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SPECIAL ISSUE PAPER

# Modeling social behaviors in an evacuation simulator

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## ABSTRACT

Building occupants perceive information about the surrounding environment and navigate for safety during emergency evacuation (egress). They often choose their actions by interacting with their social groups and observing the actions of the surrounding crowd. Most egress simulators, however, ignore individuals' crowd perceptions and social interactions. This paper presents a novel platform, SAFEgress (Social Agent For Egress), in which building occupants are modeled as agents who decide their evacuation actions on the basis of their knowledge of the building and their interactions with the social groups and the neighboring crowd. Results from the SAFEgress prototype show that both agents' familiarity with the building and social influence can significantly impact egress performance. By simulating different occupants' behaviors, architects and facility managers may better understand the influence of human and social factors on evacuation and consequently design safer buildings and egress procedures. Copyright © 2014 John Wiley & Sons, Ltd.

**KEYWORDS**

crowd simulation; egress simulation; social agents; social behavior; simulated perception

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## 1. INTRODUCTION

During evacuation, people often observe the behaviors of their social peers and the surrounding crowds when making decisions [1–3]. Exit behaviors such as following leaders or herding to an exit are commonly observed [4,5]. Despite numerous observations and studies that have shown the importance of human and social behaviors during emergencies, most simulators ignore such behaviors in their models [6,7]. Here, we present a novel egress simulation platform, SAFEgress (Social Agent For Egress), in which building occupants are modeled as individual agents with affiliations to social groups; each group is defined by a set of parameters describing the social structure. Each agent is also equipped with visual capabilities to detect the surrounding environment and other agents. The agents choose their actions and evacuation routes by considering individual preferences, as well as the roles and the behaviors of the members in the social group and other neighboring agents. The prototype system can be used to study the effects of human and social behaviors on egress performance and the emergent crowd movement patterns.

We have experimented with SAFEgress to simulate various floor plans with occupants assigned with different individual and group behaviors. Results show that congestion patterns and evacuation times depend significantly on the occupants' familiarity with the building and the groups and social interactions among the occupants. Studying the effects of group and social behaviors on crowd movement can have many applications. For instance, architects can design occupant-centric floor layouts to accommodate a broad range of occupant behaviors for safe egress. Simulations can reveal potential congestion zones, hence providing valuable information for designing exit signage systems that lead to more efficient evacuations. The simulation results can also help facility management to plan evacuation strategies and develop emergency training programs.

## 2. RELATED WORK

Human responses in emergencies and evacuations are not random actions but the results of individual experience and social characteristics. Social characteristics of individuals affect people's behaviors and actions during emergencies [2,6,7]. Theories proposed to explain human behaviors in evacuations can be classified into three main categories: individual, group, and crowd. Theories based

on individual characteristics emphasize the importance of personal knowledge and experience to predict human responses [4,5]. For example, the affiliative theory states that people's emergency responses depend on their familiarity with the surroundings and their knowledge about the severity of the situation [4]. On the other hand, the place script theory argues that people's reactions are guided by a normative 'script' that describes their expected roles and the daily norms of the place [5]. Social theories based on group memberships suggest that people with existing social relationships often exhibit pro-social behaviors even in extreme emergencies [1,2]. For example, the emergent norm theory states that people interact with their social groups to assess the evolving situation and derive solutions collectively [1]. Group characteristics, such as group size and type of relationship within the group, can significantly affect both the interaction among people and the emergence of a collective assessment of the situation [2]. Various studies have shown that information and emotions can spread within crowds and that people tend to follow instructions given by authorities, even when the information may contradict their personal preferences and intentions [5–7].

A variety of crowd modeling approaches (e.g., particle-based, cellular automata, and agent-based) have been adopted to model crowd movement. Reviews of different simulation models have been reported in [7,8]. Here, we focus on the agent-based model (ABM), which has been widely adopted in recent egress simulation research. In a typical ABM-based system tailored for egress simulation, each agent moves in a virtual environment to mimic the evacuation movement of an occupant. The agent movements are usually predefined by specifying explicitly the origins and destinations of the occupants [2,9,10]. Optimal routes (usually defined in terms of travel time or distance) are obtained by assuming that the agents have good, often perfect, knowledge of the environment. In some other ABM-based systems, the navigation decisions of an agent are the outcomes of a decision-making process, instead of a predefined or optimized route [8,11]. Agents then use perceived information as the main inputs to the decision-making process, but they do not necessarily have full knowledge of the space. Egress simulation based on such a perceptive approach is consistent with findings in the field of environmental psychology [12]. With a proper spatial representation of the environment, natural movements of the agents can be generated without pre-assigning destinations and escape routes to them [12].

