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CIFE Technical Report #TR216
November 2013

STANFORD UNIVERSITY

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

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November 19, 2013

Abstract

Studies of past emergency events have revealed that occupants' behaviors, local geometry, and environmental constraints affect crowd movement and govern the evacuation. In addition to comply with code and standards, building designers need to take into consideration the occupants' social characteristics and the unique layout of the buildings to design occupant-centric egress systems. This paper describes an agent-based egress simulation tool, SAFEgress, which incorporates human and social behaviors during emergencies. Simulation results on two scenarios are presented. The first scenario illustrates the effects of exit strategies adopted by the occupants on the evacuation. The second scenario shows the influence of social group behavior on evacuation. By assuming different occupants' behaviors using the SAFEgress prototype, engineers, designers, and facility managers can study the important human factors on 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 needs 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 and evacuation patterns. Simulation results from our case studies indicate that occupants' exit strategies and social group behavior among social groups can lead to very different congestion patterns and evacuation times. This kind of analysis can be critical in many applications. For example, architects can design occupant-centric floor layouts and ensure that the safe egress design can handle a broad range of occupant behaviors. The simulation results can also help design and placement of exit signage to guide evacuation. Last but not least, 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 (McPhail, 1991) and the pro social theory (Aguirre et al., 2011) suggest that people continue to maintain group structure and behave in a pro social manner during emergencies. 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; Hoogendoorn et al. 2010).

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, 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; Turner and Penn, 2002). 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. 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 (Turner and Penn, 2002). 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 (Zheng, Zhong and Liu, 2007). 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; Turner and Penn, 2002). 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 at. 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 evacuees use their perceptions to guide their navigation

(Gärling et al., 1986; Turner and Penn, 2002). With proper spatial representation of the environment, Turner and Penn (2002) have shown that natural human movement can be reproduced in simulations without the needs to assign the agents with extra information about the location of destination and 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 (Musse and Thalmann, 2001) 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. MASSEgress (Pan, 2006) gauges the agents' urgency level and invokes a particular behavior implemented using decision tree to determine the navigation target. 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' behaviors.

3. SAFEGRESS

SAFEgress is an agent-based model designed to simulate human and social behaviors as well as emerging crowd behaviors during evacuations. Figure 1 depicts the system architecture of SAFEgress. The key modules of the framework are the Global Database, Crowd Simulation Engine, and Agent Behavior Models Database and the supporting sub-modules include Situation Data Input Engine, Geometry Engine, Event Recorder, Population Generator, and Visualizer.

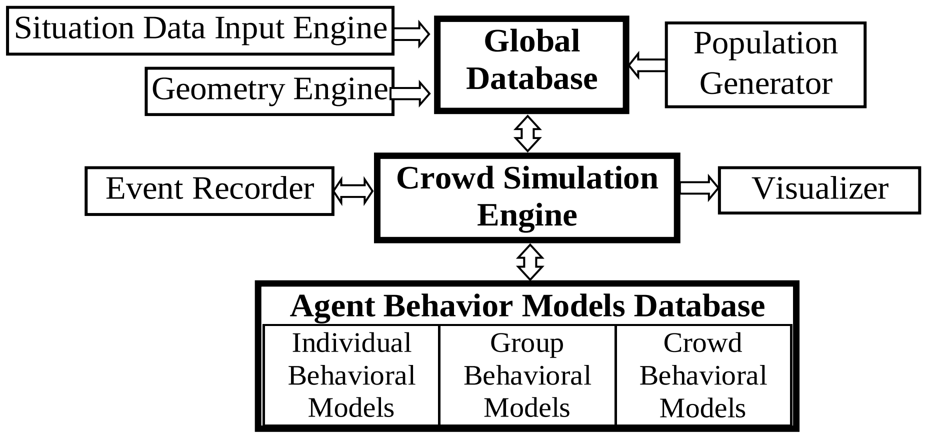


Figure 1: System architecture of SAFEgress

- 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 behavioral models, new models can be added by users to investigate different behaviors and different scenarios.

