Emotional Contagion Model for Group Evacuation Simulation

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The key role of emotions in decision-making process of human beings has been highlighted recently. Our research focuses on fear-related emotions and their positive impact on the survival capabilities of human beings in case of crisis situations. In this paper, we proposed a new model of emotional contagion based on some main findings in social psychology. This model was formalized mathematically, implemented and tested in the GAMA agent-based simulation platform in the context of evacuation simulation. We assessed experimentally the impact of three factors (emotion decay, environment, neighbors' emotional contagion) on emotion dynamics at individual and group levels. The experimental results allow us to understand the emotional contagion of agent group in several scenarios. The proposed model will help us to better study the impact of emotional contagion on evacuation safety in evacuation simulation.The entire theoretical model has been implemented in the simulation platform GAMA.

Povzetek: Prispevek analizira čustva, povezana s strahom na primeru evakuacije.

1 Introduction

Emotions, these reflexes that push human beings to make decisions quickly and without a deep and clear reasoning process, have been considered for a long time contrary to any other rational reasoning processes. Only recently the key role of emotions in decision-making process has been highlighted. We focus on fear-related emotions and their positive impact on the survival capabilities of human beings in case of crisis situations. Indeed, recent works have shown that emotion is a very important factor in the understanding of human beings behaviours in crisis situations (see [9, 10, 28, 4] for instance).

It has been studied for a long time in psychology and in philosophy, and more recently in cognitive sciences (see [27, 21, 31, 12] for instance). These works have shown the narrow relationship existing between an emotional state in a person and the action tendencies of this person. Indeed, emotions play a central role in cognition, especially when we need to react very quickly (what is the case in crisis situation). Instantaneously, emotions provide us a set of possible actions (called *action tendencies* for Lazarus [21]) that are strongly related to the situation. An emotion can be viewed as a summary of the situation, how this situation can affect ourselves, and what power we have on the real world in the aim to change the present situation in a positive one for us. So, emotions have a great power of explanation of our actions in crisis situations.

In crisis situations, the most remarkable expression of the fear is definitely panic behaviors. While early researches on panic have presented panic as groundless fear or flight behavior, others describe it as a crowd in dissolution. Nevertheless, in situation such as fire or disaster, [26] has shown that it is in fact a very meaningful behaviour and far from most conceptions of irrationality. The panic behaviour exists but is in fact quite rare. It is an individual behaviour, by opposition to a behaviour of the crowd, it is not contagious and occurs in short duration. It is not easy to be observed in crisis situations.

Some particular conditions of panic triggering have been identified such as: perception of a great threat to self, a belief that escapes from the threat is possible but is very hard to achieve, and a feeling of helplessness [28, 14]. Some additional factors may also have an influence on triggered emotions such as experience in emergency situation and information. Information is the key to make a successful evacuation strategy during a crisis [29]. The sex and age of an individual can cause a different fear level.

In addition, as it has been shown in [28], panic is not the predominant emotion in crisis situation. A lot of reports (see [11] for instance) show that when the danger increases, the mutual aid between humans exposed to this danger also increases. The persons share emotions and information, and they help each other, even if they were strangers each other before. There is a very few cases of selfish. One of the faces of this mutual aid is the constitution of groups of persons. People in a group of friends or in a family try to stay together every time it is possible. Sociological studies show that groups increase our chances to be saved [9] (evolutionary condition). In our previous work [32], we have studied the impact of group on the evacuation process. In this paper, we focus only on emotion contagion.

In the simulation area, a lot of works focus more specifically on emotion contagion. For instance, in [24], the authors present simulations about relationships between emotions, information and beliefs. All members of a group can absorb the emotion of other members (in the same group) to create an average value of emotion. But they can also be influenced by the members of other groups. In this case, the average emotion of the group can be increased (amplification) or decreased (absorption). We can understand the absorption of emotions as a bottom-up approach, and the amplification of emotion as a top-down approach. The authors propose the idea that agents with a high emotion (above a high threshold) or a low emotion (under a low threshold) will impact with different roles (increase or decrease) depending on the characters of agent like the openness, the expressiveness, the capacity of receiving or expressing from/to others. Similarly, in [5], the authors give another interesting orientation about the contagion of emotion among a group.

In the GAMA agent-based simulation community [33, 17], several models (see [25, 22] for instance) have shown the important role played by emotions in emergency situations. In [25], authors simulate the emotion dynamics in a group. They give a new operational model of the emotion contagion and implement the process of evacuation (avoiding both obstacles and the other agents). They evaluate the model with respect to the time of evacuation by applying many criteria. When the emotion intensity changes, the walking speed of the corresponding agents also changes and impacts the evacuation time. But we can also criticize here the fact that the emotion modeling is still very basic: we need a more complex cognitive model of emotions if we want to simulate agent behaviors as natural as possible.

This article provides a new model of emotions dynamics. We focus here only on fear because this emotion plays an important role in crisis situations. We propose to model the emotion following three main findings both in cognitive psychology and in social psychology:

1. Emotions have triggering conditions (see [27, 21] for instance): this is a cognitive appraisal of these conditions that determines if they are fulfilled or not[1]. Following these authors, fear is triggered when we perceive a danger for our own life. Here, perception can be direct (an agent sees a fire or hears an alarm) or indirect (some other agents having fear influence the fear level of this agent).

2. Emotion intensity decreases with time: when triggering conditions are not longer satisfied, an emotion does not disappear instantaneously (it is a process that takes time).

3. Finally, new perceptions from the environment (fires, alarms, influence of others) can modify the intensity level of fear that can increase or decrease.

As far as we know, there is no model that takes into account all these factors in an intuitive manner. More precisely, a lot of factors may impact the emotion, but here we only take into account three main ones: environment (crisis perception), emotional decay and contagion. The emotion model is implemented in GAMA [2] and is a part of a project about evacuation simulations in crisis situations.

This paper is organized as follows. We first describe the model of emotion dynamics in Section 2. In Section 3, we assess the impact of the three factors (emotion decay and contagion, environment) on the emotion dynamics. Then we conduct the sensitivity analysis of the emotion model in Section 4. Finally, we conclude our work with some perspectives.

2 Model of emotion dynamics

2.1 Agent structure

As presented above, this article focuses only on one emotion and its diffusion. So, the environment is described in a simple manner. In particular, there is neither obstacles nor exit doors (because both of them do not have any impact on our results). It will only contain some fire and human agents.

Let $AGT = \{i, j, k, ...\}$ be the finite set of human agents used in the simulation, $FIRE = \{f_1, f_2, ...\}$ the finite set of fires and $TIME = \{t_0, t_1, ...\}$ the finite set of time points where t_0 is the initial state of the simulation. The set of all the entities of the simulation is $ENT = AGT \cup FIRE$. We denote by $card(E)$ the cardinality of the set E. So, $card(AGT)$ for instance is the number of agents and $t_{card(TIME)-1}$ is the final state of the simulation.

Each agent i at time t is characterized by the 6-tuple $\langle pos_i,\ visualRadius_i,\ neighbRadius_i,\ emDecayCoeff_i,$ $fireInflCoeff_i,\ agtInflCoeff_i \rangle$ where:

[1] By this assumption, we suppose here that emotion is in cognition: this is the point of view of the great majority of psychology community (see [21, 27, 12, 31] for instance) and this view is called "cognitive theory of emotion".