Most current egress simulators ignore group and crowd behaviors, and the social effects on evacuation patterns are seldom explored [2,9]. Only recently have some efforts been made to address this shortcoming. In [13], both emotional and informational interactions among agents were simulated, and their effects on egress performance have been analyzed. In [2], an ABM-based system implements group-level interactions, such as leaders and followers within a group. In [8,14], we study group and crowd navigation and movement patterns in theme parks and sport stadiums and incorporate them into SAFEgress (Figure 1).

## 3. SAFEGRESS

SAFEgress is an ABM-based system designed to simulate both human and social behaviors, as well as emerging crowd behaviors during evacuations. Figure 2 depicts the architecture of SAFEgress. The key modules are the Global Database, Crowd Simulation Engine, and Agent Behavior Models Database. The supporting submodules include Situation Data Input Engine, Geometry Engine, Event Recorder, Population Generator, and Visualizer.

- The Global Database holds the information about the status of emergency situations, the building geometry, and the agent population, all input through the Situation Data Input Engine, the Geometry Engine, and the Population Generator, respectively.
- The Crowd Simulation Engine interacts closely with the Agent Behavior Models Database. It tracks the simulation and records and retrieves information from the Global Database. The generated simulation results are sent to the Event Recorder and the Visualizer.
- The Agent Behavior Models Database contains the individual, group, and crowd behavioral models. Apart from the default behavioral models, new models can be added by users to investigate different behaviors and different scenarios.


(a) Video image showing lane forming (as indicated by arrows) when encountering cross flow

(b) Simulation of lane forming when encountering bi-directional flow

**Figure 1.** Simulating movements of groups.

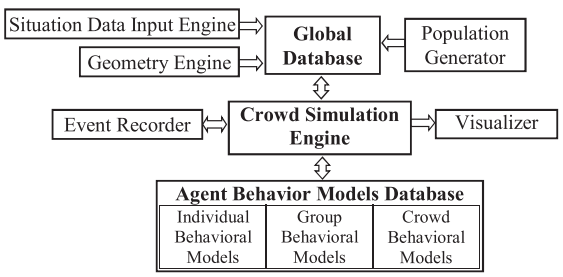


**Figure 2.** System architecture of SAFEgress.


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Details of the system have been previously described [8,14]. In the following sections, we discuss the representations of both the building occupants and their spatial environment.

## 3.1. Representation of Building Occupants

Each occupant is represented by an agent with a set of attributes describing its individual and social characteristics. An agent's decision is influenced by other agents because the agent may follow the neighboring crowd or the social group to which it belongs. Two types of attributes are defined for each agent: (i) static attributes, whose values are defined prior to the simulation, and (ii) dynamic attributes, whose values change during the simulation.

The static attributes of an agent are organized into individual, group, and crowd levels; they are described as follows (with attribute names highlighted in **bold**):

- First, at the individual level, each agent is assigned to a **physical profile** that describes its demographics, body size, and movement speed. Furthermore, the agent's decision to evacuate depends on their previous experience in the building [4,5]. An agents' experience is defined by the level of **familiarity** with the building and the prior knowledge of **known exits**. The level of familiarity determines the likelihood that an agent will follow its prior knowledge to exit the building or follow other cues, such as signs or crowds.
- At the group level, the social relationships among a group of agents are defined by **intimacy level** and **group influence** [1,2]. The intimacy level describes the closeness of the group relationship, for example, a family group has a high intimacy level. The group influence describes the agent's influence on other members in the same group. The agents within the same **group affiliation** share the same group attributes. An agent with group affiliation does not automatically exhibit group behaviors; instead, the agent exhibits group behaviors only when the agent has a high compliance to the group, which is defined using the attribute **group compliance**.
- At the crowd level, an agent's **crowd compliance** describes whether the agent will follow the directions of the crowd [1,5]. For example, when the crowd in the surrounding area exceeds the threshold value defined by **congested crowd density**, an agent follows the agent ahead, instead of navigating toward its own target.

