SAFEgress: A Flexible Platform to Study the Effect of Human and Social Behaviors on Egress Performance

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Abstract

Studies of past emergency events have revealed that occupants' behaviors, local geometry, and environmental constraints affect crowd movement and govern the evacuation. Occupants' social characteristics and the unique layout of the buildings should be considered to ensure that the egress systems can handle the actual occupants' behaviors in egress. This paper describes an agent-based egress simulation tool, SAFEgress, which is designed to incorporate human and social behaviors during evacautions. Simulation results on two scenarios are presented. The first scenario illustrates the effects of exiting strategies adopted by the occupants on evacuation. The second scenario shows the influence of social group behavior on evacuation. By assuming different occupants' behaviors using the prototype, engineers, designers, and facility managers can study the important human factors on an egress situation and, thereby, improve the design of safe egress systems and procedures.

1. INTRODUCTION

Computer simulations are often used to evaluate building egress and occupant safety. Despite observations and studies about human behaviors during emergencies, most simulation tools assume simplistic behavioral rules and mostly ignore social behaviors of the occupants. The deficiencies in modeling human behaviors for egress simulation have been echoed by authorities in fire engineering and social science (Aguirre et al. 2011; Kuligowski 2011). To address the need to incorporate human and social behaviors, we design SAFEgress (Social Agent For Egress), an agent-based model, for egress simulation. SAFEgress models occupants as agents with affiliation to social groups, each defined by a unique social structure and group norm. The agents, being part of their own group rather than isolated individuals, make decisions considering group members and neighbors, in addition to individual preferences. Moreover, each agent is equipped with the capabilities of sensing, cognitive reasoning, memorizing, and locomotion to decide and execute its actions. By incorporating the agents with plausible behaviors, SAFEgress can be used to study the effects of human and social behaviors on collective crowd movement patterns and egress performance.

The focus of this paper is to show the effects of human and social behaviors on egress performance. Simulation results from our case studies indicate that occupants' exit strategies and social behavior can lead to very different congestion patterns and evacuation times. This kind of analysis can be useful in many applications, e.g., architects can design occupant-centric floor layouts and ensure that the egress design can handle a wide range of occupant behaviors. The simulation results can also help design and placement of signage to guide evacuation. As echoed by our collaborators from theme parks and sport stadiums, such analysis can be useful for facility management to plan evacuation strategies and design emergency training programs.

2. RELATED WORK

2.1. Human behaviors during emergencies

Researchers have proposed a variety of social theories regarding human behaviors during emergencies. For example, the affiliative theory and place script theory examine individuals' behaviors based on their personal knowledge, risk perceptions, experience, and routines

(Mawson 2005; Sime 1983). The emergent norm theory and the pro social theory suggest that people continue to maintain group structure and behave in a pro social manner during emergencies (McPhail 1991; Aguirre et al. 2011). The social identity theory infers that people have a tendency to categorize themselves into one or more "in-groups," building their identity in part on their membership in the groups and enforcing boundaries with other groups (Drury et al. 2009). Moreover, studies in sociology and psychology suggest that people influence each other's behaviors through the spreading of information and emotions (Rydgren 2009).

Social theories can provide valuable insights into occupants' behaviors during emergencies. However, developing a unified theory that fully explains occupants' behaviors in different situations is difficult. We conjecture that egress models require individual, group, and crowd level characteristics and mechanisms to predict the outcome of an egress situation. At the individual level, occupants may refer to their past experiences and knowledge to decide on their actions. At the group level, the pre-existing social structure (relations between group members) and group norms (expectations of each other's behavior) would affect the behavior of an individual. Crowd-level behaviors are emergent phenomena and often follow social norms. As evidenced from recent studies of emergency incidents, occupants interact with their group members and the people nearby to guide their decision-making process (Kuligowski 2011). Therefore, an egress model should properly reflect the social structure and capture the social interactions among the occupants, in addition to assuming occupants as individual constructs (Macy and Flache 2009).

2.2. Human and crowd simulations

Humans, instead of moving randomly, tend to perform way finding when navigating the environment (Gärling et al. 1986). During the way-finding process, they examine the surrounding layout and perceive sensory (visual or audio) information, and then move towards a direction based on their purpose of navigation, destinations, and knowledge of the space (Turner and Penn 2002). The way-finding process, unlike the motion of molecules or particles that are determined by interaction with their immediate neighbors, depends on both the short-term, nearby information and the long-term decision-goal. Since human movements aggregate to form the collective crowd flow, egress simulations need to model properly the individual agent navigation decision in order to predict the overall egress performance.

