Computational Framework Incorporating Human Behaviors for Egress Simulations

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Abstract: Studies of past emergency events indicate that evacuating occupants often exhibit social behaviors that affect the evacuation process. This paper describes a multiagent-based simulation framework that enables the modeling of social behaviors during evacuation. Each agent is modeled using a three-level representation that allows users to incorporate individual, group, and crowd behavioral rules in the simulation. The authors describe the basic framework and the implementation of several social behaviors, which are based on recent social science studies about human responses in emergency situations. Simulation results from the prototype reveal that social behaviors exhibited by an evacuating crowd can have an effect on the overall egress time and pattern. By representing the virtual agents and the environment specific to an evacuation situation, the research addresses the issues in incorporating human and social behaviors in egress simulations. **DOI:** 10.1061/(ASCE)CP.1943-5487.0000313. *© 2013 American Society of Civil Engineers.*

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Introduction

Emergency evacuation (egress) is an important aspect of facility design. Safe egress is particularly crucial in today's facilities, such as office towers and shopping malls, with high occupant capacities and complex floor layouts. Besides design standards and codes (ICBO 2009), computer simulations are often used to assess egress performance. Although many simulation tools are available, there is still a need to "improve the realism and accuracy of crowd behaviors and movement, in addition to improving visual aesthetics (in existing simulation tools)" (Challenger et al. 2009). The lack of realistic social behavior in current simulation tools has been echoed by authorities in fire engineering and social science (Aguirre et al. 2011b; Santos and Aguirre 2004). This research aims to develop an egress simulation environment called Social Agent for Egress Simulation (SAFEgress), which can incorporate different social behavioral theories related to crowd dynamics and emergency evacuations. The framework is designed to facilitate implementing different agent profiles and behavioral rules for diverse populations. This paper describes the framework and the features currently incorporated in the prototype. Through implementing several well-studied social behaviors, the authors study the effects of such social behaviors on an evacuation scenario based on the fire that destroyed the Station nightclub in Warwick, Rhode Island (Grosshandler et al. 2005).

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Literature Review

Social Behaviors in Emergency Situations

Social scientists have been studying human behaviors in emergency situations and have developed a variety of theories about crowd behaviors in such situations. A comprehensive review of various social theories about crowd behaviors was recently reported by Challenger et al. (2009). Examples of prevalent theories on crowd behaviors include the panic theory (Le Bon 1960), the decision-making theory (Mintz 1951), the normative theory (Aguirre et al. 2011a; McPhail 1991; Turner and Killian 1987), the affiliative theory (Mawson 2005; Sime 1983), and the place script theory (Donald and Canter 1990). Earlier theories in crowd behaviors suggest that people tend to behave individually and show nonadaptive behaviors in dangerous situations. For example, panic theory suggests that people in an emergency situation become panicked and act irrationally. In contrast, the decision-making theory argues that people act rationally to achieve a better outcome in the situation. Recent theories emphasize the sociality of the crowd (such as preexisting social relationships or emerging identities during an emergency situation) to explain the occupants' reactions in past accidents. For example, the normative theory stresses that the same social rules and roles that govern human behavior in everyday life are also applicable in an emergency situation. The affiliative theory and place script theory further emphasize the importance of past experiences, social relationships, and roles on people's reactions in emergencies. Although there is no unified theory that fully explains human behavior in different emergency situations, recent theories suggest that evacuating crowds retain their sociality and behave in a socially structured manner.

Different social theories explain human behaviors in emergencies using different mechanisms and variables. In order to study different social theories systematically and incorporate them into a computational framework, the authors classify the theories into

three behavior categories; namely, individual, group, and crowd. These categories are characterized as follows:

- Individual: Individual behaviors are often the result of *personal knowledge and experience*. In an emergency situation, individuals refer to their past experiences and knowledge to decide on their actions. For example, the affiliative theory and place script theory examine individuals' behaviors in emergencies based on their knowledge and familiarity with the place. According to the affiliative theory, people's emergency responses depend on their familiarity with the surroundings and the knowledge of the severity of the situation (Mawson 2005; Sime 1983). When individuals are close to their familiar figures or located in familiar places with the perception of low physical danger, people tend to downplay the seriousness of the situation and delay evacuation. Otherwise, even mild environmental threats could cause people to flee in search of familiar objects. The place script theory highlights the importance of a normative *script* that guides people's reactions to emergency events (Donald and Canter 1990). The script may include people's knowledge of their roles, the daily norms of the place, and the environment. Generally speaking, these social theories suggest that individuals derive their actions based on personal knowledge, experience, perceptions, and routines.

- Group: Group behaviors depend on *group structure* and *group norms*. People often participate in mass gatherings with their social group. The social group has its own preexisting social structure (relations between group members) and group norms (expectations of each other's behavior). Several recent social theories examine the effect of groups on individuals during emergency situations. Examples of social theories on group effects are the emergent norm theory (Aguirre et al. 1998; McPhail 1991) and the pro-social theory (Aguirre et al. 2011a). The emergent norm theory suggests that people interact with their social group to assess the evolving situation and derive solutions collectively (McPhail 1991). Group characteristics, such as group size and the kind of relationship, are significant factors that affect the interaction and the emergence of a collective definition of the situation (Johnson et al. 1994; Kuligowski 2011). For example, enduring social relationships can facilitate the process of recognizing threats and initiating early evacuation (Aguirre et al. 1998). Furthermore, the pro social theory emphasizes the group process and the solidarity of a social group in an emergency situation. Based on their empirical study of the Station nightclub fire, Aguirre et al. (2011a) found that people put themselves at risk to search for others dear to them, even in a rapidly developing emergency situation. In other words, people continue to maintain their group structure and behave in a pro social manner during emergencies.

