8, 4] (this is the “emotional contagion” phenomena) and this property must be taken into account. Thus, the spreading process we use here is based on the model of [4].

Each phenomena (emotion, emotional contagion, behaviors of agents, *etc.*) has been implemented in our simulation with the GAMA multi-agents architecture [7]. We have also implemented and simulated the scenarios of an emergency evacuation in a burning shopping center.

Simulations using emotion management present at least two difficulties. First, crisis situations are hard to reproduced during artificial experiments because it would be necessary to induce in subjects some strong negative emotions without really putting them in danger. Second, it is hard to describe behaviors associated with emotions because emotion is very subjective. Nevertheless, our definition of emotions are based on previous researches following some psychological works [12, 9]. We expect it is sufficient for guaranteeing a realistic process.

After a brief review of related work (Section 2) we present the mathematical model of the main featur of our simulation (Section 3) and the obtained results (Section 4).

2 Related work

There is a considerable amount of research in integration of emotions into evacuation simulation. (See [16] for instance.) Most of the existing work concentrate in simulation of pedestrians in case of fire in a public location. Agent-based simulations are often used because they allows modelings of each pedestrian as an autonomous entity. In [10] a model of emotion with two dimensions (intensity and time) in an evacuation simulation of pedestrians is presented. This is a simplification of the four dimensions of [19] and includes emotional decay during time.

With the help from the framework ESCAPE, Tsai et al [16] simulate an evacuation scenario from airport to train. They model several kinds of agents: family members, visitors, security policies authorities. The agents interactions are one of the main aspects of the simulation. Evacuation knowledge and information events are propagated among agents. Authorities share their knowledge about the positions of exits with people which do not know the place. They also model emotional contagion using the Hatfield et al’s theory [8]. In the simulation, only fear is considered. In this model, emotion does not have ability to decay. However, authorities are able to calm other agents which decrease their fear level. The scenario with the emotional contagion (without authorities) shows that the representation of emotional contagion increases the number of collisions at high speed. The scenario with emotional contagion and authorities show that the level of fear of people is lower (and thus, results are better).

3 Simulation description

The environment of our model is represented by GIS (Geographic Information System) files which enable the simulation to know the topographical plan of the scene of the crisis. (We suppose in the following that the crisis happens in a store.) Fig. 1 shows a screenshot of the simulation: obstacles are represented by the sixteen gray rectangles, exits are represented by the three small green rectangles on the left side and on the bottom side of the figure, and human agents by small circles. These circles have different colors that represent the fear intensity degree of each agent (no fear, weak fear, medium fear and strong fear). The crisis may have several seats of fire that are represented by flames.

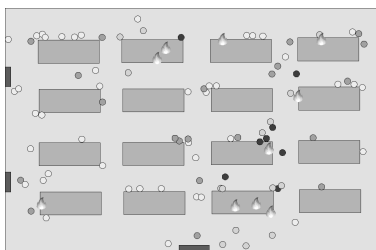


Fig. 1: Snapshot of the screen of the simulation

All the agents have the ability to avoid both obstacles and other agents while moving. In a non-evacuation situation the agents move slowly and in random directions whereas in evacuation situations, the agents try to escape from the store by moving to the nearest exit. As detailed in the following, emotion influences the behavior of agents. Thus at the highest fear level for instance, the agents move at top speed and in a random direction.

In the following: AGT_h is the set of all the human agents i, j, \dots ; AGT_f is the set of all fire agents f, f', \dots ; $AGT \supseteq AGT_h \cup AGT_f$ is the set of all the agents. We note x, y, \dots the terms of AGT .

3.1 Emotion modeling

Fear intensity. Fear intensity is modeled as a floating point number depending on time. Thus, $Int_{Fear_i}(t)$ represents the fear intensity felt by agent $i \in AGT_h$ at time t and $Int_{Fear_i}(t) \in [0, 1]$. We are rather interested by values ranges than a particular value: $Int_{Fear_i}(t) \in [0, 0.2[$ means that agent i has no fear; $Int_{Fear_i}(t) \in [0.2, 0.5[$ means that agent i feels a weak fear; $Int_{Fear_i}(t) \in [0.5, 0.8[$ means that agent i feels an medium fear; $Int_{Fear_i}(t) \in [0.8, 1]$ means that agent i feels a strong fear.

The initial value of $Int_{Fear_i}(t)$ for every $i \in AGT_h$ is fixed before the execution of the simulation. (It is a variable of a scenario; see Section 4 for more details.)

