Simulating Crowd Evacuation: From Comfort to Panic Situations

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ABSTRACT

Crowd simulation has its greatest utility in the study of safety measures for crowded events. However, total evacuation time, which is the most important feature in crowd evacuation, can vary depending on the population, the environment, the adopted strategies to decide routes, but also because people can be panicked or not. This paper presents a model to parametrize crowd simulation allowing to increase or decrease the agents stress. We use BioCrowds model and proposed an extension to consider new parameters to deal with crowd relaxing and compression, as comfort and stress. These two new parameters impact the will to go to the goal and the individual panic in trying to save itself. Indeed, our model could be integrated in other crowd simulators. This work discusses some obtained results and also presents a case study regarding a real scenario. We simulate the Hillsborough Disaster happened in 1989 in order to discuss the reliability of our method. Results indicate that our method can simulate in a coherent way the densities observed in the real life event.

CCS CONCEPTS

• **Computing methodologies → Agent / discrete models**; **Interactive simulation**; **Motion processing**; **Collision detection**;

KEYWORDS

Crowd simulation, Collision Avoidance, Crowd panic

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1 INTRODUCTION

The capacity of predicting pedestrian flow and crowd behavior is of great utility in areas such as security and safety. Crowd simulation is also useful in other applications like simulating groups of people for games and movies, recreating historical scenarios [8] and in managing groups in high density situations.

For many years one of the biggest challenge in crowd simulation was to propose free-of-collision simulation methods while presenting realistic behaviors. BioCrowds was the pioneer [3] to propose a mathematical free-of-collision model to simulate crowds while allowing the emergence of behaviors as lane formation and others. Recently, other free-of-collision approaches have been proposed, as the case of the Implicit Crowds model [14]. This model uses an energy-based model that take into account the expected future state of agents as well as their current state to reach an integration scheme for simulations. Another crowd simulator free-of-collisions proposed in literature is the well used Optimal Reciprocal Collision Avoidance (ORCA), proposed by Van Den Berg et al. [22]. They proposed a velocity-based model for n-body collision avoidance.

In this paper we will present a re-parametrization of BioCrowds [3], a collision free model based on space subdivision, that imitates leaf venation patterns. Our new model aims to introduce the concepts of stress and comfort into the agents, increasing or decreasing their sensation of panic. This work was motivated by the fact that researchers, trying to study panic in emergency situations, often have difficulty studying how people react in real-life situations [16]. In addition, ethical issues involved in studying panic behavior can also arise. To deal with these difficulties, researchers have been working with computer simulations [18]. Some evacuation simulations can be a "normal life" situation, i.e. when there is no panic and people are only moving in the same direction, sharing the same goal. Therefore, the simulation model should also include the possibility of creating panic events and imitate the people behaviors in hazardous situations.

In the basic BioCrowds, agents compete for markers positioned on the floor, and their direction vector is defined by both the markers available to them and their goals. So, one can say that agents are "panicked" but in fact they are not pushing others and trying to survive as in a panic situation, which is a common feature of crowd simulators, as described in [1]. In this work, we intend to deal with this situation by reparameterizing a crowd simulator including the possibility of vary the panic level of agents. We use two parameters: comfort and stress. Our hypotheses is that the two parameters impact the spatial behavior of agents. The comfort in our model impacts how people are distributed in the space, so agents have a tendency to be located around/close their goal but are not limited to moving simply towards it, imitating the desire to seek comfortable place. The other parameter used in our modeling is the stress, which is related with the possibility an agent has to push others, i.e. without respecting the neighbors personal space and trying to reach the goal with "urgency". In fact, a stressed agent will be able to steal markers from others, pushing others to reach the goal. Using the extended model, we simulated a case scenario inspired on the Hillsborough Disaster. In 1989, April 15th, a football match between Liverpool and Nottingham Forest was set to be played in

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the Hillsborough Stadium in Sheffield. In attempt to let all Liverpool supporters in before the match started, the police opened a gate to an already over-crowded area, which lead to a crushing accident. In this event 96 people died and 766 were injured. In addition to this analysis this paper also shows other obtained results as discussed in Section 4.

