Crowd Dynamics Simulation Research

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ABSTRACT: This paper reports on research aimed at providing a more realistic simulation model of crowd behavior under both panic and non-panic conditions by modifying the Helbing-Molnar-Farkas-Vicsek (HMFV) model. Such simulations will be of great value both in operational and training contexts. Many operations deal with crowd control and accurate simulations of crowd dynamics. The approach is based on a Social Force Model which consists of two components: social interaction and physical interaction. The social interaction relies on an individual’s desire for personal space and the physical interaction consists of body compression and friction. Ongoing research is aimed at the explicit incorporation of gender, ethnicity, age, and cultural differences as factors in the model to ensure broad applicability of the research to crowd control in nations other than the U.S.

1. Background

To be generalizable beyond the modeling of crowds in a specific country, a simulation of crowd behavior needs to capture the effect of culture on behavior. For example, culture definitely plays a key role in the size of personal space. For example, Japanese prefer a larger surrounding space than Americans, while Italians prefer a smaller personal space. Physical contact between cultural groups also varies.

Recently, a considerable amount of research has been done on simulating collective behavior of pedestrians in the street or people finding their way inside a building or a room. Comprehensive reviews of the state of the art can be found in volumes containing Schadschneider (2002) and Kessel et al (2002) and also in Batty et al (2002). Existing models can be broadly separated into the following two categories: (i) discrete-space models and (ii) continuous-space ones. Discrete-space, or cellular automata-based, models allow pedestrians to be located at nodes of a fixed or adaptive grid, and pedestrian coordinates are updated at discrete time intervals. Particular models of this category are described in Schadschneider (2002), Blue and Adler (2002), Dijkstra et al (2002) and Kessel et al (2002). The models of the second category allow pedestrians to move continuously in a part of a 2-D surface representing a street, a room, etc. The continuous-space models can further be subdivided into the following groups: fluid-analog models, optimal path models, and individual pedestrian-particle models. Some models, like the ones considered in Helbing (1992) and AlGadhi et al (2002) are based on a similarity between the dynamics of a crowd and that of a fluid or gas. Other models of the second category allow pedestrians to choose their paths by optimizing a certain cost function Hoogendoorn et al (2002). An interesting model combining the fluid dynamics approach with that of a cost function is considered in Hughes (2002); there the role of the cost function is played by a pedestrian's estimated travel time. Finally, the model considered in Helbing et al (1995 and 2000) introduces social and physical forces among pedestrians and then treats each pedestrian as a particle abiding the laws of Newtonian mechanics.

In this report, we focus our attention on the latter model, which we refer to as the Helbing-Molnar-Farkas-Vicsek (HMFV) model. We begin by summarizing the main features of this model as described in Helbing et al (2000). In the HMFV model, each pedestrian feels, and exerts on others, two kinds of forces, “social” and physical. The social forces do not have a physical source; rather, they reflect the intentions of a pedestrian not to collide with other
people in the room or with walls and also to move in a specific direction (e.g., towards an exit) at a given speed. When the crowd's density becomes so high that pedestrians are forced to collide, the physical forces of pushing and friction enter the picture. Thus, the force exerted on pedestrian \( i \) by pedestrian \( j \) has the form:

\[
\vec{f}_{ij} = \vec{f}_{\text{social repulsion}} + \vec{f}_{\text{pushing}} + \vec{f}_{\text{friction}} \tag{1}
\]

where

\[
\vec{f}_{\text{social repulsion}} = \text{Constant}_{12} \times \exp(-\text{interpersonal distance})_{\text{radial direction}}
\]

\[
\vec{f}_{\text{pushing}} = \text{Constant}_{12} \times \exp(-\text{interpersonal distance})_{\text{radial direction}}
\]

\[
\vec{f}_{\text{friction}} = \text{Constant}_{12} \times \exp(-\text{interpersonal distance})_{\text{tangential direction}}
\]

In the original study \( \text{Constant}_{12} \) was a function of the relative tangential velocity of the two pedestrians; however, in this study we set it also to a constant.