By varying the values assigned to static attributes of each agent, users can model agents with different characteristics. For example, by varying the level of familiarity and exit knowledge, the users can create agents representing frequent visitors or first-time visitors of the building. Similarly, by changing the intimacy level from high to low, the users can distinguish a closely-related group of agents (e.g., a family) from a loosely-related group (e.g., co-workers).

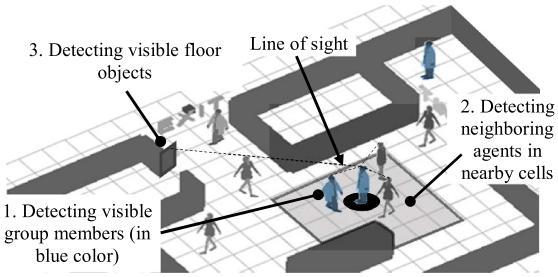



**Figure 3.** Visible objects tracked by an agent.

### 3.1.1. Agent Process Model and Dynamic Attributes.

During simulation, the states and behaviors of an agent are updated through a five-stage process (perception, interpretation, decision-making, execution, and memorization) modeled after the study of human behaviors in evacuations and emergencies [6,9,15]. At each stage, the dynamic attributes (in **bold** below) of each agent are updated as follows:

- At the perception stage, an agent tracks three kinds of objects: (i) **visible group members**, (ii) **visible neighboring agents**, and (iii) **visible floor objects** (as illustrated in Figure 3).
- At the interpretation stage, on the basis of the perceived information, the agent interprets the situation and updates its internal **urge**.
- At the decision-making stage, the agent chooses a **behavior type** (among individual, group, and crowd behaviors) depending on its compliance to the group and crowd (Figure 4). The agent then selects a decision tree associated with the chosen behavioral type. Figure 5 shows default decision trees for the

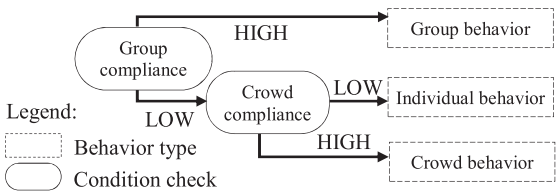



**Figure 4.** Determining agent's behavior type.

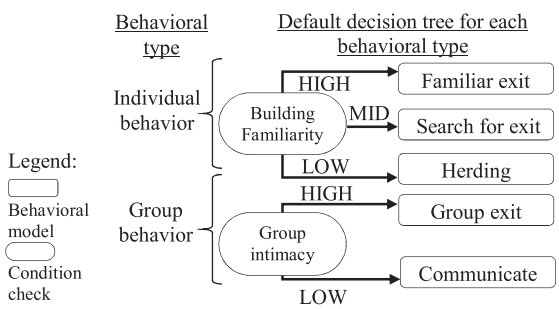



**Figure 5.** Example of individual and group behaviors.

individual and group behavioral types. Upon successive reasoning of the selected decision tree, the agent invokes a behavioral model. The outcomes of a behavioral model are the **navigation goal** and the **navigation target**. The navigation goal defines the high-level goal of the agent, such as to reach an exit or to follow another agent, whereas the navigation target describes the physical location that the agent will move toward attaining its navigation goal.
- At the execution stage, the agent moves toward the navigation target and updates its **spatial position**.
- At the memorization stage, the agent updates its **spatial knowledge**, which keeps track of the areas visited so as to avoid backtracking.

Each stage mimics a cognitive process or an act of an occupant in evacuation.

## 3.2. Representation of the Spatial Environment

Building geometry and placement of safety signage have a significant influence on occupants' choice of egress routes [5,7,12]. In SAFEgress, a model (virtual environment) is precomputed to represent the building space and its safety features. During simulation, each agent visually perceives the environment in order to avoid collision with physical obstacles, detects safety features, and determines the navigation space available in the surrounding.

### 3.2.1. Representation of Space and Features.

In SAFEgress, agents perceive and move in a continuous space. Physical obstacles of the floor plan (such as walls and furniture) are represented as rectangular parallelepipeds that are also used to define the obstacle model in the virtual space (Figure 6). The obstacle model is used to perform the following; (i) proximity/collision tests to determine the separating distance between an agent and the nearby obstacles and (ii) visibility tests to determine which subset of the virtual space is visible to an agent.