This paper is structured as follows. Related works and their importance to this model are discussed in Section 2. The method we propose is presented and described in Section 3. Simulation results are shown and evaluated in Section 4, while conclusions and possible directions this work may take in the future are addressed in Section 5.

2 RELATED WORK

Throughout decades of research in crowd simulation, many methods were created and used. Many of these models are either Physics based animations or based on agents. Although the existence of a large number of techniques in literature for control and parametrizations of crowds [2, 4, 11, 19, 21, 23], most of them are focused on a specific situation to be simulated, where agents are endowed with skills to perceive the world, seek goals, avoid collisions and other related behaviors.

One of the most known Physically based method is the social force proposed by Helbing and Molnar [12]. This method takes into account the hypothesis that agents influence each other through a social force. Consequently, agents maintain their desired personal space apart from others. In addition, they can be also attracted to others, creating groups in specific situations, like families and groups of friends. Another Physics-based model is proposed by Hughes [13], were crowds are treated as continuum flow of pedestrians.

The model we used in this paper is based on the approach proposed by de Lima Bicho et al. [3]. BioCrowds is an infinitesimal agents model based on a space colonization algorithm, where auxins are distributed on the leafs to guide the venation growing Runions et al. [20]. In BioCrowds, auxins are mapped to markers, distributed on the floor, that represent resources that agents should have to move. Indeed, agents compete for markers while also trying to reach their individual goals. Using this method, many of the phenomena seen in real crowds behavior occur, such as lane formation, smooth trajectories and speed reduction in crowded spaces.

Since one of our focus in this work is to use our model to simulate the accident occurred in Hillsborough, the more information we have about it the better we can recreate the disaster. Having that in mind, the work by Nicholson and Roebuck [17], focused on analyzing the Health and Safety Executive investigation of this specific incident, provides important information for the simulation. Approximations on the density of the crowd, characterization of the state of the barriers inside the pens, before and after the crushing, and the description of the events that occurred are examples of important characterization of the real life event. This data provides a solid base to compare to our model.

Many of the works related with crowd dynamics address the movement of crowds in a panic or urgent state. Helbing et al. [9] analyze many of the behaviors and tendencies of groups of people in those situations. He introduced the concept of creation of arcs of people in bottlenecks and concluded that when individuals try to have a really high speed in crowded situations, they end up making the average speed of the crowd go down. Lee and Hughes [15] also worked in this area and analyzed the causes of various crowd accidents and provided a mathematical model for this kind of events. In this paper, they conclude that the density of the crowd is directly related to the likelihood of an accident but the occurrence of it depends on crowd composition or random events. They also simulated the Hillsborough disaster with the model of the continuum flow of pedestrians [13] and reached density results similar to the ones from the real event.

3 OUR MODEL

This section describes our model to provide agents endowed with stress and comfort attributes, in order to allow the simulation of high compression of individuals. Firstly, in Section 3.1 we briefly describe BioCrowds.

3.1 BioCrowds Model

BioCrowds method proposes the use of space discretization, populating the environment with uniformly distributed markers. Agents in the environment compete for these markers, based on proximity criteria, and use them to determine their movement vectors. Indeed, each agent i accesses the markers inside its personal space R_i to search for markers that are closest to i than any other agent j. So, a marker is only available to the closest agent.

For a given agent i, with a set of N available markers $S = \{a_1, a_2, \cdots, a_N\}$, we calculate it's movement vector $\vec{m}$ using Equation 1:

$$\vec{m} = \sum_{k=1}^{N} w_k(\vec{a}_k - \vec{x}), \tag{1}$$

where $\vec{a}_k$ is the marker's position and $\vec{x}$ is the agent's position. w_k is that marker's weight, calculated in Equation 2:

$$w_k = \frac{f(\vec{g} - \vec{x}, \vec{a}_k - \vec{x})}{\sum_{l=1}^{N} f(\vec{g} - \vec{x}, \vec{a}_l - \vec{x})}, \tag{2}$$

where $\vec{g}$ is the position of agent i goal.