Fear decay during the time. Fear intensity varies over time with respect to its initial value (that is a variable of the simulation). The intensity can increase thanks to emotions of others (due to an emotional contagion process) or to external stimuli perceived by agents (emotional appraisal process following events or actions of others and perceived by agents). Moreover, emotions reflect short-term affect and usually decreases and disappear of the individuals focus [14]. The decay of emotion is a complex process [18] which depends on many factors like initial intensity of emotion, characteristic of agent, time, type of stimuli, *etc.* Finding a good function that exactly reflects the decay of emotion is not an easy task. In this work, we use a simplification of the emotional decay which has been proposed by Le et al [10]: for every $i \in AGT_h$,

$$Dec_{Fear_i}(t) \stackrel{def}{=} -\kappa.Int_{Fear_i}(t)$$

where $0 < \kappa < 1$ is a decay coefficient.⁴ $Dec_{Fear_i}(t)$ means that the fear intensity decay for agent i at time t is equal to some percents of the fear intensity at this step of the simulation (at time t). If κ is close to 1 the decay of the fear will be very quickly whereas it will be very slow if it is close to 0.

Fear intensity increase by emotional contagion. Emotional contagion process is a complex phenomena where a lot of parameters may play a role. An important criteria in this case concerns the distance between agents [12, Chap. 4].

In a first step, we need to define what is a neighborhood. Let ρ_i the agent i 's perception radius that determines the circle in which agent i can perceive emotions of others. Thus, the i 's neighborhood is defined as the set of agents in AGT such that the distance between these agents and agent i is lower or equal to i 's perception radius. Thus, if we note $\delta_{i,x}$ the physical distance between agent i and agent x , we have the following formal definition: for every $i \in AGT_h$,

$$Neighborhood(i) \stackrel{def}{=} \{x : \delta_{i,x} \leq \rho_i \text{ for every } x \in AGT\}$$

The value $\delta_{i,x}$ is computed dynamically at each step of the simulation. ρ_i is a variable of the simulation and is fixed at the initial state of the simulation (at time t_0). For technical reason, we impose that $\delta_{i,i} = \rho_i$ for every agent i at every time.⁵ It follows from this definition that $Neighborhood(i)$ cannot be empty because x may be i and $\delta_{i,i} \leq \rho_i$. Thus, $i \in Neighborhood(i)$ for every agent i . Note that the neighborhood of a human agent may contain any kind of agent (human, fire, *etc.*).

Moreover, we must take into account that each individual expresses his/her emotions in a different way. In accordance with our character, we will express

⁴ It is an oversimplification because, as many as cognitive processes, emotion decreases in an exponential manner. (For a theory of mind, see [2, 3] for instance.) In future works, we will use an exponential decay and we will be able to compare the results.

⁵ It would be more intuitive that $\delta_{i,i} = 0$ but this value has no effect on the simulation. By contrast, it allows that $\theta_{i \rightarrow i}(t) = 0$ (rather than $Int_{Fear_i}(t)$): thus, it means that fear of an agent does not spread on itself (see below).

our emotions with varying degrees of intensity. Thus, let ε_i be the emotional expression power of agent i . It is a variable of the simulation that is initialized for each agent in a random manner at the beginning of the simulation such that $\varepsilon_i \in [0, 1]$. This value characterizes which quantity of the intensity of an emotion felt by an agent i is expressed by this agent during an emotional contagion process. For instance, the value 0 means that agent i does not express any emotion (even if it has emotions with a high level of intensity) and the value 1 means that agent i expresses its emotions with the same degree of intensity as the degree of intensity of the emotion that it feels.

Thus, we propose to determine now the quantity of intensity emotion spread by an agent i towards another agent j as follows. This quantity depends on the fear intensity of agent i at the previous step of the simulation, the distance between agent i and agent j , the radius of perception of agent j , and the emotional expression power of agent i , as follows: for every $i \in AGT_h$,

$$\theta_{i \rightarrow j}(t) \stackrel{def}{=} \varepsilon_i \frac{\rho_j - \delta_{i,j}}{\rho_j} Int_{Fear_i}(t-1) \quad (1)$$

for every $j \in AGT_h : i \in Neighborhood(j)$

The value of $\theta_{i \rightarrow j}(t)$ is normalized and thus it is easy to check that $\theta_{i \rightarrow j}(t) \in [0, 1]$. In other words, the quantity of emotion intensity spread from an agent i towards an agent j is inversely proportional to the physical distance between i and j with respect to its own emotional intensity. Moreover, just a part of this intensity is expressed by agent i (thanks ε_i). At each step, the simulation computes each $\theta_{i \rightarrow j}(t)$ value. As $Neighborhood(i)$ cannot be empty, it follows from (1) that $\theta_{i \rightarrow i}(t)$ exists and is equal to 0 for every agent i . It means that an agent i may not spread its fear intensity to itself. Note also that $\theta_{i \rightarrow j}(t)$ may not be defined for some agents j : it just means that agent i is not in the perception radius of these agents j .

