COMPARISON OF CROWD SIMULATION FOR BUILDING EVACUATION AND AN ALTERNATIVE APPROACH

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ABSTRACT

This paper presents an overview of crowd simulation models, their limitations, and an alternative agent-based approch. First we introduce several methods and then we focus on two widely used and validated simulation tools that use grid-based models. We discus the artifacts that these models introduce regarding the way they treat the space and the implication that this has in the movement of the agents during the simulation. We also describe the limitations that current commercial software tools have in terms of simulating human psychology and physiology. The paper discusses an agent-based alternative approach developed to overcome these limitations. The model allows for the simulation of human movement that can provide results more closely describing behavior of real people during an emergency situation. Flow rates, densities and speeds emerge in our model from the physical interactions between people instead of being predefined.

KEYWORDS

Evacuation simulation tools, crowd simulation.

INTRODUCTION

Simulating building evacuation scenarios has given designers essential information, as they deal with safety issues when designing new buildings. A large number of models for pedestrian simulation have been developed over the years in a variety of disciplines. Current evacuation simulation tools allow designers to quickly evaluate and obtain the evacuation results for different situations and layouts of the internal structure of the building.

To simulate evacuation it is necessary to model accurately human behavior and psychology as well as human movement. The most typical approaches to simulate crowd movement are social forces, rule-based, and cellular automata (CA) models. None of these models can realistically animate the movement of humans in high density crowds. The next goal in crowd motion is therefore to be able to realistically animate high density crowds where agents are endowed with psychological elements that will drive not only their high-level decision making, but also their reactive behavior (pushing, moving faster, being impatient, etc.).

Social Forces Models have been used to simulate panic situations. Helbing et al. (2000) described a method to simulate the movement of pedestrians based on a social forces model which is a microscopic approach for simulating pedestrian motion. This approach solves Newton's equation for each individual and considers repulsive interactions, friction forces, dissipation, and fluctuations. Social forces modes tend to give simulations that look closer to particle animation than human movement, with agents appearing to vibrate, and not respecting any type of social rules (i.e. forming an organized line when simulating normal conditions).

Rule-based models were introduced by Reynolds (1987) by describing the first use of a distributed behavioral model to produce flocking behavior. The main limitation with rule-based models is that they either do not consider collision detection and repulsion at all, or adopt very conservative approaches through the use of waiting rules (Shao and Terzopoulos 2005). These rules work well for low densities in everyday life simulation, but lack realism for high density or panic situations.

Cellular Automata Models (Dijkstra et al. 2000, Kirchner et al. 2003) define pedestrian modeling as mathematical idealizations of physical systems in which space and time are discrete, and physical quantities take a finite set of discrete values. A cellular automaton consists of a regular uniform lattice (2D array) with a discrete variable at each cell (Figure 1). Walls and other fixed obstacles are black, while the white cells are areas that can be occupied by pedestrians. Cellular automata models limit the movement of the agents, and tend to look like a checkerboard when the density is high.
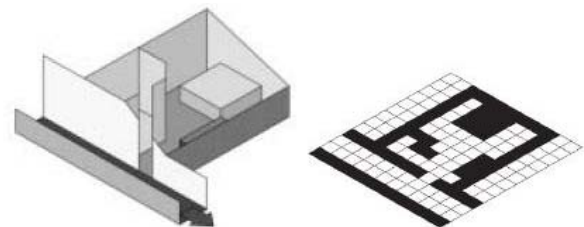

Figure 1 Example of the space representation in a Cellular Automata Model.

When simulating human behavior, it is essential to model the psychological factors that affect their

decisions. For example when simulating panic during evacuation, the following should be taken into consideration:

• Individuals may not be aware of the internal connectivity of the building and therefore may ignore some suitable paths for evacuation (Sime 1984).

• Rising stress levels have the effect of diminishing the full functioning of one's senses, which leads to a general reduction of awareness, especially the ability to orient oneself quickly in rooms and surrounding areas (Waldau et al. 2003).

• People that have not been properly trained are likely to feel stressed and might reach the point where they find themselves incapable of making the right decision due to time pressure (McGrath 1970). On the other hand, trained individuals such as firefighters deal better with a dynamically changing environment and choose the best sequence of actions based on their perception and knowledge of the environment.

