Modeling Crowd and Trained Leader Behavior during Building Evacuation

Nuria Pelechano and Norman I. Badler
University of Pennsylvania

This article considers animating evacuation in complex buildings by crowds who might not know the structure's connectivity, or who find routes accidentally blocked. It takes into account simulated crowd behavior under two conditions: where agents communicate building route knowledge, and where agents take different roles such as trained personnel, leaders, and followers.

Many applications can benefit from animated virtual crowds. These applications include site planning, education, entertainment, training, and human factors analysis for building evacuation, or other scenarios where masses of people gather such as sporting events, transportation centers, and concerts.

Animating virtual crowds is often accomplished by local rules,[1] forces,[2] or flows.[3] One of our objectives in crowd animation is to realistically simulate how human communication affects the behavior of individual agents. We have developed Multi-Agent Communication for Evacuation Simulation (Maces) to combine local motion driven by Helbing's model[2] with high-level wayfinding using interagent communication and varied agent roles. Together, these factors automatically augment an agent's mental map of the environment to produce empirically better building evacuation performance and realistic crowd movements.

Crowd evacuation from large and complex building spaces is usually hindered by people not knowing its detailed internal connectivity. In such circumstances, occupants might not be aware of the existence of suitable circulation paths or, in case of emergencies, the most appropriate escape paths. Psychology studies show that building occupants usually decide to use familiar exits, such as where they entered the building. Emergency exits or exits not normally used for circulation are often ignored. If a fire occurs, blocking some of those known paths, and smoke further obscures vision, the problem might be fatally aggravated.

In general, building evacuation due to imminent danger is accompanied by considerable physical and psychological stress. Since rising stress levels diminish full sensory functioning, there is a general reduction of awareness and increase in disorientation.

Decision skills in emergency situations are influenced by several factors such as environmental complexity, dynamically changing situations, and time pressure. If people have not been properly trained, they are likely to feel stressed and might be incapable of making good decisions. On the other hand, individuals such as firefighters are trained to make decisions in a dynamically changing environment based on perception, communication, and knowledge. For untrained individuals, too much or too little information coming at one time (several people in the same room making different decisions and shouting different information about blocked rooms) can also promote indecision.

Many different methods exist for simulating the local motion of individuals in a crowd such as cellular automata, social forces, and rules. These models simulate people moving within a familiar environment trying to reach their destination while avoiding collisions with walls, obstacles, and other individuals. None of the previous work in crowd simulation deals with unknown environments where agents must explore the building and communicate with each other to learn useful features and find their way toward an exit as real people would do.

The main novelty of our approach to crowd simulation is that we are not just animating local motion, but designing agents that perform high-level wayfinding to obtain a building's cognitive map. Wayfinding is the process of determining and following a route to some destination; it's the cognitive component of navigation and requires knowledge and a spatial reasoning process to get from an initial position to a goal position. Initially, some individuals might have only partial information about the building's connectivity, but as they explore it and communicate with other individuals they encounter, they find paths toward some of the unblocked exits.

The spatial wayfinding problem has three parts: decision making, decision execution, and information processing. To carry out wayfinding, each agent needs four components:

Published by the IEEE Computer Society

- Cognitive map: a mental model of space.
- Orientation: its current position within the cognitive map.
- Exploration: processes to learn the features of the space (doors, walls, hazards, and so on).
- Navigation: processes to move it through the environment.

In our investigation of crowd wayfinding, we manipulate groups of 10 to 1,000 agents. We simulate the evacuation time taken by a group of agents to find the exits when an emergency occurs. We assume that an accident, such as a fire, occurs simultaneously at several sites within the building. At that moment there will be different types of agents in the building. Some of them represent individuals not familiar with the environment, and therefore will know just a few paths toward the exits. Other agents are more familiar with the building and will have complete knowledge about alternative routes. So each agent has its own cognitive (or mental) map, which will be updated as it navigates the environment and communicates building path information with other agents.