[2] GAMA is a (open-source) generic agent-based modeling and simulation platform. It provides a lot of powerful tools to develop easily agent-based models, in particular using geographical data. In addition, GAMA allows the modeler to run simulation in either an interactive or a batch mode. This will allow us to launch experiment design in order to explore the model.

- $pos_i : TIME \longrightarrow \mathbb{R} \times \mathbb{R}$ is the function that maps, for each time point t, the position $pos_i(t)$ of agent i at time t. We extend this function to any entity $e \in ENT$.

- $visualRadius_i : TIME \longrightarrow \mathbb{R}$ is the function that maps, for each time point t, the visual radius $visualRadius_i(t)$ of i at time t.

  We consider here that each agent has its own perception radius and that this perception radius can change during the evacuation process (because of smoke, fire, obstacle, *etc.*).

  In some scenarios, we suppose that the value d of visual radius does not change over time and we note $visualRadius_i = d$.

- $neighbRadius_i : TIME \longrightarrow \mathbb{R}$ is the function that maps, for every time point t, the neighborhood radius $neighbRadius_i(t)$ of i at time t. We impose that $neighbRadius_i(t) \leq visualRadius_i(t)$ for every agent i and time point t.

  In some scenarios, we suppose that the value d of neighborhood radius does not change over time and we note $neighbRadius_i = d$.

- $emDecayCoeff_i \in [0, 1]$ is the decay coefficient of i's emotion intensity (see Section 2.2). From a psychological point of view, agents are more impressionable than others. It depends on personologic data [11] and we suppose here it does not change over time.

- $fireInflCoeff_i \in [0, 1]$ is the fire influence coefficient on i. Due to the fact that some agents can be more experienced in some dangers (as fire, for instance) than other agents, the impact of a given danger depends on the agent who faces this danger. The more an agent is experienced in a danger, the less its fire influence coefficient is high.

- $agtInflCoeff_i : AGT \longrightarrow [0, 1]$ maps for every agent $j \in AGT$, the coefficient of influence $agtInflCoeff_i(j)$ of agent j on i. It is well-known in social influence literature (see [19, 15] for instance) that we are influenced by others from the point of view of beliefs, desires, norms, *etc.*

  It is the same with emotional states. But, due to the personality of each person, one can be more or less influenced by others. This coefficient of influence $agtInflCoeff_i(j)$ takes into account this aspect and the more this coefficient is high, the more agent i is influenced by the point of view of agents j.

So, we are able to define the following abbreviations (for every $e, e' \in ENT$, $t \in TIME$ and $i \in AGT$):

$$distance(e, e', t) \stackrel{def}{=} ||\overrightarrow{pos_e(t)pos_{e'}(t)}||$$

$$detectedFires_i(t) \stackrel{def}{=} \Big\{ f \in FIRE : distance(i, f, t) \leq visualRadius_i(t) \Big\}$$

$$minDistFires_i(t) \stackrel{def}{=} \min \Big(\Big\{ distance(i, f, t) : \forall f \in detectedFires_i(t) \Big\} \Big)$$

$$\mathcal{N}_i(t) \stackrel{def}{=} \Big\{ j \in AGT : distance(i, j, t) \leq neighbRadius_i(t) \Big\}$$

$distance(e, e', t)$ is the distance between the positions of entity e and entity e' at time t.

$detectedFires_i(t)$ is the set of fires in the visual radius of agent i at time t.

$minDistFires_i(t)$ is the minimal distance between agent i and all the fires it perceives at time t. We suppose here that, the more a fire is close to us, the more we are afraid by it. So, for the sake of simplicity, we suppose that the emotional reaction with respect to distant dangers is subsumed by the emotional reaction with respect to the closest danger(s) that we perceive. So, only the closest fires are taken into account here.

$\mathcal{N}_i(t)$ is the function that maps, for each time point t, the set of neighbors of agent i at time t.

Finally, we will define in the next section the function $fear_i(t)$ that computes the fear level of the agent i for each time point t. At the initial time t_0, $fear_i(t_0)$ is fixed for each agent i. The fear level at time $t > t_0$ is computed dynamically during the simulation steps.

More precisely, the fear intensity change from time $t-1$ to time t (that is, the change from $fear_i(t-1)$ to $fear_i(t)$) is a three steps process depending on three different successive functions:

1. $\Delta fearDecay_i(t)$ describes the lost of emotion intensity from $t-1$ to t due to time. If $fear_i(t-1) = 0$ (that is, the fear level at time $t-1$ is 0), then $\Delta fearDecay_i(t) = 0$; else, $\Delta fearDecay_i(t)$ is the value that correspond to the lost of emotion intensity between $t-1$ and t (see Section 2.2);

2. $\Delta fearEnv_i(t)$: if the current fear level after decay is equal to 0 then a value (computed from a sigmoid function) is returned, else the variation of the fear between $t-1$ and t is added. This variation is computed from the derivative of the sigmoide between $t-1$ and t and corresponds to the effect of the fires that agent i detects around itself (if fires are detected) on its fear level (see Section 2.3);

3. $\Delta fearNeighb_i(t)$: it is the variation of the fear (that can be positive or negative) coming from the influence of i's neighbors. If these neighbors have a fear level

that is lower than the fear level of i (after decay and influence of the environment), then the fear level of i will decrease, else it will increase (see Section 2.4).

Finally, $fear_i(t)$ is the final new value of fear intensity at time t. It is defined as a composition of the above three components. Note that we could compute the fear level as the sum of three independent functions: one for the decay process, one for the environment influence process, and one for the neighborhood influence process. But such a sum could be less than 0 or to be greater than 1 (whereas we require that fear level is between 0 and 1). So, we prefer to compute the resulting emotion intensity as a composition of functions because it avoid such situations where the results could not be between 0 and 1.

2.2 Emotion Decay over Time

As highlights in the literature [27, Chap. 4], without any stimulus, agents' fear intensity will decrease over time. This decay is often described as faster for higher values of emotion intensity, and it slows down when the emotion intensity is low.

At time t and for every agent $i \in AGT$, the value of the fear decay (the loss of emotion intensity) is noted $\Delta fearDecay_i(t)$. This value is a function of the previous emotion level at time $t-1$ ($fear_i(t-1)$) and of $emDecayCoeff_i \in [0,1]$ (the *decay coefficient* that depends on some attributes of each agent like genre, age, sex, *etc.* [11]). Moreover, we suppose that this decay coefficient does not vary over time.

These requirements lead us to use the following function for emotion decay over time (see Figure 1):

$$\Delta fearDecay_i(t) \stackrel{def}{=} - emDecayCoeff_i \times fear_i(t-1) \quad (1)$$

We can first notice that, if $fear_i(t-1) = 0$ (*e.g.* at the simulation initial step) then $\Delta fearDecay_i(t) = 0$ and then, $fear_i(t)$ (the emotion level at time t) will not be modified by (1). So it does not trigger any emotion, but only decreases its value with time.

Moreover, the more $emDecayCoeff_i$ is great, the more emotional level decreases quickly.

Finally, note that the emotion decay has the same shape as the "activation level decreasing" in the Anderson's theory of central cognition [3]. It could certainly be oversubtle but this form has the advantage to be computationally interesting.