But, as the fear intensity is not necessarily entirely expressed by an agent, the fear intensity received is not necessarily absorbed (we are more or less permeable to emotion of others, we have more or less empathy). Thus, let α_i the emotional absorption power of agent i . Similarly to ε_i , $\alpha_i \in [0, 1]$ and its value is initialized for each agent in a random manner at the beginning of the simulation. For instance, $\alpha_i = 0.8$ means that agent i absorbs only 80% of the emotion intensity received.

We are now able to define the quantity of fear received through an emotional contagion process by an agent i from other agents j that are in its perception radius: for every $i \in AGT_h$,

$$EC_i(t) \stackrel{def}{=} \alpha_i \max(\{\theta_{j \rightarrow i}(t) \text{ for every } j \in AGT_h\}) \quad (2)$$

This quantity is the maximum between all the quantities spread by the agents in the perception radius of agent i .⁶ Only a part of this quantity is absorbed by

⁶ Note that we do not take the sum here. The reason is that when the number of agents in the perception radius of agent i is substantial, the fear intensity of agent

agent i (thanks to α_i). Note that, by (1) the set $\{\theta_{j \rightarrow i}(t)$ for every $j \in AGT_h\}$ contains at least $\theta_{i \rightarrow i}(t)$ and it is thus never empty. If the case there is no agent different of agent i in its neighborhood, this set is thus reduced to the singleton $\{\theta_{i \rightarrow i}(t)\}$ with $\theta_{i \rightarrow i}(t) = 0$ and thus $EC_i(t) = 0$. It means that an agent does receive fear intensity from itself.

Note that $EC_i(t)$ can be greater than, equal to, or lower than, the current fear intensity of agent i ($Int_{Fear_i}(t)$). It remains to determine how this value should update the current level of fear of agents. Two choices have been made here. First, just the difference between $Int_{Fear_i}(t - 1)$ and $EC_i(t)$ is taken into account (because we want to slow down the the increase of fear level); second, $EC_i(t)$ is updated only if this difference is greater to 0 (this constraint will be dropped in future works). In other words, the update operation of the current fear level is of the form $\max(Int_{Fear_i}(t - 1), EC_i(t))$.

Fear intensity increase by crisis perception. Typically in our simulation, crisis is caused by fire. When an agent perceives fire its emotion intensity increases. Similarly to the computation of emotional propagation, we define: for every $f \in AGT_f$,

$$\theta_{f \rightarrow i}(t) \stackrel{def}{=} \frac{\rho_i - \delta_{f,i}}{\rho_i} Int_f(t - 1) \quad (3)$$

for every $i \in AGT_h : f \in Neighborhood(i)$

$Int_f(t)$ is the intensity of fire f at time t . In the simulation, $Int_f(t_0) = 0$ (the fire f is initially put out) or $Int_f(t_0) = 1$ (the fire f is initially lighted). Moreover, $Int_f(t) = Int_f(t_0)$ for every tt (the state of fires does not change during the time).

We propose a function to calculate the portion of fear generated by fires: for every $f \in AGT_f$,

$$Fires_i(t) \stackrel{def}{=} \alpha_i \sum_{f \in AGT_f} \theta_{f \rightarrow i}(t) \quad (4)$$

This quantity is directly added to the intensity of agent i . For ensuring that the result is lower than or equal to 1, the update function is of the type: $\min(1, Int_{Fear_i}(t) + Fires_i(t))$.

The dynamics of fear intensity. Following the previous decay and increases of fear intensity, we are now able to present the complete equation of the fear intensity during the time: for every $i \in AGT_h$,

$$Int_{Fear_i}(t) = \min(1, \max(Int_{Fear_i}(t - 1) + Dec_{Fear_i}(t - 1), EC_i(t)) + Fires_i(t)) \quad (5)$$

This update function means that in the simulation, the updated fear intensity of agent i is a three steps process:

i converges too quickly toward 1 (that is the maximum value). In future works, we will study how a sum-based approach could be integrated to our simulation.

1. $Int_{Fear_i}(t - 1)$ is updated by the decay $Dec_{Fear_i}(t - 1)$;
2. the updated fear intensity is compared with the maximum intensity of fear generated by emotional contagion ($EC_i(t)$) and we keep the maximum between these two values (reasons are given above);
3. finally, we add to the previous result the sum of fear generated by fire around agent i ($Fires_i(t)$) and we ensure that the result is not greater than 1 (because 1 is the greatest value of fear) by keeping the minimal value between 1 and the new updated value on fear intensity.