- Crowd: Crowd behaviors are emergent phenomena and often follow social norms. Mass gathering events (such as concerts and theme parks) typically compose of small groups and nonsocially bonded individuals. The interactions among the occupants can greatly affect their collective actions during emergencies. For example, social identity theory suggests that people have a tendency to categorize themselves into one or more *ingroups*, building their identities in part on their membership in the groups and enforcing boundaries with other groups (Drury et al. 2009). Increasing threats would intensify the sense of *we-ness* within the crowd, and the emerging collective identity motivates people's social behavior, such as mutual assistance among strangers. Studies of past accidents have shown that people exhibit altruistic behaviors among other people who are not socially bonded as they continue to respect social norms (Drury et al. 2009; Johnson et al. 1994). In addition, psychological

models of social diffusion indicate that people influence each other's behavior through the spreading of information and emotions (Hoogendoorn et al. 2010). Social identity theory and social diffusion theory suggest that people continue to interact with and influence other people, maintain their social awareness, and follow social norms in emergency situations.

As is evidenced from the selected prevailing social theories on human behaviors, social characteristics of individuals play an important role in determining their behaviors during emergencies. The authors conjecture that human behaviors in egress are influenced at three levels: individual experience, social group, and crowd interactions. The staged representation of social effects forms the basis of the design of this egress simulation framework.

Egress Simulation Models and Human Behavior Modeling

Different crowd modeling approaches can be classified according to the virtual representation of the building environment and the occupants. The three most common approaches are particle systems, cellular automata systems, and agent-based systems, which are characterized as follows:

- Particle systems consider each individual as a self-driven particle that is subject to social and physical forces. One example of this approach is the social force model (Helbing et al. 2000), which simulates evacuees' movement based on forces due to external factors and internal motivations. Moussaïd et al. (2011) extended the social force model by including visual information. Physical models derived from conservation laws of mass, momentum, and energy also have been developed to simulate crowd flow (Hoogendoorn and Bovy 2000).

- In cellular automata systems, the environment is divided into a uniform grid of discrete cells, representing floor areas, obstacles, areas occupied by people, or other attributes such as exits and doors. Individuals move to unoccupied neighboring cells based on defined rules. For example, Burstedde et al. (2001) developed a two-dimensional (2D) cellular automaton model that uses the static floor field (generated based on the physical floor geometry) and the dynamic floor field (updated based on the past locations of the pedestrians) to guide occupant movement in the simulation. Being computationally efficient, many simulation systems, such as Simulex (Thompson and Marchant 1995), are implemented using this approach. However, as noted by Tsai et al. (2011), the cellular automata approach lacks the flexibility in simulating heterogeneous populations and restricts occupants' spatial movement.

- Agent-based systems model the crowd as a collection of autonomous entities known as *agents*, which represent the occupants. It allows emergent phenomena as a result of interactions among the virtual agents. Many egress models recently have adopted this approach and proposed different representations of the spatial environment and the agents. One common way of representing the spatial environment is dividing the space into a 2D array of cells, with each cell containing up to a certain number of agents. The agent-based models developed by Lin et al. (2010), as well as buildingEXODUS (Galea et al. 1998), are examples of models that adopt a grid-based representation. While the grid-based spatial representation benefits from its computational efficiency, similar to the cellular automata approach, the representation limits an agent's spatial movements and can potentially show an unnatural checkerboard pattern when crowd density is high. Another approach is to represent the spatial environment as a continuous space that allows agents to navigate naturally on a continuous plane while considering

constraints imposed by the physical geometry of the building. Examples of continuous space representation are the HiDAC model (Durupinar et al. 2011), which parameterizes virtual agents based on individual personalities in order to mimic human behaviors in normal and panic situations, and ViCrowd (Musse and Thalmann 2001), which simulates virtual crowds with user-specified or default behavioral rules. The simulation framework uses continuous spatial representation, which allows a wider array of locomotions of the agents and the simulation of high-density crowd scenarios, such as overcrowding and pushing at exits (Aguirre et al. 2011a).

As noted by Kuligowski and Peacock (2005), many computational tools for egress simulation are available; however, human and crowd behaviors are often ignored and group effects on evacuation pattern are seldom explored (Challenger et al. 2009; Aguirre et al. 2011b). Only recently have efforts been made to incorporate social behaviors into egress simulations. For example, Tsai et al. (2011) examined the effects of exit knowledge, families, and emotional contagion on evacuation. Similarly, Aguirre et al. (2011b) described an agent-based model that attempts to implement the pro social model in simulating emergency evacuations. Features such as the leader and followers within a group have been used to simulate populations at a group level and observe emergent patterns as a result of social relationships.

As already discussed, most egress simulations have focused on the context of individuals. The effects of social groups and crowds on individual behaviors in emergencies and on the way people evacuate are often ignored. This research attempts to develop a flexible framework that allows the modeling of different behaviors, particularly group and crowd behaviors. This paper describes the representation of the virtual environment and the construction of a virtual agent. Users can define and select different behavioral models, which relate an individual agent to its personal traits, its social affiliations, and the characteristics of the surrounding crowd in different emergency situations.