Agent-based modeling (ABM) has been widely adopted for crowd simulation, among many other different simulation approaches. In most ABMs, the agent navigation routes are usually pre-defined by specifying explicitly the origins and destinations of the occupants (Aguirre et al. 2011; Veeraswamy et al. 2009). 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. Examples are the way-finding model in EXODUS (Veeraswamy et al. 2009) and the simulation model proposed by Kneidl et al. (2013). In real situations, however, occupants usually decide their final destinations dynamically in real time and may not have complete knowledge of the space, particularly during emergencies in an unfamiliar environment. Researchers in environmental and cognitive psychology have argued that the people use their perceptions to guide their navigation (Gärling et al. 1986). With proper spatial representation of the environment, Turner and Penn (2002) have shown that natural human movement can be reproduced in simulations without the need to assign the agents with extra information about the location of a destination and an escape route.

Other ABMs model agents' navigation decisions as the outcomes of decision-making processes, rather than pre-defined or optimized routes. For example, ViCrowd is a crowd simulation tool in which crowd behaviors are modeled as scripted behaviors, as a set of dynamic behavioral rules using events and reactions, or as externally controlled behaviors in real time (Musse and Thalmann 2001). MASSEgress gauges the agents' urgency and invokes a particular behavior implemented using a decision tree (Pan 2006). These models consider agents' behaviors as a perceptive and dynamic process subjected to external changes. SAFEgress also adopts the perceptive approach when updating the agents' knowledge of the environment. The agents, each representing an occupant, use both the perceived states of the environment and their background knowledge of the building to determine their behaviors.

3. SAFEGRESS

SAFEgress is an agent-based model designed to simulate human and social behaviors during evacuation. Figure 1 depicts the system architecture of SAFEgress. The key modules are the Global Database, Crowd Simulation Engine, and Agent Behavior Models Database, which are described as follows:

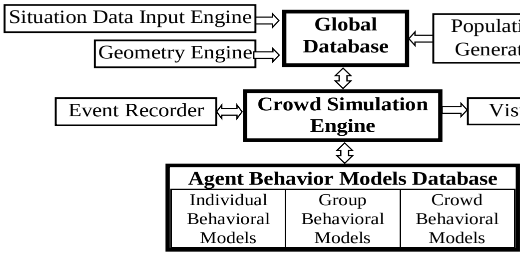


Figure 1: System architecture of SAFEgress

- The Global Database holds all the information about the geometry of the building, the status of emergency situations, and the agent population, which are input through the Situation Data Input Engine, the Geometry Engine, and the Population Generator.
- The Crowd Simulation Engine interacts closely with the Agent Behavior Models Database. It keeps track of 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 models, new models can be added to investigate different behaviors and different scenarios.

Details of the system have been described in our previous work (Chu and Law 2013). In particular, algorithms (proximity and visibility computation) have been carefully designed to allow the platform to handle a large number of agents.

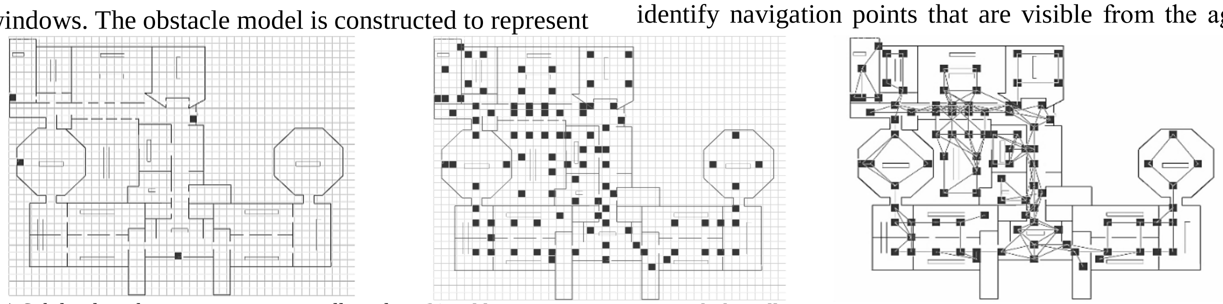
3.1. Spatial representation of the environment