The first term in Equation (1) describes the social force, while the second and third terms describe the physical forces of pushing and sliding friction between the two pedestrian bodies. The form of the latter two terms ensures that they vanish when the pedestrian bodies are not in physical contact. An expression similar to Equation (1) holds for a force between a pedestrian and a wall or another immobile obstacle (e.g., a column) in the room.

Two additional forces, which arise from the pedestrian's personal considerations, also affect his motion. (Note: Here and below we refer, for brevity of notation, to the pedestrian as “him” rather than “her”.) The first force is an attraction force which makes pedestrians move towards (one of) the exit(s). Following Helbing and Molnar (1995) we took this force to have the same functional form as that of \( f_{\text{social repulsion}} \), but with different numerical values for the exponential decay, for \( \text{Constant}_{11} \), and also of possibly opposite sign, corresponding to attraction rather than repulsion. If there is more than one exit, we assumed that the pedestrian is attracted to the nearest exit that he “sees”.

The second of the previously mentioned “personal” forces makes pedestrians attempt, at all times, to move at their own preferred velocities. The preferred velocity of a pedestrian is a weighted average between his “own” velocity (having a specified direction) and a “collective” velocity that he perceives around himself. This force has the form:

\[
\vec{f}_{\text{preferred}} = \text{Constant}_{p} \times \frac{\text{vectorial deviation from preferred velocity}}{\tau}
\]

Where \( \tau \) is his “reaction time”. The preferred velocity is a combination of desire to move toward the exit at velocity, \( v_{b} \), and the average velocity that the person perceives others moving within the radius of 2 to 3 meters around himself. The weighting is determined by a parameter \( p \), referred to in Helbing et al (2000) as a “panic parameter”, that determines the relative weights of the “own” and “collective” contributions to the preferred velocity. It characterizes how strongly a pedestrian aligns his preferred velocity with the motion of the crowd around him; it might more aptly be called a “co-motion” parameter.

As summarized in Helbing et al (2000), the HMFV model is able to reproduce such phenomena as: (i) formation of lanes in both uni- and bi-directional traffic, (ii) arc-shaped clogging at an exit when the crowd's desired speed of leaving the room is “too high” [the “faster is slower” effect, see also Predtechenskii and Milinski (1978)], (iii) inefficient use of alternative exits when the panic parameter \( p \) is either too small or too large, and (iv) oscillations of the pedestrian flux at a door, through which pedestrians are trying to pass in opposite directions. The reader is referred to a website [http://angel.elte.hu/panic] for an impressive collection of interactive Java applets illustrating the above phenomena. The source code used to obtain the results on this site has recently been made available to the public (Helbing et al 2003). It is also interesting to point out that a quite different, discrete-space model, described by Burstedde et al (2001), is also reported to be capable of reproducing the effects of lane formation and periodic oscillations in the pedestrian flux at a door. We emphasize that both this discrete model and the HMFV model do not provide pedestrians with any “intelligence" or decision-making capabilities.

2. Modifications to the HMFV Model

Our research suggests that a deficiency in the HMFV model of crowd behavior is how it handles high density crowds. The approach taken to modifying the HMFV model was to introduce a density dependent magnitude to the social force of the crowd that surrounds a pedestrian. We observed that if the magnitude of \( f_{\text{social}} \) is independent of the crowd's density, the following two kinds of unrealistic behavior would occur: First, if there occurred a few-second delay in the crowd's exiting, pedestrians located at the
outer edge of the crowd (i.e. those farthest from the exit) would turn and run away as a group. Figures 1a and 1b show snapshots of the crowd just before and a few seconds after this happens in a particular simulation. Second, when the crowd is very dense, even pedestrians who tend to walk with the “normal” speed of 1.5 m/s begin to collide and clog the exit. Avoiding this requires a greater repulsive force

To correct these behaviors, we found it sufficient to include density effects into the magnitude of the force in the simplest possible, i.e. linear, manner. The density $\rho$ is the fraction of area occupied by individuals and thus varies between 0 and 1. The social force was multiplied by the sum of two terms:

$$K_0(1-\rho) + K_1\rho$$

The first term is there to gradually suppress the social repulsion as the person approaches a dense crowd. It is only effective for people located at the crowd's edge where they see a relatively low density around themselves. The reasoning for this is that if a non-panicking person approached a slowly moving crowd, he needs to become more patient and willing “to wait in line”, which corresponds to reducing his tendency to be repelled from others as he approaches the crowd. We have found a value of $K_0 = 0.3$ to work very well in modeling this behavior.