In this paper we will explain the main challenges when simulating building evacuation and also the limitation of the tools studied which are based in Cellular Automata approaches. The simulation software utilized for this study is STEPS and EXODUS. Our main motivation is to explore the possibilities in terms of simulating human behavior under emergencies, and the accuracy of these softwares in simulating real evacuation scenarios. After introducing the functionality of theses software tools and describing their main limitations, we will introduce a new approach to achieve more realistic agents' movement and better integration of psychological factors that can simulate a more accurate human-like behavior.

CELLULAR AUTOMATA SYSTEMS

For the purpose of this work, two good representatives of cellular automata approaches (EXODUS and STEPS) have been selected to study how accurately this type of model can simulate human behavior. First we will introduce these commercial tools and then we will describe in detail our observations regarding their limitations. Finally a new approach for pedestrian movement is described and results are shown to compare them against the CA simulations.

EXODUS

It was developed by the Fire Safety Engineering Group at the University of Greenwich (Galea and Perez 1993). The system is able to simulate the evacuation of large numbers of individuals from large multi-floor buildings. By adopting fluid dynamic models, coupled with discrete virtual reality simulation techniques, the program tracks the trajectories of individuals as they make their way out

of the building or are overcome by hazards (e.g. fire and smoke). The output of EXODUS includes overall evacuation time, individual waiting and evacuation time, and individual paths.

STEPS

STEPS is an agent-based model with coarse grid geometry. Each individual occupies one cell at any given time and moves in the desired direction if the next cell is empty. Each occupant has its own characteristics (i.e. speed, familiarity, etc.).

In STEPS (MacDonald 2003) the fundamental driving mechanism for individual movement is the desire to move at a free walking speed towards the next target point in the shortest amount of time and without collision. The decision process is adhered to by every individual in the model. For each target (exit point), a potential is calculated at each grid cell on the plane. The potential value represents the distance between individual cells and the targets considering the presence of blockages (walls, columns, etc.). The individual located in a cell attempts eight possible directions at every time step.

MAIN LIMITATIONS OF CA MODELS

In order to understand the potential of current models for crowd simulation models, it is essential to understand their main limitations when it comes to simulate human movement and psychological issues.

Grid size

Cellular Automata models are specially limited by the grid size used to discretize the space. This space utilization yields fixed maximum densities, that are usually below real maximum densities for which movement is still possible. The grid also limits the possible movements at any given time to the eight adjacent cells (Andersen et al. 2005).

The main problem with this space representation arises when part of the geometry slightly overlaps one of the cells, turning the entire cell into an "occupied" cell where no agent can walk through and thus provokes an unrealistic artifact in space utilization. Figure 2 shows an example where the available space through a 1m. door is limited to one cell because the other one (in yellow) slightly overlaps with the wall, and thus only one person (in blue) can walk at a time through the door.
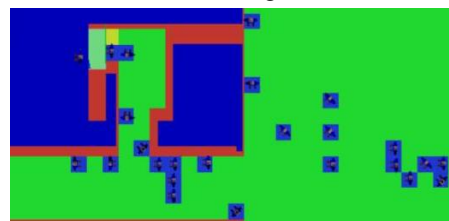

Figure 2Discrete space limiting movement

Having a grid size also limits the possibility of simulating a heterogeneous crowd, with different agent sizes. On one hand, a small cell size will not allow the program to simulate larger individuals or people carrying big gear (such as the fire fighters); and on the other hand, a big cell size will not allow it to optimize the space utilization when the simulated individuals are mostly smaller than the cell size.

Fixed flow rates

An important inconsistency in cellular automata models is the fact that maximum flow rates are fixed throughout the simulation. The user can generally specify the desired maximum flow rate which will be reached when the density is also maximum. This contradicts the hydraulic model presented in the SFPE Handbook of Fire Protection Engineering (2002), where the flow rate increases as the density increases, until it reaches a maximum and from then on the increment in density actually decreases the flow rate.