In emergencies, people often follow the directions from safety features (such as exit signs) to search for exits. SAFEgress represents a building safety feature as a floor object; each floor object is defined by its type, position, orientation, and, in some cases, directional information. The current system has four types of floor objects (Figure 6):

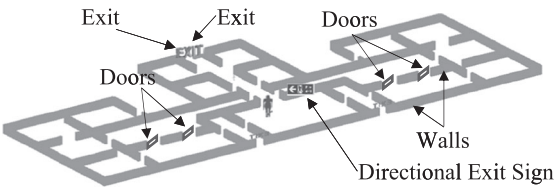



**Figure 6.** Floor objects represented for the simulation.

- Exit: this type of floor object represents an outlet of the floor. If an agent decides to escape through a specific exit, it navigates toward the location of the exit. As soon as the agent reaches the exit, the agent is removed from the floor.
- Door: this type of floor object is similar to the exit objects. However, upon arrival to a door, an agent is not removed from the floor.
- Nondirectional exit sign: this type of floor object represents an exit sign installed in a building. Each object serves as an attraction point for agents to move toward.
- Directional exit sign: this type of floor object is similar to the nondirectional exit sign, except that it also provides navigation instruction, for example, move toward the left.

Although exits, doors, and exit signs do not represent all possible building safety features, they are the most salient features pertaining to egress design and have a significant influence on people's evacuation decisions.

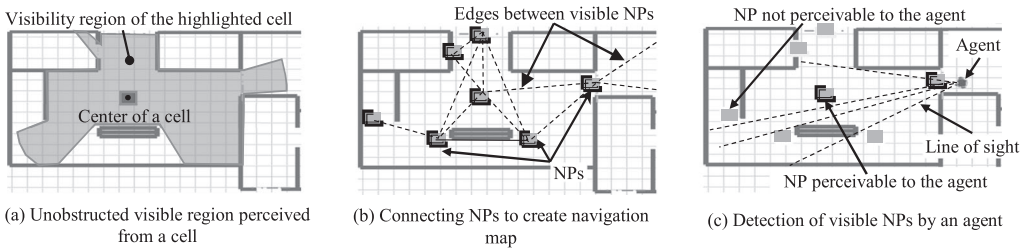
### 3.2.2. Representation of Navigation Space.

Even with no apparent visual cues in the surrounding, humans move naturally in a direction that allows them to explore the environment further [12]. This navigation strategy is similar to the next-best view method used by robots when constructing the map of an unknown environment. At each step, the robots maximize the expected amount of new spatial information they will get at their next position [16]. To emulate such behavior, we define navigation points (denoted as 'NP') and create a navigation map (network of NPs).

Navigation points are the points in the virtual environment where visibility is locally maximal and are computed as follows:

- The continuous space is first discretized into a regular grid of square cells. For each cell, the visibility region of the cell is defined as the region that can be seen without any obstruction from the center of the cell (Figure 7a).
- If the area of the visibility region of a cell is greater than the area of the visibility region of every neighboring cell, then the center of the cell is marked as a NP.
- The centers of all the cells containing floor objects (namely, exits, doors, and exit signs) are also marked as NPs.

Edges are then added to link the NPs that are visible to each other to generate a navigation map, which represents the connectivity of the accessible space and building features (Figure 7b). If necessary, additional NPs are introduced to obtain a connected graph. These additional NPs are either introduced at random locations or selected in regions of the virtual environments where NPs are sparse.




(a) Unobstructed visible region perceived from a cell (b) Connecting NPs to create navigation map (c) Detection of visible NPs by an agent

**Figure 7.** Representation of free space with navigation points and navigation map.

For computational efficiency, the NPs and the navigation map are precomputed and reused throughout a simulation run unless changes are made to the building layout that triggers an update. During simulation, each agent can determine the NPs that are visible from its current location (Figure 7c). This agent's perception capability is consistent with human visual capability of seeing only their obstacle-free surroundings. The capability of each agent to identify visible NPs enables the agent to (i) determine possible navigation directions in the virtual environment, (ii) travel to a known destination that is not directly visible to the agent (e.g., a familiar exit) through intermediate NPs, and (iii) memorize the traveled space to avoid backtracking.

## 4. AGENT BEHAVIORAL MODELS

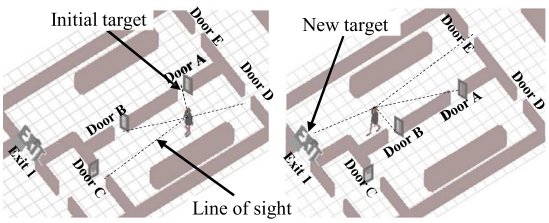
We now discuss in detail several selected behavioral models, namely following familiar exits, exiting through visible exits, following crowd, and navigating with group members.

