Emotion in the Evacuation Process

Formal Model and Simulation*

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ABSTRACT

Recently the key role of emotions in decision-making process has been highlighted. In this article, we focus on fear-related emotions and their positive impact on the survival capabilities of human beings in case of crisis situation. The purpose of this paper is to clarify the impact of emotion on agents in the evacuation process; we only focus here on emotions and not on the evacuation process itself. We formalize the influence of three factors (decay, environment, contagion) on agents emotion and explore the influence of each of them. The emotion intensity of agents will be tested in case of moving or without moving. We will make some experiments to estimate the impact of three coefficients of decay, environment, contagion on the emotion intensity of groups such as max, min, mean and standard deviation value. The entire theoretical model has been implemented in the GAMA simulation platform.

Keywords

Emotion; simulation; agent-based model; GAMA platform; crisis situation; evacuation process

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 rational reasoning process. 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 situation: indeed recent works have shown that emotion is very important in the understanding of human beings behaviours in crisis situations (see [5, 6, 24, 2] for instance).

It has been studied for a long time in psychology and in philosophy, and more recently in cognitive sciences (see [23, 17, 27, 8] 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, emotion plays a central role in cognition, especially when we need to react very quickly (what is the case in crisis situation). Instantaneously, emotion provides us a set of possible actions (called *action tendencies* for Lazarus [17]) 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 situation for us. So, emotions have a great power of explanation of our action in crisis situation.

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, [22] has shown that it is in fact a behaviour very meaningful and far from most conceptions of irrationality. The panic behaviour exists but is in fact quiet rare. It is an individual behaviour, by opposition to a behaviour of the crowd, is not contagious and it occurs in short duration. It is not easy to observe in natural and technological disasters.

Some particular conditions of panic triggering have been identified such as: perception of a great threat to self, a belief that escape from the threat is possible but is very hard to achieve and a feeling of helplessness [24, 10]. Some additional conditions may occur such as experience in situation emergency, information. Information is the key to make a successful evacuation strategies during a crisis [25]. The sex and age can cause the different fear level.

In the simulation area, a lot of works focus more specifically on

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emotion contagion. For instance, in [20], the authors present simulations about relationships between emotions, information and beliefs. All the members of a group can absorb the emotion of others members (in the same group) to create an average value of emotion. But they can also be influenced by the members of other groups.[1] 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 have proposed 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) to the characters of agent like the openness, the expressiveness, the capacity of receive or express from/to others. Similarly, in [3], the authors give another interesting orientation about the contagion of emotion among a group.

In the GAMA [12] community, several models (see [21, 18] for instance) have shown the important role played by emotions in emergency situations. In [21], authors simulate the emotion dynamics in a group. They gave a new operational model of the emotion contagion and have implemented 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, modifying the evacuation time. But we can also criticize here the fact that emotion modeling is very basic: we need a more complex cognitive model of emotion if we want a natural agents behavior.

This article provides a new model of emotions dynamics and follows previous results about the impact of groups on evacuation process [28]. The emotion model has been implemented in GAMA and is a part of a more general project about evacuation simulations in crisis situation.

We only focus here on fear emotion because this emotion plays an important role in crisis situations. In the following, we propose to model emotion following some main results in psychology. First, emotions have triggering conditions (see [23, 17] for instance): this is a cognitive appraisal of these conditions that determines if they are fulfilled or not.[2]. 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). Second, 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). 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 take into account all these parameter in an intuitive manner.

More precisely, a lot of factors may impact the emotion, but here we only take into account three main ones: decay, environment (fire perception) and emotional contagion. The corresponding equations of emotion change are presented in Section 2. All the figures presented in this section come from the implementation of these equations using the GAMA platform.[3] We give preliminary results about the various combinations of the factors in Section 3 and explore the model behavior in Section 4.

