Modeling Individual Behaviors in Crowd Simulation

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Abstract

This paper presents a model for studying the impact of individual agents characteristics in emergent groups, on the evacuation efficiency as a result of local interactions. We used the physically based model of crowd simulation proposed by Helbing (6) and generalized it in order to deal with different individualities for agent and group behaviors. In addition, we present a framework to visualize the virtual agents and discuss obtained results. A variety of simulations with different parameter sets shows significant impact on the evacuation scenario.

1. Introduction

The aggregated motion is both *beautiful* and *complex* to contemplate. *Beautiful* due to the synchronization, homogeneity and unity described in this type of motion, and *complex* because there are many parameters to be handled in order to provide those characteristics.

History reveals a great amount of interest in understanding and controlling the motion and behavior of crowds of people. Psychologists and sociologists have studied the behavior of groups of people during several years. They have been mainly interested in the effects occurring when people with the same goal become one entity, named crowd or mass. In this case, persons can lose their individualities and adopt the behavior of the crowd entity, behaving in a different way when they are alone (2).

The mass behavior and motion of people have also been studied and modeled in computers for different purposes. An application aims to simulate the ***motion of crowds*** providing the evacuation of people in complex environments, for example, in a football stadium or in buildings.

The goal of this paper is to present a model for studying the impact of the agents´ individual characteristics in emergent groups obtained on the evacuation efficiency and its dependence on local interactions. The starting point for the following discussion is the physically based model of crowd simulation proposed by Helbing (6), which is generalized in order to deal with different individuals and group behaviors.

To this end, this paper is organized as follows: in Section 2 some related works are presented, in Section 3 we briefly describe the work developed by Helbing. Section 4 is dedicated to a generalization of the model. Section 5 presents obtained results, while Section 6 shows the system architecture and discusses the 3D visualization. In Section 7, conclusions and future works are addressed.

2. Related Work

Some authors have discussed how to simulate virtual crowds. Reynolds (10) described a distributed behavior model for simulating *flocks of birds* formed by actors endowed with perception skills. In fact, the birds (or 'boids') maintain proper position and orientation within the flock by balancing their desire to avoid collisions with neighbors, to match the velocity of neighbors and to move towards the center of the flock. Reynolds's work shows realistic animation of groups by applying simple local rules within the flock structure.

Le Goff (7) described an approach to create a behavioral model of groups formed by heterogeneous entities. His concept of groups is related to an association of individual behaviors and the management of internal resources as well as a decisional process inherent in the group entity.

Tu and Terzopoulos (11) have worked on *behavioral animation* for creating artificial life, where virtual agents are endowed with synthetic vision and perception of the environment. The repertory of fishes' behaviors relies on their perception of the dynamic environment, and the fishes' reactions are not entirely predictable because they are not scripted.

Bouvier et. al (3) used particle systems adapted for studying crowd movements where human beings are modeled as an interactive set of particles. The motion of people is based on Newtonian forces as well as on human goals and decisions. They introduced the concept of "decision charges" and "decision fields" modeled by using notions of the so called decision charges of a person, interacting with a surrounding decision field in the same way an electric charge is influenced by an electric field.

Brogan and Hodgins (4), (5) have used dynamics for modeling the motion of groups with significant physics. They reproduced movements of legged robots, bicycle

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riders and point-mass systems based on dynamics, considering an algorithm to avoid collisions, which determines the desired position for each individual, given the locations and velocities of the visible creatures and obstacles. Indeed, a perception model to determine creatures and obstacles visible to each individual in the group precedes the displacement algorithm.

Musse and Thalmann presented a hierarchical model to describe crowds with different levels of control: from guided to autonomous ones (8). The behavior of crowds is based on rules dealing with the information contained in the groups of individuals.