The second term, $K_1\rho$, corrects for the tendency of very dense crowds, even when the pedestrians tend to walk with “normal” speed of 1.5 m/s, they begin to collide and clog the exit. This effect is only substantial for large crowd densities. Numerical simulation was needed to determine the range of the parameter $K_1$. Some results from these simulations are presented below.

3. Results of Simulation

For emergency planning and crowd management purposes a key quantity is the number of people that can exit a room under emergency conditions. This section presents the results of our room exist numbers from several simulation runs using our modified HMFV model.

The number of people exiting the room in 100 s and having the preferred velocities $v_0 = 1.5$, 3.0, and 4.5 m/s is shown in Figure 2 for a fixed value of the parameter $K_1 = 1.8$ which models the effect of crowd density. The free parameter that we vary in this set of simulations is the magnitude of the face-to-face social repulsion force $F$. Each point in Figure 2 represents an average over 25 simulations with randomly selected initial locations and velocities of the pedestrians. Error bars, showing the standard deviations from the mean values, are also plotted. It is clear from these results that our modification of the HMFV model with force parameter, $300 \leq F \leq 700$ N, does indeed show that the “fastest” pedestrians, who prefer to exit at 4.5 m/s, would actually exit at a much lower rate than the “moderately fast” ones (with $v_0 = 3$ m/s). In movies that we made from the simulation results, we also observed arc-shaped clogging at the door.
In the next set of simulations the parameter $K_1$ which models the dependence of $f_{\text{social}}$ on crowd density was varied. The curves in Figure 3 show the dependence of the number of exiting pedestrians on the coefficient $K_1$ for a fixed value of $F = 600 \text{ N}$. The ‘faster is slower” effect is evident here as well for $K_1 = 1.8$. However, this effect is violated in the simulations presented in both Figures 2 and 3 when the repulsive force, either face-to-face or face-to-back, is 'too high” in a very dense crowd. This is manifested by a dramatic increase of the number of exiting pedestrians with the highest simulated value of the preferred speed, $v_0 = 4.5 \text{ m/s}$, when either $F$ or $K_1$ exceed certain critical values. This effect may be explained as follows: The stronger the repulsion is among pedestrians, the further away from each other they tend to stay. For the ‘fastest” pedestrians, who become most densely packed near the exit, the additional distance that they gain by repelling more strongly may be sufficient to reduce their squeezing so as to, in turn, reduce the friction and pushing forces that make them clog the door and prevent exit. It is not clear, however, why the same explanation, at least partially, does not apply to pedestrians who prefer to move at 3 m/s.

Furthermore, we mention two observations that either go counter to the results of Helbing et al (2000) or which we cannot fully explain based on our intuition. First, in Helbing et al (2000), it was pedestrians with $v_0 = 1.5 \text{ m/s}$ who were found to exit at the highest rate, with the exit rate decreasing with the increase of $v_0$, while we found that pedestrians with $v_0 = 3 \text{ m/s}$ exit the room most quickly. The exit times reported in Helbing et al (2000) are also substantially shorter than those deduced from Figures 2 and 3 above. Second, Figure 3 suggests that the number of moderately fast pedestrians, with $v_0 = 3 \text{ m/s}$, who are able to exit the room decreases with the increase of the parameter $K_1$, while that number increases for the pedestrians with $v_0 = 4.5 \text{ m/s}$. The above observations, pointing to differences between simulations of the original HMFV model and our modification of it, call for more observational data on pedestrian egress of a room under various conditions.

4. Model Validation and Verification

To establish the validity of the HMFV model and our extensions to it, video of movement within real crowds was obtained. It was hoped that newsreel video of events involving crowds might provide a source of data. But it was found that cinematic and editorial considerations dictated what was recorded. Instead of the ideal of a fixed camera observing crowd behavior for an extended period of time, the camera operators would zoom and pan through the crowd to focus on events of interest. As a result crowd behavior as a whole was observable for a most a few seconds in most
news videos so that they were useless for model verification purposes.