2. MODEL OF EMOTION DYNAMICS

2.1 Evacuation Model and Notations

As presented above, this article focuses only on one emotion and on its diffusion. So, the environment is described in a simple manner. In particular, there is neither obstacle nor exit door (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. 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 7-tuple $\langle visualRadius_i, emotionDecayCoeff_i, fireInfluenceCoeff_i, agtInfluenceCoeff_i, detectedFires_i, distMin_i(t), \mathcal{N}_i(t), fear_i(t)\rangle$ where:

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

• $emotionDecayCoeff_i \in [0, 1]$ is the decay coefficient of i's emotion intensity (see Section 2.2).

• $fireInfluenceCoeff_i \in [0, 1]$ is the fire influence coefficient on i.

• $agtInfluenceCoeff_i : AGT \longrightarrow [0, 1]$ maps for every agent $j \in AGT$, the coefficient of influence $agtInfluenceCoeff_i(j)$ of agent j on i.

• $detectedFires_i : TIME \longrightarrow 2^{FIRE}$ is the function that maps, for each time point t, the set of fires $detectedFires_i(t) = \{f \in FIRE : distance(i, f, t) \leq visualRadius_i(t)\}$ where $distance(i, f, t)$ is the distance between i and f at time t.

• $distMin_i : TIME \longrightarrow \mathbb{R}$ is the function that maps, for each time point t, the distance from agent i to fires in its perception radius $distMin_i(t) = \min\{distance(i, f, t), \forall f \in detectedFires_i(t)\}$.

• $\mathcal{N}_i : TIME \longrightarrow 2^{AGT}$ is the function that maps, for each time point t, the set of neighbors $\mathcal{N}_i(t) = \{j \in AGT : distance(i, j, t) \leq visualRadius_i(t)\}$.

• $fear_i : TIME \longrightarrow [0, 1]$ is the function that maps, for each time point t, the fear level of the agent i. 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 changes 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 formalized by three different successive functions :

1. $fearDecay_i(t)$: if the fear level at time $t-1$ (that is, $fear_i(t-1)$) is 0, the result of this function is 0, else the result is a value that is lower than $fear_i(t-1)$ because an emotion level decreases over time (see Section 2.2);

2. $fearEnv_i(t)$: if the value returned by $fearDecay_i(t)$ is 0 then a value (computed from a sigmoid function) is return, else the sum of $fearDecay_i(t)$ and just the variation of the fear between t and t' is added. This variation corresponds to the effect of the fires that agent i has detected around itself (if fires are detected) on iself (see Section 2.3);

[1]As it has been suggested by one of the anonymous referees, the concept of emotion contagion could be considered in terms of crowd dynamics following the Social Force Model of [14]. We will investigate this way in future works.

[2]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 [17, 23, 8, 27] for instance) and this view is called "cognitive theory of emotion".

[3]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.

3. $fear_i(t)$ is the final new value of fear intensity at time t. This function returns the value $fearEnv_i(t)$ plus the variation of the fear (that can be positive or negative) coming from the influence of the neighbors of i. If these neighbors have a fear level that is lower than the fear level of i, then the fear level of i will decrease, else it will increase (see Section 2.4).

2.2 Decay over Time

As highlights in the literature [23, Chap. 4], without any stimulus, agents' fear intensity will decrease over time. This decay is often described as faster for higher values and it slows down with the emotion intensity. At time t, the emotion intensity is the emotion intensity at time $t-1$ minus some part $emotionDecayCoeff \in [0, 1]$ of this previous value. The *decay coefficient emotionDecayCoeff* depends on some attributes of each agent like genre, age, sex, *etc.* [7]. 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):

$$fearDecay_i(t) \stackrel{def}{=} fear_i(t-1) * (1 - emotionDecayCoeff_i) \quad (1)$$

Note that if $fear_i(t-1) = 0$ then $fearDecay_i(t) = 0$.

This equation has the same form of "activation level decreasing" in the Anderson's theory of central cognition [1]. It could certainly be oversubtle but this form has the advantage to be computationally interesting.