3.2 Behavior of human agent

Our behavior is the result of a complex decision making process where many variables are analyzed and integrated with different weights. Emotion plays a crucial role in this process with the help of coping process (see [9], where coping process is viewed as a link between a triggered emotion and the actions following the triggering of this emotion, especially in case of negative emotions). Here, we propose to dynamically compute the behavior of agents with respect to their emotional state (emotion-based model of behavior).⁷

We have defined several behaviors that depend on both the situation and the fear intensity of agents. In the normal state, agents move with a low speed that simulates they do shopping in a store whereas in evacuation situations, evacuees try generally to leave the store. In these situations, we distinguish two kinds of behaviors.

1) As long as its fear intensity is not strong, an agent can find its way out of the store and follows this way. It is able to avoid collisions both with other agents and with obstacles. In order to archive this requirement, we use a heuristic approach that calculates the next position N of the agent which depends on the current position C and the position of the exit E . If there is no obstacle between C and E , the agent go towards the exit by following the direction \vec{h} (see Fig. 2). As soon as there an obstacle between C and E , we compute the next position N with the help of the vector \vec{f} such that $\vec{f} = \vec{g} + \frac{\vec{h}}{\gamma}$ where γ is an adjustment factor. When γ is increases (respectively, decreases) the angle between \vec{g} and \vec{h} decreases (respectively, increases).⁸

2) As soon as the fear intensity of an agent is strong, it moves both with a very high speed and without target. In the extreme danger case, humans tend to react instinctively [13]. When an agent doesn't know what is the best way out of the store, it tries to evacuate with the other agents who know well the way out. Thus, agents with a strong level of fear can move along with group of agents having a lower level of fear and knowing where the exit is.

⁷ This is a restriction with respect to other variables that may influence the behavior of agents, but we can argue that emotion is certainly one the most influential variables in these situations.

⁸ Our heuristic algorithm does not always provide the shortest path from C to E due to evasive actions.

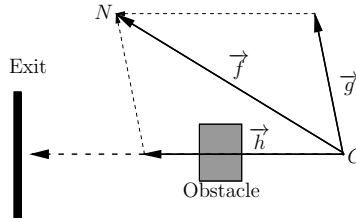


Fig. 2: Evasive action

4 Experiments

4.1 Scenarios

The impact of the emotional agents and of emotional contagion is tested with the help of different scenarios modeled in the multi-agent architecture GAMA [7]. Each scenario describes a supermarket where agents do the shopping. These agents can be emotional agents (that is, agents capable of having emotions) or not. The part of such emotional agents can vary from a scenario to another (0%, 25%, 50%, 75% or 100%). In the initial state, emotional agents can already have (or not) fear with different degrees of intensity (0, 0.2, 0.5 or 0.8 respectively for no fear, weak fear, medium fear, and strong fear) from a scenario to another. In case of emotional agents, an emotional contagion process or emotional decay (or both together) can be enabled or not. (Emotional decay formalizes the fact that emotion intensity decreases during the time. When emotional decay is disabled, every emotion felt by agents are kept during all the simulation.) It can be asked to them to evacuate the supermarket (or not) and the reason for that can be a fire or just the closing of the supermarket.

Let AGT be the set of agents used in our simulation. Our simulation is based on several scenarios. Let be \mathcal{V} the set of the scenarios variables such that

$$\mathcal{V} = \{\varepsilon_0, \varepsilon_{0.25}, \varepsilon_{0.5}, \varepsilon_{0.75}, \varepsilon_1, fear_0, fear_{0.2}, fear_{0.5}, fear_{0.8}, \varepsilon_{Contagion}, Evac, \varepsilon_{Decay}, fire\}$$

For every $x \in \{0, 0.25, 0.5, 0.75, 1\}$, ε_x is read: there are exactly $x\%$ of AGT that are emotional agents (the remainder of AGT does not contain any emotional agent). For every $x \in \{0, 0.2, 0.5, 0.8\}$, $fear_x$ is read: the initial threshold of fear intensity is x . (It means that every agent will initially have a fear intensity greater or equal to x .) $\varepsilon_{Contagion}$ is read: the emotional contagion process is enabled. $Evac$ is read: the group evacuation is enabled. ε_{Decay} is read: the emotion intensity decreases with time (else, it is a constant). $fire$ is read: there is a fire at the shopping center.