Instead events accessible for videotaping within institutional review board (IRB) guidelines were attended and taped from a fixed location and viewpoint so that long term comparisons of actual crowd motion with simulations were made possible. Figure 4 shows a frame of video taken of the crowd exiting the Orlando Citrus Bowl after a UCF-Tulane football game (American).

Figure 4: Frame captured from video of crowd leaving UCF-Tulane football game (American).

To make quantitative comparisons between the video and the model predictions possible, the video was processed to extract optical flow using the Lucas-Kanade algorithm (Lucas and Kanade, 1981) within the Open-CV (Intel, 2001) image processing environment. The results of processing the video stream for a time interval centered on the frame shown in Figure 4 are shown in Figure 5.

Comparing Figure 4 and Figure 5, it is evident that the Lucas-Kanade optical flow captures the motion of the crowd upward and to left through the exit gate. Interesting subflows and “eddies” are also evident in Figure 5. Currently the optical flow calculated from the video is not precisely calibrated. Work is ongoing to calibrate the optical flow by comparing it with the results of manual hand-counting analysis of the motion of individuals within the video.

Once the optical flow is calibrated and corrections are made for camera perspective, the observed data will be compared with model predictions. The model parameters that best match statistically the observed crowd behavior can then be determined.

In addition to a number of football-game crowds, video has been taken at Universal Studios (an Orlando area tourist attraction) and at Holy Cross Church. The variety of venues and types of people in the crowds should provide significant variation for realistic model testing.

5. Future Research Directions

5.1 Incorporation of Age

One of the first additional factors that will be considered within the models is age. This will be accomplished by dividing the populations into age groups. Each age group will have a different set of parameters.

The age groups being considered are young children (ages 3 to 8), middle age (ages 18-40), and older individuals (ages over 70). The variable characteristics associated with each age group were decided to be:
1. How close an individual is willing to get to an obstacle (Personal Space).
2. How fast an individual tends to move (Speed).
3. How much random movement an individual has (Randomness).

These characteristics were considered to be distinct enough between the three age groups as to demonstrate noticeable differences in crowd movement.

The middle age group is considered to be the baseline for which the original simulation parameters were constructed. We expect to see younger children having a more erratic movement, and tending to move faster than the other groups. Also children would be willing to get much closer to both obstacles and other individuals. The older groups will tend to move slower and be much more conscious of the spacing between themselves and others. This gives a starting idea of the
directions to modify different parameters and which parameters need to be adjusted.

The implementation of the age groupings was done by modifying the strength of the different forces based on age of the individual. Each characteristic can tie to one or more forces acting on an individual. Therefore a mathematical representation of how age affects these strengths will be developed.

5.2 Personality Factors

Psychologists have identified five personality factors – “the big five” – that capture individual variability (Costa et al, 1991). They are:
1. Neuroticism (N),
2. Extroversion (E),
3. Openness (O),
4. Agreeableness (A), and
5. Conscientiousness (C).

Various ethnic groups would be expected to be comprised of individuals with varying distributions of personality factors. Thus the big five formalism should be able to model ethnicity.

Using the big five factors, any individual, \( u \), can be described by a 5-vector \( P_u = (N,E,O,A,C) \). Personality can then be incorporated within the HMFV framework by adding an additional social force between individual \( u \) and \( v \) would be modified by a factor of the form \( f_{\text{inter-personal}} = P_u BP_v \) where \( B \) is a 5 by 5 symmetric matrix describing the quadratic-form interaction. In general \( B \) has 15 coefficients and these coefficients would be functions of physical separation between individuals and other factors. This project will initially focus on one or two of the personality factors.