A floor space includes physical obstacles, such as walls and furniture. Agents navigate the virtual space and avoid colliding with physical obstacles. To enable the agents to "sense" the vicinity of the physical obstacles and the visible space, an obstacle model is built according to the user-input building geometry, which describes the locations and the dimensions of different building objects, such as walls, doors, and windows. The obstacle model is constructed to represent the boundary surfaces of the physical obstacles as a set of polygon planes. Using the obstacle model, an agent can perform proximity tests to determine the distances from nearby obstacles and visibility tests to determine if a given point in the virtual space is visible to the agent.

Besides avoiding collisions with the obstacles, agents also need to detect the obstacle-free space in their surroundings for navigation. According to prior way-finding studies, the choice of next navigation direction is motivated by the subsequent movements to get closer to the final destinations (Gärling et al. 1986). To facilitate this navigation decision process, a navigation map, which represents the obstacle-free space, is constructed. This map is then used by SAFEgress to facilitate the computations that allow agents to "perceive" the possible navigation directions in the virtual space. The navigation map is constructed using the following procedure:

1) The continuous space is discretized into square cells to form a 2-D grid. The cells with the building features (such as exits, doors, and windows) are identified to form the initial set of navigation points (Figure 2a).
2) The algorithm computes the area of visibility for each cell on the 2-D grid. Then, each cell's visibility area is compared to the area of its neighboring cells. The cells with the largest locally visible areas become additional navigation points (Figure 2b).
3) Edges are added to link the navigation points that are visible to each other within a certain radius. The resulting navigation map is a graph representing the connectivity of the obstacle-free space (Figure 2c).

In the real world, humans can only perceive their local obstacle-free surroundings. Similarly, in SAFEgress, the virtual agents can access only the "visible" portion of the navigation map to decide their navigation directions. More precisely, every agent can query the navigation map to identify navigation points that are visible from the agent's



(a) Subdividing the space into square cells and initializing exits as navigation points

(b) Adding navigation points with the cells with large areas of visibility

(c) Linking the navigation points which are visible to each other within a certain radius

Figure 2: Procedure for generating navigation map

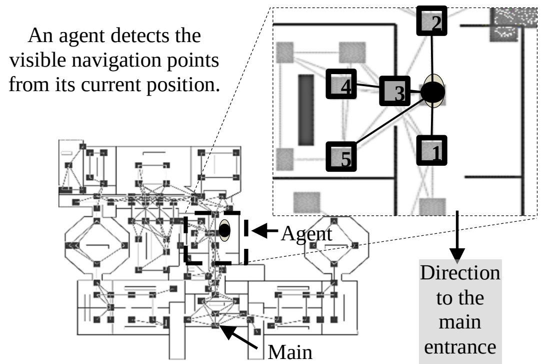


Figure 3: Illustration of an agent's visible navigation points

current position. Then, the agent selects its navigation target based on its motivation and its prior knowledge and working memory of the building layout. For example, an agent having the knowledge of a familiar exit might choose a navigation point that is near the familiar exit. In Figure 3, the agent, with knowledge of the main entrance, can choose the point labelled "1" to move closer to the main entrance among the 5 visible navigation points. On the other hand, if an agent does not have prior knowledge of the spatial layout, the agent would assign equal weight to all the options and choose a navigation target randomly. For example, if the agent in Figure 3 is unfamiliar with the environment, it can choose randomly one of the five navigation points to explore the space. Finally, each agent can "memorize" the areas traveled by registering the visited navigation points in its cognition module. Therefore, an agent can avoid repeated visits to the same area, because it will assign less weight to the visible navigation points that it has visited before. This cognitive ability to memorize the previously travelled areas is particularly important for modeling a natural navigation trajectory when an agent has no prior knowledge of the environment and needs to explore the surroundings for exit.