In Figure 1, the fear function is limited to the fear decay effect (what we call $fearDecay_i(t)$), so its evolution is described by

$$fearDecay_i(t) = fear_i(t-1) + \Delta fearDecay_i(t).$$

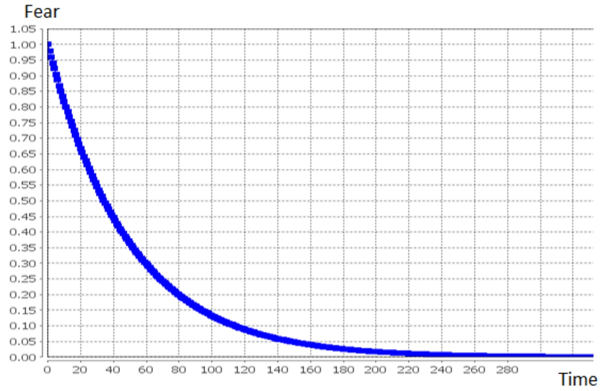


Figure 1: Fear decay with $emDecayCoeff_i = 0.02$ for any agent i and without any other stimulus.

2.3 Environment Influence on Emotion

The environment contains dangers (fires for instance), warnings (alarm...) or other elements (smoke...) that may have an impact on emotions. In particular, dangers may trigger a fear emotion or increase the fear intensity.

In the following, we consider two distinct processes: a) emotion is triggered when the agent does not feel fear yet and b) the fear level is updated when an agent is already feeling fear and has to face a hazard.

Emotion triggering (when $fearDecay_i(t) = 0$). When agent i does not feel fear at time t just after the emotion decay computation ($fearDecay_i(t) = 0$) and perceives a hazard or hears an alarm, this stimulus appraisal will trigger an emotion. We make the assumption that both the distance to the danger and the number of dangerous elements the agent has perceived influence the intensity of the triggered emotion.

The fear degree function should be an increasing function of the number of hazards, but a logarithm-like function to capture the fact that the difference in terms of intensity is greater if the agent observes a small number of fires (for instance, 2 fires instead of 1) rather than if it observes a huge number (for instance, 102 fires instead of 101). In addition, we consider that the intensity should also be a decreasing function of the distance to hazard and we assume that the relevant distance $minDistFires_i(t)$ at time t from agent i to hazards is here the distance to the closest hazard and not the average distance to all fires in i's neighborhood (see Section 2.1).

As a consequence, emotion triggering when fires occur in the perception radius $visualRadius_i(t)$ of agent i at time t is formalized as follows. When $fearDecay_i(t) = 0$, we define the intensity of the triggered fear by:

$$\Delta fearEnv_i(t) \stackrel{def}{=} \frac{1}{1 + e^{-\lambda_i (1 - \frac{minDistFires_i(t)}{visualRadius_i(t)})}} \quad (2)$$

Clearly, $\Delta fearEnv_i(t)$ is a sigmoid function where λ_i characterizes the steepness of the curve. λ_i should increase together with the number of fires in the i's perception area at time t (that is, formally, $card(detectedFires_i(t))$) and it also depends on the fire influence on agent i ($fireInflCoeff_i$). So:

$$\lambda_i \stackrel{def}{=} fireInflCoeff_i \times \left(1 - \frac{1}{card(detectedFires_i(t)) + 1}\right) \quad (3)$$

Note that $fireInflCoeff_i$ could depend on the knowledge about and the experience with fire of i [23].

Figure 2 illustrates the impact of the number of fires and of their distance on the initial fear level.

Note that (2) ensures that $\Delta fearEnv_i(t) \in [0, 1]$. We have chosen here a sigmoid function because this type of function illustrates perfectly the switch between a low level of the fear intensity[3] and the triggering of fear. We use here a particular steepness λ_i that must be easily changed, depending of the experimental situation.

In Figure 2[4], fear at time t is computed only from the environment influence (neither emotion decay is applied nor neighbors influence). It is supposed here that the more time increases, the more fires number decreases. Several simulations have been executed, corresponding to several minimal distances between agent i and fires (that is: $minDistFires_i(t) \in \{0.0, 5.0, 10.0, \cdots, 40.0\}$). So, its evolution is described by

$$fearEnv_i(t) = \Delta fearEnv_i(t).$$

Note that the more $minDistFires_i(t)$ is low, the more the intensity of fear is high when the number of fires is maximal.

Emotion update (when $fearDecay_i(t) > 0$). When $fearDecay_i(t) > 0$, fear has already been triggered and we assume that the perception of fires must change this previous fear level. So, we use the derivative (4) of the previous sigmoid described in (2) to update step by step the emotion level.

For convenience' sake, let be

$$\lambda'_i \stackrel{def}{=} \lambda_i \times \left(1 - \frac{minDistFires_i(t)}{visualRadius_i(t)}\right).$$

So, $\Delta fearEnv_i(t)$ is just the variation of fear following from the environment influence on the emotion level at time t. That is:

$$\Delta fearEnv_i(t) \stackrel{def}{=} fearDecay_i(t).(1 - fearDecay_i(t)).\lambda'_i \quad \text{when} \quad 0 < fearDecay_i(t) < 1 \quad (4)$$

[3] By *low level*, we means a level that is under the triggering threshold of fear.

[4] The numerical values chosen in this section have been chosen with a case study of the size of a supermarket in mind. For the other coefficients, they have been chosen in order that results to be good illustration of the equations. The exploration of the various values of parameters is provided in the Section 4

$\Delta fearEnv_i(t)$ is here the variation of i's fear level at time t after the influence of the environment on the emotion level (without taking into account the emotion decay).

Figure 3 presents the evolution of the fear level under the single influence of the environment (fire).The fear evolution is thus described by the equation:

$$fearEnv_i(t) = fearDecay_i(t) + \Delta fearEnv_i(t).$$

2.4 The Neighbors' Emotional Contagion

The two previous subsections focused on the individual part of the emotion. We consider here its social aspect: emotions can spread among neighbors. This has already been investigated in many works, such as [13, 5] where the emotion of an agent tends to the average value of all the agents over time (as in our model).

In our model, an agent detects its neighbors at time t based on its visual radius (see $\mathcal{N}_i(t)$ in Section 2.1). So, the emotional influence of agent j on agent i at time t is the difference between the emotion level of i and the emotion level of j at time t. This influence is weighted by the influence coefficient $agtInflCoeff_i(j)$ of j on i. So, formally:

$$InfluenceOf_{j \rightsquigarrow i}(t) \stackrel{def}{=} \Big(fear_j(t-1) - fearEnv_i(t)\Big) \times agtInflCoeff_i(j) \quad (5)$$

$agtInflCoeff_i(j)$ depends on the relationship between i and j: stronger theses relationships are, higher this value is. This equation is based on the bounded confidence model of [18]. Some equations have been proposed in the social network analysis area (see [7, 20, 19, 16, 30] for instance) corresponding to the modelling of different situations.

Note that if $fear_j(t-1) > fearEnv_i(t)$ then $InfluenceOf_{j \rightsquigarrow i}(t) > 0$: it means that the fear level of i will increase. Conversely, if $fear_j(t-1) < fearEnv_i(t)$ the i's fear level will decrease. If the levels are the same, it means that i is not influenced by j ($InfluenceOf_{j \rightsquigarrow i}(t) = 0$).

So, we are now able to compute the influence of all the i' neighbors that is the average value of all the individual influences:

$$\Delta fearNeighb_i(t) \stackrel{def}{=} \frac{1}{card(\mathcal{N}_i(t))} \sum_{j \in \mathcal{N}_i(t)} InfluenceOf_{j \rightsquigarrow i}(t) \quad (6)$$

Note that the influence of neighbors is computed as the average value of each neighbor.