Computational Simulation Framework for Modeling Social Behaviors

SAFEgress extends a multiagent-based simulation framework called MASSEgress (Pan 2006), which is designed to model human and social behaviors in emergency evacuations. In the following sections, this paper first provides an overview of the SAFEgress framework and describe each major component of the system. It then discusses the parameters used to model human behaviors in egress and the methodology used to model occupants' behaviors in an emergency situation.

System Architecture

Fig. 1 schematically depicts the system architecture of the multi-agent-based simulation framework. The Global Database, Crowd Simulation Engine, and Agent Behavior Models Database constitute the key modules of the framework and are supported by a set of submodules (namely, the Population Generator, the Geometric Engine, the Situation Data Input Engine, the Event Recorder, and the Visualizer). The submodules are characterized as follows:

- The Population Generator receives input assumptions of the agent population and generates the agents using physical (such as age, mobility, and physical size) and behavioral profiles. This module also can generate both predefined and random social groups to study different human and social behaviors.
- The Geometric Engine maintains spatial information, such as the physical geometry, exit signs, and openings in a facility.
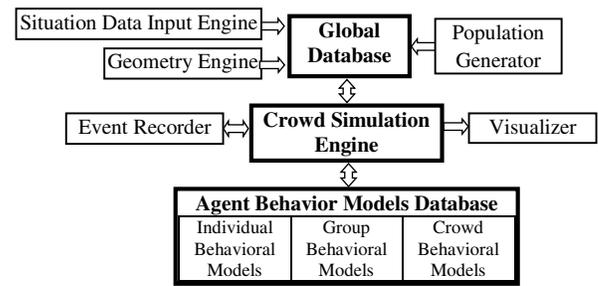

Fig. 1. Overall architecture of the framework

A virtual three-dimensional (3D) model is built based on this spatial information and is used for collision avoidance and agents' perceptions, as well as visualizing a simulation.
- The Situation Data Input Engine contains the properties of the emergency cues and threats, such as fire alarms, smoke, and fire, that the virtual agents perceive during the simulation.
- The Global Database stores all the information about the agent population, the physical geometries, and the status of emergency situations. It maintains the state information (such as mental states, behavioral decisions, and locations) about the agents.
- The Agent Behavior Models Database contains the individual, group, and crowd behavioral models. Apart from default behavioral models, new models can be created by users to investigate a range of behaviors under different scenarios.
- The Crowd Simulation Engine is the key module of the system. It 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 Visualizer.
- The Event Recorder stores the simulation results at each time step for playback. The results can be retrieved for further analysis, such as identifying congestion areas and exit usages. The events captured also can be used to compare with known and archived scenarios.
- The Visualizer, currently implemented using OpenGL, receives the positions of agents and then dynamically generates and displays simulation results as 2D or 3D visual images.

The modular simulation framework allows the investigation of crowd dynamics and incorporation of different behavioral models. Diverse populations of individuals and groups can be modeled, and emergent collective behaviors can be simulated.

Agent Representation

In the simulation system, each individual is modeled as an autonomous agent who interacts with the dynamic environment and other agents. Agents are defined by parameters that specify their population types, experience profiles, group affiliations, and social traits prior to the simulation. These parameters (given in italics) are described as follows:
- Population type: Human individuals differ from each other by their physical traits and demographics. An agent is assigned to one of five categories: median, adult male, adult female, child, and elderly (Thompson and Marchant 1995). Each category represents one typical population and has distinct physical characteristics. The parameters used to define the agent are *age*, *gender*, *body size*, and *traveling speeds*.
- Individual experience profile: Past experience has a profound effect on people's evacuation actions (Donald and Canter 1990;

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Mawson 2005; Sime 1983). Relevant history is important to model the behaviors of humans more realistically. In the prototype, each agent is defined with an experience profile that describes its level of *familiarity with the building* prior to the event and the exits that the agent has knowledge of (*known exits*).

- Group membership: Individuals interact with their social groups to make decisions in emergencies (Aguirre et al. 1998, 2011a; McPhail 1991). This study models the group effect by assigning agents to affiliate with one or more social groups. Within the same *group affiliation*, the member agents share the same group profile, which describes the existence of a *group leader*, the kind of group relationship and the *group intimacy level* (for example, a family group will have a high *group intimacy level*), the *group-seeking* property that describes the willingness of the group to search for missing members, and the *group influence* between a group member and others in the same group.

- Social traits: Even in situations where individuals are not socially bonded to others in an emergency, they still will be influenced by their surrounding crowd and act in a social-orderly manner (Drury et al. 2009; Johnson et al. 1994). The authors define the social position of an agent with the parameter *social order*, which measures how other agents respect and exhibit deference to the individual agent. For example, other agents would give access priority to the agent with higher *social order* by allowing the individual agent to pass through, and therefore the agent with higher *social order* can navigate a congested area more easily. Moreover, in highly congested areas, occupants are impeded in their movement, and instead they are carried by the *supra force* due to the extreme density of the crowd (Aguirre et al. 2011a). The *navigation crowd density* parameter defines the maximum crowd density in which the agent can choose to execute individual and group behaviors. Once the surrounding crowd density exceeds the value of *navigation crowd density*, the agent considers only crowd behaviors.