To determine function f, let us first assume that all markers $\vec{a}_k$ affecting agent i are at the same distance $\vec{a}_k - \vec{x}$ from this agent. Such function should prioritize markers that lead the agent directly to its goal, i.e., it should (i) reach its maximum when the (nondirected) angle θ between $\vec{g} - \vec{x}$ and $\vec{a}_k - \vec{x}$ is equal to 0°; (ii) reach its minimum when $\theta = 180°$; and (iii) decrease monotonically as θ increases from 0 to 180°. Also, if the distances $\vec{a}_k - \vec{x}$ differ, the markers further from the agent should have relatively smaller weights, to prevent them from dominating the computation of the tentative motion vector $\vec{m}$. A possible choice for f that satisfies these assumptions is defined in Equation 3:

$$f(x, y) = \frac{1 + cos\theta}{1 + ||y||}, \tag{3}$$

where θ is the angle between x and y. Please refer to BioCrowds original paper [3] for further details about the method.

The weights will cause the agent to move towards it's goal as long as there are markers available along the way. An agent's movement will be blocked by the absence of markers.

3.2 BioCrowds Extension

The original BioCrowds does not allow the agents motion when there are no attainable markers on the ground. Because this characteristic of BioCrowds (agents move only when there are available markers), the method achieves the collision avoidance, but as an effect there is a maximum density (people per sqm) that BioCrowds permits as a function of available markers in the space, and agents do not push to open free space to move. Again, this is a common characteristic in many crowd simulators [5] [7] [9]. Firstly, as seen before, BioCrowds is a goal based approach. It means that agents have goals and try to achieve them. BioCrowds model achieves emergent behaviors, e.g. lanes formation, so people respect the others personal space in the sense that there is a maximum density achieved in the method.

In this work we use two agent factors (comfort and stress) to improve the realism of agents behaviors in evacuation scenarios. These factors are used to model agent behaviour according to the context of the evacuation. Next sections describe our model to simulate normal life and panic situations in BioCrowds.

3.2.1 Normal Life Evacuations. Helbing et al. [10] present some main characteristics of people in normal life evacuations: *i)* In general, pedestrians take into account detours as well as the comfort of walking, thereby minimizing the effort to reach their destination; *ii)* Pedestrians prefer to walk with an individual desired speed, which corresponds to the most comfortable walking speed as long as it is not necessary to go faster in order to reach the destination in time; *iii)* Pedestrians keep a certain distance to other pedestrians and borders. We propose the term comfort (c) as a function of available area for each agent. According to Helbing et al. [10] this area is smaller the more a pedestrian is in a hurry, and it also decreases with growing pedestrian density. In the case of this work, we adapted the sense of personal area to the number of markers a each agent has (as discussed in previous section).

So, c is defined as a function of the number of available markers of agent (the set S_i) a certain agent i has. If the number of markers N_i decreases, then c_i decreases too. So, the agent will gradually shift its focus from its designated goal to looking for a more comfortable space i.e. with more available markers. Actually, we normalize S_i dividing by the maximum number of markers (empirically defined as 80, once it is impacted by the world configurations). With this definition, we maintain a comfort factor range in the interval $[0; 1]$ for agent i, according to $c_i = \frac{N_i}{M}$, where N_i is the number of markers for agent i and M is the maximum number of markers for all agents, considered fixed the size of their personal region R.

Original BioCrowds computes the weight of each marker, as defined in Equation 2, by comparing the angle difference between the direction defined from the agent towards its goals and all available markers.

Figure 1a shows an environment (100 sqm) where 100 agents have the same goal (indicated as a black rectangle in the image). The arrows indicate the places from where the agents arrive, the figure shows the final situation of the simulation. The maximum observed density in the simulation utilizing original BioCrowds is 7.75 people/sqm. In this work, we propose a new way to compute the markers weights in order to endow agents with the previously described behavior, i.e to look for more comfortable space. The new weight affected by comfort (w'_k) for agent i is defined by Equation 4:

$$w'_{k,i} = \delta_i . w_{k,i} + (1 - \delta_i), \tag{4}$$

where $w_{k,i}$ is the original weight calculated by BioCrowds in Equation 2 and δ_i is the comfort bias for agent i defined by Equation 5:

$$\delta_i = \sin(c_i . \frac{\pi}{2}). \tag{5}$$

Related to Equation 4, agents behave according to original BioCrowds when $\delta_i = 1$, i.e. markers weights vary according to the goal direction. However, when the number of markers decreases, the bias decreases as well, resulting in their weights being more similar, causing the agent to go towards the available markers, even if those do not lead to the goal. Figure 1b shows the same scenario simulated in Figure 1a. It is easy to see how the densities are lower. Important to highlight that in this simulation we do not have group behaviors, that could be a reason why agents are homogeneously distributed in the space. If we simulate groups, maybe people could be closer to the members of their groups. The situation illustrated in the figure imitates a situation where people should evacuate from the same place, share the same goal, but they are not friends with others.

3.2.2 Panic Situations. In order to simulate the panic situation, we propose a stress level (μ) for the agents. The goal is to include some extreme behaviors that will arise from stressed agents, such as pushing and disrespect to others spaces. Crowd density will increase as a consequence of a decreasing respect for others' personal space. If $\mu_i = 0$, the agent is calm and will walk without pushing others pedestrians. Otherwise, agent's ability to take markers from other agents, when competing for free space, is increased. We introduced a stress factor which can change as a function of two situations: *i)* lack of movement and *ii)* amount of agents inside the intimate distance, as defined by Hall [6]. That is accomplished by the following Equations. Equation 6 states for the stress factor related to the number of agents inside the intimate distance [6] (45 cm) as a function of time:

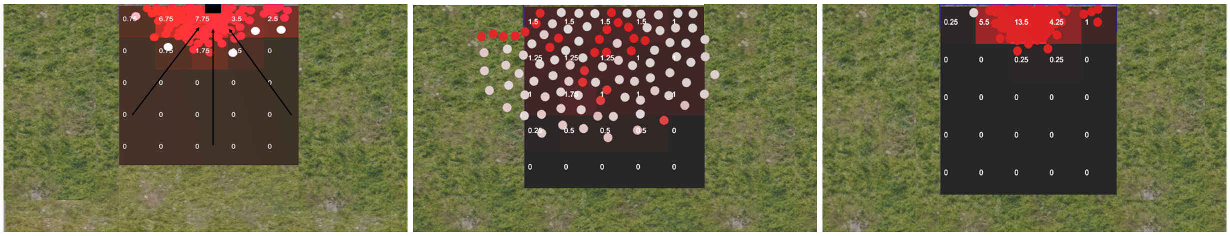
$$\vartheta^i_f = \beta . n^i_f + \frac{\beta}{k_1} . t_\vartheta, \tag{6}$$

where ϑ^i_f states for the stress factor related to the density for agent i at frame f, β and k_1 are constants and regulates the obtained values (we used $\beta = 0.02$ and $k_1 = 10$). n^i_f is the number of agents in intimate distance of agent i and t_ϑ is the counter of time that determines how much time (in frames) that $n^i_f > 0$.

Equation 7 describes the stress caused by the lack of movement, i.e. we assume the hypothesis that agents are more stressed when there are no motion allowed.

$$\gamma^i_f = \rho . (1 - mov^i_f) + \frac{\rho}{k_1} . t_\gamma, \tag{7}$$

where γ^i_f states for the stress factor related to the lack of motion for agent i at frame f, ρ is a constant and regulates the obtained range of values (we used $\rho = 0.4$). mov^i_f is a value in the interval $[0; 1]$



(a) Original BioCrowds (b) With Confort Factor (c) With Panic Factor

Figure 1: Scenarios containing 100 agents simulated using BioCrowds: (a) shows Original simulation without added parameters, in (b) the simulation uses the comfort factor and in (c) it uses the stress factor

and states for a normalization value using the maximum speed. t_γ is the counter of time that determines how much time (in frames) that $mov_f^i < k_2$, where k_2 is a threshold defined as 0.2. Finally the stress factor of agent i at frame f is given by $\alpha_f^i = \vartheta_f^i + \gamma_f^i$. The stress factor works as an incremental value in the stress attribute of each individual at each frame, as described in Equation 8:

$$\mu_f^i = \mu_{f-1}^i + (\alpha_f^i - \alpha_{f-1}^i)(1 - \mu_{f-1}). \tag{8}$$