Algorithm overview

Maces is a distributed multiagent system without a centralized controller. Each agent has its own behavior based on simple personality variables that represent real psychological factors. At the global level, Maces is a collection of reactive behaviors relying only on local perception and communication. Agent movement is computed at two levels. The high level corresponds to the wayfinding process that generates a sequence of rooms, while the low level corresponds to the local motion within a room. Maces receives as an input the characteristics of the maze-like environment—dimensions, number of exits, and number of hazards—or a building's floor plan, and the parameters necessary for the simulation—number of agents, percentage of trained agents, and the percentage of leaders.

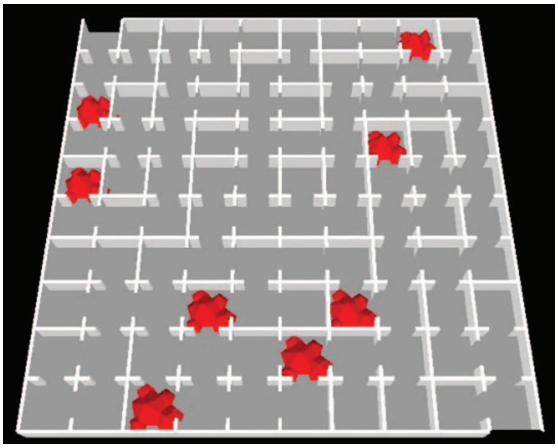
We can either create a maze-like environment (see Figure 1) or we can input a building floor plan (see Figure 2). For the given environment, we create a cell and portal graph, and for each cell the algorithm automatically generates the shortest path to each exit. We can interpret this information in two ways. On the one hand, this shortest path stored in the cell corresponds to the path that an agent in that cell would have followed when entering the building and therefore is the only one known. On the other hand, we can consider this shortest path as being the one indicated by the emergency exit signs in a building and therefore would be followed in case of emergency.

An agent's memory consists of a mental map: its own cell and portal graph. The mental graph removes the actual building geometry. Nodes are added as the agent navigates and explores the building. At any time, each agent needs to know which rooms have been fully explored and which still have portals that lead to rooms not yet visited. Later, we'll use the actual building geometry to compute local motion transit times and portal bottlenecks.

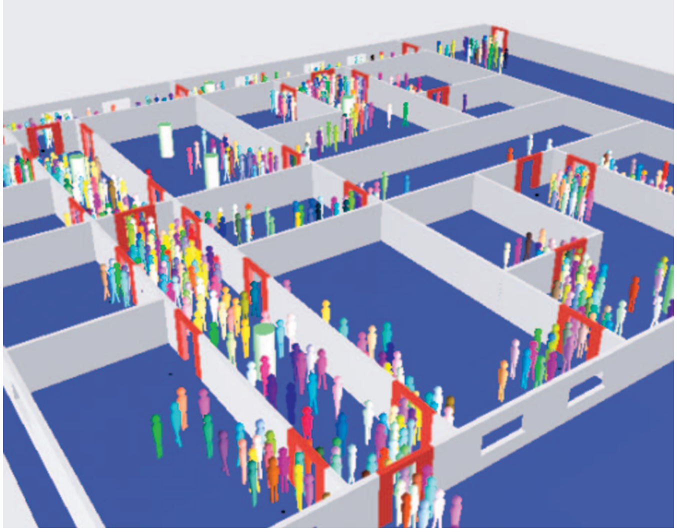
Another crucial information source is communication with other agents. Whenever two or more agents meet in a room, they share two pieces of information: locations of some of the hazards that are blocking paths, and parts of the building that have been fully explored by other agents and found to have no accessible exit (passed along by previous communications). The communication is local to a room, so agents exchange only relevant information about neighboring rooms—that is, do not go through that door (there is fire), do not go in that direction (there is no exit), or follow me. This localized sharing of mental models is the key to Maces' wayfinding behavior.