We impose some constraints on these variables because some scenarios do not make sense:

- (1) each variable has a boolean value, that is, there exists an assignation function $I : \mathcal{V} \longrightarrow \{0, 1\}$ where 0 names the false and 1 names the true as usual;
- (2) there exists $x \in \{0, 0.25, 0.5, 0.75, 1\}$ such that $\varepsilon_x = 1$;
- (3) for every $x, y \in \{0, 0.25, 0.5, 0.75, 1\}$, if $\varepsilon_x = 1$ then $\varepsilon_y = 0$ for every $y \neq x$;
- (4) there exists $x \in \{0, 0.2, 0.5, 0.8\}$ such that $fear_x = 1$;
- (5) for every $x, y \in \{0, 0.2, 0.5, 0.8\}$, if $fear_x = 1$ then $fear_y = 0$ for every $x \neq y$;
- (6) for every $x \in \{0.2, 0.5, 0.8\}$, if $fear_x = 1$ then $\varepsilon_0 = 0$;
- (7) if ($\varepsilon_{Contagion} = 1$ or $\varepsilon_{Decay} = 1$) and $fire = 0$ then necessarily $\varepsilon_0 = 0$.

(1) means that every variable is true or false (but not both together). (2) means that *AGT* does not contain any emotional agent ($\varepsilon_0 = 1$) or that exactly 25 percent of *AGT* are emotional agents ($\varepsilon_{0.25} = 1$) or that exactly 50 percent of *AGT* are emotional agents ($\varepsilon_{0.5} = 1$) or that exactly 75 percent of *AGT* are emotional agents ($\varepsilon_{0.75} = 1$) or that every agent of *AGT* is an emotional agent. (3) means that one and only one of the four above states is true while the others are false. (4) means that there exists at least one initial threshold of fear intensity, and (5) says that there are one and the same. (6) means that if the fear threshold is not zero then there exist emotional agents in *AGT*. It follows from this constraint together with (5) that: if $\varepsilon_0 = 1$ then $fear_0 = 1$, which means that if there is no emotional agents, then have necessarily no fear at all. Finally, (7) means that if emotional contagion mechanism or emotional decay mechanism are enabled and fire is not presence then there are emotional agent in *AGT*. (No other particular constraint is given on *fire* that can happens when there are emotional agents or when there is no emotional agent at all.)

Thus, what the number of possible scenarios? It follows from both (5) and (6) together that if there is no emotional agent then $fear_0$ is true. Moreover, (7) entails that if there is no emotional agent and no fire then necessarily there is neither emotion contagion nor emotional decay. In other words, when there is no emotional agents (that is, $\varepsilon_0 = 1$) only scenarios 1 to scenario 10 in Table 1 are possible. In this figure, $x = 0, x = 0.25 \dots x = 1$ mean respectively that $\varepsilon_0 = 1, \varepsilon_{0.25} = 1 \dots \varepsilon_1 = 1$. Things are similar in the third column. In the fourth column, \checkmark means that $\varepsilon_{Contagion} = 1$ (else $\varepsilon_{Contagion} = 0$) and things are similar in the last columns. If we consider now the fact that there are emotional agents (thus, $\varepsilon_x = 1$ for every $x \in \{0.25, 0.5, 0.75, 1\}$), it remains four cases. For each case, the fear threshold can have four different values. And for each value, there are 2^4 possible values for the 4-tuple $\langle \varepsilon_{Contagion}, Evac, \varepsilon_{Decay}, fire \rangle$. That is, there are $10 + 4 \times 4 \times 2^4$ possible scenarios, that is, 266 different scenarios have been used.

For each simulation scenario, we ran 50 times. We measure both the number of collisions and the evacuation time. Simple models without emotion are used as reference (see scenarios 1–4 in Table 1).

4.2 Experimental results and evaluation

In this subsection, we show and analyze results of different scenarios. The goal is to examine how emotion and variables (presented in Section 4.1) affect the evacuation efficiency. As presented above, evacuation efficiency is measured by

Table 1: Number and parameters of scenarios

Scenario	ε_x	$fear_y$	$\varepsilon_{Contagion}$	$Evac$	ε_{Decay}	$fire$
1	$x = 0$	$y = 0$				
2	$x = 0$	$y = 0$				✓
3	$x = 0$	$y = 0$			✓	✓
4	$x = 0$	$y = 0$		✓		
5	$x = 0$	$y = 0$		✓		✓
6	$x = 0$	$y = 0$		✓	✓	✓
7	$x = 0$	$y = 0$	✓			✓
8	$x = 0$	$y = 0$	✓		✓	✓
9	$x = 0$	$y = 0$	✓	✓		✓
10	$x = 0$	$y = 0$	✓	✓	✓	✓
11	$x = 0.25$	$y = 0$				
12	$x = 0.25$	$y = 0$				✓
13	$x = 0.25$	$y = 0$			✓	
...		
26	$x = 0.25$	$y = 0$	✓	✓	✓	✓
...		
266	$x = 1$	$y = 0.8$	✓	✓	✓	✓

the number of collisions and the evacuation time. Here, the number of collisions is the total number of collisions among agents in each scenario. Evacuation time is the average of every agent’s individual evacuation times.