### 4.1. Following Familiar Exits

Agents having a high level of familiarity with the building recognize the environment and are able to navigate to the desired exits along the shortest path even when the exits are not within their sight. In the prototype, we make use of the agents' static attribute, **known exits**, and the notion of NPs to model agents who follow familiar exits. Figure 8 illustrates an agent exiting the building via the nearest known exit. Prior to the simulation, we assign the known exits with parameter values to Exit 1 and Exit 2 (i.e., all the exits in this example) to the agent. During the simulation, the agent invokes the behavioral model of following familiar exits and chooses the nearest exit among its known exits as the navigation goal. In this case, Exit 2 is selected (Figure 8a). The agent then calculates the shortest path to reach Exit 2 and sets the navigation target to be the visible NPs along the shortest path. As the agent travels, it resets the navigation target to be the visible NP that is closer to the navigation goal (Figure 8b) until it reaches the goal (Figure 8c).

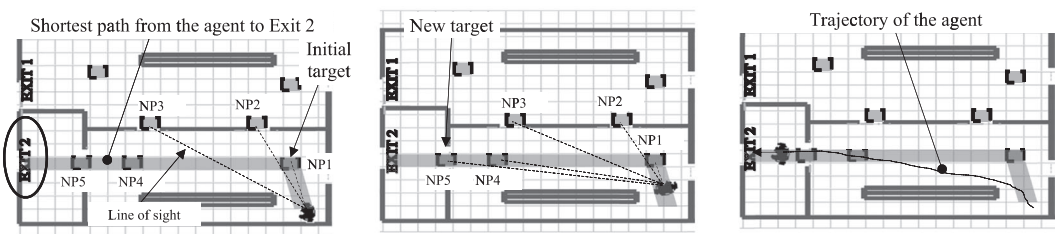
### 4.2. Exiting Through Visible Exits

When agents do not have prior knowledge of the exits, they perceive the environment and explore the space to find an exit. To model the process of searching for exits, we make use of the dynamic attribute, **visible floor objects**, which represent possible areas that the agent can explore to search for exit. The agent detects visible floor objects and weighs each object according to the object type (namely exits, doors, and signs), its distance from the agent, and the number of times of prior visits to the objects. Figure 9 illustrates an agent exploring visible




(a) Initial setting @ t = 0 sec (b) Simulation @ t = 10 sec

**Figure 9.** Behavior modeling for 'exiting through visible exit'.




(a) Initial setting @ t = 0 sec (b) Simulation @ t = 3 sec (c) Simulation @ t =15 sec

**Figure 8.** Behavior modeling for 'following familiar exit'.

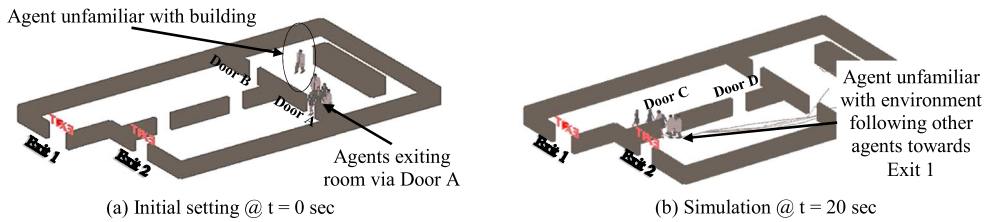



**Figure 10.** Behavior modeling for 'following crowd'.

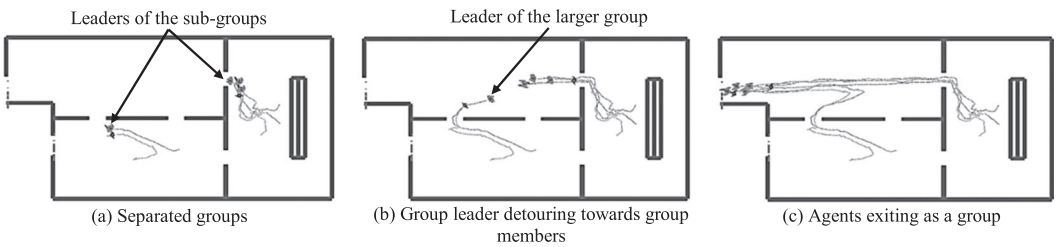



**Figure 11.** Behavior modeling for 'navigating with group members'.

floor objects and escaping via visible exits. In Figure 9a, the agent, with no previous visited areas, chooses the nearest objects, Door A, as the navigation goal and the navigation target. After arriving at Door A, the agent detects new floor objects and sets Exit 1 to be the next navigation goal and navigation target (Figure 9b).