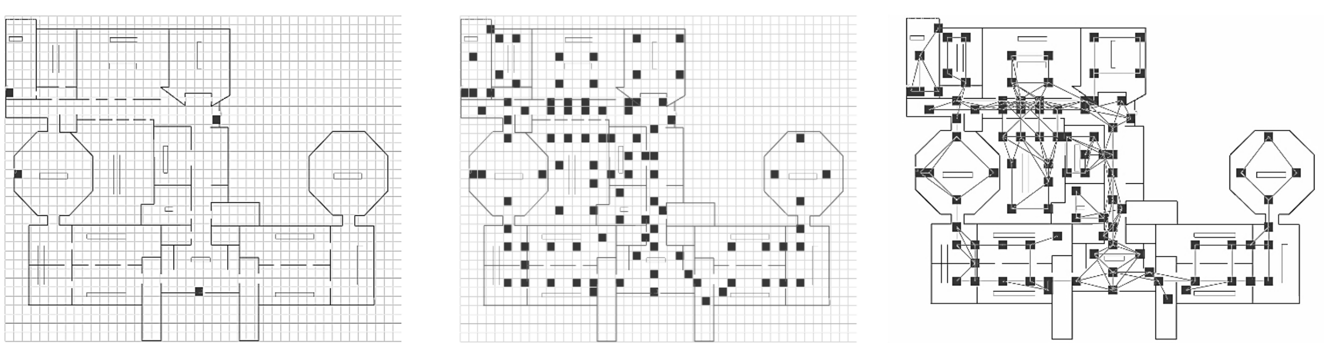
- Details of the system have been described by Chu and Law (2013). In particular, some algorithms (proximity and visibility computation) have been carefully designed to allow the platform to handle a large number of agents.

3.1. Spatial representation of the environment

A floor space includes physical obstacles, such 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 (Gärling et al., 1986; Turner and Penn, 2002), the choice of next navigation direction is motivated by the subsequent movements to get closer to the final destinations. To facilitate this navigation decision process, a navigation map is constructed, which represents the obstacle-free space. This map is later used by SAFEgress to speed up 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 first discretized into square cells to form a 2-D grid for computational efficiency. The cells with the building features (such as exits, doors, and windows) are identified to



(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

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 locally largest 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 a navigation points that are visible from the agent's 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 the navigation point that is near the familiar

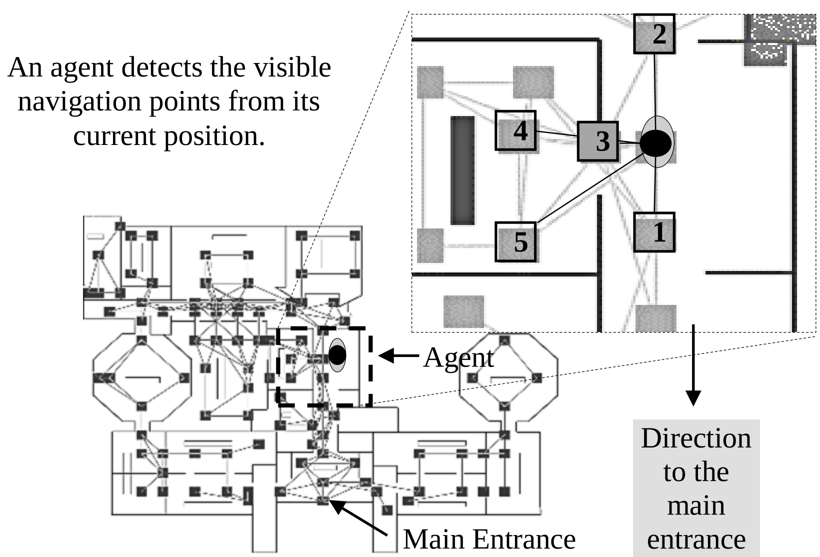


Figure 3: Illustration of visible navigation points given the agent's position

exit. In Figure 3, the agent, with knowledge of the main entrance as its familiar exit, 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 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 generating a natural navigation trajectory when an agent has no prior knowledge of the environment and attempts 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 users can do with SAFEgress. To make this choice we relied mainly of published work (See Section 2). The agent 1attributes, 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**:

- At the individual level, an agent has a **physical profile**, a **level of familiarity** (Mawson, 2005) with the building, and prior **known exits** (Sime, 1983) of at least one that the agent enters.
- At the group level, social groups are defined by the following attributes (Aguirre et. al., 2011, McPhail, 1991): a **group leader** (if any), 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** (Drury et. al., 2009), stating the likelihood to exhibit deference behavior. 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 personal, 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 (Lindell and Perry, 2011; Kuligowski, 2011) about emergency occupant behaviors, a five-stage process model, perception – interpretation – decision-making – execution – memorization, is executed to update the agents' behaviors. Each stage may lead to changes in parameter values for 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). They also detect the **visible group members**, and **neighboring agents** within a certain radius.

Table 1: Agents' static and dynamic attributes

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.

- 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.
- 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.
- 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 in this cycle and update the **spatial knowledge** about their previous locations and visited areas.

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

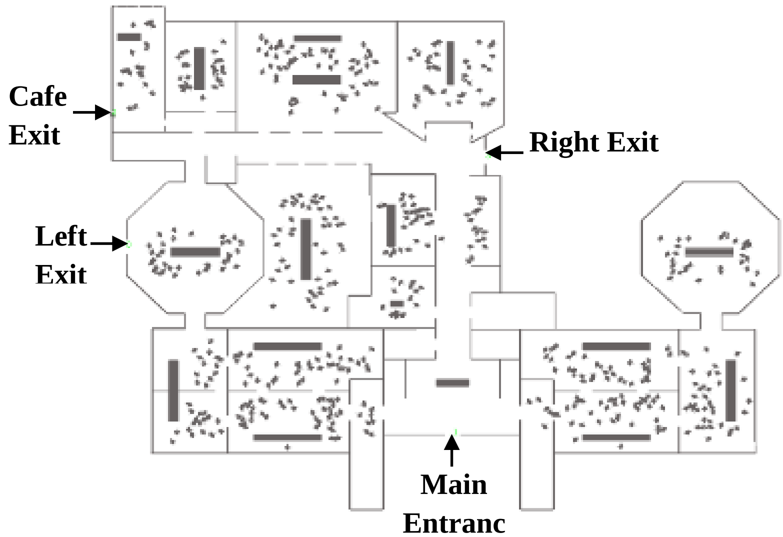


Figure 4: Geometry of the building and initial locations of 550 agents

4. CASE STUDIES

In this section, we study the impacts of different behavioral assumptions on egress performance. 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. Assuming an occupancy load of $30ft^2$ per person in exhibition areas, 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 in an emergency situation. 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 (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. In this study, 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.

Table 2 summarizes the results of each case, 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 machines at 3.2 GHz.

Table 2: Results of simulation runs assuming different exiting strategies adopted by the agent population