3.2. Agent representation of occupants

Each agent is given a set of static and dynamic attributes to model the occupants. Static attributes are defined prior to the simulation and dynamic attributes are updated during the simulation. The choice of the attributes is crucial since it implicitly determines the range of tests that the users can do with SAFEgress. To make this choice we relied mainly on published work (See Section 2). The agents' attributes, listed in Table 1, can be further categorized into three levels—individual, group, and crowd as described below with the static attributes shown **in bold**:

Level	Individual	Group	Crowd
Static	• Physical Profile[1] • Familiarity • Known Exits	• Group Affiliation[2]	• Social Order • Assigned Roles
Dynamic	• Spatial Position • Urge • Spatial Knowledge	• Visible Group Member	• Neighboring Agents

[1] The physical profile includes attributes such as age, gender, body size, travel speed, and personal space.
[2] The group characteristics include group leader(s), group intimacy level, group seeking, and group influence.

Table 1: Agents' static and dynamic attributes

- At the individual level, an agent has a **physical profile**, a **level of familiarity** with the building, and prior **known exits** of at least one that the agent enters (Mawson 2005; Sime 1983).
- At the group level, social groups are defined by the following attributes (Aguirre et al. 2011; McPhail 1991): a **group leader** (each group has one default leader), the **group intimacy level** (e.g., high intimacy among a family group), the **group-seeking property** (describing willingness to search for missing members), and the **group influence** (describing the influence of a member to the others in the same group). The agents belonging to the same group share the same group attributes.
- At the crowd level, an agent's social position is defined by the **social order**, stating the likelihood to exhibit deference behavior (Drury et al. 2009). The lower the social order, the higher the chance for the agent to defer to other agents when negotiating the next move. A special agent, such as authorities, a safety personnel, etc., may have **assigned roles**, which is responsible to execute actions, such as sharing information and giving instructions (Kuligowski 2011).

Based on the studies by researchers in disaster management and fire engineering about emergency occupant behaviors, a five-stage process model, perception – interpretation – decision-making – execution – memorization, is executed to update the agents' behaviors (Lindell and Perry 2011; Kuligowski 2011). Each stage may lead to changes in the parameter values of the dynamic attributes (shown **in bold**), as described below:

- At the perception stage, the agents perceive the nearby environment by detecting threats and visible features nearby, such as exits and doors (Lindell and Perry 2011). They detect **neighboring agents** within a certain radius (Aguirre et al. 2011). If an agent is affiliated with a social group, it also updates the **visible group members**. When the default group leader is not visible, the agent searches for a temporary group leader who has the highest group influence among the visible group members**.**

- At the interpretation stage, the agents revise their internal **urge level** according to the perception and the perceived urge level of the visible social group and neighbors (Rydgren 2009).
- At the decision-making stage, the agents select and invoke the behavioral decision trees according to their urge level, social affiliation, and crowd condition. A behavioral decision tree consists of intermediate nodes (which compare the agents' attributes and parameter values to the threshold values defined by users) and leaf nodes (which are either conditional checks leading to another decision tree, or low-level locomotion functions). The outcomes of decision-making are the exhibited behaviors and the navigation targets. The current implementation is a rule-based reasoning system.
- At the execution stage, the agents perform low-level locomotion to move toward a navigation target determined by the decision-making process.
- Finally, at the memorization stage, the agents register the decision made and update the **spatial knowledge** about their previous locations and visited areas (Turner and Penn 2002; Sime 1983).

Each stage mimics a cognitive process or an act by an occupant during evacuation. Collectively they define the behavioral process of the occupants.

4. CASE STUDIES

In this section, we demonstrate the flexibility of SAFEgress to explore different human and social behaviors on egress performance. Two different case studies are presented. In the first case study, we vary the level of familiarity and the known exit to examine the effect of individual knowledge on evacuation patterns. In the second case study, we test the group effects by varying the intimacy

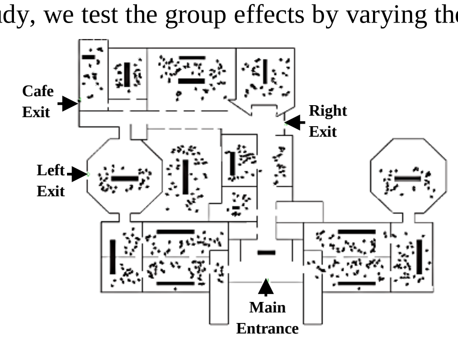


Figure 4: Geometry of the building and initial locations of 550 agents

level of the groups that the agents are affiliated with. The agents' static attributes are defined prior to simulation. In all cases, the population consisted of 50% male and 50% female. All the agents have no assigned role and have equal social order, and they begin to evacuate immediately upon the start of the simulation (no delay time).