To model different personalities that would occur in a real crowd, each agent has high-level behaviors that depend on leadership and training attributes:

- Agents who are leaders, are trained, and have complete knowledge about the internal building connectivity and would help others during the evacuation process. Firefighters would be an example of this type of agent.



1 **Example of one of the mazes used for our experiments, with two exits and eight hazards.**



2 **Building plan used for evacuation simulations.**

Related Work

There have been several cognitive agent architectures proposed to generate crowd behaviors. They generally consist of knowledge representation, algorithms that learn, and modules that plan actions based on that knowledge. Funge, Tu, and Terzopoulos have worked on behavioral animation for creating artificial life, where virtual agents are endowed with synthetic vision and perception of the environment.[1] Massive SW has also developed a crowd simulation system with vision-based behavior.

Rule-based systems can be used with dozens of agents in real time. Reynolds describes the first use of a distributed behavioral model to produce flocking behavior.[2] Brogan and Hodgins use particle systems and dynamics for modeling the motion of groups with significant physics.[3] Helbing, Farkas, and Vicsek simulates pedestrians using a microscopic social force model that solves Newton's equation for the position of each individual by considering repulsive interactions, friction forces, dissipation, and fluctuations.[4] These traditional crowd simulators ignore the differences between individuals and treat everyone as having the same behavioral set, but there are other models that control each agent by individual rules or physical laws.[5] In a multiagent crowd system, the agents are autonomous, typically heterogeneous, and concerned with coordinating intelligent behaviors among the group.

Other models have been used in commercial tools for ship and fire evacuation. Some of the most common models include regression, route choice, queuing, gaskinetics, and cellular automata. Regression models use statistically established relations between flow variables to predict pedestrian flow under specific circumstances. Route-choice models describe pedestrian wayfinding based on utility: choosing destinations to maximize the utility of their trip (such as comfort, travel time, and so on). Queuing models use Markov chains to describe how pedestrians move from one network node to another. Gaskinetics models use fluid or gas dynamics analogs (partial differential equations) to describe how density and velocity change over time. Cellular automata models represent space by a uniform grid of cells with local states depending on a set of rules describing pedestrian behaviors.

To reduce the complexity of controlling all the agents in the crowd while still guaranteeing detailed behaviors, several systems have attached information to the environment.[6,7] The Multi-Agent Communication for Evacuation Simulation (Maces), described in the main text, also embeds environmental information such as shortest paths. Individual agents will have differential access to that information and use it in different ways. Depending on their individual roles and behavior at any given moment, they will adopt different decision-making processes.

References

1. J. Funge, X. Tu, and D. Terzopoulos, "Cognitive Modeling Knowledge, Reasoning and Planning for Intelligent Character," *Proc. ACM Siggraph*, ACM Press, 1999, pp. 29-38.
2. C. Reynolds, "Flocks, Herds, and Schools: A Distributed Behavior Model," *Proc. ACM Siggraph*, ACM Press, 1987, pp. 25-34.
3. D. Brogan and J. Hodgins, "Group Behaviours for Systems with Significant Dynamics," *Autonomous Robots*, vol. 4, 1997, pp. 137-153.
4. D. Helbing, I. Farkas, and T. Vicsek, "Simulating Dynamical Features of Escape Panic," *Nature*, vol. 407, 2000, pp. 487-490.
5. A. Braun, B.E.J. Bodmann, and S.R. Musse, "Simulation of Virtual Crowds in Emergency Situations," *Proc. ACM Symp. Virtual Reality Software and Technology* (VRST), ACM Press, 2005, pp. 244-252.
6. N. Farenc, R. Boulic, and D. Thalmann, "An Informed Environment Dedicated to the Simulation of Virtual Humans in Urban Context," *Proc. Eurographics, Computer Graphics Forum*, Blackwell Publishing, 1999, pp. 309-318.
7. F. Tecchia et al., "Agent Behavior Simulator (ABS): A Platform for Urban Behavior Development," *Proc. Game Technology* (GTEC), CD-ROM, 2001.