Route selection and movement

Path finding in grid-based models consists of traversing the centers of squared cells. Distances between centers can be stored before the simulation takes place. The method is usually based on "potential maps" which identify a discrete approximation of the shortest path towards the destination and store this information in the cells in order to achieve an efficient simulation. The main problem that potential maps have is that they favor 45 degrees diagonal movement, and the resulting routes are not always realistic. Figure 3 shows the unnatural paths followed by the people in a CA model (grey paths) compared to some of the real paths that should have been followed if the space was continuous (red lines).
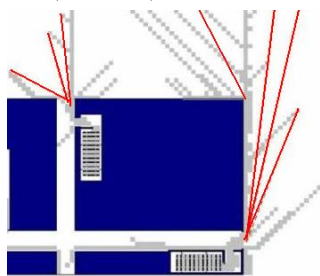

Figure 3 Route selection in CA

Since route selection is based on shortest distances and calculated before the simulation takes place, these models do not consider re-planning the route when changes occur in the environment (fire blocking paths, doors appearing to be locked, etc.) or the agents' ability to modify their route if they are impatient and observe a bottleneck in their desired path. This leads to uneven use of stairwells as we can observe in Figure 4, since the agents follow the previously calculated routes and are unable to explore the environment or try to follow a different path. A large queue apprears in one of the stairs while others are completely or almost empty (In the image we can see a section of the building showing 5 floors and 4 staircases. From left to right, the first one is already empty, the second one has a big bottleneck and the last two staricases appear with low and medium occupancy respectively).
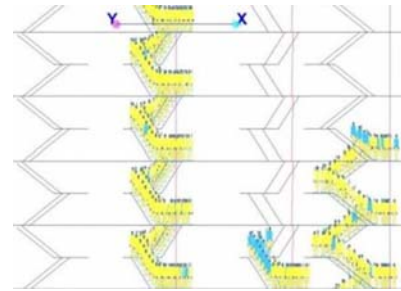

Figure 4 Uneven use of stairwells. 3D people appear in blue or yellow depending on their speed.

In a CA simulation, agents move from one cell to another empty cell, which implies that movement occurs in an organized manner and only when an entire cell is available. This model limits the range of human behavior to simulating only organized behavior, and it is impossible to simulate, for example, the effect of panicking people pushing through a crowd.

A NEW APPROACH

In order to simulate human movement in a more accurate way, it is essential to allow the virtual agents to move in a continuous space. For this purpose our model is based on a forces model where agents' movement is driven by a set of attractors to steer their movement towards the destination while avoiding obstacles and other agents in the virtual environment. This forces model is parameterized with a set of rules that mimic human personality and behavior in normal and panic circumstances (Pelechano et. al. 2007).

In our model we can specify different personality types by assigning different roles to the agents in the simulation (i.e. trained personnel, leaders and followers), so that each individual will exhibit its own behavior (Pelechano and Badler 2006). Agents can communicate with each other to share information about exit routes and hazards found within the building while they navigate and learn the internal
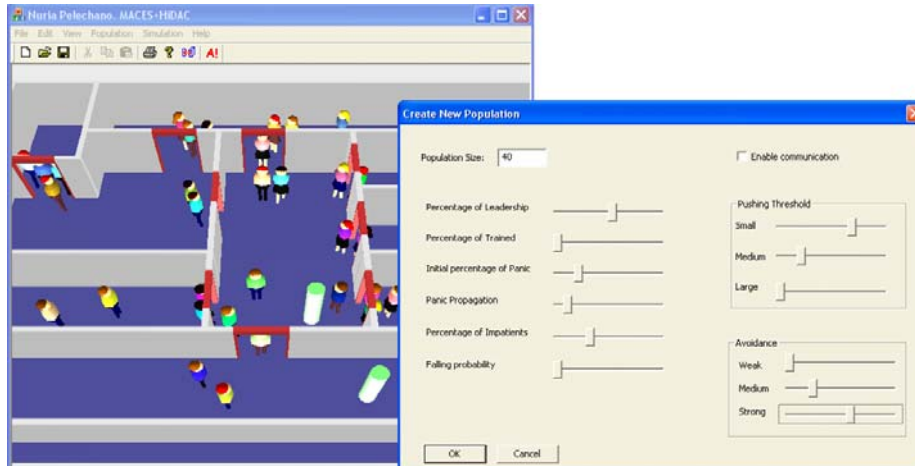
Figure 5 Interface to specify agents' personality

features of a possibly unfamiliar environment. Finally we can specify the percentage of agents in the crowd that will exhibit impatience behavior, panic or panic propagation, tendency to fall, pushing predisposition, and weaker of stronger avoidance behavior. Figure 5 shows the interface of our system.