Stress was modeled to affect the agent's competition for markers. Our goal is to define behaviors such that when an agent's stress is increased, it has a higher chance of acquiring a marker in it's desired path than a calm agent. The idea is to change the competition for space between agents, giving more priority for agents who are more stressed. In standard BioCrowds, such comparison aims to allow the marker to be taken by the closer agent, as described in $C(a_k) = ||d_{k1}|| < ||d_{k2}||$, where d_{kn} is the distance vector between agent n and marker k, defined as $d_{kn} = a_k - x_n$, where a_k is the marker's position and x_n is the agent position, where agent 1 is the the current owner of marker k. In the new model, a weight has been added to the previous comparison $C(a_k) = h_{k1}||d_{k1}| < h_{k1}||d_{k2}||$, where h_{kn} is defined in Equation 9 and aims to propose a weight where agents with high stress have a higher chance to capture markers currently positioned in the agent's desired path. Thus, h should be minimized if the marker's position coincides with the agent's goal vector while the agent's stress is maximum.

Thus, equation 9 was defined to follow the specified properties:

$$h_{kn} = s\omega(g_n - x_n, d_{kn}) + (1 - s), \tag{9}$$

where:

$$s = \sin(\mu_f^i \frac{\pi}{2}), \tag{10}$$

$$\omega(x, y) = \frac{3 - cos\theta}{2}, \tag{11}$$

where θ is the angle between x and y .

The ω function calculates the new weight according to the angle difference between the relative distance vector between the agent and the auxin (d_{kn}) and the agent's goal vector ($g_n - x_n$, where g_n is the goal position and x_n the agent's position), and the s parameter modulates ω's effect according to the agent's stress. s has a similar function to the δ parameter in comfort weight Equation 5, but using stress as a parameter instead of comfort: when μ is 0, s is zero causing the weight h to equal 1, with this the agent's distance comparison parameter will be the same as regular BioCrowds. When the stress is maximum, $s = 1$ and $h = \omega$, causing the new weight to fully affect the comparison. When the angle difference is 0 degrees, ω is minimum, returning 1. When the difference is 180 degrees, ω is maximum at value 2. When the weight is affecting the comparison, since the agent with the lowest distance factor takes the auxin, stressed agents will more easily take markers located in the direction they want to move towards than those in other directions. In a crowd of stressed agents, this translates to agents "stealing" markers from other agents in front of them, increasing the crowd density.

Figure 1c shows the same scenario simulated in Figure 1a. It is easy to see how the densities are much greater (maximum 13.5 people/sqm). The situation illustrated in the figure imitates a situation where people should evacuate from the same place, share the same goal and are very stressed. As discussed later we set the maximum stress as 1, so this is the final frame when the situation is stable, i.e. agents can not take markers from each other, because they are all very stressed, so there is not priority in the comparisons. If we do not set a maximum value for stress attribute, the agents could be more compacted. Next section presents some obtained results with our model.