- Agents who are leaders, are untrained, and correspond to people that can handle stress better and would tend to help others and explore the building searching for new paths.
- Agents who are not leaders, are untrained, and represent dependent people (followers) who might panic during an emergency situation and reach the point where they are incapable of making their own decisions.

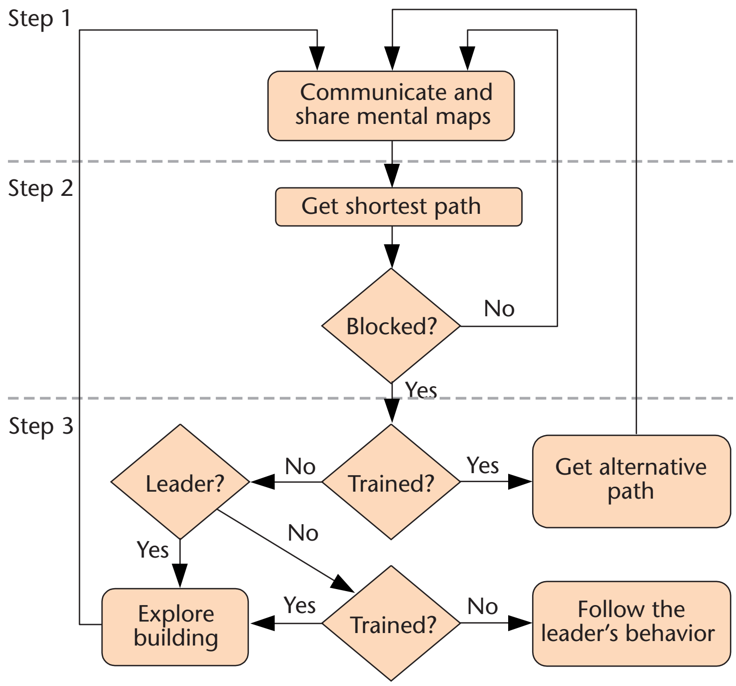
These personality types abstract the main characteristic behaviors that would occur during real evacuations according to the psychological literature.[4]

High level: wayfinding

Once the algorithm creates the cell and portal graph and automatically generates the cell information, the crowd simulation algorithm proceeds through three main steps (see Figure 3):

1. Leaders within a room share their knowledge about the environment with the other agents (their mental maps contain information about blocked cells and local subgraphs or directions that have been fully explored finding no exit). At every time step we compute a high-level path over the cell and portal graph, which then stores the

order in which the cells should be visited to get to an exit.
2. Agents check their known shortest path for known hazards. Agents use the information gathered through communication or direct perception of the environment. If its current path is hazard free, then the agent will just follow it and add the next cell to its mental map.
3. Depending on their type, agents react differently if some hazard blocks the shortest known path. A trained agent has a mental map containing the entire building's connectivity graph with all the portals and therefore follows the next shortest path known from its current cell. An untrained agent explores the building to find new routes using a depth first search (DFS). Since the untrained agent initially lacks the entire building connectivity graph, this DFS is implemented in an iterative way, so the agent discovers new rooms only when it sees a portal and crosses it. Untrained, follower agents won't know what to do and will follow the decisions taken by the other person in the room instead of doing a DFS.