Framework

Each agent has its own behavior based on personality variables that represent physiological and psychological factors observed in real people. Agent behaviors are computed at two levels that we refer to as high-level and low-level (Figure 6).

The high-level behavior deals with navigation, learning, communications, and decision making. Using high-level behavior, each agent receives information about bottlenecks and door changes that have been perceived by the agent and makes decisions based on that information and its current knowledge of the environment that may have been gathered through exploring the building and communicating with other agents. Once the high-level module decides the next room to walk to, it sends the next attractor point to the low-level module to carry out the required motion to reach it.

The low-level deals with perception and a set of reactive behaviors. When the agent reaches the attractor, the low-level module queries the high-level module for the next attractor in its path towards the destination. The motion sub-module queries the perception sub-module about positions and angles of obstacles, crowd density ahead of the agent, and velocity of dynamic obstacles. Based on information perceived and the internal state of the agent (current behavior, panic, impatience, etc.), the motion sub-module calculates the velocity and next position of the agent, and sends a message to the locomotion sub-module to execute the correct feet movements.

Both high-level and low-level behavior are affected by a module representing the psychological and physiological attributes of each agent.

The high-level is affected by changes in psychological elements such as panic or impatience, by altering the decision-making process (e.g. an impatient agent will select a different route after perceiving congestion in a door). Other elements such as an agent's memory and orientation abilities can be affected by high-level behavior (psychological studies show that a person under panic may suffer disorientation). Finally an agent's psychological state may trigger changes in roles (e.g. a leader changing to follower when its panic level gets very high or a trained agent exhibiting untrained behavior when suffering from disorientation).
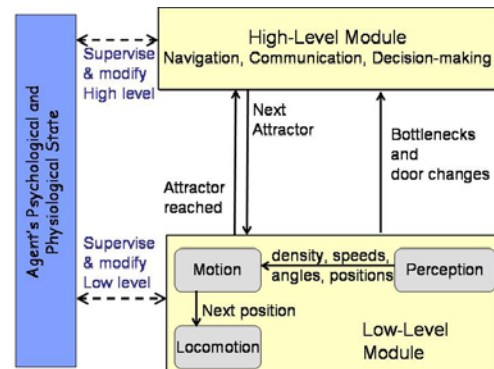

Figure 6 Framework overview

The low-level module is also affected by changes in the psychological state of the agent which will trigger modification of the agent's speed, probability to fall, pushing thresholds, etc. The psychological model needs to have as input information about environment events detected by the agent's perception system and information obtained through communication. Then this information will be combined with the agent's current emotional state in order to modify it if necessary and send back the right input to both low-level and high-level modules.

In order to make the agents' behavior closer to real humans, we need to have some considerations in mind. For example:

• People during a conversation are unable to give much detailed information in terms of room connectivity about large areas of the building. Therefore the information is limited to two levels of adjacency from the current cell in the cell-and-portal graph representing the virtual environment. (We can think of it as, for example, "The door on the left leads nowhere," or "the room on the right leads to another office, where there's no exit either.")

• People in panic tend to get disoriented. Therefore when an agent is in panic, part or all of its internal memory could be "forgotten."

• People in panic may also change their role from leader to follower. Therefore an agent that was performing a search, after being affected by the panic behavior, may start following others instead of performing its own search.

• When dealing with dynamic environments (e.g., portals that are locked or unlocked at different times) agents may have explored the entire graph, but if no exit has been found yet, then they will keep on searching hoping for a door to get re-opened.

Navigation

In order to have pedestrians able to navigate the virtual environment, it is necessary to provide them with the ability of having some abstract high-level representation of the space. In our approach, cell-and-portal graphs are used to represent the mental maps that the virtual agents have of the building. Depending on the role of each agent, they may start the simulation with a complete representation of the space, or with a partial representation (i.e. only knowing about the way they entered the building).