An agent behavior model consists of three basic components: namely, perception, decision making, and execution, as illustrated in Fig. 2. At each step, an agent first updates its perceived environmental and crowd information through the sensors. The updated information includes (1) floor objects such as windows, door exit signs, and assembly locations (*visible objects*); (2) nearby agents within a certain radius (*neighboring agents*); (3) visible agents in the same social group (*visible group members*); and (4) locations and properties of cues and threats (*threat objects*), such as alarms and fire. At the decision-making stage, based on the perceived information and its traits, an agent chooses a behavior by reasoning through the rules of the behavioral models, which are classified into individual, group, and crowd behaviors, and selects the model(s) with all the conditions satisfied. Upon successively reasoning

the behavioral models at each level, the agent makes a decision on the behavior selected among the three levels and defines a specific target. At the execution level, the agent navigates toward the goal with low-level locomotion. Each agent can detect physical collisions and recognizes the location of the collision. Each potential move is assigned with a value based on the heuristics about the target distance, interpersonal distances, and obstacle avoidance. The agent then executes the optimal move associated with the largest value.

Implementing Social Behaviors in a Simulation Framework

This section describes the capability and the implemented behavioral models of the simulation framework. It has defined a set of behavior models that an agent can choose among during decision making, including escape (choosing the exit based on vision and experience profiles) and delay (exploring the floor and gathering information) at the individual level, group following/seeking and information sharing at the group level, and crowd following at the crowd level. In particular, the following discussion focuses on group and crowd behavioral models that consider social relationships and the presence of neighboring agents.

Group Following/Seeking

Studies have shown that people belonging to the same group tend to evacuate as a group and escape through the same exit, even during emergency situations (Aguirre et al. 2011b; Donald and Canter 1990; Mawson 2005; Sime 1983). Several typical group behaviors can be observed. For example, in a highly hierarchical group, people follow their group leader when making decisions and navigating the floor (Kuligowski 2011). Moreover, members tend to stay close to each other and navigate as a group (Aguirre et al. 2011a). When group members are missing, other members in the group likely attempt to search for the missing members (Sime 1983). Current implementation includes three typical group behaviors: namely, leader following, group member following, and group member seeking. Each of these behaviors is defined by a set of decision rules, as shown in Fig. 3.

To illustrate the capability of the framework to incorporate different behaviors, this paper discusses the implementation of one particular group behavior, group member seeking, and compares the simulation results with and without such behavioral assumptions. During evacuation, members belonging to a group, such as families and close friends, are concerned with the safety of other members and often seek and evacuate with the entire group, even when evacuation is urgent (Aguirre et al. 2011a; Sime 1983). The authors modeled this group member–seeking behavior with the parameters *group intimacy level* (measured as the desirable physical distance between members) and *group seeking* (measured as the desirable percentage of members that are visible). They assigned a high *group-intimacy* value (i.e., agents try to maintain close proximity with other group members) and a high *group-seeking* value (i.e., all group members have to be visible to the group) to model agent groups with close relationships. Fig. 4 shows a comparison of the evacuation patterns resulting from varying the *group-seeking* parameter. In this demonstration, it is assumed that all 50 agents on the simple floor plan evacuate without delay. Fig. 4(a) shows the movement pattern of agents without any group affiliation. The agents evacuate through their familiar exit (which is assumed to be the nearest exit to them) and the average evacuation time is 29 s (with a standard deviation of 2.0 s over 10 simulations). When the agents are affiliated to a group which has a high *group-seeking*
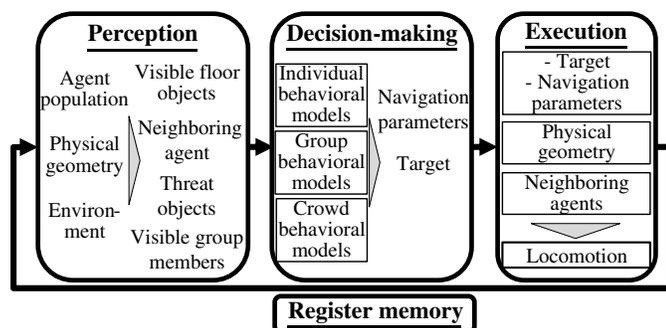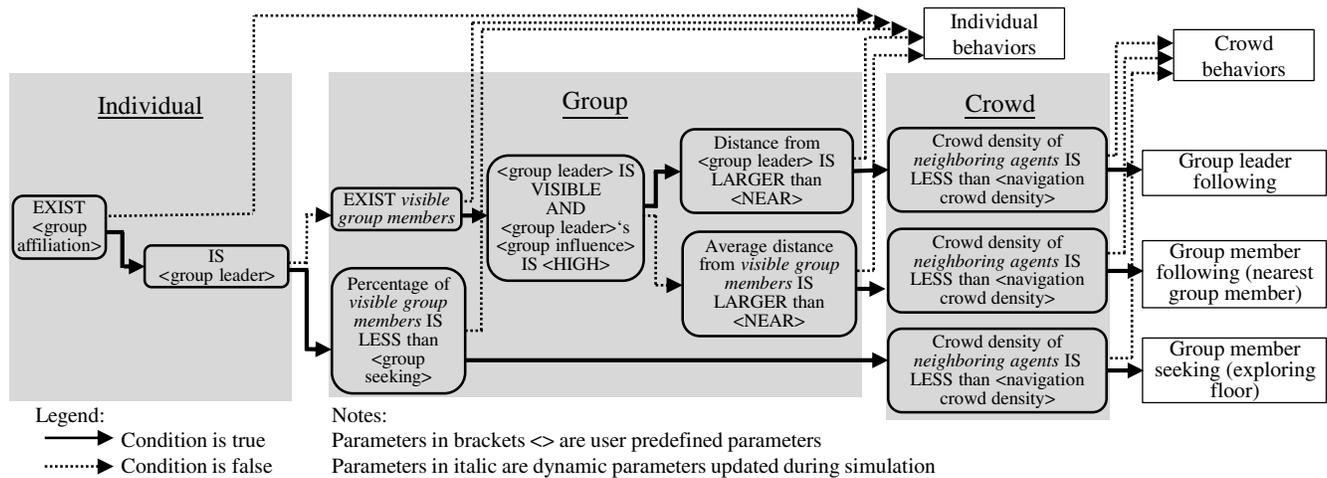
Fig. 2. Components of an agent behavior model
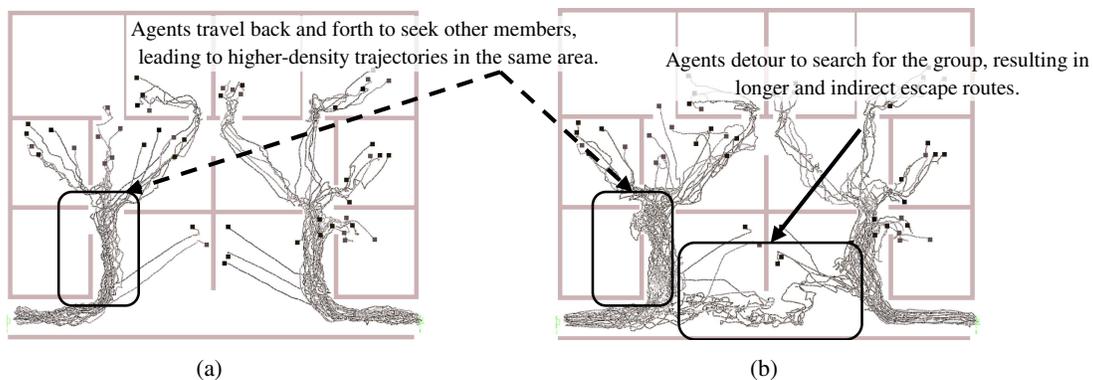
Fig. 3. Process of group behaviors