More recently, *Ulicny* (12) proposed a model for crowd simulation based on combination of rules and a Finite State Machine for controlling agents' behaviors in a multi layer approach. At higher levels, the rules select complex behaviors based on agents and environment states. At lower levels, complex behaviors are implemented by Hierarchical Finite State Machines. Each behavior is controlled by one Finite State Machine.

In this paper, the groups' behavior is attained as an emergent function of local interactions between individuals. We generalized the Helbing model in order to include different individualities in the particle systems as well as group behaviors.

3. The Helbing Model

Helbing (6) proposed a model based on physics and socio-psychological forces in order to describe the human crowd behavior in panic situations. It uses a particle system where each particle i of mass m_i has got a predefined speed v_i^o**,** i.e. the desired velocity, in a certain direction $\vec{e}_i^{\,o}$ and to which it tends to adapt its instantaneous velocity $\vec{v}_i$ within a certain time interval τ_i (1st term of Equation 1). Simultaneously, the particles try to keep a velocity-dependent distance from other entities j and walls w using interaction forces $\vec{f}_{ij}$ and $\vec{f}_{iw}$ (2nd and 3rd term of Equation 1), respectively. The change of velocity in time t is given by the dynamical equation:

$$m_i \frac{d\vec{v}_i}{dt} = \underbrace{m_i \frac{v_i^o(t)\vec{e}_i^{\,o}(t) - \vec{v}_i(t)}{\tau_i}}_{1^{st}} + \underbrace{\sum_{j \neq i} \vec{f}_{ij}}_{2^{nd}} + \underbrace{\sum \vec{f}_{iw}}_{3^{rd}} \quad \textbf{(1)}$$

This model generates realistic phenomena, as arcs formation in the exit (Fig. 1) and the increasing evacuation time with increasing desired velocity as described by Helbing (6).

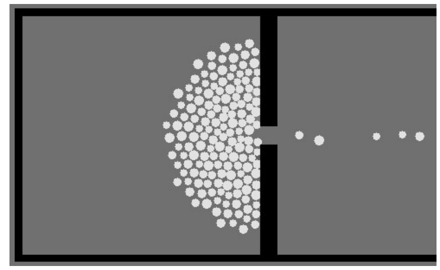

Figure 1: An image of Helbing´s Model Simulation.

4. The Generalized Model

The main motivation for our model is the fact that different people can react in different ways depending on their *individual characteristics* and on *group structure*. For instance, an adrenaline maniac is less affected in panic situation than an always concerned being, who probably stops walking all of a sudden and thus interferes in the crowd dynamics as a whole. Furthermore, depending on the *group structure*, the individual action can change because the agent is part of a group, e.g. returning to the dangerous place in order to rescue a member of that group. Situations like those motivated our work, in order to enrich the simulation beyond a scenario where agents react only as individual and physically identical particles.

The first contribution of our work is to attribute individuality to each agent, and thus allows the model to deal with different agent behaviors generated as a function of individual parameters. Session 4.1 describes the parameters treated in order to define our virtual agents.

The second fundamental aspect in this model is the possibility of grouping people. In this case, agents are able to form groups which cause them to change their individual behavior as a function of emerged group structure. Session 4.2 is dedicated to the question how group behaviors are generated depending on the interaction between individuals.

4.1. The Agents

The agents' population can be composed heterogeneously by individuals with different characteristics. Each agent$_i$ is defined according to the following parameters:

- Id$_i$ – Identifier of the agent.
- IdFamily$_i$ – Identifier of the family. A family is a predefined group formed by some agents who know each other. All of them are indicated by the same color (in this paper represented by the same gray scale), to facilitate group identification during the simulation as shown in Figure 6.

- DE_i – Dependence level of the agent represented by a value in the interval [0,1], which mimics the need for help of agent$_i$.
- AL_i – Altruism level of the individual represented by a value in the interval [0,1]. It represents the tendency of helping an other agent. For simplicity, we consider altruism existent between members of the same family only, i.e. agents with high altruism try to rescue dependent agents of the same family.
- v_i^o – Desired speed of the agent.