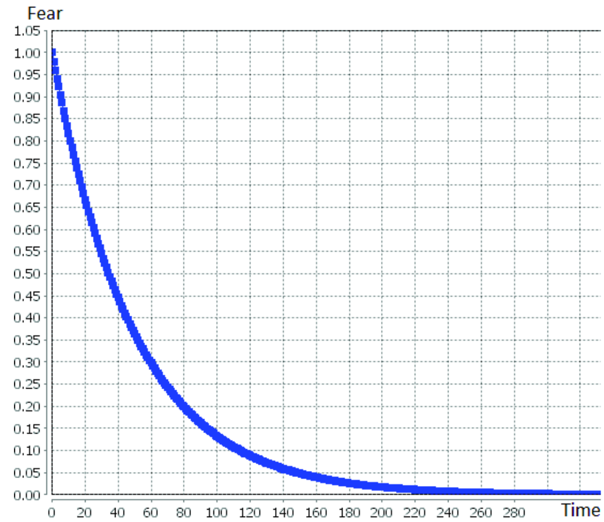

Figure 1: Emotion (*i.e.* fear) decay with $emotionDecayCoeff_i = 0.02$ and without any other stimulus. In this case, the $fear_i$ function is limited to $fearDecay_i(t)$, so its evolution is described by $fear_i(t) = fear_i(t-1) * (1 - emotionDecayCoeff_i)$.

2.3 Influence of the Environment

The environment contains dangers (fires for instance), warnings (alarm...) or other elements (smoke...) that may impact on emotions. In particular, dangers may increase the fear intensity. We consider that the number of hazards and the distance of the agent to them needs to be taken into account in the emotion computation.

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 (no longer).

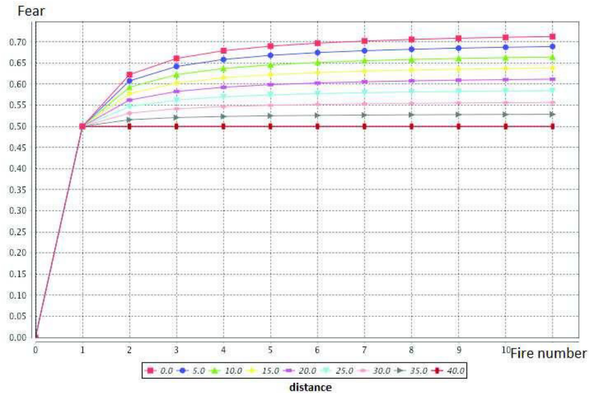

Figure 2: Fire number and distance impact on the emotion (with $visualRadius_i(t) = 40, fireInfluenceCoeff_i = 1$).

Emotion triggering.

When agent i does not feel fear at time t ($fear_i(t) = 0$) 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 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 $distMin_i(t)$ 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:

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

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

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

$fireInfluenceCoeff_i$ could depend on the knowledge about and the experience with fire of i [19]. Figure 2 illustrates the impact of the number of fires and of their distance on the initial fear level.

Note that (2) ensures that $fearEnv_i(t) \in [0, 1]$. We have chosen here a sigmoid function because this type of function illustrates perfectly the switch between a low level of the fear intensity[4] and the triggering of fear. We use here a particular steepness λ_i that must be easily changed, depending of the experimental situation.