Impact of emotion. To evaluate the impact of emotion on the evacuation, we analyze several scenarios with different rates of emotional agents (ε_x) and fear levels ($fear_y$) while disabling other variables (emotional contagion, group evacuation, emotional decay, fire). We can see in Fig. 3 that when we integrate fear in our agents, the number of collisions increases. However, the increase rate depends on the percentage of emotional agents (ε_x) and of the fear level ($fear_y$). With $\varepsilon_{0.25}$, the number of collisions increases a few with all the values of $fear_y$ while with higher percentage of emotional agents we see a high increase in collisions in scenarios with $fear_{0.8}$ (strong fear). Indeed, at this highest level of fear, the agents run with a higher speed, in random directions, the situation thus becomes more chaotic, the number of collisions increases as a consequence. We also observe that the number of collisions in the scenarios where all agents are emotional (except scenario with $fear_{0.8}$), is the same as scenario without emotional agent. This observation suggests that when agents run with the same speed, collisions occur less often.

The evacuation time, on the other hand, decreases when fear level increases except in case of agents having a strong fear level. At that maximum fear level the evacuation time significantly increases. Indeed, when the fear level increases the agent’s speed increases which leads to a shorter evacuation time. However, when agents feel a strong fear, they run in random directions (unless they see an exit) which leads to an increase of the evacuation time.

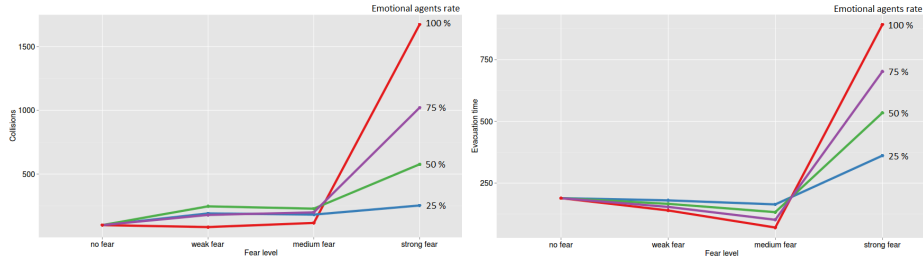


Fig. 3: Summary of scenarios without emotional contagion.

Impact of emotional contagion. We evaluate the impact of emotional contagion on evacuation efficiency by comparing scenarios with $\varepsilon_{0.25}, fear_y \in \{0, 0.2, 0.5, 0.8\}$, $\varepsilon_{Contagion=1}$ and other variables disabled and scenarios with $\varepsilon_{0.25}, fear_y \in \{0, 0.2, 0.5, 0.8\}$, $\varepsilon_{Contagion=0}$ and other variables disabled. The results are presented in Fig. 4. In scenarios with emotional contagion, there are more collisions

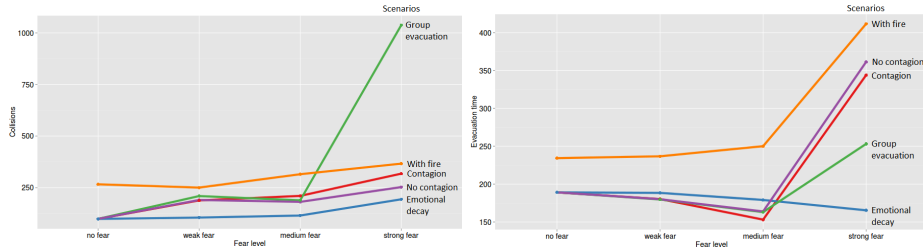


Fig. 4: Summary of scenarios with 25% of emotional agents at beginning, in each scenario one variable is enabled, others are disabled

in comparison with the scenarios without emotional contagion. That is, with the emotional contagion, fear is spreading in the crowd; as a result we have higher number of feared agents. This increase of feared agents leads to an increase in collisions. But when $\varepsilon_x > 0.5$ emotional contagion can lead to a decrease in collisions as showed in previous subsection (when the rate of emotional agents is close to 100%, the number of collisions is almost the same as when there is no emotional agent).