Fig. 4. Typical trajectories of 50 agents, with and without group affiliation; black squares indicate the initial position of 50 agents: (a) evacuation as individual via their familiar (nearest) exit; (b) evacuation with group affiliation

value, all members have to be visible to each other before the group evacuates. In this case, as shown in Fig. 4(b), agents pace back and forth (as indicated by the dotted arrows) and even take detours (as indicated by the solid arrow) as they seek other group members. Moreover, the average evacuation time increases to 39 s (with a standard deviation of 5.6 s for 10 simulations). The longer evacuation time in the group-seeking scenario is possibly caused by the longer and indirect routes taken by the agents as they search for the missing group members. By varying the *group-seeking* parameter, the level of desire of the group to look for other members can be altered. Similarly, by adjusting the *group intimacy level* of the social group, different types of groups with different levels of intention to follow other group members can be simulated. Group behaviors in egress simulation would affect the evacuation time and the escape routes, depending on the initial distribution of the group members and their relationships.

Group Member Information Sharing

Another commonly observed group behavior is the sharing of information among group members during emergency situations (Donald and Canter 1990; Kuligowski 2011; Turner and Killian 1987). While individuals in the same group may have different interpretations of a situation, their roles in the group

can influence others' evacuation decisions. The authors' group member information sharing model implements the group members' influence on an agent's exit route choice through the following process:

1. During the perception stage, an agent receives the information about the exit (*known exits*) from other group members (*visible group members*).
2. At the decision-making stage, the agent weights the different exit information shared by other members on the basis of each member's influence defined using the parameter *group influence*. The agent may or may not follow the direction to the most-weighted exit, depending on the influence of the information-sharing agent.
3. The agent executes the suitable locomotion toward the selected exit.

Fig. 5 shows an example of information sharing and group influence behavior. In this example, the group is initially separated from the leader, and the members intend to go to the nearest exit [Fig. 5(a)]. When the members see the leader, they receive the shared information from the leader about escaping through Exit B. The high influence of the group leader causes the members to change their exit route [Fig. 5(b)]. As the leader exits through Exit B, the rest of the group follows the leader's instruction to escape through the same exit, even though they are closer to Exit A
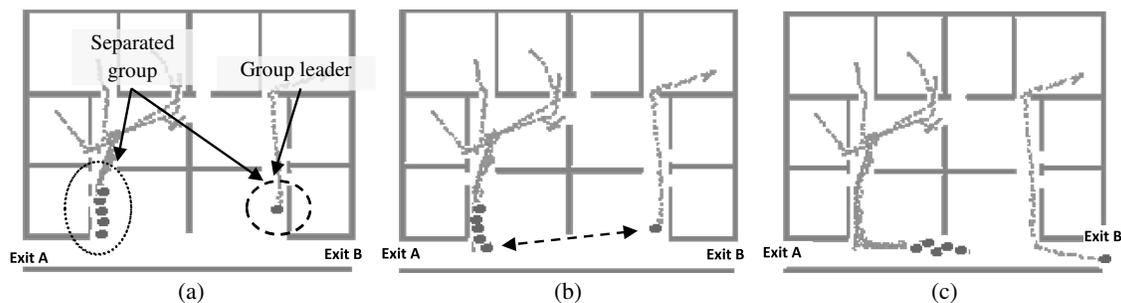
Fig. 5. Group influence process: (a) group leader prefers Exit B; (b) leader shares information with the group upon seeing them; (c) the rest of the group detours to Exit B

[Fig. 5(c)]. This scenario is consistent with real-life observations of group navigation, in that members in a group would choose their preferred exit by considering information from the leader and other group members, rather than simply selecting the nearest exit (Sime 1983; Johnson et al. 1994). That is, group affiliation can influence an agent's exit route choice, and hence the evacuation pattern and time.