3 **High-level wayfinding diagram.**

Low level: local motion

An agent's local motion within a room is based on Helbing's mode,[2] which describes human crowd behavior with a mixture of sociopsychological and physical forces. Pedestrians $1 \times i \times N$ of mass m_i like to move with a certain desired speed v_i^0 in a certain direction $\mathbf{e}_i^0$ and they tend to adapt their instantaneous velocity $\mathbf{v}_i(t)$ within a certain time interval τ_i. At the same time, the individuals try to keep a distance from other individuals j and from the walls w using interaction forces $\mathbf{f}_{ij}$ and $\mathbf{f}_{iw}$. The change of velocity in time t is given by the acceleration equation:

$$m_i \frac{d\mathbf{v}_i}{dt} = m_i \frac{\mathbf{v}_i^0(\mathbf{t})\mathbf{e}_i^0(\mathbf{t}) - \mathbf{v}_i(\mathbf{t})}{\tau_i} + \sum_{j(\neq i)} \mathbf{f}_{ij} + \sum_{w} \mathbf{f}_{iw}$$

This model generates realistic phenomena such as arching in the portals and the faster-is-slower effect.

In Maces, the desired velocity direction within each room is given by an attractor point located close to the next portal the agent must cross. We also add repulsion forces with static obstacles, such as columns. The agent walks within a room trying to reach its next attractor point. Each portal has two attractor points (in front and behind the door) to steer the agents' movement in the desired direction. The portal that an agent needs to cross is given by the high-level algorithm, which uses information about desired destination and distances from current position to portals to assign the next portal.

Results and analysis

Our goal is to study evacuation algorithms' performance when large groups of agents with individual personalities use communication to reduce their graph search space. Our motivation is to produce results that closely simulate real human behavior in these situations, and we do this by modeling the psychological factors—such as following known paths, herding behavior, loss of orientation, and so on—that affect human performance under stress and panic.

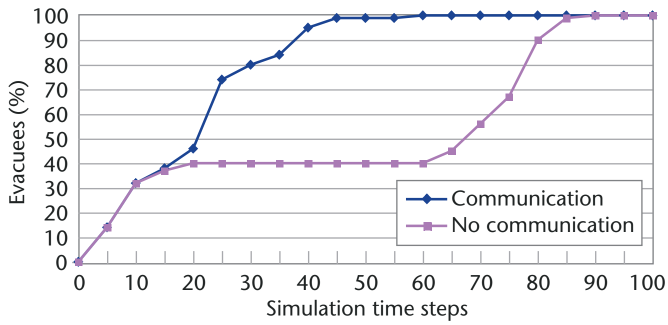
We implemented a random search exclusively for benchmarking purposes, since this is not a realistic human behavior. In another comparison, we'll see the significant impact that communication has on crowd behavior when executing wayfinding. Finally, we'll examine the impact of having trained agents in the crowd, such as firefighters, and analyze the percentage of leaders needed to speed up the evacuation process.

For the experiments, we use three scenarios, all of them maze-like. We randomly generated two scenarios and created the third with a building editor to produce an environment better resembling a real building. The three mazes each contain 100 rooms with eight of them blocked by some hazard, such as fire. For each parameter set, we run 25 randomly generated starting configurations for the crowds.

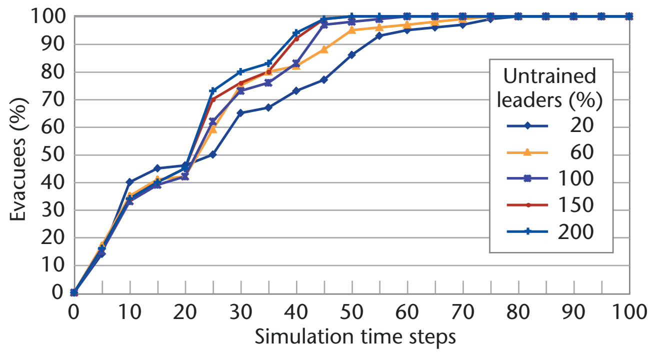
The populations used for these trials range from $N =$ 20 to 200 agents. The leadership levels range from 0 to 100 percent. No leaders means they are all followers, and therefore when several agents meet in a cell, one random agent makes a decision and the others will follow. Followers are dependent agents, when they find themselves in a panic situation they will always follow other agents instead of making their own decision, thus simulating the herding behavior observed in real crowds during evacuation. On the other hand, 100 percent leadership means each of them will perform its own decision-making process, with its current, complete building knowledge.