As expected the evacuation time decreases slightly when emotional contagion is enabled because the feared agents run with a higher speed.

Impact of group evacuation. As we discussed, the evacuation in group often happens in an evacuation. In reality, the evacuees can help each other and this can reduce the damages of the crisis. To evaluate the impact of the evacuation in group we compare scenarios with $\varepsilon_{0.25}, fear_y \in \{0, 0.2, 0.5, 0.8\}$, $\varepsilon_{Group=1}$ and other variables disabled and scenarios with $\varepsilon_{0.25}, fear_y \in \{0, 0.2, 0.5, 0.8\}$,

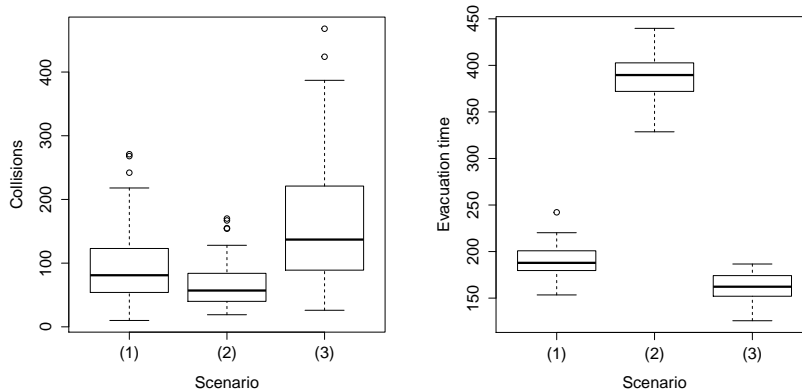


Fig. 5: Scenarios with 0 % of agents feeling fear initially: (1) without emotion; (2) no crisis; (3) with emotional contagion, without group evacuation, emotion decay and fire

$\varepsilon_{Group=0}$ and other variables disabled. Fig. 4 shows that when there are agents have a strong fear, the evacuation in group increases the number of collisions, mainly because evacuation in group leads to a higher density of agents.

However, the evacuation time is lower than in reference scenarios. In fact, the evacuation in group helps the agents having a strong fear to evacuate faster by following other agents and thus decreases the evacuation time.

Impact of emotional decay. To evaluate the impact of emotional decay, we compare scenarios with $\varepsilon_{0.25}$, $fear_y \in \{0, 0.2, 0.5, 0.8\}$, $\varepsilon_{Decay=1}$ and other variables disabled and scenarios with $\varepsilon_{0.25}$, $fear_y \in \{0, 0.2, 0.5, 0.8\}$, $\varepsilon_{Decay=0}$ and other variables disabled.

Fig. 4 shows that when emotional decay is enabled, the number of collisions is two times smaller than the scenarios without emotional decay. As the emotional decay decreases the intensity of emotion, fear subsides and the strong fear of an agent can become a medium fear, its medium fear can become a weak fear, and its weak fear can disappears (it has no fear at all). This reduces collisions among agents.

The evacuation time, on the other hand, increases slightly because at lower level of fear, agents move slower. But in scenarios with both agents having a strong fear and emotional decay enabled, the evacuation time significantly decreases because of the decrease in the number of agents having a strong fear.

Impact of fire. To evaluate the impact of fire, we compare scenarios with $\varepsilon_{0.25}$, $fear_y \in \{0, 0.2, 0.5, 0.8\}$, $fire = 1$ and other variables disabled and scenarios with $\varepsilon_{0.25}$, $fear_y \in \{0, 0.2, 0.5, 0.8\}$, $fire = 0$ and other variables disabled. The presence of fire cause an increase in the number of collisions (see Fig. 4). As we presented, fire is a stimulus that can increase fear level of agents overtime. Especially in the second half of the simulation, when fire propagated everywhere

in store, we observe many agents having a strong fear and the situation becomes more chaotic.

The evacuation time also increases when there are fires because of the increase of agents having a strong fear.

Impact of the combination of all variables. We want to analyze a scenario in which all variables are enabled. This scenario begin with ε_0 , $fear_0$, $\varepsilon_{Contagion}=1$, $\varepsilon_{Group}=1$, $\varepsilon_{Decay}=1$, $fire = 1$. This ultimate scenario simulates a real life scenario when people are shopping, fire sudden appears and people begin to evacuate. Fig. 5 shows the result of this scenario. We can see in this figure that in this scenario (column (3)), collisions among agents occur more often than in the scenario with no emotion (column (1)). Moreover, as showed by the box plots in Fig. 5, the number of collisions of the scenario with all variables enabled have a great variation among experiments.