Without the decay and without the environment influence, the emotion of all simulated agents reaches average values as illustrated in Figure 4. It corresponds to the following equation:

$$fearNeighb_i(t) = fearEnv_i(t) + \Delta fearNeighb_i(t)$$

Depending on $agtInflCoeff_i(j)$ for every neighbor j of i, the time to reach this equilibrium can be different.

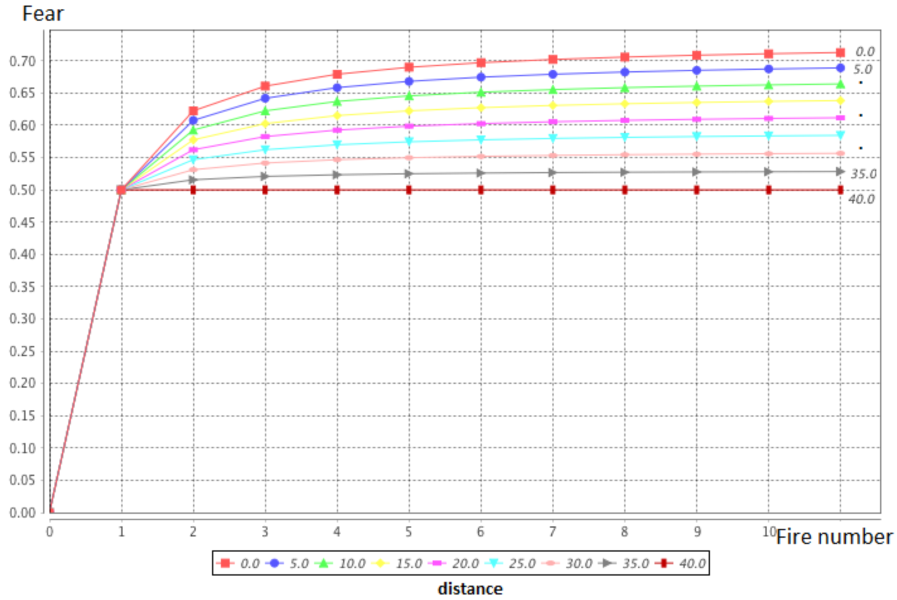


Figure 2: Fire number and distance impact on the emotion level (with $\mathit{visualRadius}_i = 40, \mathit{fireInflCoeff}_i = 1$).

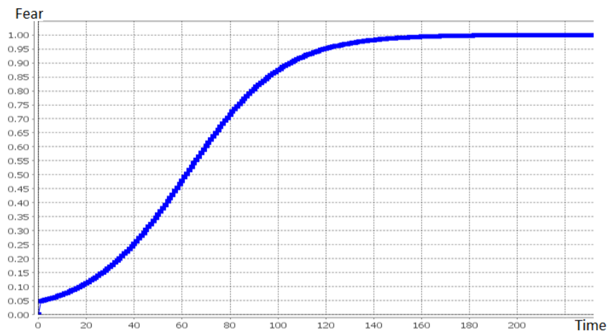


Figure 3: Emotional level dynamics only influenced by environment ($\mathit{emDecayCoeff}_i = 0$) with (for every $i \in AGT$ and $t \in \mathit{TIME}$): $\mathit{fireInflCoeff}_i = 0.1$, $\mathit{card}(\mathit{detectedFires}_i(t)) = 2$, $\mathit{minDistFires}_i(t) = 10$, $\mathit{visualRadius}_i(t) = 40$ and with $\mathit{fear}_i(t_0) = 0.05$.

2.5 The Emotion Level Global Equation

The new emotion level of agent i at time t, after the decay due to time (see Section 2.2), the influence of the environment (see Section 2.3), and the influence of i's neighbors (see Section 2.4) is nothing else that:

$$\mathit{fear}_i t = \mathit{fearNeighb}_i(t) \tag{7}$$

(It is due to the fact that we have chosen to compute fear at time t as a composition of functions.)

2.6 Additional Influences of the Environment on Emotion

Some other factors may impact agents' emotions in different manners. For instance, the influence of smoke is similar

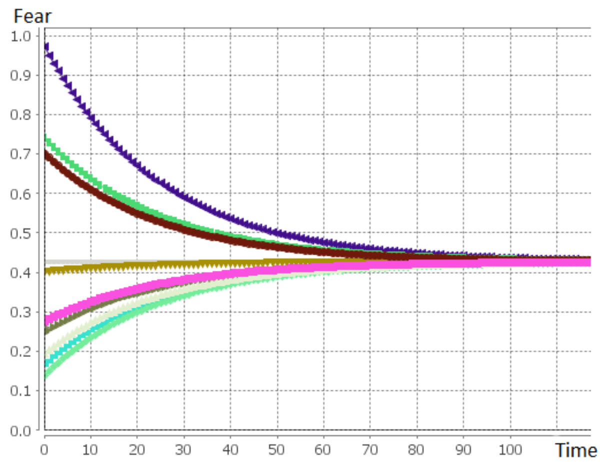


Figure 4: Fear level dynamics of every agent i under the only influence of emotion contagion process ($\mathit{emDecayCoeff}_i = 0$ and $\mathit{fireInflCoeff}_i = 0$), with $\mathit{agtInflCoeff}_i(j) = 0.02$ (for every neighbor j of i), $\mathit{card}(AGT) = 10$. The inital fear value is chosen randomly in $[0, 1]$.

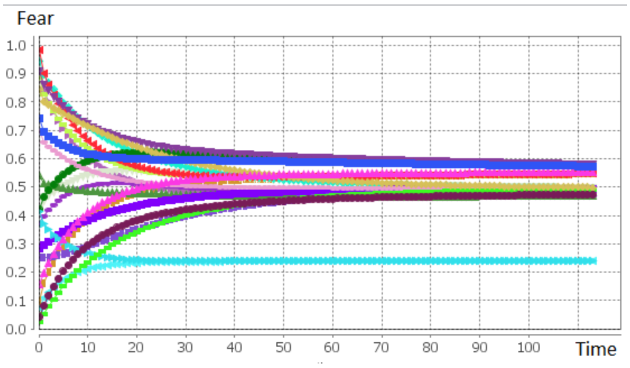


Figure 5: Emotion evolution of all the agents under the only effect of emotional contagion.

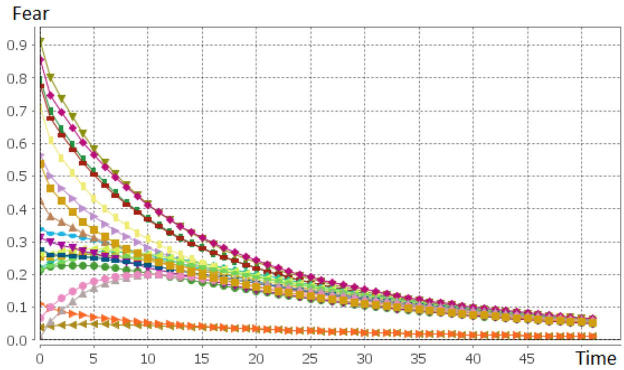


Figure 6: Emotion evolution of all agents under both the decay and the contagion effects.

to the fire one but the impact coefficient can be different. The influence of alarm does not depend on the distance as we could suppose that all people could hear the alarm.

Finally, we can also mention as additional factors influencing agents' emotions: the fear reduction due to a security agent, the impact of the perception of an exit door, or the impact of the help received from others.