Figure 7 represents a simple building (on the left) with its corresponding complete cell-and-portal representation (on the right).
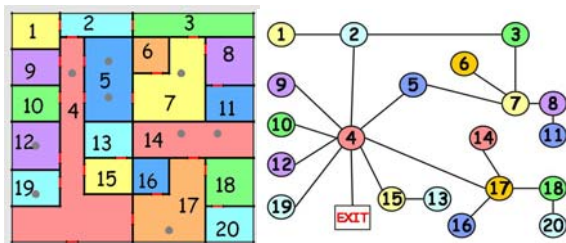

Figure 7 Building and agent's mental map

Each agent knows either one path towards an exit (if they are not very familiar with the environment, e.g. visitors) or several paths (if they are very familiar with the building, e. g. workers). Table 1 shows several examples of shortest paths and alternative

paths that can be used if the shortest one happens to be blocked.

Node	Shortest path	Alternative path
1	{2,4}	{2,3,7,5,4}
2	{4}	{3,7,5,4}
3	{2,4}	{7,5,4}
4	{}	{}
5	*{4}*	*{7,3,2,4}*

Table 1 Examples of pre-calculated paths.

As indicated previously, an agent unfamiliar with the environment can "learn" the features of a building by exploring or through communication with other agents.
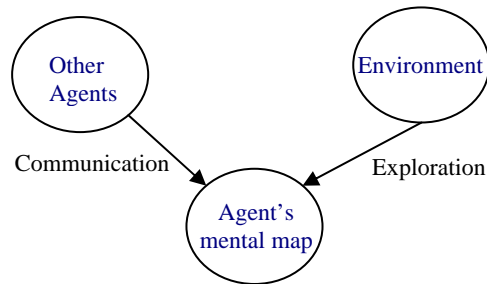

Figure 8 Sources of information to increase an agent's mental map

DISCUSSION AND RESULT ANALYSIS

In this section we enumerate the results achieved by using our parameterized forces model together with the psychological factors that are used to model human personality and decision making. In the results it can be observed how our new approach not only avoids all the limitations that we showed for cellular automata models, but also it adds a larger variety of pedestrian behaviors both for panic or stressful scenarios as well as for normal conditions.

Improvements by moving in continuous space

By having agents being able to move in continuous space (Figure 9) instead of discrete steps, we can observe how the simulated individuals follow straight trajectories when possible, instead of the 45 degree paths as shown in Figure 3 for CA models.
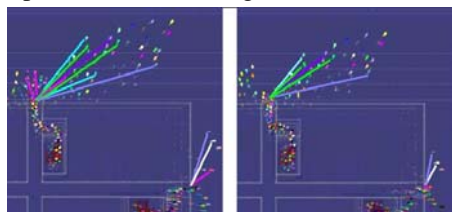

Figure 9 Trajectories followed with our approach

Another advantage of not discretizing the space is that densities emerge from the interaction between individuals instead of being the result of a fixed number specified by the user. Movement is therefore possible for densities higher than the ones achieved

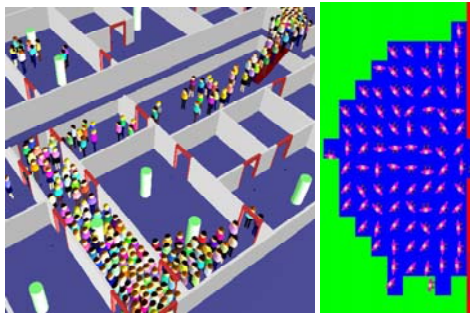in CA, as indicated in the literature on human motion (Andersen et al. 2005).

Figure 10 Real densities emerging in our approach (left) and fixed densities in a CA model (right)

The resulting flow rates in our simulation also emerge from the interactions between agents. Therefore, it depend on body contact behavior, desired speeds, and real dimensions of the building, instead of fixed flow rate values, and availability of space based exclusively on empty/free cells. This not only gives realistic flow rates based on the actual door width, but also can simulate human panic behavior such as slower flow rates when the number of people pushing to get through the door is high, as indicated in the SFPE Handbook of Fire Protection Engineering (2002).