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

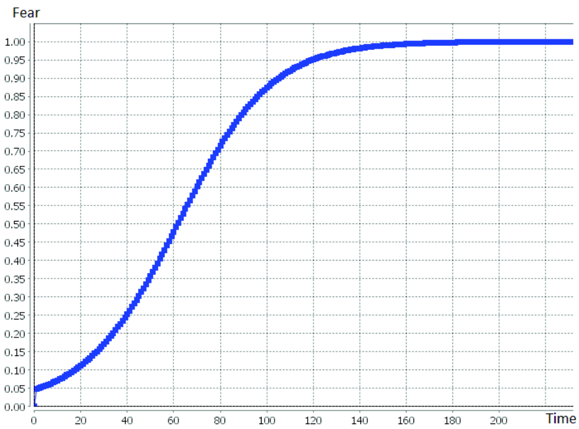

Figure 3: Influence of only the environment (fire) on emotion with: $fireInfluenceCoeff = 0.1$**,** $card(detectedFires_k(t)) = 2$**,** $distMin = 10$**,** $visualRadius = 40$**. The fear evolution is thus described by the equation:** $fear_i(t) = fear_i(t-1) + fear_i(t-1).\left(1 - fear_i(t-1)\right).\lambda'_i$**, with** $fear_i(t_0) = 0.05$**.**

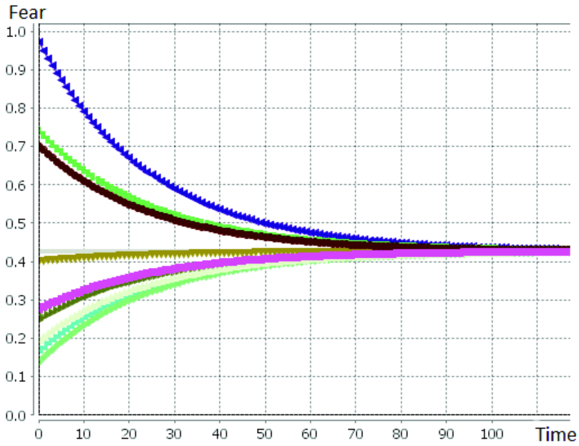

Figure 4: Fear level evolution of all the agents of a simulation under the only influence of the emotion contagion, with $agtInfluenceCoeff_i(j) = 0.02$ **(for every neighbor** j **of** i**),** $card(AGT) = 10$**. The inital fear value is chosen randomly in** $[0, 1]$**.**

Emotion update.

When $fearDecay_i(t) > 0$, fear has been triggered and we assume that the perception of fires must change this initial fear level. So, we use the derivative (4) of the previous sigmoid (see (2)) to update step by step the emotion level. Let be $\lambda'_i = \lambda_i\left(1 - \frac{distMin_i(t)}{visualRadius_i(t)}\right)$. So:

$$fearEnv_i(t) \stackrel{def}{=} fearDecay_i(t) + fearDecay_i(t).\left(1 - fearDecay_i(t)\right).\lambda'_i \quad (4)$$

$fearEnv_i(t)$ is here the i's level of fear at time t after both the possible decay of the previous emotion level and the influence of the environment on the emotion level after this decay.

The Figure 3 presents the evolution of the fear level under the single influence of the environment (fire).

2.4 Emotional Contagion

The two previous subsections focused on the individual part of the emotion. We consider here its social aspect: emotion are spread among neighbors. This has already been investigated in many works, such as [9, 3] 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 current emotional intensity and the emotional intensity at the previous step, multiplied by the influence coefficient $agtInfluenceCoeff_i(j)$ of j on i:

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

$agtInfluenceCoeff_i(j)$ 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 [13]. Some equations have been proposed in the social network analysis area (see [4, 16, 15, 11, 26] for instance) corresponding to the modelling of different situations.

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 is thus defined as follows:

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

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

Without the influence of the decay and of the environment, the emotion of group reaches average values as illustrated in Figure 4.

2.5 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 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. RESULTS AND ANALYSIS

In this section, we assess the various possible combinations of the three factors (decay, environment and neighbours) on the emotion dynamics. We first investigate the emotion dynamics only and then couple it with a second dynamics, the movement. (Note that $visualRadius_i(t) = visualRadius_i(t')$ for every $(t, t') \in TIME^2$; so, we denote it by $visualRadius_i$ in the following.)

