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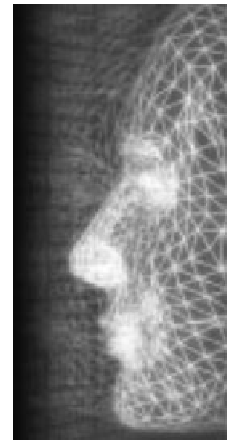
Agent-based human behavior modeling for crowd simulation



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Human crowd is a fascinating social phenomenon in nature. This paper presents our work on designing behavior model for virtual humans in a crowd simulation under normal-life and emergency situations. Our model adopts an agent-based approach and employs a layered framework to reflect the natural pattern of human-like decision making process, which generally involves a person's awareness of the situation and consequent changes on the internal attributes. The social group and crowd-related behaviors are modeled according to the findings and theories observed from social psychology (e.g., social attachment theory). By integrating our model into an agent execution process, each individual agent can response differently to the perceived environment and make realistic behavioral decisions based on various physiological, emotional, and social group attributes. To demonstrate the effectiveness of our model, a case study has been conducted, which shows that realistic human behaviors can be generated at both individual and group level. Copyright © 2008 John Wiley & Sons, Ltd.

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Introduction

Human crowd is a fascinating social phenomenon in nature. In some situations, a crowd of people shows well-organized structure and demonstrates tremendous constructive power. While in other situations, people in a crowd seem to abandon their social norms and become selfish animals. Numerous incidents with large crowd have been recorded in human history, and many of these incidents have led to severe casualties and injuries.[1] How to predict and control the behavior of a crowd upon various events is an intriguing question faced by many psychologists, sociologists, and computer scientists. It is also a major concern of many government agencies.

The research on crowd behavior modeling can be broadly classified into two categories. The first category treats the crowd as a collection of homogenous individuals which react to the events and environment according to some simple rules. Typical approaches of this category for crowd simulation include the cellular automata model[2] and particle system model.[3,4] Although some significant results have been achieved, these models are in general not adequate for investigating complex crowd behaviors, for example, human decision-making process, and the social and psychological factors are either neglected or greatly simplified. The second category treats the crowd as a collection of heterogeneous individuals that are empowered with significant decision-making capabilities like real human. A typical approach of this category is the agent-based model[5–8] of which each agent represents an individual in the crowd. The agent-based approach to crowd modeling and simulation has gained tremendous momentum recently due to the significant increase in computing power.

We adopt an agent-based approach to behavior modeling. A key issue in the agent-based approach is how to model the decision-making process of individual in a crowd. Existing decision-making frameworks include Bayesian networks,[9] fuzzy logic,[10] neural networks,[11] BDI,[12] and decision networks.[13] These different decision-making methods have been successfully used in different

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applications for decision making (e.g., BDI is used in Reference [6]). However, most of these methods are focused on the mathematical and computational framework rather than on the imitation of the way real human makes decisions. In this paper, we propose a human behavior modeling framework that naturally reflects human decision-making process. We consider the fact that the external stimulus (events, objects, and people) usually have direct effects on a person's physical condition, emotion, and social coping styles. These factors, in turn, collectively influence a person's decision making. Therefore, our framework is designed to model the two stages of the cognitive process involved in human's decision making, which generally includes a person's awareness of the situation and consequent changes on the internal attributes. The framework allows proper allocation of the computational tasks between an agent and the proposed inference engine, which is important for the real-time simulation of a large crowd in complex environments.

Most often, the social and psychological factors have significant influences on human decision-making process. This is especially true in a crowd—it is well known that an individual in a crowd, depending on the social context, may behave quite differently as when she/he is alone. In Reference [6], various psychological elements were considered in the navigational behavior of a crowd for evacuation simulation. In Reference [14], a psychologically based collision avoidance model was proposed for behavior simulation. Based on social comparison theory, a cognitive model of crowd behavior was proposed in Reference [15] to simulate pedestrian movement in a simple environment. In Reference [5], a cognitive model was proposed to determine how an agent will behave by selecting a suitable behavior from a repertoire of basic behaviors according to the agent's cognitive state. In our model, we identify a series of physiological, emotional, and social group attributes, which have immediate influences on agent's decision making and behavior execution in a crowd under normal and emergency situations. We also attempt to incorporate some social group and crowd-related theories and findings from social psychology (e.g., social attachment theory) in order to reflect realistic social phenomenons that occur in a real crowd.