## 4.3. Following Crowd

In ambiguous emergency situations, the movements of other evacuees provide social cues of the availability of alternative exits [1,3,5]. In SAFEgress, an agent who is unfamiliar with the building would select one of the **visible floor objects** that are chosen by other agents. To determine the preferred floor object, the agent calculates, for each visible floor object, the number of agents who are leaving an area through the floor object. After assessing the crowd flow at each floor object, the agent sets the navigation goal and target as the floor object that has the highest number of agents leaving the area. Figure 10 illustrates the crowd following behavior of an agent who has low familiarity with the building (circled in Figure 10a); the agent follows a group of agents that prefer Exit 1. In Figure 10a, the agent with low familiarity assesses the number of agents who are traveling through Door A and Door B, as well as the number of agents leaving the area through the two doors. All other agents are leaving the area via Door A but none through Door B. Because of more agents leaving the room via Door A, the agent having low familiarity with the building then sets Door A as the navigation goal and navigation target, despite that Door B is closer to the agent. Once exiting the area, the agent continues to assess visible floor objects and chooses to exit via Door C and Exit 1 (Figure 10b).

## 4.4. Navigating with Group Members

During evacuation, members belonging to a group, such as families, often seek out and evacuate with the entire group even when evacuation is urgent [4–6]. We model this group behavior with the group-level static attribute **group influence** and the dynamic variable **group separation distance** (calculated dynamically during the simulation by averaging the distances between an agent and its **visible members**). Depending on the group influence among the visible group members, an agent can be either a leader or a follower. We model the group navigation as follows: (i) if the agent is a leader, the leader agent will exhibit individual behavior to exit the building, unless the group members are walking too slow or are far apart. In the case that the group is walking too slowly (i.e., the group separation distance is constantly increasing), the leader will slow down to wait for the group members. If the group is too far away (i.e., the group separation distance is larger than the prespecified separation threshold), the leader will navigate toward the group. The navigation goal of the leader is then set to the group members, and the navigation target is set to

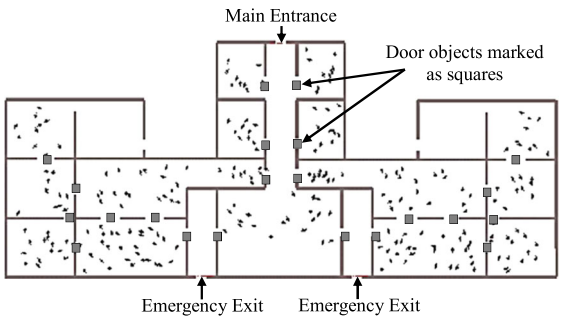



**Figure 12.** Example floor plan for simulations.

**Table I.** Behaviors of the agent population.

| | Familiarity with the building | | |
|---|---|---|---|
| Behavior | High | Medium | Low |
| I. Individual | All individuals follow familiar exits | 50% of individuals follow familiar exits<br>50% of individuals exit via visible exits | 50% of individuals follow familiar exits<br>50% of individuals follow crowd |
| II. Group | All group leaders follow familiar exits | 50% of group leaders follow familiar exits<br>50% of group leaders exit via visible exits | 50% of group leaders follow familiar exits<br>50% of group leaders follow crowd |

the centroid of the group. (ii) If the agent is a follower, it simply follows the leader by setting the group leader as the navigation goal and the leader's spatial position as the navigation target. Figure 11 illustrates the process of group navigation. The group consists of six members who are initially separated into two subgroups. Each subgroup leader leads the followers to exit until they 'see' other group members (Figure 11a). The leader of the merged group moves closer to the group centroid because the group members are too far apart (Figure 11b). The leader navigates to the exit only when all the visible group members are close to the leader (Figure 11c).