3.1 Emotion Dynamics with Unmoving Agents

The following results are computed with, for every agent $i \in AGT$, the following values for simulation parameters: $card(AGT) = 20$ and $card(FIRE) = 10$, $emotionDecayCoeff_i = 0.02$, $fireInfluenceCoeff_i = 0.1$, $agtInfluenceCoeff_i(j) = 0.04$ for

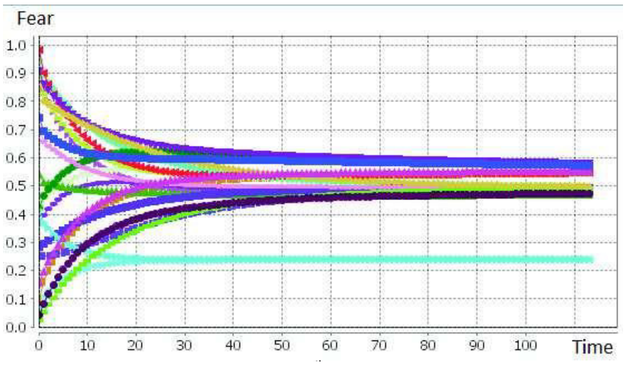

Figure 5: Emotion evolution of all the agents under the only effect of emotional contagion.

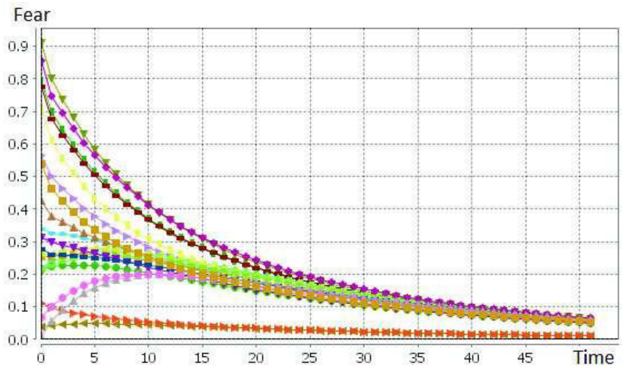

Figure 6: Emotion evolution of all agents under both the decay and the contagion effects.

every $j \in AGT$ and every time t, 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 cannot be able to diffuse their emotion to all the 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.

3.1.2 *Coupling 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 2 factors decay and contagion. The result is presented in Figure 6. With no influence of fire, $fear_i$ (for every i) converge (due to the emotional contagion) and tends towards 0 (due to the decay).

3.1.3 *Coupling 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 some agents j keep or tend towards $fear_j = 0$, because they cannot perceive any fire. The main observation is that $fear_i$ reaches a stable value for each agent i. This value depends on the number fire and distance to these fires. This shows that the

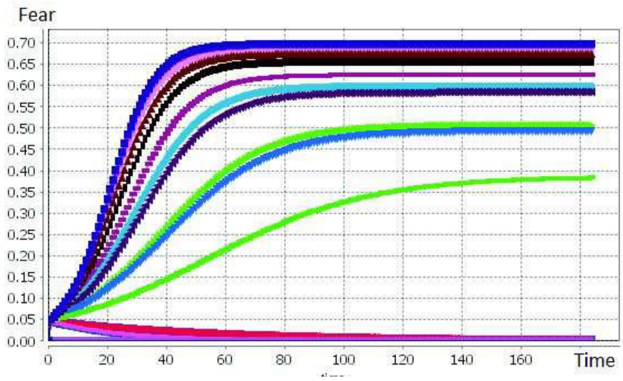

Figure 7: Emotion evolution of all the agents under both the decay and the environment effects.