3 Experiments on the emotion dynamics

In this section, we assess the impact of various possible combinations of the three factors (emotion decay, contagion and environment) on the emotion dynamics. We first only investigate the emotion dynamics and then couple it with a second dynamics: agents' moves. (Note that in the following, i's visual radius does not change over time and we note it: $visualRadius_i$.)

3.1 Emotion Dynamics with Unmoving Agents

The following results are computed with $card(AGT) = 20$ and $card(FIRE) = 10$ and with the following values of agent parameters (for every agent $i \in AGT$): $emDecayCoeff_i = 0.02$, $fireInflCoeff_i = 0.1$, $agtInflCoeff_i(j) = 0.04$ for every $j \in \mathcal{N}_i(t)$ and every $t \in TIME$, and $visualRadius_i = 40$. Neither the agents nor the fires move.

3.1.1 Emotional Contagion

In these simulations, we first check the impact of the random distribution of agents in the environment on the contagion. As they have a limited perception radius, agents are not able to diffuse their emotion to all other agents. We initialize agents' fear level to a random value in $[0, 1]$. The result is presented in Figure 5. We observe that the agents' emotion tends towards a limited number of values. Each of these values correspond to a spatially clustered set of agents.

This convergence state with several stable values becomes quite common in the related field of social opinion dynamics. In particular, [8] has proposed the bounded confidence model that uses continuous opinion value and an acceptability threshold. When two agents (representing individuals moving in an abstract environment) meet each other they share their opinions. If they are not too far (distance in terms of opinion below a given threshold), opinions are altered in order to come closer. Depending on parameters (interaction frequency, initial opinion distribution, or even interaction network topology), various kinds of convergence can appear: either convergence to an intermediate consensus or to one or two extremist opinions. In our case, we recognize basically the same pattern, the acceptability threshold of [8] is for us the perception radius that will limit the agents that can interact together.

3.1.2 Coupling Emotion Decay and Contagion

As we do not take into account the process triggering emotions from environment stimuli, we initialize randomly $fear_i(t_0) \in [0, 1]$ for every agent $i \in AGT$ and test the influence of the two decay and contagion factors.

The result is presented in Figure 6. With no influence of fires, the fear level of each agent i converges (due to the emotional contagion) and tends towards 0 (due to the decay). Nevertheless we can notice that even without stimulus, the fear level of some agents starts increasing due to the contagion dynamics before finally decreasing when the decay becomes the dynamics that have the greatest influence on the system.

3.1.3 Coupling Emotion Decay and Environment

Let be $fear_i(t_0) = 0$ for every $i \in AGT$. The emotion will be triggered by the perception of fires. The result is presented in Figure 7. We first observe that fear level of some agents keep or tend towards 0, because they can not perceive any fire. The main observation is that $fear_i(t)$

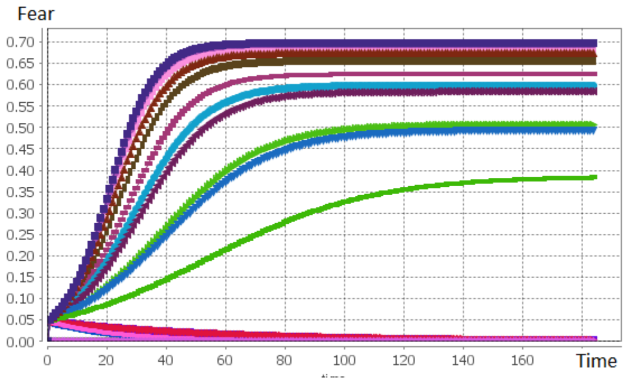


Figure 7: Emotion evolution of all the agents under both the decay and the environment effects.

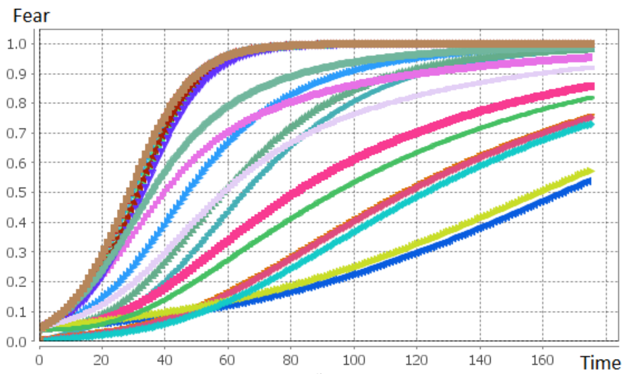


Figure 8: Emotion evolution of all agents under both the environment and the contagion effects.

reaches a stable value for each agent i when t increases. This value depends on the number of fires and the distance to them. This shows that the simulation reaches an equilibrium between the two processes influencing the emotion dynamics. In addition the stable value is always smaller than the maximum value due to the effect of the decay.

3.1.4 Coupling Environment and Emotion Contagion

Again we conside the situation where $fear_i(t_0) = 0$ for every $i \in AGT$ and the emotion will be triggered by fires in the environment. We consider in this case the coupling between the emotion triggered by fire and the emotion contagion among agents. The result is plotted in Figure 8. Without emotion decay, agents fear tends to reach the maximal value (*i.e.* 1). Time to reach it depends on the distance to fires and the number of neighbours. Nevertheless we can again observe a stability of the results.

In addition, due to emotional contagion over agents, no agent has its fear level staying at the value 0. Even agents that cannot perceive the danger start to feel fear because of their neighbors.

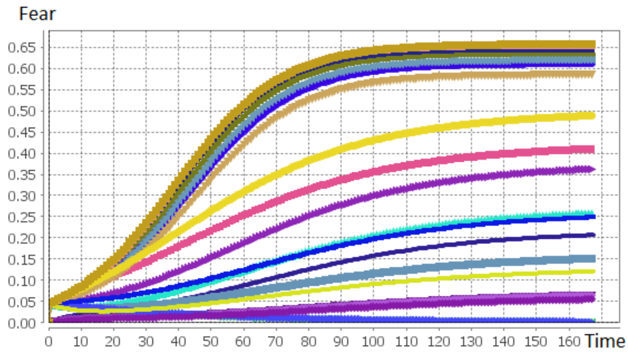


Figure 9: Emotion evolution of all the agents under the decay, the environment and the contagion effects.

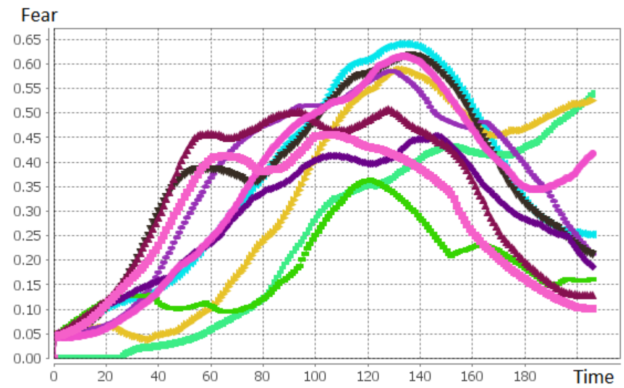


Figure 10: Impact of all the factors (decay, environment, contagion) on the emotion intensity in case of moving agents.

3.1.5 Coupling Emotion Decay, Environment and Emotion Contagion

Finally we couple the three processes in a single model. Figure 9 displays the results. The results show again that fear levels tend to a stable value. This value is obviously lower than the value obtained without decay (see Figure 8). But it is interesting to note that the fear level values are also lower than the ones in the case without contagion (see Figure 7). The contagion process indeed drives fear level values to the average value which induces a decrease of the maximum value.