Another factor aside from the big five that is seldom mentioned is gender. Interactions between genders could be modeled in a way similar to the big five. Individuals are described by a 2-vector \( g_u = (F,M) \) and a gender related force \( f_{\text{gender}} = g_u G g_v \) where a 2 by 2 gender interaction matrix \( G \) has been introduced. This gender force has the advantage that experimentally \( g \) is easy to determine by simple observation, to first approximation anyway. Similarly, \( G \) would have a form like
\[
\begin{bmatrix}
1 & -\sigma \\
-\sigma & 1
\end{bmatrix}
\]
so that the force between male-male and female-female pairs, \( F^M F^M \), or \( M^M M^M \), is unmodified and there is a slight attraction, \( -\sigma F^M M^F \), between male and female pairs.

Preliminary work with this model shows that a little attraction goes a long way; a small value of \( \sigma \) tends to segregate the crowd into a number of male-female pairs.

5.3 Experimentation

Videos of crowds have been taken in a variety of environments. The experimental comparison with models in most cases is limited to determining improvement in the model to observation fits by the introduction of additional factors such as age or gender.

The football-game data are fairly age homogenous being comprised of a college-age population. Conversely the Universal Studio’s data are more a mixed age population, children with grandparents etc. Comparing how the age model performs for these two cases should help determine coefficients.

A particularly interesting data set was obtained at a local church. Video was taken of the congregation exiting two different services: an early morning English language service and a later morning Spanish language service. The ethnicity of these two crowds is thus significantly different but also known. Comparison of these videos should thus provide information on ethnicity related coefficients.

6. Conclusions

We have explored a range of numerical values of parameters of the model proposed by Helbing and Molnar (1995) and Helbing, Farkas, and Vicsek (2002). We have proposed a number of modifications to the model in order to produce a more realistic behavior of an isolated pedestrian or a small number of pedestrians, while maintaining the realism of the original HMFV model for simulating large crowds.

We explored the choice of parameters for the social repulsive force among pedestrians. Most importantly, we demonstrated how to obtain the fall-off length of that force from the empirical velocity-versus-density curve (Weidmann 1992) of pedestrian flows in walkways. We found that additional changes were required. Specifically, we had to allow the social force to depend on the density of the crowd surrounding a given pedestrian, as well as on whether the pedestrian exerting the force is orientated with his face or back towards the pedestrian on whom the force is exerted. We also found an advantage in assigning to pedestrians, a memory of the location of exit(s).
We verified that the qualitative results produced by the modified model remained essentially the same as the corresponding results of the original model by producing numerical results showing how the time in which pedestrians exit a room, depends on parameters of the social force. Our results did exhibit the presence of the “faster is slower” effect, originally demonstrated in Helbing, Farkas and Vicsek, (2000). However, the preferred velocity for which the quickest exit time was observed in our simulations was around 3 m/s, i.e. higher than the 1.5 m/s, reported in Helbing, Farkas and Vicsek, (2000). This discrepancy calls both for experimental data on exit times from a room and possibly for further modifications of the HMFV model with moderately long-range repulsion forces. Finding those modifications could be a subject for future research.

We would like to conclude with a few thoughts concerning crowd modeling using the model based on the social force concept. The main strength of the HMFV model, based on the notions of social repulsive forces that keep pedestrians at a distance from each other, is that it does not require any “decision making” by pedestrians. This, however, may also be a weakness of this model. Namely, in many simulations of exiting pedestrians, we observed that often, two non-panicking pedestrians would stay face-to-face in front of the door for quite a while (ten seconds and even more) without either of them making a decisive step towards the door and the other pedestrian letting the way. This does not appear to be representative of what actually happens in reality, where similar deadlocks, often caused by “politeness”, are normally resolved more quickly. Therefore, it seems that the output of the pedestrian model could become even more realistic if some amount of “decision-making” capability were assigned to the pedestrians.

Finally, no matter which specific model is implemented, it will be of limited use until its results can be compared against measured data on pedestrian dynamics. Thus, the greatest need in this field at the moment seems to be to obtain observational data relevant to the existing models.

The results will support research in sociology, economics, and psychology. It will also provide improved implementation of emergency management simulations thereby providing broad societal benefits. Additionally architectural design for work and public spaces or for egress during panic conditions will be improved. This research supports the needs of both training and planning for crowd control situations in a wide variety of cultures. Operationally oriented crowd models such as the Crowd Federate developed at VMASC (Peck, 2006) should greatly benefit from this research.

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