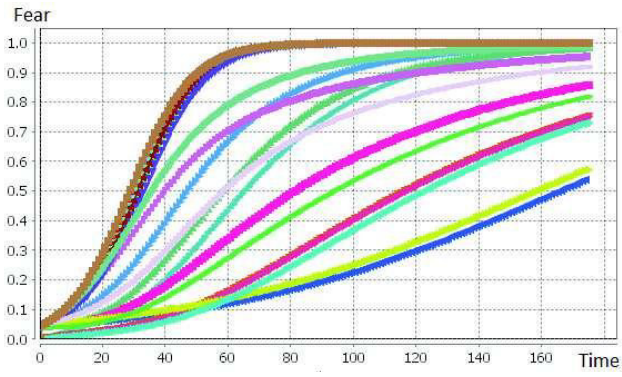

Figure 8: Emotion evolution of all agents under both the environment and the contagion effects.

simulation reaches an equilibrium between the 2 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 Contagion*

Again $fear_i(t_0) = 0$ for every $i \in AGT$. The result is plotted in Figure 8. Without emotion decay, the agents' $fear_i$ tend to reach to 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 j has its $fear_j$ staying at the value 0. Even agents that cannot perceive the danger starts to feel fear because of their neighbors.

3.1.5 *Coupling Decay, Environment and Contagion*

Finally we couple the three processes in a single model. Figure 9 displays the results. 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 it is also lower than 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

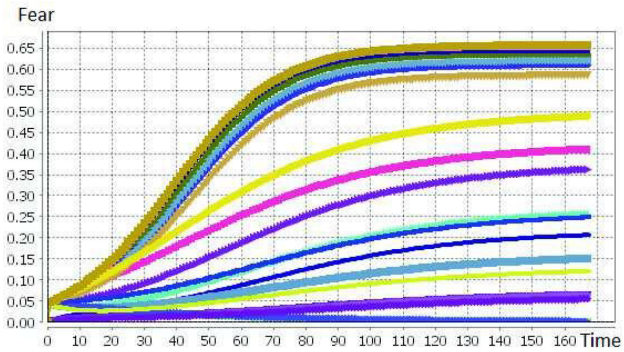

Figure 9: Emotion evolution of all the agents under the decay, the environment and the contagion effects.

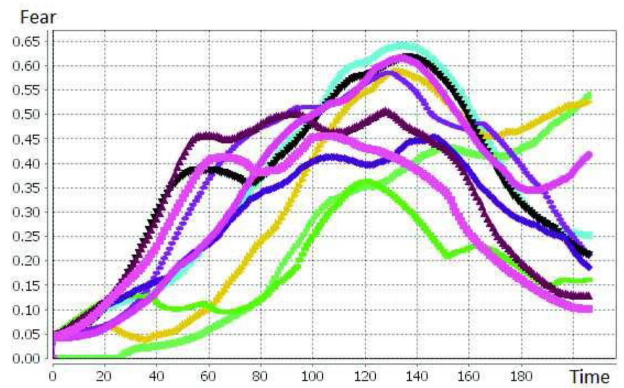

Figure 10: Impact of all the factors (decay, environment, contagion) on the emotion intensity in case of agent moving.

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. 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 with moving agents that each agent fear level converges toward the same value. Contrarily to Figure 5, we can observe here a convergence toward as the agents' moves remove the cluster effect that can occur when agents do not move.

4. EXPLORATION OF PARAMETER VALUES

In this section, we explore the model behavior with respect parameters variations. We only focus here on the three coefficients for a given agent i: $emotionDecayCoeff_i$, $fireInfluenceCoeff_i$ and $agtInfluenceCoeff_i$, that characterize each step of the $fear_i$ change from a time point to another. So, we will measure the maximum, minimum, average and standard deviation values of the agents' fear level at the end of the simulation. In addition we will compare results with and without agents moves.

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

$\{emotionDecayCoeff, fireInfluenceCoeff, agtInfluenceCoeff\}$

we run 10 replications and measure on each of them the maximum of the agent fear level, the minimum, average and standard deviation at the step number 100. When agents can move, they choose a random target, go to it and when reached they pick randomly a new one.