## 5. SOCIAL EFFECTS ON EGRESS SIMULATION

### 5.1. Simulation Scenarios

In this section, we study the effects of social behaviors and agents' familiarity with the building on evacuations. A modified floor plan of a museum is used as the building model. As shown in Figure 12, the building has one main entrance and two emergency exits and is occupied by 220 agents. We investigate the change in egress performance by varying two agents' attributes. The first attribute is the level of **group compliance** with two possible values: low degree of compliance (I) or high degree of compliance (II). The second attribute is the level of **familiarity** with three possible values: high level of familiarity (A), medium level of familiarity (B), or low level of familiarity (C). For all six cases, we assume 50% of the agents have a high familiarity with the building.

### 5.2. Agent Population Assumption

The agents' static attributes are defined prior to the simulations, except for the variable's familiarity and group compliance. Table I lists the agent population assumptions and the corresponding agent behaviors in all six cases. All other static attributes are defined as follows: (i) at the individual level, all agents have the physical profile attribute set to 'adult male'. For high familiarity agents, all exits are assigned as the known exits; for agents having a medium or low level of familiarity, no known exit is assigned. (ii) At the group level, the agents are assigned to social groups; each group has five members, and the members are assigned with high intimacy. One agent in the group is assigned to have the highest group influence among the members. (iii) At the crowd level, all agents have a low degree of crowd compliance. The threshold value of congested crowd density is set to 2 sq ft/person.

**Table II.** Results of egress time (seconds).

| | Familiarity with the building | | |
|---|---|---|---|
| Behavior | High | Medium | Low |
| 1. Individual | 45+/−3 | 72+/−5 | 63+/−5 |
| 2. Group | 52+/−4 | 105+/−7 | 81+/−6 |

Times shown are the averages and standard deviations over 10 simulation runs.
Average computing time for a simulation is 1 minute and 15 seconds.

During the simulation, the agents invoke the behavioral models by reasoning using the decision trees shown in Figures 4 and 5. The behavioral models invoked are following familiar exits, exiting through visible exits, following a crowd, and navigating with group members.

### 5.3. Simulation Results and Discussion

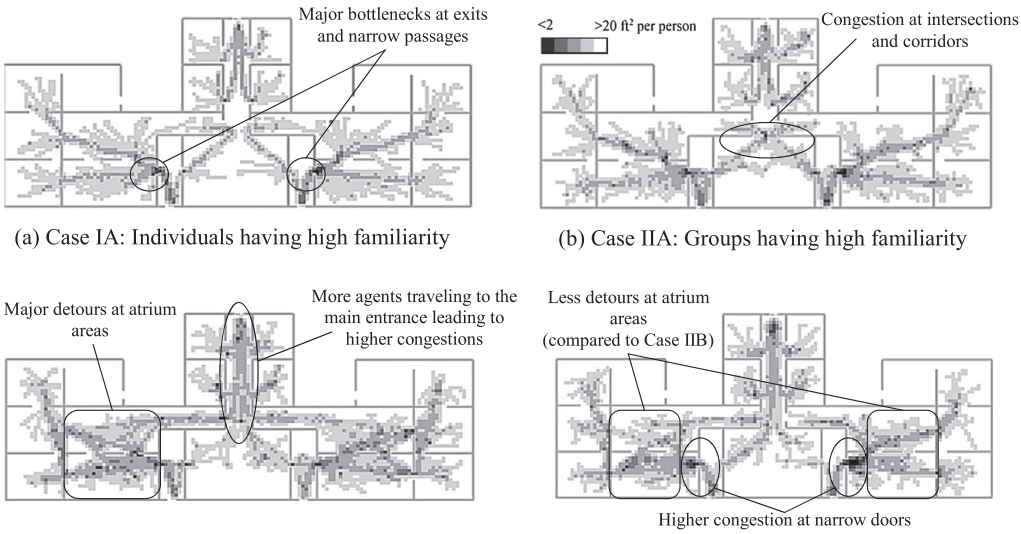
We use the total egress time as the key performance indicator. Table II summarizes the egress times for all six simulation cases.[†] We also examine the congestion patterns to understand how the social behaviors affect the trajectories of the crowd. Figure 13 shows the congestion patterns from the selected results:

(a) Case IA: individuals with high familiarity.
(b) Case IIA: groups with high familiarity.
(c) Case IIB: groups with medium familiarity.
(d) Case IIC: groups with low familiarity.