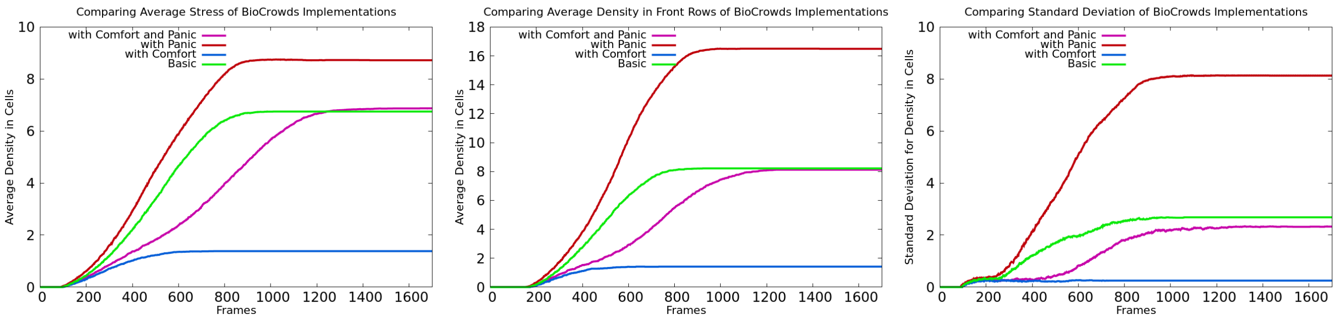
4 EXPERIMENTAL RESULTS

This section presents results obtained with our method. We firstly compare the four configurations: *i)* BioCrowds, *ii)* BioCrowds with Comfort, *iii)* BioCrowds with stress and *iiii)* BioCrowds with stress and Comfort. Later we discuss the real case scenario where we simulate a situation inspired on Hilsbourough.

4.1 Comparing BioCrowds implementations

To analyze the impact of our methodology to simulate Comfort and Panic in Biocrowds model, we subdivided the space into a 25 cells (5x5 meters) distribution in the area where agents should pass to reach the goal. We then compared the average density (in all cells and also in the more critical ones - front rows - close to the door) and the standard deviation of obtained density. We simulated with 100, 300 and 900 agents the 4 versions of BioCrowds reparameterization and next we present a discussion about results obtained with 900 agents simulation. The remaining populations present the same characteristics so we detail only the most critical scenario.

In Figure 2a we present the average density in all cells. The panic simulation, due to the effects of stress, presents high levels of density in the front rows and this leads to the higher average. In contrast, the comfort affects the agents in a way that they tend to



(a) Average density in area. **(b) Average Density in two front rows.** **(c) Standard Deviation.**

Figure 2: Analysis of the average densities in the area, its two front rows, and the standard deviation in the density metric.

avoid high density situations. It is interesting to notice that original BioCrowds (Basic in the figure) and implementations including Panic and Comfort ends in a very similar way, however, in the second scenario it is easy to remark that density grows up slower when compared to original BioCrowds. It illustrates our proposed dynamic to having the panic as an increasing factor, as discussed in last section. Similar behavior can be seen in Figure 2b where the density is compared only in the two front rows of cells, the ones with the biggest concentration of agents in the final state of the simulation.

In Figure 2c we compare the standard deviation of the density in all cells. A small deviation means that the agents are evenly distributed between the cells. A larger deviation indicates that the density of some cells (probably the ones of the front rows) are large in the same time as other ones are basically empty (the ones in the back rows). As can be seen in this graphic, the higher standard deviation (8.13) happens quickly as an effect of stress, once there is a large accumulation in the front rows and the lack of agents in the back rows causing the deviation to be large in this simulation. On the other hand, when only comfort is activated, agents spread as much as possible in the space and standard deviation is very low (0.25). The behavior seen in discussed graphics can be qualitatively accessed in Figures 3a, 3b, 3c for crowds with 100, 300 and 900 agents. Simulations where agents are stressed (bottom-left in the figures) show a large concentration of agents in the front and display extremely high densities (3.25 p/sqm with 100 agents, 18.5 p/sqm with 300 and 20.5 p/sqm with 900).

When only comfort (top-right in the figures) is used, the agents try to avoid concentrations and the crowd becomes very dispersed. This leads to the low observed densities (1.75 p/sqm with 100, 300 and 900 agents). When both comfort and stress act in the crowd, it is possible to see a similar behavior to the basic BioCrowds. However, in more lower densities, as in Figure 3a, it is possible to observe the arc formation, very well emerged, as a function of two new parameters in BioCrowds and higher densities if compared to original BioCrowds.

Comparing the comfort in different rows (regions in the environment as shown in Figure XX) for both the comfort and the comfort with stress simulations, it is noticed that, in general, the average comfort value remains high in the comfort simulation, and very low in the comfort and stress simulation. It happens except in the row further from the objective which average comfort value is similar in both simulations. The acting of stress leads to decrease in comfort in the rows that are more densely occupied and closer to the goal.