Impatience behavior

Since agents have mental maps of the environment that can be augmented with more knowledge as they explore the building and communicate with others, they should also be able to use this knowledge to select alternative routes of escape not only when a path is blocked but also when they have an impatient personality and observe a bottleneck in their current trajectory. Figure 11 shows an example of this type of behavior, where impatient agents are represented with red hair.
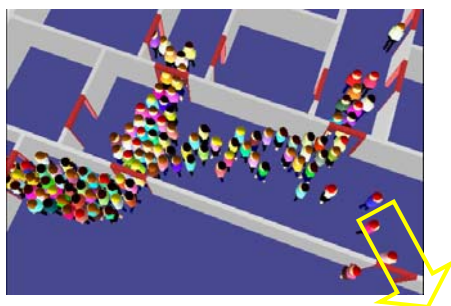

Figure 11 Exhibiting impatient behavior

Figure 12 shows an example where agents can re-plan their trajectories based on chages in the environment such as a door suddenly appearing loocked.
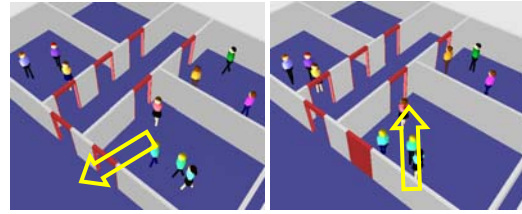

Figure 12 Reacting to changes in the environment

Pushing allows to simulate panic and panic propagation

The combination of movement in continous space, with repulsion forces between agents and different personalities, allows us to simulate pushing behavior. This proves to be very useful when simulating panic individuals or just people trying to get through the crowd faster. Panic can also be propagated to other individuals, based on their personality. Figure 13 shows an example of this behavior, where people pushing through the crowd are represented with red hair, and we observe how it propagates to nearby individuals as they move towards the exit.

This type of behavior cannot be realistically simulated with a discrete grid model, since they fail to model such a body-to-body contact.
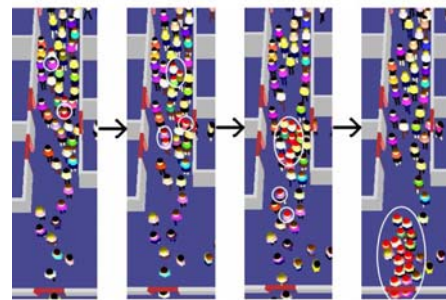

Figure 13 Panic propagation and pushing

Navigation with learning and simulation of disorientation under panic

When agents have the ability to navigate a building and learn unknown parts of it, instead of assuming that every individual has complete knowledge of the environment from the beginning of the simulation, we can also model the effects of panic over orientation abilities. An agent under panic, will try to figure out the way to exit a building when the known path appears to be blocked, but its ability to remember the different features can be altered by the effect of stress. Therefore the search for the exit will be more chaotic, with the possibility of walking over and over to parts of the environment that have previously been explored. We can observe an example of this chaotic search in Figure 14, where the complete path followed has been rendered with a white spots-line.
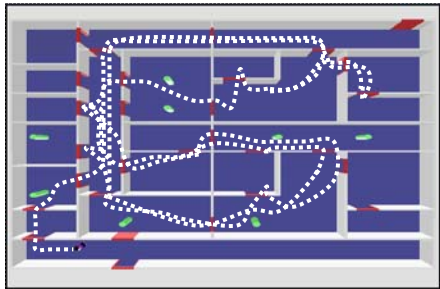
Figure 14 Agent exhibiting disorientation

Emergent overtaking and bidirectional flows

When a counterflow appears, our approach simulates the emergent lane formation that appears in real crowds. Our agents tend to avoid people walking towards them, and this results in the alignment with those walking in the same direction (Figure 15).
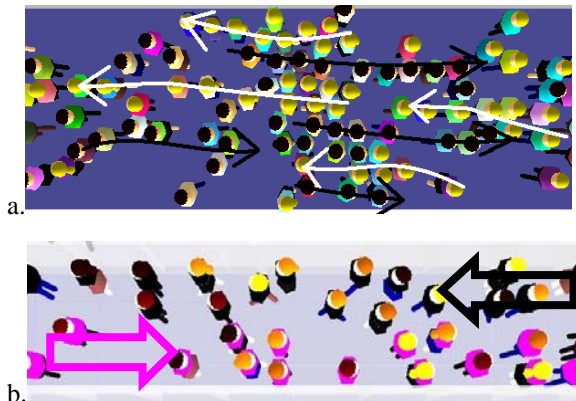