3.2 Emotion Dynamics with Moving Agents

The previous results come from simulations with static agents and environment, providing, as expected, stable results. In this section we will introduce agents mobility. We launch the simulations in the same conditions as the previous ones, except that we have 10 agents. Agents move randomly in the environment: they pick a random target in the environment, move to it and when they reached it they choose a new one. Figure 10 displays each agent emotion evolution.

We can observe that the results are not stable anymore.

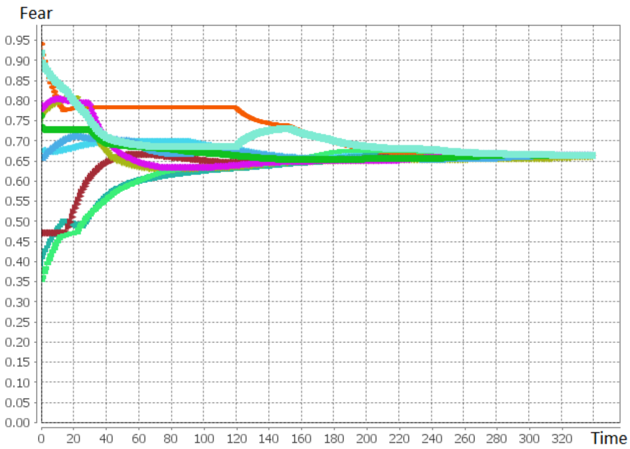


Figure 11: Impact of only the emotion contagion on the emotion intensity in case of moving agents.

Indeed as the agents can move they will be sometimes close to fires, increasing their level fear, and sometimes far from them, decreasing their fear level.

If we activate only the emotional contagion, we observe in the Figure 11 with moving agents that each agent fear level converges toward the same value. Contrarily to the results in Figure 5, we can observe here a convergence having moving agents removes the cluster effect that can occur when agents do not move.

4 Sensitivity analysis

In this section, we explore the model behavior with respect to parameters variations. We only focus here on the three following coefficients for a given agent i: $emDecayCoeff_i$, $fireInflCoeff_i$ and $agtInflCoeff_i$, that characterize the three processes making emotion dynamic during the simulation. So, we will measure the maximum, minimum, average and standard deviation values of the agents' fear level at the end of the simulations. In addition we will compare results between two cases: with and without moving agents.

We initialize simulations with $card(AGT) = 50$, $card(FIRE) = 10$, randomly located. For each parameters tuple

$$\langle emDecayCoeff_i, fireInflCoeff_i, agtInflCoeff_i \rangle$$

(where $i \in AGT$) we run 10 simulations and measure the maximum, the minimum, the average and standard deviation values of the agent fear level at the step number 100. When agents can move, they choose a random target, go to it and when reached the target it picks randomly a new target.

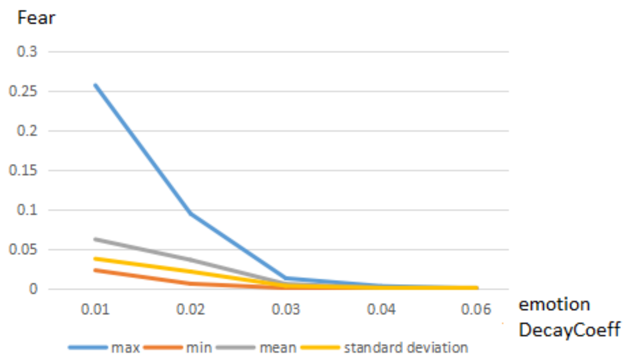


Figure 12: Impact of $emDecayCoeff_i$ (for every $i \in AGT$) on the fear level of moving agents in case of $fireInflCoeff_i = 0.05$ and $agtInflCoeff_i = 0.01$.

4.1 Exploration in the Case of Moving Agents

4.1.1 Exploration of the Impact of the Decay Coefficient $emDecayCoeff_i$

For every agent $i \in AGT$, let $fireInflCoeff_i = 0.05$, $agtInflCoeff_i = 0.01$ and $emDecayCoeff_i \in \{0.01, 0.02, 0.03, 0.04, 0.06\}$. We measure the 4 indicators presented above and denoted them $\max$, $\min$, mean and standard deviation. We observe the results in Figure 12. We can observe that when $emDecayCoeff_i$ increases, the fear level tends toward 0. This means that when the decay coefficient is more important, the decay process has more influence on the simulation results.

4.1.2 Exploration of the Impact of all the Parameters

The previous Section 4.1.1 shows the impact of the $emDecayCoeff_i$ parameter single-variation on the fear level. We launch now an exhaustive exploration of the model with (for every agent $i \in AGT$):

- $emDecayCoeff_i \in \{0.01, 0.02, 0.03, 0.04, 0.06\}$
- $fireInflCoeff_i \in \{0.05, 0.1, 0.2, 0.3, 0.5\}$
- $agtInflCoeff_i \in \{0.01, 0.06, 0.1, 0.2, 0.3\}$

For each parameter tuple

$$\langle emDecayCoeff_i, fireInflCoeff_i, agtInflCoeff_i \rangle$$

we launched 10 simulations and store the average value of each indicator. The complete results are summarized in Figure 13 and Figure 14.

These figures display the scatter plots of all possible pairs of parameters and indicators. For example in Figure 13, the upper-right frame plots the max indicator with relation to the $emDecayCoeff_i$ parameter[5]. All the bullets

[5]This has been plotted using the R software: `https://www.r-project.org/`

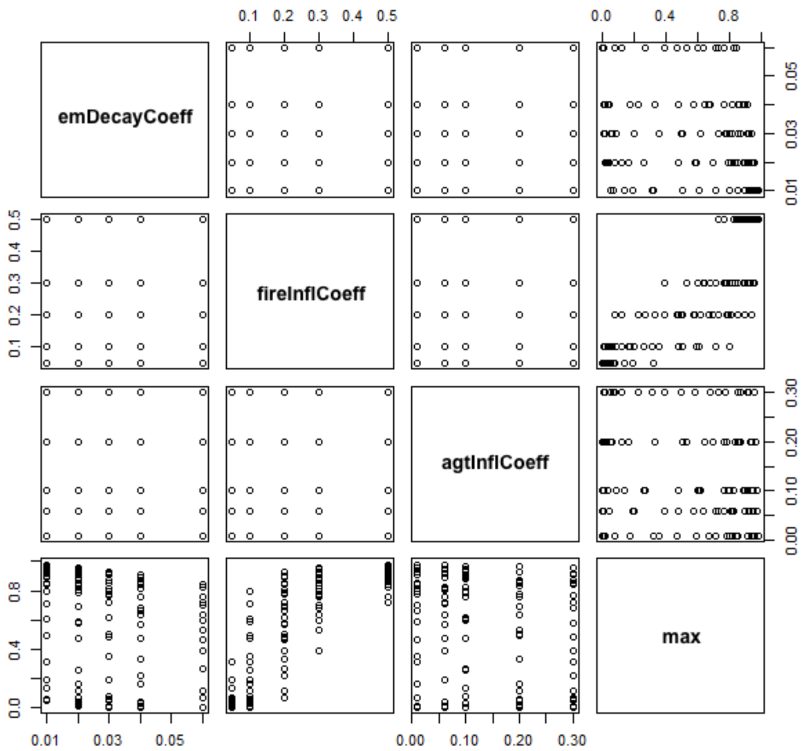


Figure 13: For every agent $i \in AGT$, max indicator depending on $emDecayCoeff_i$, $fireInflCoeff_i$ and $agtInflCoeff_i$ values.