4.2 Simulation of Hillsbourough

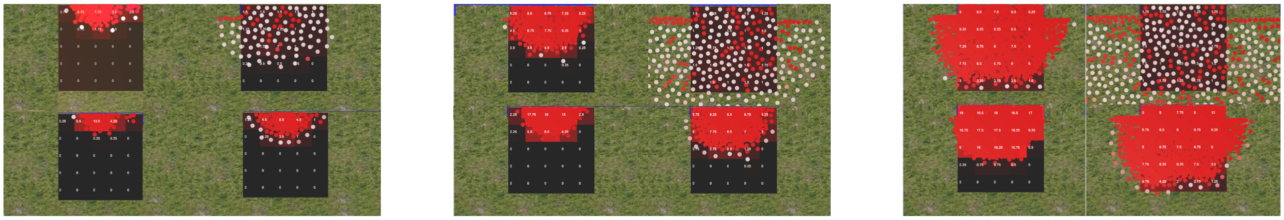
To simulate Hillsbourough, a scenario was modeled according to the specifications found in Nicholson and Roebuck [17], specifically Pen 3, where the estimations for number of individuals and crowd densities were completely assessed. The goal of our simulations is to populate the pen with the estimated number of individuals (1500), in the literature, and verify if the row densities match those that were estimated. The densities of the rows 4 and 3 are the most important, since it is the place where the people died by high densities in 1989.

We run simulations of Pen 3, having 1500 agents, both with and without the comfort and stress parameters included. Table 1 presents results of simulation using BioCrowds with comfort and stress (column 3) and the original BioCrowds (column 4). As it can be seen, the simulation with BioCrowds with comfort and stress present a good compromise when compared with real life data, except in the row 1. Therefore, this region (row 1) represents the farthest region from where people were crushed. So, agents were still far from their goal, not so concentrated in one place and they have more free space and less density of people, so their stress were lower. That is why the agents could be more dispersed. Comparing the two implementations of BioCrowds, we can observe that when in a panic situation, extended BioCrowds simulate in a more realistic way a real life event than original BioCrowds.

5 FINAL CONSIDERATIONS

In this paper we propose an alternate version of the BioCrowds model. This version implements the concepts of comfort and stress in crowds, resulting in the possibility to simulate calm and panic people.

The BioCrowds model, as a collision free model, display many realistic agent behaviors, but it has a local density ceiling, i.e. the agents "respect" each others personal space and do not get close enough to achieve high densities. This make it impossible to simulate panic situations. To solve this problem we introduce the concept of stress that allows agents to push others in the path to his goal



(a) Simulating 100 agents. **(b) Simulating 300 agents.** **(c) Simulating 900 agents.**

Figure 3: Simulations for different quantities of agents. On the top-left there is the result of original BioCrowds when all agents are trying to reach the door (center of the red arc); on the top-right, we show the same simulation with activated comfort behaviour; on the bottom-left we show very stressed agents, and finally on the bottom-right we present the result of activated stress and comfort behaviors.

Table 1: Information about density (people/sqm) in the 4 rows at Pen 3 in Hillsbourough. In column 2 we can see the data estimated in literature about the real event, in column 3 we see the data obtained with BioCrowds including comfort and stress, while in Column 4 we see the results of Original BioCrowds execution.

Rows	Estimated in real life	BioCrowds with Comfort and Stress	BioCrowds
1	7.5	1.89796084	2.18367544
2	7.6	8.857146	4.4897972
3	8.1	9.6938798	7.6734714
4	**10**	**10.0204108**	**9**

when in panic. Other concept we introduced into the model is comfort. This is, the tendency of agents to avoid getting too close to others in normal life situations. This disperse the crowd and produces an homogeneous distribution of agents.We show comparisons of BioCrowds with and without one or both of these concepts. We also simulated the Hillsborough disaster and obtained comparisons between our obtained densities and the ones of the real event. The results show that the extended BioCrowds, including panic and comfort is more adequate to simulate this real life event.

As future works in this area, we would like to adapt this model to simulate crushing and trampling of crowds. Crushing happens when a static crowd becomes so dense that the pressure in people thorax unable them to breath. This is what happened in the Hillsborough accident. Trampling happens in dynamic crowds, when someone in a moving crowd falls and others, unaware of the fallen person, step over. We believe this can be achieved with few changes in our panic model.

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