Crowd Following

People tend to follow people ahead of them, which causes them to form *lanes* and leads to a bidirectional flow. Aguirre et al. (2011a) pointed out that in high-density crowds, an individual may not have the choice of navigating, but rather follows the general direction of the crowd. Norm-following behavior and lane-forming patterns are commonly observed. In the simulation, the agent updates its *neighboring agents* and their locations during the perception stage. When the crowd density (as calculated using the number of *neighboring agents*) is higher than *navigation crowd density*, instead of navigating to its own target, the agent follows an agent ahead and sets that person as the temporary target. Simulating crowd-following behavior is particularly important in areas where crowd density is very high, such as areas along a critical exit route.

Simulation Scenario Studying the Effects of Group Behaviors

In this section, the authors apply the prototype of SAFEgress to study the effects of group behavioral assumptions on the evacuation time and pattern using a historical event. The scenario is based on the Station nightclub fire, which occurred in Warwick, Rhode Island, in 2003. The Station nightclub fire, involving 452 people and causing 100 deaths, was one of the most lethal and well-studied fire accidents. A band accidentally ignited the polyurethane foam installed at the platform during the performance. The fire began at 11:08 p.m., and evacuation was delayed as patrons were engaged in different activities and were making sense of the situation. The band stopped performing 30 s after the fire started, and they started evacuating. The main entrance was clogged 1 min and 40 s later, and some people began to escape from the windows at the bar area and sunroom. The latest time recorded for an individual escaping from a window was 4 mins and 8 s after the initiation of the fire.

The floor plan of the nightclub (adapted from Grosshandler et al. 2005) is shown in Fig. 6. The following discussion first provides a comparison study between this simulation and the research results reported by the National Institute of Standards and Technology (NIST) (Grosshandler et al. 2005) and other researchers (Aguirre et al. 2011a, b). The baseline comparison, however, does
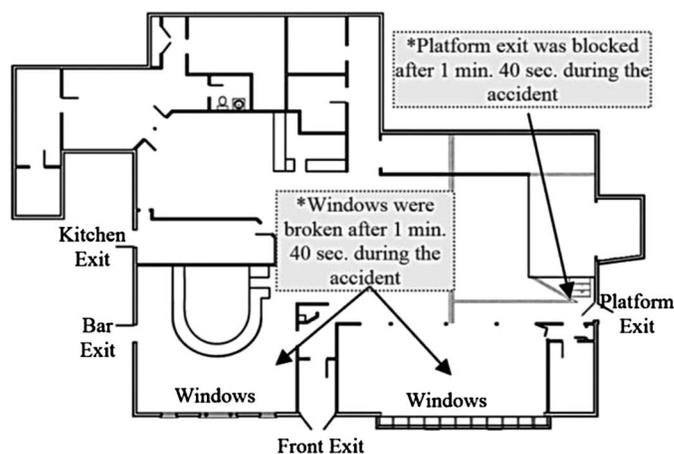
Fig. 6. Floor plan of the Station nightclub and the changes of geometry during the fire

not take into consideration the possible effects of group behaviors during the evacuation. The authors then examine qualitatively the effect of group behaviors with the simulation model.

Baseline Comparison Results

The purpose of establishing the base models is to test whether the results generated by the simulations are reasonable and to set the baseline for sensitivity analysis by comparing these results to the analyses conducted by the authorities. The first test compares the total evacuation time and exit usages of the model to the simulation results in the NIST report (Grosshandler et al. 2005). The second test compares the simulated evacuation pattern (exit usages) to the actual evacuation pattern (Aguirre et al. 2011b), taking into consideration the changes in the physical environment and the delayed response during the evacuation.

NIST Simulation Results Comparison

NIST conducted simulations of the Station nightclub building with two egress software, Simulex (Thompson and Marchant 1995) and buildingEXODUS (Galea et al. 1998). The simulation test conducted in this study is based on test scenario 1, as described in the NIST report (Grosshandler et al. 2005). The scenario involves 420 occupants who are to evacuate under normal circumstances (i.e., all occupants evacuate). The purpose is to compare the evacuation time and exit usages obtained from the simulations. The authors follow closely the model assumptions described in the NIST report (Grosshandler et al. 2005):

1. Agent population and characteristics
   - There are 420 agents, the maximum occupant capacity allowed for the facility.
   - The population consists of 60% men and 40% women.
   - Occupants' spatial distribution follows the patterns described in Appendix L of the NIST report.
   - Individual agents choose to escape through the nearest visible exit.
2. Evacuation delay
   - There is no preevacuation delay time (i.e., all occupants evacuate instantaneously).
3. Evacuation behavior
   - All agents exhibit individual behaviors and escape through the nearest exit.
4. Physical geometry change during simulations
   - No change of the building geometry is considered.
5. Condition for terminating the simulation
   - All 420 agents evacuate.

As shown in Table 1, the evacuation pattern and time from 50 simulation runs of SAFEgress are comparable to the results in the NIST report.