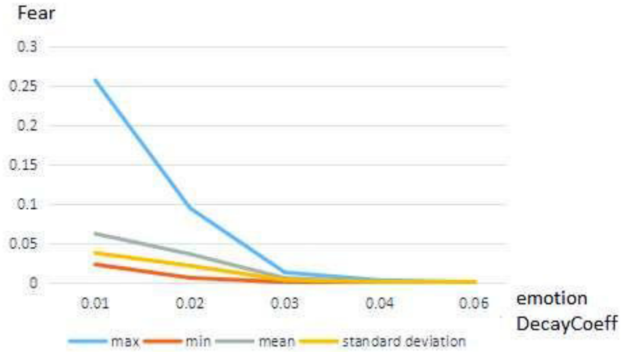

Figure 11: Impact of *emotionDecayCoeff* **on the fear level of moving agents in case of** *fireInfluenceCoeff* $= 0.05$ **and** *agtInfluenceCoeff* $= 0.01$**.**

4.1 Exploration in the Case of Moving Agents

4.1.1 Exploration of the Impact of the Decay Coefficient *emotionDecayCoeff*

Let $fireInfluenceCoeff = 0.05$, $agtInfluenceCoeff = 0.01$ (constant values) and *emotionDecayCoeff* takes its value among [0.01, 0.02, 0.03, 0.04, 0.06].[5] We measure the 4 indicators presented above and denoted them max, min, mean and standard deviation. We observe results on Figure 11. We can observe that when the *emotionDecayCoeff* value 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 shows the impact of a single parameter variation (*emotionDecayCoeff*) on the fear level. We launch now an exhaustive exploration of the model with:

- $emotionDecayCoeff \in [0.01, 0.02, 0.03, 0.04, 0.06]$
- $fireInfluenceCoeff \in [0.05, 0.1, 0.2, 0.3, 0.5]$
- $agtInfluenceCoeff \in [0.01, 0.06, 0.1, 0.2, 0.3]$

For each parameter set $\{emotionDecayCoeff, fireInfluenceCoeff, agtInfluenceCoeff\}$, we launched 10 replications and store the average value of each of the indicators. Complete results are summarized in Figure 12 and Figure 13. These plots display the scatter plots of all possible pairs of parameters and indicators. For example in Figure 12, the upper-right frame plots the max indicator with relation to the *fireInfluenceCoeff* parameter[6]. All the bullets correspond to the projection of tuples

[5] In the following, when a coefficient has the same value for every agent we omit its index. For instance, $fireInfluenceCoeff = 0.05$ is the same as $fireInfluenceCoeff_i = 0.05$ for every $i \in AGT$.

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

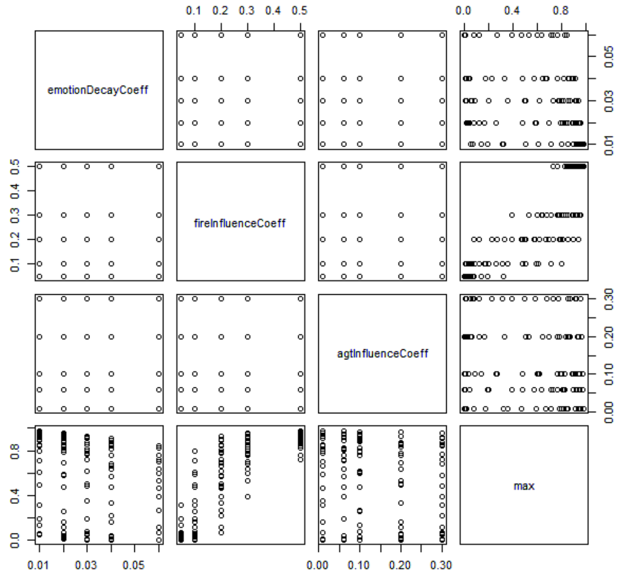

Figure 12: Max indicator depending on *emotionDecayCoeff***,** *fireInfluenceCoeff* **and** *agtInfluenceCoeff* **values.**

⟨*emotionDecayCoeff*, *fireInfluenceCoeff*, *agtInfluenceCoeff*, max⟩ in a 2 dimensions plan.