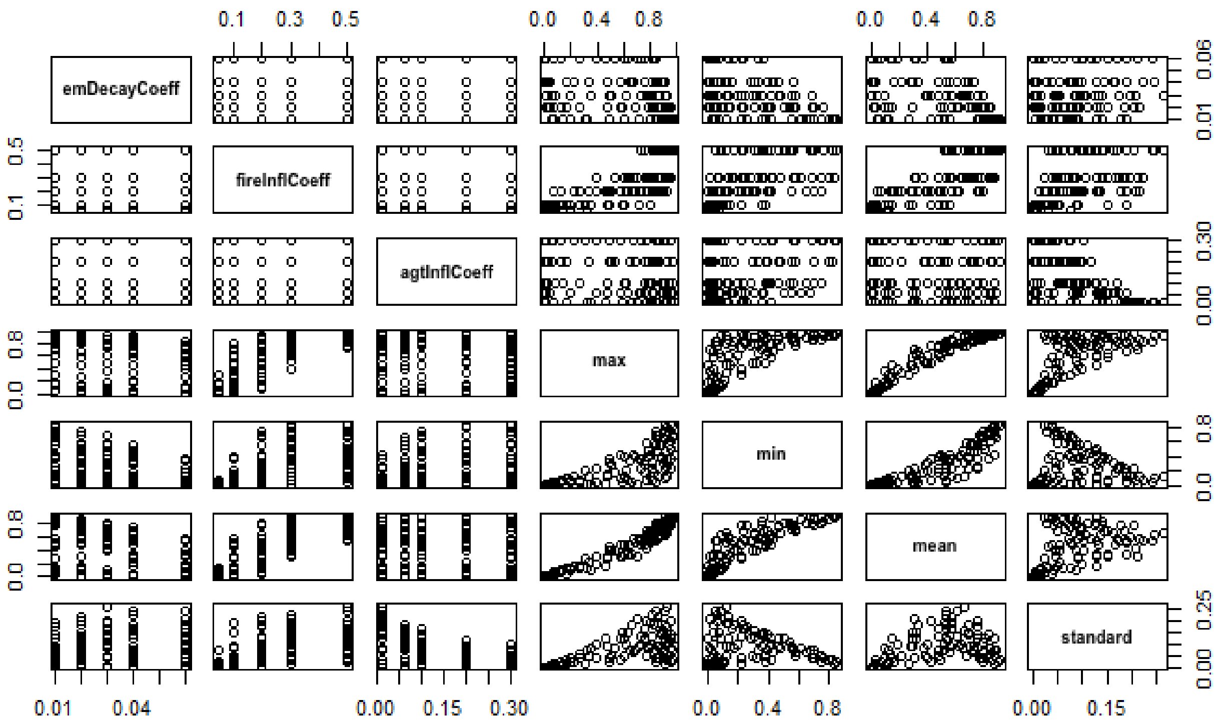


Figure 14: max, min, mean and standard deviation values depending on $emDecayCoeff_i$, $fireInflCoeff_i$ and $agtInflCoeff_i$ values for every agent $i \in AGT$.

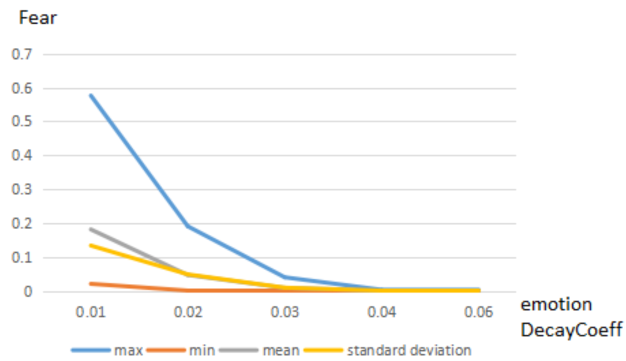


Figure 15: Impact of $emDecayCoeff_i$ on the fear level of unmoving agents when $fireInflCoeff_i = 0.05$ and $agtInflCoeff_i = 0.01$ (for every agent $i \in AGT$).

correspond to the projection of tuples

$$\langle emDecayCoeff_i, fireInflCoeff_i, agtInflCoeff_i, \max\rangle$$

(for every $i \in AGT$) in a 2 dimensions plan. This representation allows the modeler to isolate the influence of one single parameter evolution on one single indicator.

In addition, still looking at the upper-right frame, we can observe possible values of the $emDecayCoeff_i$ parameters on the right and the value range of the max indicator on the top.

We can thus observe that (for every $i \in AGT$) $fireInflCoeff_i$ has a huge influence on the max indicator: when $fireInflCoeff_i$ is high (0.5) the maximum fear levels are also very high (between 0.7 and 1). And this result is independent from the other parameter values. When $fireInflCoeff_i$ is low (0.01 and 0.02) the maximum is lower and close to 0.

Similarly we can observe that the $emDecayCoeff_i$ parameters have an effect on the boundaries of the max indicator: for every $i \in AGT$, when $emDecayCoeff_i$ is high, the maximum of the max indicator is limited to 0.8 whereas, with the lowest value of this coefficient, the limit is around 1, and many plots are concentrated around this value. We can notice that for intermediate values of the $emDecayCoeff_i$ coefficient, plots are concentrated around 0.0 and 0.8. We thus have a polarization of the results around two main values, corresponding to the minimum and maximum values that the max can take.

We can also observe that $agtInflCoeff_i$ does not have a visible impact on the max indicator: with high or low values of this coefficient, the max indicator takes values everywhere in $[0, 1]$.

Looking at Figure 14, we can also notice that $fireInflCoeff_i$ has a smaller influence on the min indicator, but $emDecayCoeff_i$ has a higher one. In particular, when $emDecayCoeff_i$ increases the min indicator takes lower values.

It is also interesting to notice that, when we consider $emDecayCoeff_i$, the distributions of min and mean plots are very close, whereas when we consider $fireInflCoeff_i$, max and mean plot distributions are close (and different from the min distribution). This means that, in average, plots are closer the min (resp. the min) plot distribution.

Finally we can observe that, even if the $agtInflCoeff_i$ does not have a significant influence on the max and mean indicators, it tends to reduce the standard deviation. That means that the emotional contagion tends to level fear level values.

4.2 Exploration in the Case of Unmoving Agents

We run simulations with the same initial conditions as in the previous section but agents don't move now. The results are quite similar to the results in case of moving agent (Figure 15).

This is due to the high number of agents and the chosen visual radius ($visualRadius_i = 40$ for every $i \in AGT$).

We continue to expand this experiment by changing $emDecayCoeff_i$, $fireInflCoeff_i$ and $agtInflCoeff_i(j)$ (for every agent i and every $j \in \mathcal{N}_i(t)$). The comparison is presented in Figure 16(a), Figure 16(b), Figure 16(c) and Figure 16(d).

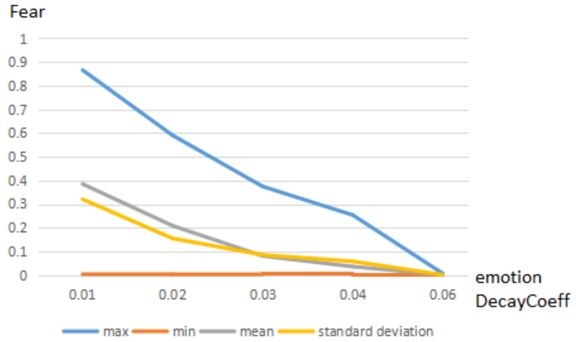
We can observe that there is only a small difference in the emotion level values between both cases. It seems that the emotion of agent in these cases do not depend on moving or unmoving agents.