The evacuation time is instead lesser than the scenario without emotion.

Scenario of a closing store. In this scenario, we simulate the people to quit the store in a non-crisis manner. Instead of evacuate immediately like in cases of crisis, in this scenario, agents may not quit the store immediately when hearing the closing message. In Fig. 5, we observe that collisions occur less than in scenarios with crisis (both with emotion and no emotion).

The evacuation time is significantly more than in scenarios with crisis because of two reasons: agents do not quit the store immediately and the speed of movement is lower in case of crisis.

5 Conclusion

Integration of emotions in simulation of evacuation is often complex and difficult. In this paper, we implemented a simulation of evacuation with the integration of fear in GAMA language. Ours experiments show that emotion has a great impact on the simulation results. As with emotion integrated, collisions occur more often but evacuation time decreases.

A major difficulty of this kind of simulation is its validation by real experiments. In crisis situations, humans are always disturbed and have a lot of difficulties to explain how was their behavior during the crisis. Sociological works show that panic is a myth, but to feel fear leads to several behaviors.

A limitation of the presented simulation is that evacuees cannot change the exit they want to use, even if this exit is blocked. Thus, dynamic change of exit target seems an interesting perspective.

References

- [1] C. Adam, A. Herzig, and D. Longin. "A logical formalization of the OCC theory of emotions". In: *Synthese* 168.2 (2009), pp. 201–248.
- [2] J.R. Anderson. *The architecture of cognition*. Harvard, 1983.

- [3] J.R. Anderson et al. “An integrated theory of the mind”. In: *Psychological Review* 111 (2004), pp. 1036–1060.
- [4] T. Bosse et al. “A multi-agent model for mutual absorption of emotions”. In: *Proc. of the 23rd European Conference on Modelling and Simulation*. European Council on Modeling and Simulation, 2009, pp. 212–218.
- [5] J. Drury and C. Cocking. *The mass psychology of disasters and emergency evacuations: A research report and implications for practice*. Report. University of Sussex, 2007.
- [6] P. Gantt and R. Gantt. “Disaster Psychology: Dispelling the Myths of Panic”. In: *Professional Safety* Aug. (2012), pp. 42–49.
- [7] A. Grignard et al. “GAMA 1.6: Advancing the Art of Complex Agent-Based Modeling and Simulation”. In: *PRIMA 2013: Principles and Practice of Multi-Agent Systems*. Ed. by G. Boella et al. Vol. 8291. LNCS. Springer, 2013, pp. 117–131.
- [8] E. Hatfield and J.T. Cacioppo. *Emotional contagion*. Cambridge, 1994.
- [9] R.S. Lazarus. *Emotion and Adaptation*. Oxford, 1991.
- [10] Le Le V.M. et al. “Simulation of the Emotion Dynamics in a Group of Agents in an Evacuation Situation”. In: *Principles and Practice of Multi-Agent Systems* (2012), pp. 604–619.
- [11] G. Loewenstein and J.S. Lerner. “The role of affect in decision making”. In: *Handbook of affective science*. Oxford, 2003. Chap. 31, pp. 619–642.
- [12] A. Ortony, G.L. Clore, and A. Collins. *The cognitive structure of emotions*. Cambridge, 1988.
- [13] E.L. Quarantelli. “The Nature and Conditions of Panic”. In: *American J. of Sociology* 60.3 (1954), pp. 267–275.
- [14] Z. Ruttkay. *From Brows to Trust: Evaluating Embodied Conversational Agents /ed. by Zsófia Ruttkay XD-US. ...* Human-computer interaction series. Kluwer, 2004.
- [15] C.A. Smith and P.C. Ellsworth. “Patterns of cognitive appraisal in emotion.” In: *J. of personality and social psychology* 48.4 (1985), p. 813.
- [16] J. Tsai et al. “ESCAPES: evacuation simulation with children, authorities, parents, emotions, and social comparison”. In: *The 10th Int. Conf. on AAMAS*. International Foundation for AAMAS. 2011, pp. 457–464.
- [17] O. Vartanian and D.R. Mandel. *Neuroscience of decision making*. Psychology Press, 2011.
- [18] P. Verduyn et al. “Predicting the duration of emotional experience: two experience sampling studies.” In: *Emotion* 9.1 (2009), p. 83.
- [19] A. Zoumpoulaki, N. Avradinis, and S. Vosinakis. “A multi-agent simulation framework for emergency evacuations incorporating personality and emotions”. In: *Artificial Intelligence: Theories, Models and Applications*. Springer, 2010, pp. 423–428.