#### 5.3.1. Effect of Group Behaviors.

When the agents have a high group compliance to their social groups, the presence of other group members change the trajectories of individual agents, resulting in different overall congestion patterns. On average, the agents with group behaviors take longer to evacuate, as shown in

[†]Simulation videos are available at eig.stanford.edu/SAFEgress/CASA.




(a) Case IA: Individuals having high familiarity

(b) Case IIA: Groups having high familiarity

(c) Case IIB: Groups having medium familiarity

(d) Case IIC: Groups having low familiarity

**Figure 13.** Crowd density patterns for Cases IA, IIA, IIB, and IIC.

Table II. In Case IA (Figure 13a), when agents exit individually according to their familiar exits, congestions occur at the exits and at the narrow openings. In Case IIA (Figure 13b), when agents navigate as a group, additional high crowd densities are observed at the intersections of the corridors and at the locations connecting the exhibition halls to the corridor. Congestion patterns between Cases IA and IIA are different because the agents in groups (Case IIA) tend to pace back-and-forth to move closer to the group, therefore causing congestion at the corridors and the intersections. The congestion is also more severe at the exits and the narrow openings because the agents wait for other group members before leaving the room or exiting the building.

### 5.3.2. Effect of Known Exits.

The agents having a high familiarity with the building evacuate much faster than those who are unfamiliar with the building. The agents in Cases IA and IIA are familiar with the building, have knowledge of the floor plan, and choose to evacuate through the nearest exits. The evacuations in both Cases IA and IIA are the most efficient, and the egress times are governed by the bottlenecks at the narrow passages (as indicated in Figures 13a and b). By assuming agents with limited knowledge of the building, we observe that both the total egress times and the levels of congestion increase. For example, in Case IIB, 50% of the agents have medium familiarity with the building and need to explore the floor for exits. More agents use the main entrance because it is easier to access compared with the emergency exits. As a result, higher congestion is observed at the main corridor and the entrance in Case IIB (Figure 13c) when compared with Case IIA (Figure 13b). Moreover, the resulting egress time is much longer when 50% of the population has a medium level of familiarity. The longer egress time is caused by the agents who are not highly familiar with the building and need extra time to explore the floor. As shown in Figure 13c, the agents in the atriums take detours as they explore different areas. The random movements of the agents in the atriums indicate that the egress performance can be improved by placing additional exit signs to guide the agents to the main entrance or the emergency exits.

### 5.3.3. Effect of Following Crowd.

The agents who are totally unfamiliar with the building and follow the neighboring crowd (Cases IC and IIC) evacuate faster than the agents who have medium level of familiarity and try to search for visible exits (Cases IB and IIB). For the Case IIC, 50% of the population who are familiar with the floor plan would travel to the nearest exits directly; the other 50% of the population who are not familiar with the floor plan would detect visible floor objects and follow the paths that the familiar agents traveled. Herding to exit, as shown in Figure 13d, results. As more agents follow the crowd to arrive at the emergency exits, a higher level of congestion is observed at the narrow doors leading to the exits. The simulation results suggest that, with this particular population assumption, widening the doors that lead to emergency exits can potentially improve egress performance.

## 6. CONCLUSION

SAFEgress models occupants in evacuations and emergencies as social agents with affiliations to groups and crowds. Agents are equipped with the capabilities to perceive their environment, make decisions, and navigate in a social manner. By considering salient social attributes describing groups and crowds, emerging crowd phenomena (such as herding and group movement) are observed. The results confirm the significant effects of social behaviors on egress performance (such as the prolonging effect on evacuation due to group movements and the change of

congestion patterns in herding situations). Future work on SAFEgress will include further refinements of the computational algorithms, in particular proximity tests of agents and visibility computation, so that the platform can eventually simulate large facilities such as stadiums within reasonable computing times. Furthermore, the model can be extended to include role of authorities and spread of information within social groups and crowds [5,6,15]. By incorporating the computational algorithms developed in the fields of agent-based modeling and robotics, SAFEgress represents a step further toward integrating the knowledge of social interactions in engineering models that capture human behaviors.

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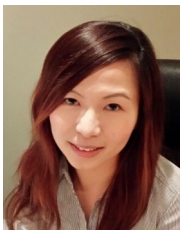

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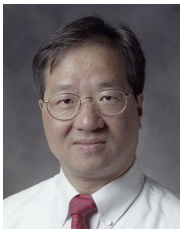

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