We can thus observe that *fireInfluenceCoeff* has a huge influence on the max indicator: when *fireInfluenceCoeff* is high (0.5) the maximum fear levels are also very high (between 0.7 and 1). An this result is independent of the other parameter values. When *fireInfluenceCoeff* is low (0.01 and 0.02) the maximum is lower and close to 0.

We can also observe that *agtInfluenceCoeff* 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 13, we can also notice that *fireInfluenceCoeff* has a smaller influence on the min indicator. But the *emotionDecayCoeff* has a higher one. In particular, when *emotionDecayCoeff* increases the min indicator takes lower values.

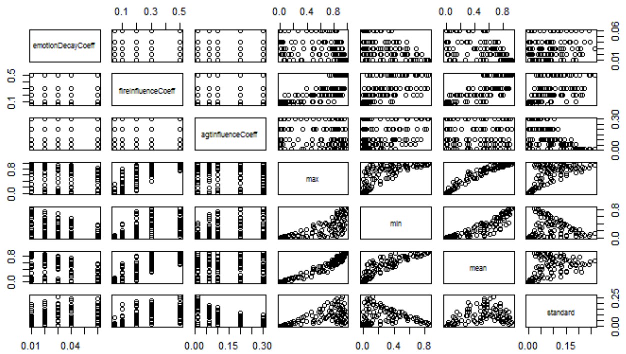

Figure 13: Max, min, mean and standard deviation values depending on *emotionDecayCoeff***,** *fireInfluenceCoeff* **and** *agtInfluenceCoeff* **values.**

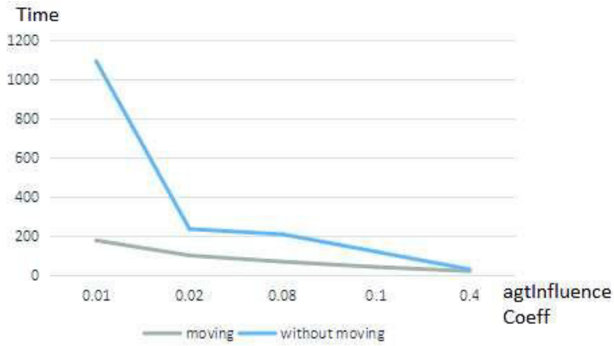

Figure 14: Relationship between *agtInfluenceCoeff* **and time in the case where all the agents reach to the equivalent emotion.**

Finally we can observe that, even if the *agtInfluenceCoeff* 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 can now move. For the sake of space limitation we can provide here the results, but it appears that they are quite similar to the results without moving. This is due to the high number of agents and the chosen visual radius (*visualRadius* = 40).

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 the *agtInfluenceCoeff* 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. Results are displayed in Figure 14.

We can observe that the number of steps to reach the equilibrium is higher for unmoving agent than for moving agents: moving agents tend to meet more other agents and this mix fasten the emotion convergence. This mix has a huge impact when *agtInfluenceCoeff* is low, but decrease when the parameter value increases.

5. CONCLUSION AND FUTURE WORKS

In this article we propose a model of fear level dynamics. Our aim here was to give an intuitive formalization of the computation process. These equations have been implemented in GAMA platform. We made many test cases to find the equivalent value of three coefficients influencing the emotion intensity. We present results about the impact of decay, environment, and agents neighbors (*i.e.* emotional contagion) on emotion intensity. Results are extracted from GAMA simulation execution. We have 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 particular 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.

In the future, our aim is to add this emotional framework to our simulation of evacuation process. Emotions will be used at several steps: physical properties of agents, decision-making process, and social process (group constitution).

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