Random search versus depth first search

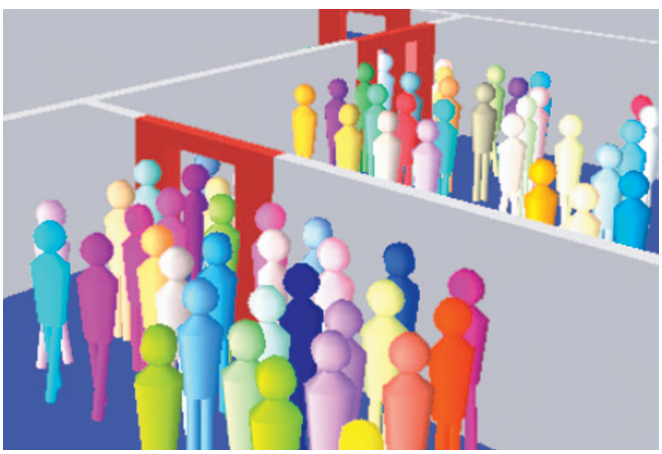
To explore the building once an agent knows that all the known shortest paths are blocked, we implement-



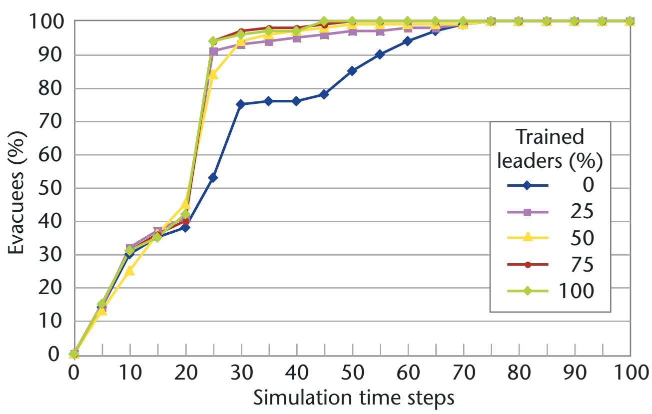
4 Communication versus no communication.



5 Evacuation time for different crowd sizes using communication but 100 percent untrained leaders.



6 Congestion at doors.



7 Evacuation time for 0, 25, 50, 75, and 100 percent trained leaders.

ed two algorithms. The first one represents a naive search, where individuals explore adjacent rooms randomly and try not to go backward unless they find themselves trapped. In this naive search, agents lack a mental map of the model nor can they create one while navigating the environment, therefore the emergent behavior obtained looks quite chaotic. A DFS algorithm makes the agents search adjacent rooms in a more structured way while they create their mental maps. The results obtained show not only that DFS was about 15 times faster than random search, but also the emergent behavior obtained was visually closer to the behavior expected of a real crowd.

Communication versus noncommunication

In Figure 4 we can readily observe the algorithm's different performance with and without communication for 200 agents. The simulation with communication converges to 100 percent evacuated in about half of the time that it takes the noncommunication case to converge.

Figure 5 shows the results obtained for different crowd sizes where all the agents represent independent (leader) individuals who make their own decisions during wayfinding instead of following others. In this simulation we don't have any trained agents, therefore everyone is unfamiliar with the building connectivity and must discover how to evacuate based entirely on exploration and shared communication. The graph shows the evacuation times for crowd sizes of 20, 60, 100, 150, and 200.

Evacuation time decreases as the crowd size increases. This can be explained by the fact that for bigger crowds the probability of meeting another agent increases, and therefore the important information about hazards in the building and explored areas spreads faster among the individuals. This information helps agents to prune their graph search and therefore find the correct path sooner. It's important to notice though, that this holds as long as the crowd is not so large that congestion blocks the doors, which will obviously decrease the evacuation time. This problem can be observed for crowds of more than 500 agents, where the evacuation time is constrained by the number of exits and the flow rate through each of the doors (see Figure 6).