Based on real-life observations and social studies, we construct different plausible agents' behavioral models and compare the results of different simulations using a museum as the physical setting. The museum consists of several exhibition halls with four exits (the main entrance, the right exit, the left exit, and the café exit), as highlighted in Figure 4. A total of 550 agents are assigned in the simulation runs.

4.1. Effects of different individual exiting behaviors

In an emergency situation, the primary goal of the occupants is to exit the building safely. Depending on their familiarity with the building and previous experience, the occupants may adopt a broad range of strategies in choosing an evacuation route. For example, occupants who are unfamiliar with the building may select the entrance they used to enter the building as the possible exit (Mawson 2005; Sime 1983). On the other hand, occupants who visit the building regularly may have learned their preferred exit over time or have knowledge of the nearest exit. We study the effect of individual exit knowledge_by varying the values assigned to the **known exits** and assume all agents have no group affiliation. We conjecture and design four simple individual exiting behaviors as follows:

- Case 1: agents have the knowledge of the main entrance of the museum and exit through the main entrance.
- Case 2: agents have the knowledge of all four exits and choose to evacuate through the nearest exit given their initial starting position.
- Case 3: agents have knowledge of one pre-defined familiar exit and escape through the familiar exits; in this case, we assign the agent population evenly to the four exits.
- Case 4: agents have no prior knowledge of any exits and solely follow the visual cues at their spatial position to
- guide their navigation and exit the building when a visible exit is detected.

Agent exiting behavior	Egress time (s)[1]	Exit usage			
		Main	Left Exit	Right Exit	Cafe Exit
1-Main Entrance	200 +/- 5	100%	-	-	-
2-Nearest Exit	84 +/- 4.5	39%	16%	31%	14%
3-Known Exit	180 +/- 10	25%	25%	25%	25%
4-Visible Exit	166 +/- 22.6	30%	30%	30%	10%

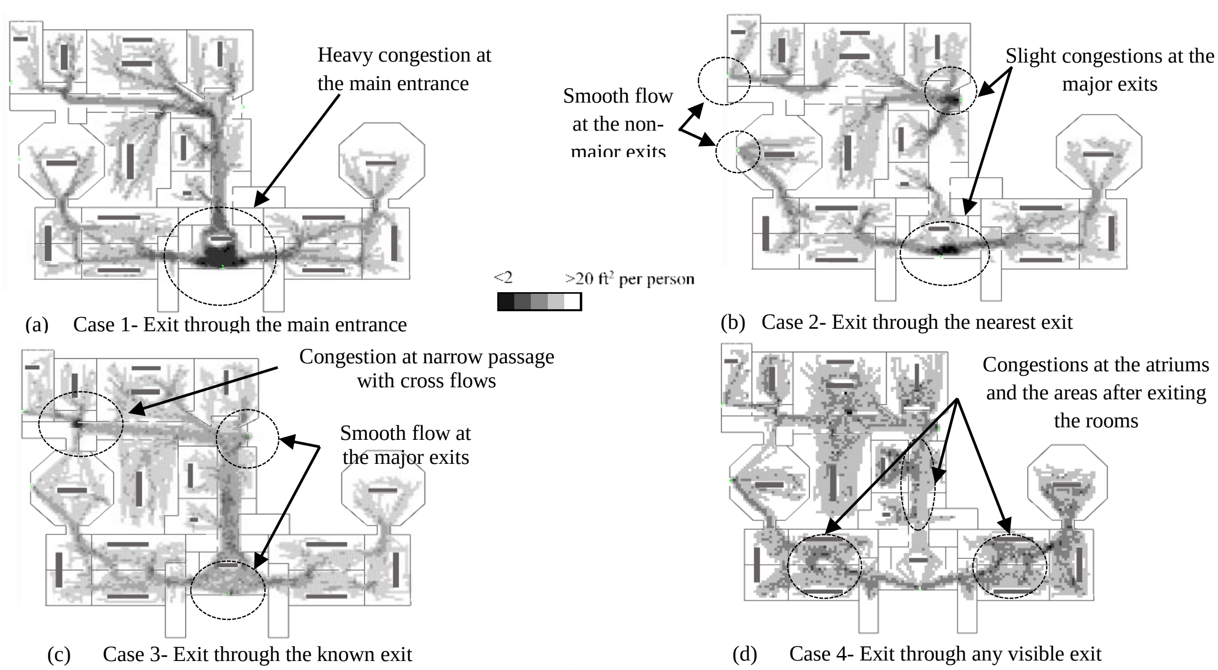
[1] Results are averaged over 10 runs, with +/- one standard deviation