In order to model the effect of the dependence parameter in the individual velocity, we computed v_i^o as a function of DE_i and maximum velocity v_i^m, as follows:

$$v_i^o = (1 - DE_i) v_i^m \qquad \textbf{(2)}$$

If the agent is totally dependent (DE_i=1), v_i^o will be equal to zero, which is typical for disabled people, small children, etc. In the case of $DE_i = 0$ for all agents one recovers Helbing´s original model.

The impact of parameter AL_i is presented in the next section where the altruism force is introduced according to the interaction between agents, the forming of groups of altruist and dependent individuals.

4.2. Group Formation

Group formation is related to $\overrightarrow{Fa_i}$ (altruism force) which is implemented as an interaction between two or more agents who are part of the same family. The resultant $\overrightarrow{Fa_i}$ is mathematically described as follows:

$$F\vec{a}_i = K.\sum_j AL_i DE_j \left| \vec{d}_{ij} - \vec{d}_{ip} \right| \vec{e}_{ij} \qquad \textbf{(3)}$$

The vector $\vec{d}_{ij}$ represents the distance between the two agents with the origin at position of agent$_i$ and $\vec{d}_{ip}$ is the distance vector pointing from the agent$_i$ to the door´s position *p* of the simulation environment (Figure 2). K is a constant and $\vec{e}_{ij}$ is the unitary vector with origin at position *i*.

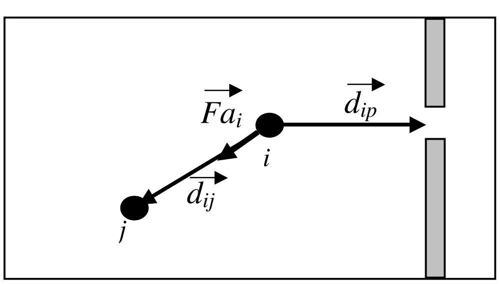

Figure 2: Representation of vectors for a pair of agents.

Consequently, the greater the parameter AL_i of agent$_i$, the bigger will be $\overrightarrow{Fa_i}$ which points to the agent$_j$ and has the high level of DE_j. When both agents are close enough to each other, the one with high DE (agent$_j$ in this example) adopts the value of agent$_i$ ($DE_j = DE_i$). This means that the evacuation ability of *agent$_i$* is shared with *agent$_j$* and both start moving together (shown in Figure 6).

5. Results Analysis

The results analyzed in this work are subdivided in two parts. First, we present a discussion about the impact of average *DE* and *AL* parameters on the resulting flow of people passing the door per second, during the simulation. We investigated these parameters varying *DE* with *AL* fixed and vice-versa.

In the second set of simulations, we compared the average flow of people per second obtained with different distributions of initial populations. Moreover, these flow values are compared with the one obtained by Helbing´s model.

5.1. The Impact of Individualities in the resulting average Flow of People

We performed 25 simulations using 5 different seeds for the random number generator with evaluated values of AL (0.1, 0.3, 0.5, 0.7 and 0.9), as shown in the following list of parameters:

Value of *DE* = 0.5
Standard Deviation of DE_i = 0.5
Value of *AL* = (0.1, 0.3, 0.5, 0.7 and 0.9)
Standard Deviation of AL_i = 0.1

Figure 3 presents the average flow of people per second obtained with the 25 simulations with fixed *DE* and variable *AL*.

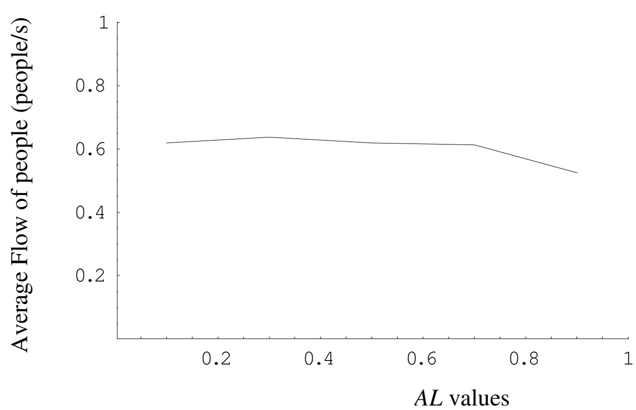

Figure 3: Flow of people *x* *AL* values.