It can be explained by the higher value of the visual radius: an agent can detect more agents, so it will be influenced by more of them. Evidently, an agent moving has more opportunity to detect the others. But with a large visual radius, there is not much difference between 2 types of agent. And one thing important, we don't account into the influence of neighbours, therefore the distance between agents when they move, does not play an important role.

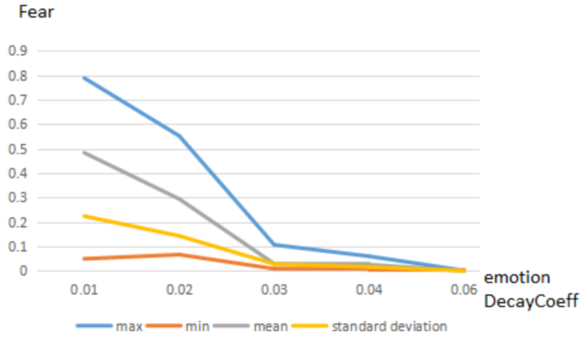
Nevertheless we go a little deeper in the comparison between simulations with moving and unmoving agents. We aim at evaluating the time for fear levels to converge under the influence of the emotional contagion process only and the influence of $agtInflCoeff_i(j)$ (for every $j \in \mathcal{N}_i(t)$) on the convergence.

We run simulations and stop them when the standard deviation indicator becomes lower than 0.01. We count the number of simulation steps necessary to reach this state. The results are shown in Figure 17.

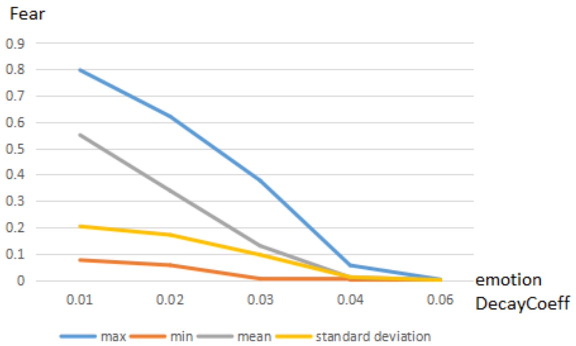
We can observe that the number of steps to reach the equilibrium is higher for unmoving agents case than for moving agents one: moving agents tend to meet more other agents and this mix fasten the emotion convergence. This mix has a huge impact when $agtInflCoeff_i(j)$ (for every $j \in \mathcal{N}_i(t)$) is low, but decrease when the parameter value increases.



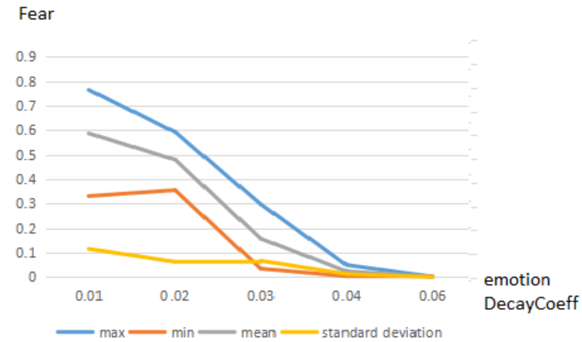
(a) Unmoving agents in case of changing $emDecayCoeff_i$ while $fireInflCoeff_i = 0.1$ and $agtInflCoeff_i(j) = 0.01$ for every $j \in \mathcal{N}_i(t)$.



(b) Unmoving agents in case of changing $emDecayCoeff_i$ while $fireInflCoeff_i = 0.1$ and $agtInflCoeff_i(j) = 0.08$ for every $j \in \mathcal{N}_i(t)$.



(c) Moving agents in case of changing $emDecayCoeff_i$ while $fireInflCoeff_i = 0.1$ and $agtInflCoeff_i(j) = 0.01$ for every $j \in \mathcal{N}_i(t)$.



(d) Moving agents in case of changing $emDecayCoeff_i$ while $fireInflCoeff_i = 0.1$ and $agtInflCoeff_i(j) = 0.08$ for every $j \in \mathcal{N}_i(t)$.

Figure 16: Comparing moving and unmoving agent in case of changing 3 factors $emDecayCoeff_i$, $fireInflCoeff_i$ and $agtInflCoeff_i(j)$

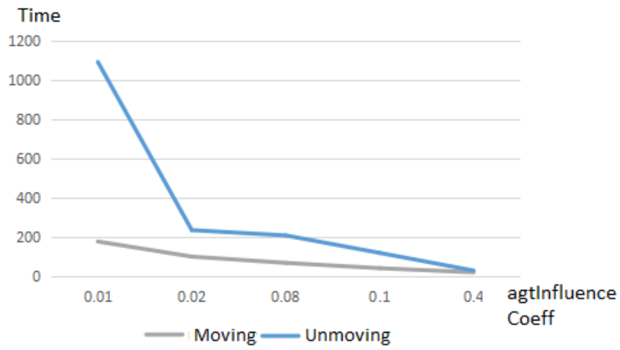


Figure 17: Relationship between $agtInflCoeff_i(j)$ (for every $j \in \mathcal{N}_i(t)$) and time in the case where all the agents reach to the equivalent emotion.

5 Conclusion and future works

In this article we proposed a model of fear level dynamics based on some main findings from social psychology. Our aim here is to provide an intuitive formalization of the computational process for emotion modeling.

The model was implemented in GAMA agent-based simulation platform. We conducted an intensive experiments to find the equivalent value of three coefficients that have impact on the emotion intensity of agent group. We presented our results about the impact of decay, environment, and agents neighbors factors (*i.e.* emotional contagion) on emotion intensity.

We shown how emotion evolves over time and the role played by each variable of the simulation by using several scenarios. In particular, the impact of the environment (in case of the fire perception) has a great influence on the maximum fear level, whereas the emotional contagion tends to bring closer emotions in the agent population.

Although this paper context is about crisis situation and evacuation, the study remains abstract: the purpose of this article is mainly to focus on the emotion dynamics model and its exploration.

The next step will be to integrate this emotional framework into a simulation of evacuation in crisis situation. Emotions will be used at several steps: physical properties of agents (strong emotions can make people move faster or slower), decision-making process (it is now established that emotions help to make decisions and often fasten the decision-making process with a risk of making less efficient decisions), and social process (in particular the group constitution and the effects of the group on the group members). The main objective will be to provide more realistic evacuation simulations, in terms of human behaviors, and thus to reach decision-support systems to support crisis managers. We thus attempt to make simulations more realistic by improving the human agents behaviors (in line with [1, 6]).

More particularly, two application cases can be very interesting. First it could help architects and urban planners to better design public spaces to help people to better evacuate taking into account cognitive attitudes such as emotions or social binds and not only simple physical flow of individuals. Second we plan to apply this framework on the cases study of Australian bushfires simulations [2]. This case of bushfires has killed hundreds of people and has been deeply studied, in particular through interview of most of the survivors. An important conclusion of this survey was that civilians have not reacted and acted as expected by authorities in charge of the preparedness against fires and rescue to victims. First models of the evacuation has been implemented, with a focus on the distinction between objective and subjective civilian capabilities and perception of the environment. We argue that it could be improved by introducing emotional capabilities that can influence these biases in the representation of the world.

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