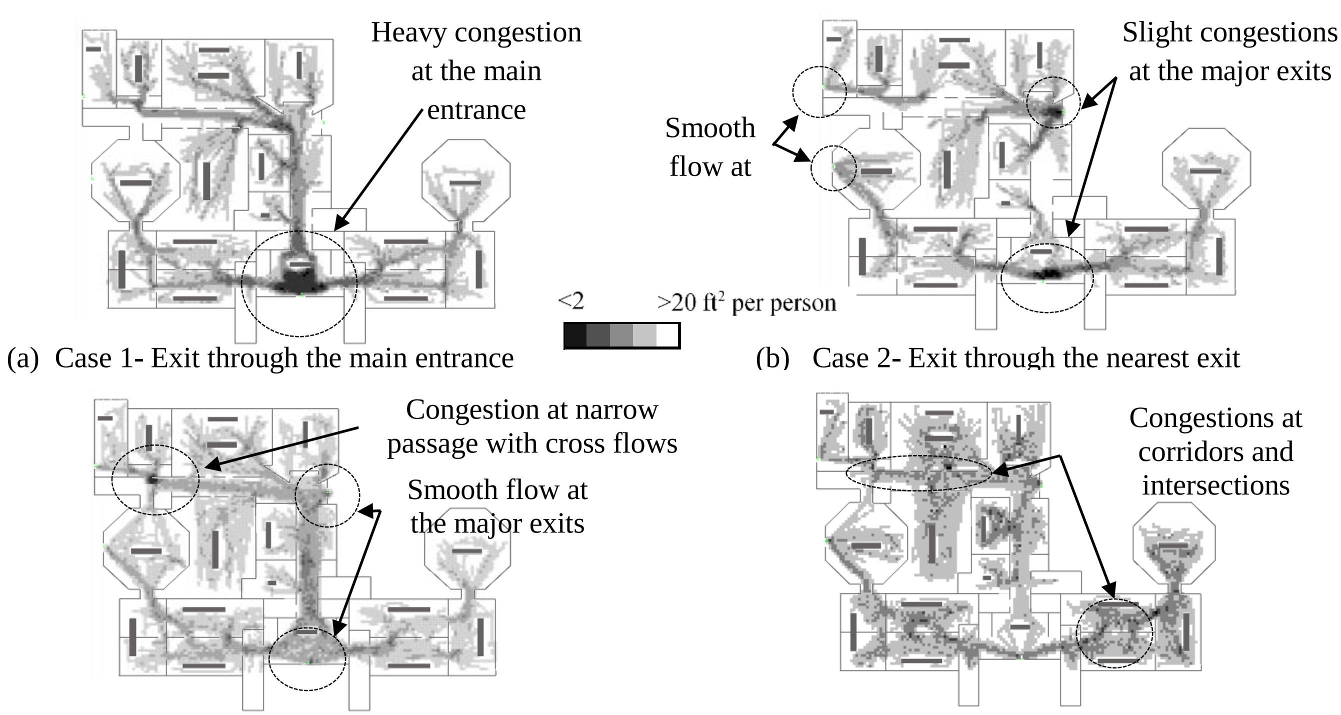
Agent exiting behavior	**Egress time (s)**[1]	**Exit usage**				**Max. retention time (s)**[2]
		Main	Left Exit	Right Exit	Cafe Exit	
1-Main Entrance	200 +/- 5	100%	-	-	-	62
2-Nearest Exit	84 +/- 4.5	39%	16%	31%	14%	30
3-Known Exit	180 +/- 10	25%	25%	25%	25%	30
4-Visible Exit	166 +/- 22.6	30%	30%	30%	10%	30

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

[2] Maximum retention time measures the maximum time that an agent remains within an area of $1m^2$

The result from Case 1 and Case 2 generated by SAFEgress are consistent with the common understanding of crowds. In Case 1, there are high level of congestion at the main entrance, as shown in Figure 5a which leads to long retention and egress times. In Case 2, when all agents exit through the nearest exit, the evacuation time is significantly shorter and there is less congestion at the exits (by comparing the crowd density at the exits in Figure 5b to that in Figure 5a). Escaping through the nearest exit is often considered as 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



(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

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. As shown in Figure 5d congestion occurs along the corridor and intersections than at 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.

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. We vary the parameter value of the attribute "group intimacy level" of the group 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.