Twenty five simulations (using also 5 different seeds) were performed considering the following data:

Value of DE = (0.1, 0.3, 0.5, 0.7 and 0.9) Standard Deviation of DE_i = 0.1 Value of AL = 0.5 Standard Deviation of AL_i = 0.5

Figure 4 presents the average flow of people per second obtained with the 25 simulations with fixed AL and variable DE.

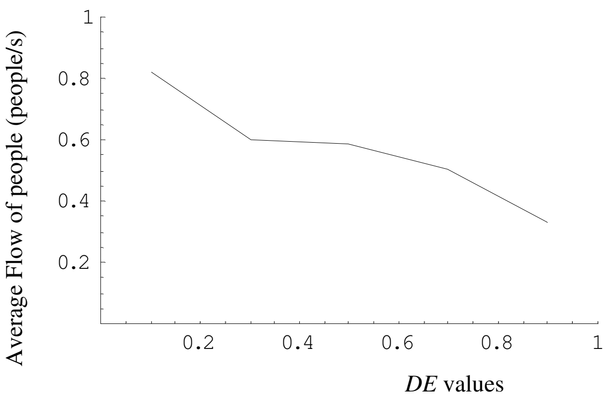

Figure 4: Flow of people *x* *DE* values.

From those plots one can perceive that the average flow of people per second decreases according to the increased values of DE. Figure 3 indicates that the flow of people does not increase or decrease significantly, for a more accurate study considering a combined AL-DE dependency we refer to future work. In the next section we provide more detailed results defining different possibilities of initial populations.

5.2. The Impact of the Population Distribution in the Resulting Average Flow of People

We performed further 25 simulations using 5 different seeds, considering the following populations:

A)	Value of DE = 0.0 Standard Deviation of DE_i = 0.0 Value of AL = 0.0 Standard Deviation of AL_i = 0.0

B)	Value of DE = 0.9 Standard Deviation of DE_i = 0.2 Value of AL = 0.9 Standard Deviation of AL_i = 0.2

C)	Value of DE = 0.8 Standard Deviation of DE_i = 0.2 Value of AL = 0.1 Standard Deviation of AL_i = 0.2

D)	Value of DE = 0.5 Standard Deviation of DE_i = 0.5 Value of AL = 0.5 Standard Deviation of AL_i = 0.5

E)	Value of DE = 0.1 Standard Deviation of DE_i = 0.2 Value of AL = 0.9 Standard Deviation of AL_i = 0.2

An interpretation for each type of population is described bellow:

Population A reproduces Helbing´s implementation, i.e. individuals are considered homogeneous and without altruism or dependency. Population B describes a socially complicated configuration since the major part of agents are altruist and are also dependent. We have classified these agents as problematic since they want to help others but their ability to escape from dangerous locations is limited. Population C describes a more egoist population; only the minor part desires to help others but the major part of agents needs help. Population D is described with a normal distribution and serves as a mean reference sample. Population E presented the higher values of flow of people since major part of agents desires to help others and there is a small portion of them who needs help.

Figure 5 presents average flow of people per second obtained in these 5 simulations.