Figure 15 Counter flows with our approach, for different width passageways

This is contrary to CA models, where counter flow models appear unrealistic. For example, when using a very narrow passage, where only one person can walk at a time, the simulated pedestrians appear to traverse each other as can be observed in Figure 16a. When the counterflow occurs in a wider passage, the emergent behavior is still far from real since the different groups appear to move against each other without lane formation, reducing the overall speed considerably, and finally traversing each other instead of walking around.
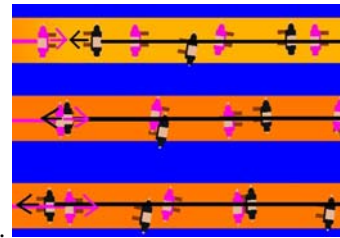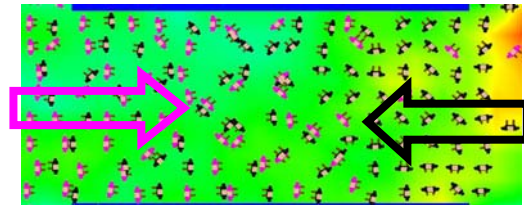
Figure 16 Counter flow in a CA model

Different types of queuing behavior leading to more realistic types of bottlenecks

In the CA models, agents try to move towards an exit by moving to the cell that appears closer to the destination. This yields to people forming arcs around doors when bottlenecks appear. Although this could be a desired behavior under some circumstances, it does not simulate real human queuing. Our approach allows the user to specify the type of queuing behavior so that organized lines can also be observed in the simulation. This is important, since it simulates more accurately how people will behave in a non-panic situation. Figure 17 shows two screenshots with different types of queues, an organized one on the left, and a more chaotic one on the right.
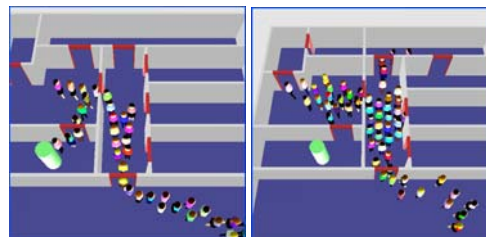

Figure 17 Different types of queue formation

Falling people becoming new obstacles

Finally, one of the interesting elements to consider when simulating panic evacuation is the fact that some individuals could fall and thus become new obstacles for the rest of the people trying to escape. Our approach can also simulate this effect as we can observe in Figure 18. When an individual falls due to the strong pushing from the crowd, the other individuals will walk around to avoid it until the individual would eventually stand up and continue walking. When the crowd is very dense, some individuals may not be able to walk around and so could also fall down.
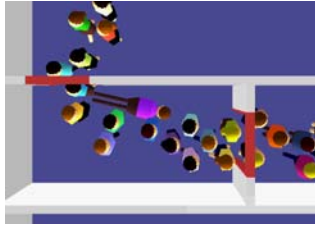
Figure 18 Agents avoiding a fallen individual

CONCLUSION

We have presented in this paper a common approach for pedestrian behavior that has been widely used to simulate building evacuation. Our main interest was not only to point out the main limitations that these models have and that any designer using them should be aware of, but also we have introduced a novel approach that lacks those limitations, and in addition offers the possility to exhibit a larger variety of behaviors depending on the desired situation to be modeled. We have shown the importance of considering physical interactions between individuals and the resulting impact of those interactions in the behavior of the virtual humans (trajectories, bottlenecks, flow rates, pushing, falling, etc.).

Finally we have also introduced psychological factors into the agent-based model to be able to simulate agents' mental states, memory, and roles. Through the use of communication we can moreover simulate the exchange of information between individuals during an evacuation.

Our current system can be validated and calibrated based on studies on real people movement. The SFPE guide provides some of this valuable data to calibrate the system in terms of egress (flow rates, speeds, densities, etc). But further psychological studies need to be carried out so that the psychological factors built in our system (i.e: panic, impatience, etc.) could also be calibrated accurately. Some of this work is currently under research using virtual reality environments to evaluate human performance under different situations including fire propagation within a building.

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