Trained versus untrained leaders

We performed 25 simulations using a crowd size of 100 with 0, 25, 50, 75, and 100 percent trained agents. Figure 7 shows the average evacuation times obtained.

As expected, the percentage of evacuees converges to 100 percent faster as the percentage of trained people increases. This seems an obvious result given that trained people know how to evacuate a dangerous location because they have more information about the environment, and dependent agents will follow them. Therefore, the overall evacuation time will decrease as the number of trained agents in the environment increases.

Not everyone needs to be trained, however. We can find out what is an adequate percentage of trained leaders needed to have a speedy evacuation. We have previously observed that there is not a big difference in the convergence values between 50 percent and 100 percent leadership, which means that there is no need to have a great proportion of trained leaders. Figure 8 shows smaller percentages of leaders.

Here we can conclude that an optimal percentage of trained people during an evacuation would be only about 10 percent. For lower values the evacuation time for the same percentage of evacuees takes at least twice the time. On the other hand, having more than 10 percent trained people only increases evacuation time by at most 0.16 times.

Importance of leadership

In real life, some people have a higher probability of becoming leaders when an emergency occurs. They are usually independent individuals that by nature are able to handle emergency situations better and also tend to help others. Maces models these people as untrained leaders.

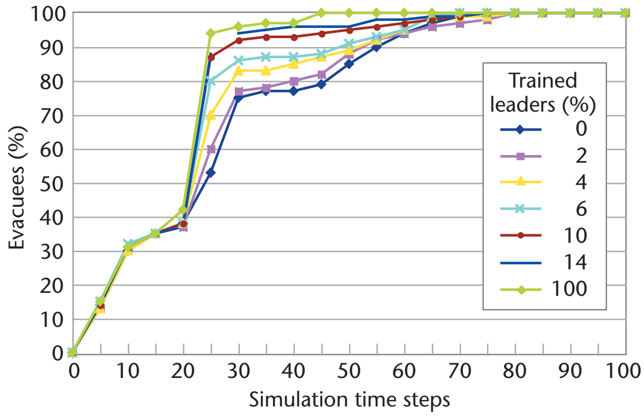
Figures 9a and 9b are two snapshots of an evacuation process. Figure 9a illustrates a population with a high percentage of leaders, so that most of them tend to make their own decisions when attempting to exit. Figure 9b shows a population with a high percentage of dependent people who tend to follow any leader instead of deciding routes by themselves. In the first population we can observe an emergent behavior with lots of small groups of people.

In the second population, the emergent behavior shows fewer but larger groups of individuals. When the number of dependent individuals is higher and there are few leaders, the size of the groups formed tends to increase, since dependent people will not leave a group to try to explore new paths on their own. Instead, they tend to stay together and just follow a leader.

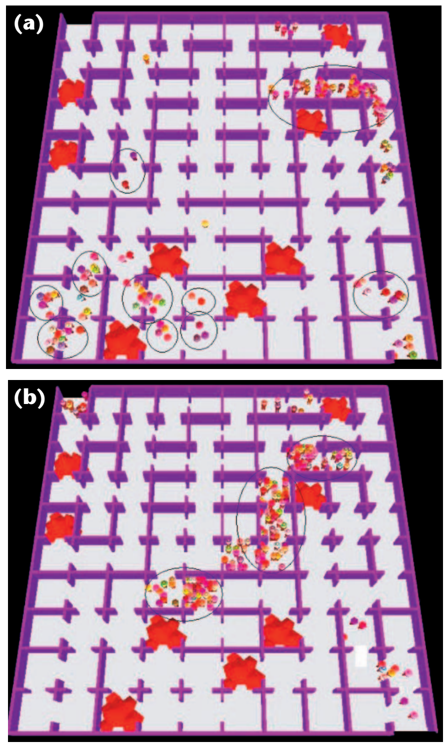
Conclusions and future work

Our evaluation has shown a significant improvement in evacuation rates when using interagent communication. We can also observe the grouping behavior that emerges when there is a high percentage of dependent agents in the crowd. Only a relatively small percentage of trained leaders yields the best evacuation rates. We can visualize these results in real time with either our simple 2D or 3D viewer. We also created an Autodesk Maya application for higher quality renderings (see Figure 10).