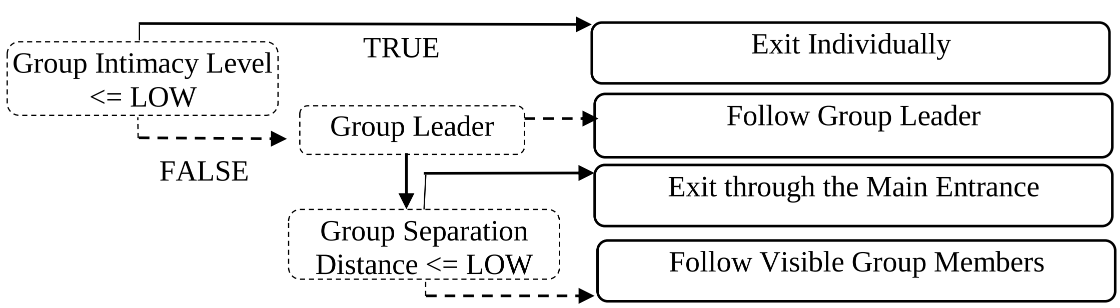
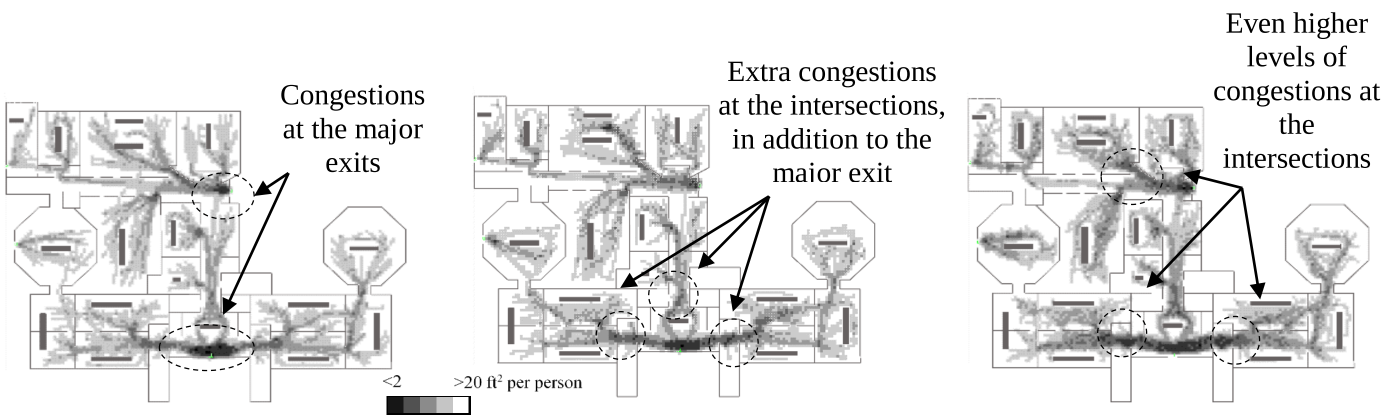


Figure 6: Group exiting behavioral decision tree, BEHAVIOR [Exiting with Group]



(a) Case 1- low intimacy among groups; exit individually

(b) Case 2 -50% of group with high intimacy

(c) Case 3- all groups with high intimacy

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

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 machines at 3.2 GHz.

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

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

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 simulation runs, with +/- one standard deviation

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 and 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 of 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 and their relationships with the building. Our framework 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 different plausible occupant behaviors in emergencies. Sensitivity analysis on different simulation parameters can be conducted to identify and assess the impacts of important 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.

Our simulation results confirm the needs of incorporating social behaviors in egress simulation. We show that the inclusion of a social parameter like group intimacy significantly alters the behavior of the agents in scenarios of emergency. 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 (Rydgren, 2009, Hoogendoorn et al. 2010) and the role of authorities (Kuligowski 2011). The described platform represents a step forward toward incorporating social science knowledge of social interactions into engineering models that capture human behaviors.

Acknowledgements

This research is partially supported by the Center for Integrated Facility Engineering at Stanford University. The first author is also supported by the Croucher Foundation Scholarship and Stanford's Leavell Fellowship.

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