Our objective is not to develop some specific behavior rules for the agents in some typical applications. Instead, we aim to develop a generic behavior modeling and simulation framework that is able to efficiently generate realistic behaviors for large-scale crowd simulations. In terms of realism of behavior model, our philosophy is that a human behavior model should not only be able to generate seemingly realistic behaviors in some given situations, but also *work like* a human brain in the sense that the decision-making process of an agent should be similar to that of a human being. That is, we emphasize on the architectural and procedural realism in addition to the end-result realism of the behavior model.

Design of Behavior Modeling Framework

Generally, the design of human behavior model can be regarded as a process of mapping a human's perceptional, mental, and physical functions into a computationally tractable approximation at certain degree of accuracy. More specifically, this includes many different modeling issues such as population classification, situation awareness, cognition, and multi-agent coordination. In order to produce realistic behaviors in a crowd scene, our behavior model is implemented based on a layered framework to naturally reflect human-like decision-making process, which generally involves a person's awareness of the external situations and consequent changes on the internal attributes.

Figure 1 shows the conceptual design of the framework. The framework consists of three modules, namely crowd behavior module, individual behavior module, and physical behavior module. It is naturally divided into two logical layers. The upper layer (i.e., the inference engine) contains the crowd behavior module and the individual behavior module and is responsible for making inference about current situation and selecting proper behavior for each agent. The lower layer, which only contains the physical behavior module, is responsible for feeding the sensory inputs into the upper layer and executing the selected behavior by decomposing the behavior into sequences of basic actions.

In the upper layer, the crowd behavior module captures the social relationships of agents and updates the group and crowd level attributes for different social groups. The relationships of agents can be either static (e.g., kinship) or evolving (e.g., leaders and followers). A crowd can emerge by the interactions amongst individuals. Individuals involved in this emerging process may change their behaviors after a crowd is formed. As an individual joins a crowd or a group, the behavior of the individual will be determined by

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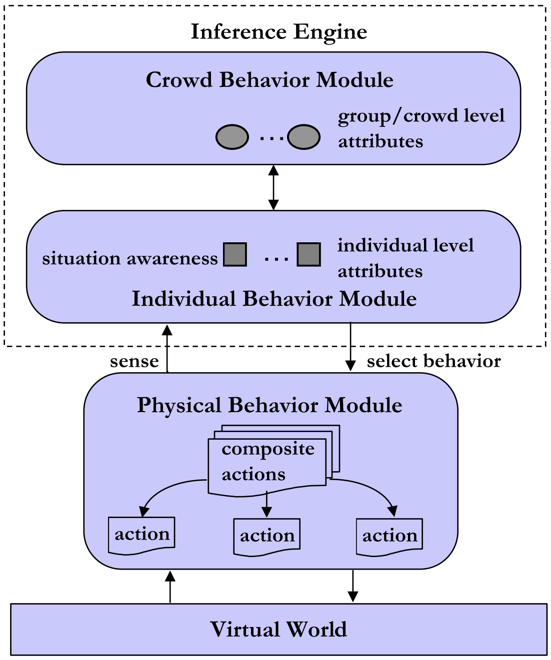

Figure 1. Conceptual design of the framework.

both the crowd behavior module and the individual behavior module. The individual behavior module processes the sensory inputs provided by the lower layer and updates the individual level attributes accordingly. Depending on their intrinsic characteristics, agents may acquire different understandings or awareness about the situation with the same sensory inputs provided. The set of group and crowd level attributes and the set of individual level attributes, both affected by an agent's awareness of the situation, can also have mutual influence on each other. The final selection of an agent's behavior is determined by verifying the agent's internal attributes at both group and individual levels and the selected behavior is sent to the lower layer for execution.