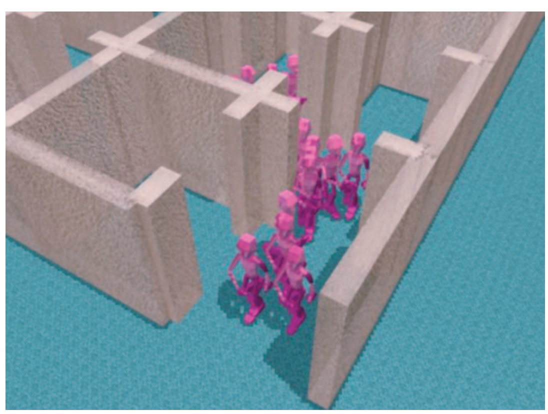
Areas where there is room for improvement include adding individualism into Helbing's model so that agents would have different local motions depending on their roles. The high-level wayfinding must be modified because people should be less likely to enter a congested room when there are other possible paths available. Although it's important to closely model what the psychology literature reports as real behavior in crowds—studies show that people tend to have herding behavior even though there could be alternative doors in a room leading to the same corridor—people under panic still tend to all follow the same choices. In general, we want to provide the agents with psychological elements that will let us model more closely real human



8 Evacuation times for small percentages of leaders.



9 Snapshot of crowd evacuation with (a) a high percentage of leadership and (b) a low percentage of leadership.



10 Close-up view of an Autodesk Maya animation.

behavior and therefore simulate crowd behavior more accurately. ■

Acknowledgments

This research was partially supported by the National Science Foundation grant IIS-0200983, Office of Naval Research Virtual Technologies and Environments grant N0001 4-04-1-0259, Army Research Office grant N61339-05-C-0081, and a Fulbright scholarship. We also thank Autodesk for its software.

References

1. C. Reynolds, "Flocks, Herds, and Schools: A Distributed Behavior Model," *Proc. ACM Siggraph*, ACM Press, 1987, pp. 25-34.
2. D. Helbing, I. Farkas, and T. Vicsek, "Simulating Dynamical Features of Escape Panic," *Nature,* vol. 407, 2000, pp. 487-490.
3. S. Chenney, "Flow Tiles," *Eurographics/ACM Siggraph Proc. Symp. Computer Animation*, ACM Press, 2004, pp. 233-242.
4. N. Pelechano et al., "Crowd Simulation Incorporating Agent Psychological Models, Roles and Communication," *Proc. 1st Int'l Workshop Crowd Simulation*, EPFL, 2005, pp. 21-30.

***Nuria Pelechano** is a postdoctoral researcher in computer and information science at the University of Pennsylvania. Her research interests include crowd simulation for real-time 3D graphics and modeling high-level behaviors in interactive multi-agent environments. Pelechano has a BA in computer science from the Universitat de Valencia; an MSc in vision, imaging, and virtual environments from the University College London; and a PhD in computer and information science from the University of Pennsylvania. Contact her at npelecha@seas.upenn.edu.*

***Norman I. Badler** is a professor of computer and information science at the University of Pennsylvania, where he directs the Center for Human Modeling and Simulation. His research interests include animation via simulation; embodied agent software; and computational connections between language, instructions, and action. Badler has a PhD in computer science from the University of Toronto. He is a coeditor of* Graphical Models. *Contact him at badler@seas.upenn.edu.*

Article submitted: 7 Sept. 2005; revised: 17 Jan. 2006; accepted: 20 Apr. 2006.