Table 2: Results assuming different exiting strategies

Table 2 summarizes the results for the four cases, assuming all agents act as an individual (without group affiliation) and exhibit the same exiting behavior. The average computation time for each simulation run is 4 minutes 30 seconds using an Intel Core i5-650 machine at 3.2 GHz.

The result from Cases 1 and 2 are consistent with the common understanding of crowds – occupants who are familiar with the building evacuate faster than occupants who just use a single exit. From the simulation result, we explore how familiarity leads to faster evacuation. In Case 1, as all the agents travel to the main entrance, high levels of congestion occur at the main entrance, as shown in Figure 5a, which leads to long egress times. In Case 2, when all agents exit through the nearest exit, the distance travelled for each agent is shorter, and as they navigate to different exits, much less congestion occurs at the exits (by comparing the crowd density at the exits in Figure 5b to that in Figure 5a). In this setting, escaping through the nearest exit is the most efficient exiting strategy.

By including the spatial cognitive ability and the visual sensing capability of the agents, we observe some interesting results in the egress patterns and performances. In Case 3 wherein all agents "know" and follow their familiar exit, the evacuation time is only slightly less than that for Case 1, implying that following familiar exits may well be as inefficient as congestion at the main entrance. In this case, the inefficiency and prolonged egress time are due to the long distances for some agents to travel from their initial position to their familiar exit. As shown in Figure 5c, congestion due to cross flow at narrow corridors occurs. For Case 4, when agents follow visual cues as a guide, evacuation appears to be a more random process as reflected from the large standard deviation (shown in Table 2) on egress time. This situation may occur when the occupants are unfamiliar with the building and have to explore the building. The prolonged egress time is due to the time spent exploring the space without predefined routes before the agents "see" an exit for evacuation. Congestion occurs at the connections between the rooms and main corridors and the two atriums (as indicated by the arrows in Figure 5d), instead of the exits. As depicted in Figure 5, the agents' knowledge of the building and visual capability can affect the choice of egress route, and thus lead to different flow patterns. The higher congestion level at the atriums also suggests that signage should be placed at the atriums to provide navigation guidance to the occupants who are unfamiliar with the buildings.



(a) Case 1- Exit through the main entrance

(b) Case 2- Exit through the nearest exit

(c) Case 3- Exit through the known exit

(d) Case 4- Exit through any visible exit

Figure 5: Density patterns of resulted from different exiting strategies

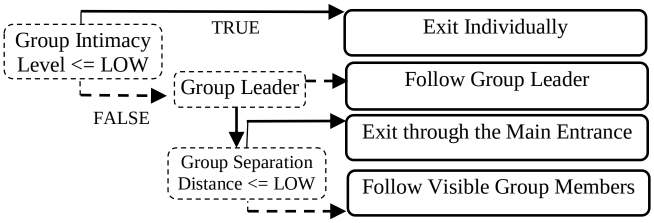


Figure 6: Group exiting behavioral decision tree, BEHAVIOR [Exiting with Group]

4.2. Effects of social group

Studies have shown that people in the same group tend to evacuate as a group and escape through the same exit (Aguirre et al. 2011). The social structure and norm persist and guide the evacuation behaviors. As depicted in Figure 6, we simulate the social effect of the group behavior by constructing a decision tree that takes into consideration of group-level parameters: "group intimacy level", "group leader(s)", and "group separation distance". In this study, agents are assigned to affiliate with a group with size ranging from one to six, and each group has one default group leader. Group members start in the same room and are visible to each other at the beginning of the simulations. We vary the value of **group intimacy level** of the groups to test the effect of group behaviors. A high intimacy level group represents a closely-related group, like family or couple, while a low intimacy group represents a loosely-related group, such as co-workers. In the baseline model, Case 1, all groups are defined to have a low group intimacy level, in which all agents are loosely affiliated to their group and choose to exit individually through either the main entrance or a visible exit. In Case 2 and Case 3, a high group intimacy level is assigned to 50% and 100% of the groups, respectively. Table 3 summarizes the simulation results for the three cases with different group assumptions. The average computation time for each simulation run is 5 minutes 45 seconds using an Intel Core i5-650 machine at 3.2 GHz.