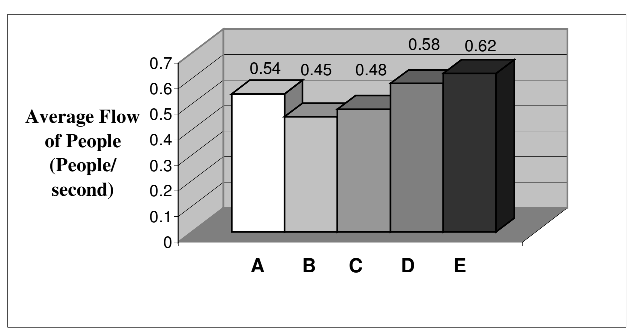

Figure 5: Flow of people *x* Initial Population.

Comparing the results A to E, one observes that including individuality into agents, permits to simulate different populations which is manifest in a change in the average flow of people passing the door per second. For instance, we can simulate a population of children in a school (like Population B) and observe that the average flow of people decreases compared to other populations, as described by Helbing´s case (Population A).

On the other hand, we are able to simulate a population of trained people who knows how to evacuate a dangerous location. In this case, people can help others if necessary, but in fact, there are not enough people with necessity for assistance. This situation can be an example of Population E) and in this case, we obtained the highest flow compared to all other populations simulated.

The sequences of images A and B shown in Figure 7 describe group formation with time. In A and B, the agents are positioned according to subsequent instances of grouping. In order to provide a better visualization of group effects, we artificially increased the size of involved particles.

6. The Visualization Framework

Due to the time needed to solve differential equations, our simulations can not be provided in real time yet. For this reason we performed the simulations in two separated phases. The first executes the simulation process, followed by the visualization. Figure 6 shows the architecture of the framework.

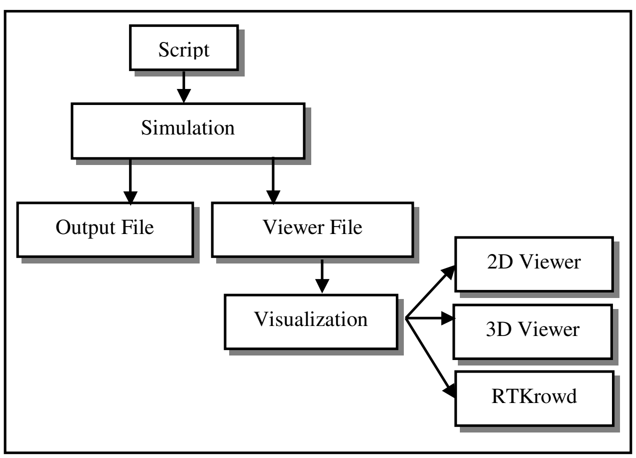

Figure 6: The Visualization Framework.

The information contained in the *script* are: number of agents, parameters related to the forces of Helbing´s model, the values and standard deviation for *AL* and *DE* parameters and total time of simulation. Due to the benefits - computational time required and minimization of errors - we chose the Verlet-Leap Frog algorithm (9) for the *simulation* process. In order to simulate a crowd formed by 80 agents in a total time of simulation of 120 seconds, 12 minutes are required in a PC Pentium IV, 1.8GHz.

During the simulation, two files are generated: *Output* and *Viewer file*. The first one is to register information about the relevant events, for instance when an agent passed through the door and when an altruist agent rescued a dependent agent. In the viewer file the simulator registers positional information about the agents as well as the membership (as the agents are represented with different colors).

In the visualization process it is possible to select among three viewers according to required realism and computational time. The first one is a 2D viewer as illustrated in Figure 6. One 3D viewer is based on the OpenGL package and shows the agents as cubes with same colors presented in the 2D viewer. See Figure 8.

The RTKrowd viewer (1) is based on the RTK Motion toolkit, a commercial product developed by Softimage. It is a more realistic viewer, capable of displaying more complex models, with more polygons and textures (see Figure 9).

7. Conclusions

This paper presented the generalization of Helbing´s model in order to include individualism into the agents. As a consequence of certain individual parameters, group behavior emerges as demonstrated in the situation where altruist people, instead of saving their own life straight away, tend to rescue dependent people.