Actual Evacuation Pattern Comparison

The second comparison test takes into account the occupants' statistics in the fire, the changes in the physical environment during the evacuation, and the initial delay. Several assumptions, as derived from postfire studies (Aguirre et al. 2011a, b), have been made in the simulation:

1. Agent population and characteristics
   - There are 452 agents, the number of occupants at the nightclub at the time of the fire.
   - The population consists of 70% men and 30% women.
   - Occupants' spatial distribution follows the report by Aguirre et al. (2011a).
   - Individual agents choose to escape through the nearest visible exit.
2. Physical geometry change during simulations
   - At 1 min 40 s into the simulation, the building model is updated (using the Situation Data Input Engine) to allow agents to pass through windows and to disable the platform exit, which was impassable due to fire.
3. Condition for terminating the simulation
   - 352 agents, the number of survivors of the fire, evacuate.

Since there was no data on the preevacuation delay time available, the authors assumed each agent's preevacuation delay time using a truncated normal distribution, with a mean of 15 s and standard deviation of 10 s within the interval [0, 41 s] (as the alarm rang 41 s after the start of the fire).

To evaluate the overall evacuation pattern, the authors compared the simulation results with the exit usages reported by Aguirre et al.

Table 1. Comparison of Exit Usages and Egress Time under Normal Conditions

Exit location	SAFEgress[a]	Simulex[b]	EXODUS[b]
Front entrance	50.0% ± 9.4%	50.7%	51.0%
Bar exit	41.7% ± 8.4%	43.8%	42.9%
Kitchen exit	1.2% ± 0.2%	0.7%	1.0%
Platform exit	7.1% ± 1.7%	4.8%	5.2%
Total time	183 s ± 21 s	188 s	202 s

[a]Results reported are the average and the standard deviation over 50 simulation runs.
[b]Simulation results are reported in Grosshandler et al. (2005).

(2011a, b). As shown in Table 2, which tabulates the usage of different exits, the result of major exit usages (i.e., front entrance, bar exit, and windows) from the simulation of individual behaviors (i.e., 0% of groups with group behaviors) compares favorably to the data reported. Capturing the exit usages is an indication that this egress simulation reflects the flow patterns and the potential congestion areas. The average evacuation time is 167 s, with a standard deviation of 15 s over 50 simulation runs. The shorter evacuation time in this simulation, compared to the actual evacuation time of 248 s, can be attributed to many factors, such as the omission of other dimensions of the incident (e.g., the effect of smoke and fire on people's movements). Nevertheless, the results from the evacuation patterns provide a good starting point to compare the group effects on emergency evacuation with the simulation prototype.

Simulation Results Incorporating Group Behaviors

This section describes the simulation results considering group and social behaviors and their effects on the evacuation time. In order to test the group effect, agents were assigned to affiliate with different groups. In the Station nightclub fire, most of the occupants were in a group of two or more people (group sizes ranged from 2 to 9). Following the postfire study by Aguirre et al. (2011b), the authors assumed that there were 43 individual agents. The remaining 409 agents were associated with social groups, where 118 agents were assigned to groups of 2, 54 agents to groups of 3, 72 agents to groups of 4, and the rest to larger groups ranging from 5 to 9 people. Furthermore, the authors considered that in overcongested situations, [i.e., when the average occupant area was less than 0.19 to 0.28 m^2/person (2 to 3 sq ft/person) (the level of service E for queuing) (Fruin 1971)], the crowd following model overrides other social behavioral models.

Effect of Group Behavior on Exit Time and Exit Usages

Group behaviors can have a significant effect on total evacuation time. Evacuees reported behaviors such as searching for and staying with group members, even when facing extreme danger (Aguirre et al. 2011a). The group effect was captured in the simulation by modeling group behaviors for agents who belong to a social group. The study tested the effect of the group behaviors on evacuation time by varying the percentage (from 0 to 75%) of the total number of groups that exhibits group behaviors. Under group behavioral assumptions, if other group members are visible,

Table 2. Comparison of Exit Usages and Egress Time with Group Behaviors

Exit location	Total time (s)	Front entrance (%)	Bar exit (%)	Windows (%)	Kitchen exit (%)	Platform exit (%)
Actual data[a]	248	36.4	22.2	29.9	4.7	6.8
SAFEgress 0%[b]	167	33.2	23.7	31.6	1.2	10.3
	±15	±4.9	±5.5	±5.9	±0.3	±2.1
SAFEgress 25%[b]	225	22.2	18.5	49.9	1.1	8.3
	±41	±7.0	±5.1	±8.9	±0.3	±2.7
SAFEgress 50%[b]	265	20.4	15.7	55.8	1.2	6.9
	±48	±6.1	±4.3	±7.1	±0.4	±2.2
SAFEgress 75%[b]	277	21.3	14.4	57.7	1.2	5.5
	±42	±4.3	±3.2	±6.3	±0.3	±2.3

[a]Data reported by Aguirre et al. (2011a).
[b]Percentage of groups that exhibits the group behaviors. Results are average over 50 simulation runs.

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agents choose the leader following behavior model, as described in Fig. 3; otherwise, they choose to exit through the nearest visible exit. As shown in Table 2, the evacuation time increases as the percentage of groups with group behaviors increases (the average time is 265 s, compared to 167 s with an individualistic behavioral assumption). The result also shows that the lengthening of evacuation time varies nonlinearly, and the effect levels off as the percentage of groups with group behaviors increases.