Group intimacy level assumption	Egress time (s)[1]	Exit usage			
		Main	Left Exit	Right Exit	Cafe Exit
1 - low intimacy; exit Individually	120 +/- 15	58%	7%	29%	6%
2 - 50% high intimacy	140 +/- 16.5	59%	6%	28%	7%
3 - 100% high intimacy	152 +/- 18	58%	6%	28%	8%

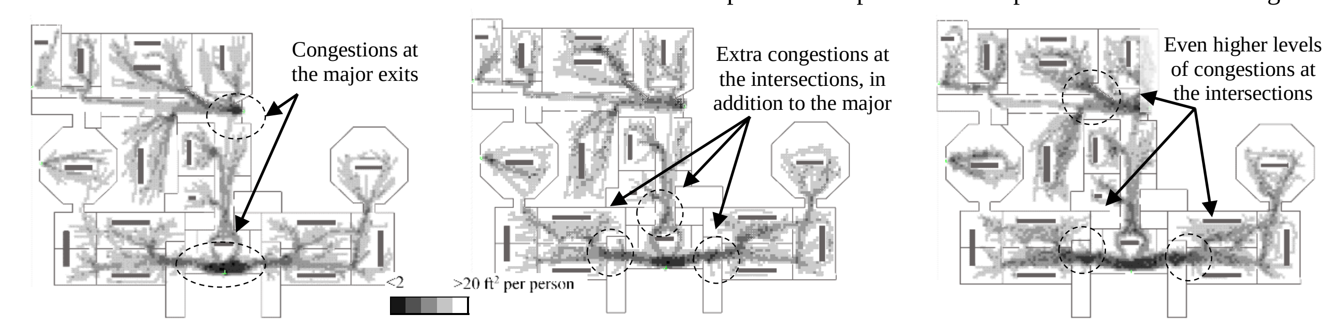
[1]Results are averaged over 10 runs, with +/- one standard deviation

Table 3: Results assuming different group traits of the agent population

As shown in the simulation results, we found that the group behaviors can have significant effects on the evacuation patterns and performances. In Case 1, as shown in Figure 7a, congestions occur at the exits where the agents exhibit individual behaviors exiting the building. In Case 2 and Case 3, as shown in Figure 7b and 7c, the crowding is less serious at the exits, but high crowd densities are observed at the intersections of corridors and at the locations connecting the exhibition halls to the corridor. The result also shows that group behaviors have a prolonging effect on evacuation. The effects on congestion patterns and lengthened evacuation are due to the waiting time for group members as well as the fact that agents may take a detour in order to move closer to the group, therefore causing congestion at the corridors and the intersections as they leave the exhibition halls.

5. DISCUSSION

To realistically predict the building egress performance, designers and managers of the building need to consider the building geometry unique to each building, and more importantly, the occupants' individual and social characteristics. With the proper representations of space and occupants, SAFEgress allows users to assume a wide range of combinations of occupant populations and behaviors in a convenient and flexible manner. Agents' behaviors are modeled as different behavioral decision trees, which represent the plausible occupant behaviors in emergencies.



(a) Case 1- low intimacy groups (exit individually) (b) Case 2 -50% of group with high intimacy (c) Case 3 -all groups with high intimacy

Figure 7: Density patterns of Case 1, 2, and 3 assuming different group intimacy levels

Sensitivity analysis on different agents' static attributes can be conducted to identify and assess the impacts of social factors in different physical and environmental settings, like the case studies we present in this paper. This kind of analysis can give insights to architects, building designers, and facility managers to design user-centric safe egress and improve emergency procedures and training programs.

Studies of past emergency events emphasize for the needs of incorporating social behaviors in egress simulation. Through the case studies in this paper, we show that the inclusion of a social parameter like group intimacy significantly alters the behavior of the agents during evacuation. By embedding individuals into groups, our model adds flexibility to established plausible occupant models based on the spreading of information within social groups and crowds and the role of authorities (Rydgren 2009; Hoogendoorn et al. 2010; Kuligowski 2011). The described platform represents a step forward toward incorporating social interactions into engineering models that capture human behaviors.