The main motivation of our work is to incorporate successively realistic aspects in a physically based simulation. To be more specific, the idea is to formalize those features by physics analogies. In this spirit, we consider our contribution as a first step in this direction. We understand that people in real life are not similar with respect to their ability to move, the groups they are members of, among other features, which we believe may be translated into a mathematical form.

We simulated different configurations of parameters and found convincing similarities with intuitively accepted scenarios (the animations may be accessed at http://www.inf.unisinos.br/~cglab/equipe/adrianab/). In some simulations we obtained smaller values for the flow of people (the cases of populations B and C). compared to Helbing´s model (population A). The cases B and C represent socially complicated configurations as for instance populations of almost only children or disabled people. The opposite occurred in population E where a group of trained people is understood. When we applied tests of our model with a normally distributed population (case D) we obtained similar results to Helbing´s case. In case of population E, the average flow of people increased by roughly 20% if compared to case A.

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A)

B)

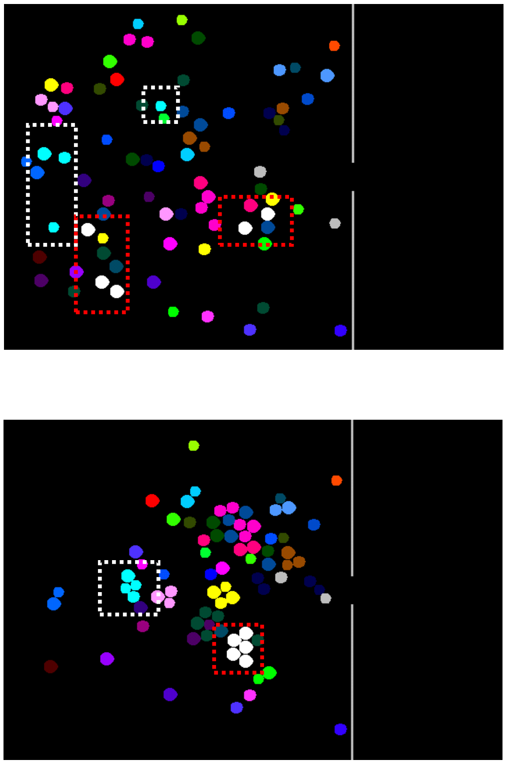

Figure 7: Snapshots showing grouping of families. In A) we can see 4 boxes (2 red and 2 white ones) representing two families of agents that are going to group. In B) they are already grouped and moving together.

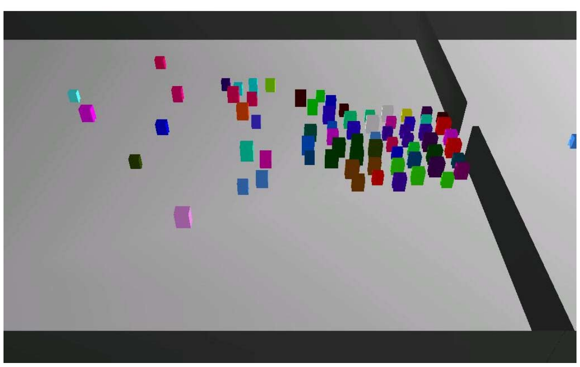

Figure 8: The 3D Viewer.

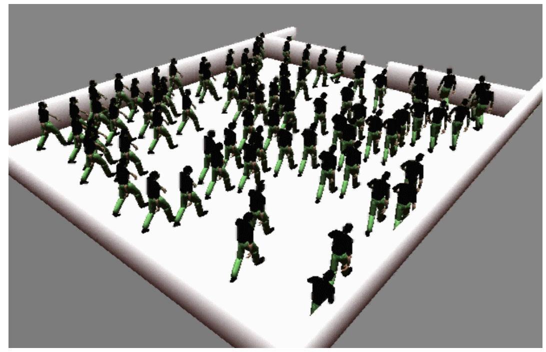

Figure 9: The RTKrowd Viewer.

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