Group behaviors affect the evacuation pattern, as reflected in the results of different exit usages under the different behavioral assumptions listed in Table 2. Fig. 7 shows the accumulative number of evacuees over time. Several observations can be made to explain the differences in the evacuation patterns. Fig. 7(a) shows the evacuation history of a typical simulation run with an individualistic behavioral assumption, and Fig. 7(b) shows the one with a 50% group behavioral assumption. As shown in Fig. 7(b), at 1 min 40 s, a higher portion of the population remains in the building and detects the windows as potential exits in the simulation with group behaviors. Subsequently, more agents exit through the windows in the group scenario than the individual scenario. Moreover, there is a difference between the two simulation scenarios in usage of the front entrance after the windows are available as exits. In the scenario with individual behavior [Fig. 7(a)], the front entrance usage levels off (i.e., none evacuate through the front entrance) within 30 s after the windows are broken. This may be because the windows are more visible and closer to most of the agents; because of the current implementation of selecting the nearest exit by an agent, the agents choose to evacuate through the windows rather than the regular exits. In the scenario with group behavior [Fig. 7(b)], the number of agents using the front entrance and the bar exit increases, even after the windows are available as exits. This can be attributed to the fact that the agents belonging to a group evacuate together

Fig. 7. Typical examples of accumulated number of evacuees over time: (a) simulation assuming individual behaviors; (b) simulation assuming 50% of groups with group behaviors

and follow other members' preference for the front entrance, even though the front entrance is not directly visible to them and farther from them.

Discussion

Human and social behaviors are still seldom considered and modeled in current egress simulation tools. This paper describes a research effort to develop a modular and flexible computational framework called SAFEgress, which allows a user to incorporate human and social behavioral models for egress simulations, and assess the impact of such behavioral assumptions on egress performance. The authors have implemented several behaviors, namely group behaviors, group information sharing, and crowd following, to demonstrate the potential effects of group and social behaviors for egress simulations. Although the implemented social behaviors do not represent all possible behaviors that may occur during emergencies, the selected behaviors are commonly observed and reported in postfire studies (Aguirre et al. 2011a, b; Donald and Canter 1990; Drury et al. 2009; Johnson et al. 1994; Kuligowski 2011; Sime 1983).

To incorporate social behaviors into egress simulation, a set of variables were designed to describe the agents not only in an individual context, but also from the social group and the crowd perspective. With the three-level representation of individual, group, and crowd, agents' decisions not only are determined by their traits and behavioral profiles, but also are influenced by the group profile and the neighboring crowd. By adopting a perception-decision-execution simulation cycle for each agent, the authors were able to model some commonly observed social behaviors during emergencies in the simulations.

To represent the dynamic environment of an emergency situation, the authors established a generic data structure of environmental objects to represent exits, alarms, and other evacuation-related information. Users can define the characteristics of the objects created and assume relationships and rules among these objects and the virtual agents for simulation purposes. It is important to represent the emergency situation in the context of threats (such as fire and smoke) and floor components (such as signage and openings) that can change the occupants' perception during egress. For example, in the Station nightclub fire, the alarm rang 41 s after the fire started. Emergency signals, together with the fire and smoke, presented a cue to the patrons and initiated their escape behaviors, particularly to those who previously were unsure about the emergency situation.

Using the case of the Station nightclub fire, the authors have compared the overall evacuation patterns to the actual data and conducted a sensitivity analysis showing the effects of group behaviors on the simulation results. The simulation results show that group behaviors would lengthen the overall evacuation time and lead to different evacuation patterns. The simulation assuming individualistic behavior in an emergency evacuation underestimates the total evacuation time, as comparing to the actual data reported.

This line of research continues to incorporate additional social behaviors and to consider the uncertainties in the information that the occupants perceive and interpret in emergency situations. The authors plan to investigate the effect of emotion contagion and information diffusion, which could influence people's decision to start evacuation (Kuligowski 2011; Hoogendoorn et al. 2010). Sensitivity analyses on different simulation parameters can be conducted to identify and assess the impacts of important factors in different physical and environmental settings. For further development of the simulation framework, model validation presents the
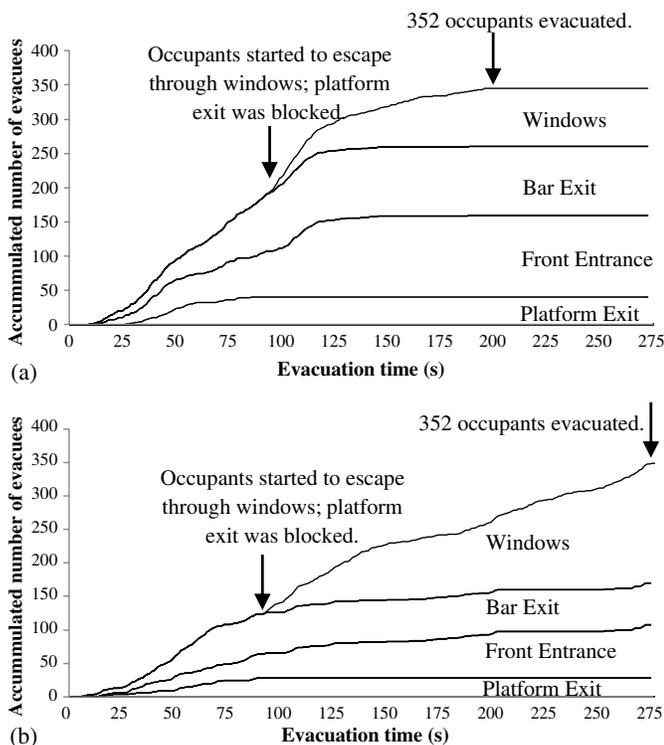
next challenge. As typical of the research in egress simulation, validation is a continuing process as evacuation and emergency drills data are being collected. The authors plan to develop methodologies to analyze real-life data, establish benchmark scenarios for validation, and carry out model validation at different levels (Galea et al. 1998) by working closely with public safety agencies.

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