Based on the synthesis of social studies of past emergencies, we conjecture that SAFEgress is a reasonable and sufficient platform to model a range of evacuation behaviors of occupants. Given the flexibility of framework, reasonable initial assumptions of the occupants' characteristics (such as demographics, how familiar the occupants are with the building, and their preference to use different exits) are important in order to generate realistic and relevant simulation results. We continue to gather feedback on the framework from our industry collaborators. Moreover, as a part of our on-going validation effort, we establish benchmark scenarios based on modeling guidelines and real-life data (Chu and Law 2013; videos: eig.stanford.edu/SAFEgress).

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References

Aguirre, B. E., Torres, M. R., Gill, K. B., and Hotchkiss, H. L. (2011). "Normative collective behavior in the station building fire," *Social Science Quarterly*, 92(1), 100–118.

Chu, M. L., and Law, K. H. (2013), "A Computational Framework Incorporating Human Behaviors for Egress Simulations, " *ASCE Journal of Computing in Civil Engineering*, 27(6), 699–707.

Drury, J., Cocking, C., and Reicher, S. (2009). "Everyone for themselves? A comparative study of crowd solidarity among emergency survivors," *British Journal of Social Psychology*, 48, 487–506.

Gärling, T., Böök, A., and Lindberg, E. (1986). "Spatial orientation and wayfinding in the designed environment: A conceptual analysis and some suggestions for post-occupancy evaluation," *Journal of Architectural and Planning Research*, Vol 3(1), 55-64.

Hoogendoorn, M., Treur, J., Wal, C. v. d., and Wissen, A. v. (2010). "An agent-based model for the interplay of information and emotion in social diffusion," *Proceedings of: Web Intelligence and Intelligent Agent Technology (WI-IAT)*, 439–444.

Kneidl, A., Hartmann, D., and Borrmann, A. (2013). "A hybrid multi-scale approach for simulation of pedestrian dynamics." *Transportation Research Part C: Emerging Technologies*, available online 18 April 2013, http://dx.doi.org/10.1016/j.trc.2013.03.005

Kuligowski E. D. (2011). *Terror defeated: occupant sensemaking, decision-making and protective action in the 2001 World Trade Center disaster*, Ph.D. Thesis, University of Colorado, Boulder.

Lindell, M. K., and Perry, R. W. (2011). "The Protective Action Decision Model: Theoretical Modifications and Additional Evidence," *Risk Analysis*, 32(4), 616-632.

Macy M, and Flache A. (2009). "Social dynamics from the bottom up: Agent-based models of social interaction," In: Hedström P, Bearman P (eds) *The Oxford Handbook of Analytical Sociology*. Oxford: Oxford University Press, 245–268.

Mawson, A. R. (2005). "Understanding mass panic and other collective responses to threat and disaster," *Psychiatry*, 68, 95–113.

McPhail, C. (1991). *The Myth of the Madding Crowd*, Aldine de Gruyter, New York.

Musse, S. R., and Thalmann, D. (2001). "Hierarchical model for real time simulation of virtual human crowds," *IEEE Transactions on Visualization and Computer Graphics*, 7, 152-164.

Sime, J. D. (1983). "Affiliative behavior during escape to building exits," *Journal of Environmental Psychology*, 3(1), 21–41.

Turner, A., and Penn, A. (2002). Encoding natural movement as an agent-based system: an investigation into human pedestrian behaviour in the built environment. *Environment and Planning B: Planning and Design*, 29(4), 473-490.

Pan, X. (2006). *Computational modeling of human and social behavior for emergency egress analysis*, Ph.D. Thesis, Stanford University.

Rydgren, J. (2009). "Beliefs." In: Hedström P, Bearman P (eds) *The Oxford Handbook of Analytical Sociology*. Oxford: Oxford University Press, 72–93.

Veeraswamy, A., Lawrence, P., and Galea, E. (2009). "Implementation of cognitive mapping, spatial representation and wayfinding behaviours of people within evacuation modelling tools," *2009 Human Behavior in Fire Symposium*. Available at: http://gala.gre.ac.uk/1297/