In the lower layer, the physical behavior module interacts with the virtual world to obtain sensory information and carries out the behavior by generating sequences of basic actions. The actions are sequences of animation frames which define the locomotive capabilities of virtual humans in the simulation. The physical behavior module transfers actions into atomic commands (e.g., *walk forward*, *run forward*, *turn*, *stand still*, and *jump*) and sends them into the virtual world to control the agent's locomotion. The behaviors are composed by basic actions; however, the actual way of behavior synthesis is open to the system designers so that they can apply different approaches and algorithms as required by different applications and simulation architectures. For example, to simulate coordinated group behaviors, either a force-based approach (e.g., flocking algorithm[16]) or an environmental planning approach (e.g., roadmap[17]) can be employed, depending on the complexity of environment abstraction.

Our behavior modeling framework is a natural reflection of human-like decision making and behavior execution process, as we consider the two stages of the cognitive process involved in human's decision making. The first stage is a person's awareness of the current situation, which is based on the existing expectations about people, social roles, and events, and is triggered by some external stimulus (the sensory inputs). The second stage is the consequent changes on internal attributes, which delineate a person's internal feelings, social states, as well as physical conditions. The decision making will be directly affected by these internal attributes and people can make different decisions under the same situation due to the different levels of variations on their internal attributes. The layered framework is also generic and flexible to employ different implementations within each module for different simulation purposes and scenario requirements. The modular approach ensures that the changes in one module will have minimum effects on other modules.

The hybrid approach toward the agent-based simulation distinguishes our framework from the traditional reactive or deliberative approach in agent systems. In our framework, the behavior selection is directly based on the updates of agent attributes, while the situational stimulus affect agent's decision making by modifying agent attributes. The separation of different tasks in decision making can facilitate the agent system to balance workloads among reactive updating, self-reasoning, and executing behaviors. In reactive updating of the sensory information, only the general knowledge of surrounding environment (e.g., presence of family members), rather than the precise information (e.g., position) need to be maintained by an agent. As a result, the provision of only critical sensory data can reduce the complexity of self-reasoning.

Development of Behavior Model

Our behavior model is developed and integrated into the crowd simulation architecture as shown in Figure 2. In our simulation, the crowd population needs to be

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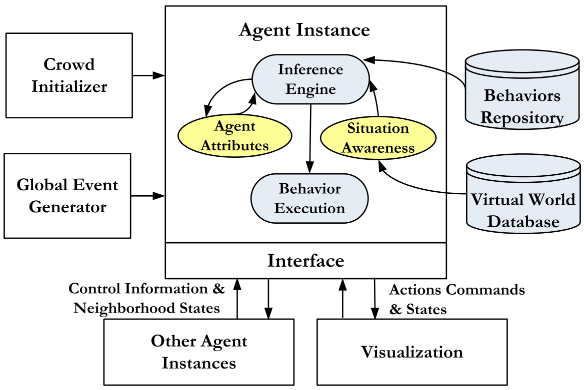

Figure 2. Agent-based crowd simulation architecture.

first generated and initialized in the *crowd initializer* by setting the distribution of different types of agents based on their roles, ages, social relationships, and personalities. After that, in the process of agent execution at each simulation step, the *agent instance* accesses the shared state maintained by the *virtual world database*. The *situation awareness* module inside the *agent instance* collects "observations" on the surroundings and the happenings in the virtual world. Meanwhile, the *global event generator* may generate events that significantly affect the environment and possibly some agents. These events can also be detected and maintained by the *situation awareness* module. The situational changes affect the agent's internal attributes, which are kept in the *agent attributes* module. The *inference engine* analyzes the information perceived from the *agent attributes* module and the *situational awareness* module, and then makes inference about the next behavior of agent (not necessarily to be different from the current behavior) according to the decision rules. The selected behavior is then retrieved from the *behaviors repository* and is eventually executed by the *Behavior Execution* module. An agent can also interact with other agents through the exchange of control information and neighborhood states. The sequences of agent's locomotive actions are sent to the *visualization* platform and rendered. The core of the agent architecture is the internal mechanism for the behavior inference of each agent, which follows the behavior modeling framework introduced in the last section. The behavior inference is facilitated by the agent's ability for situation awareness and variations of agent attributes. The following subsections describe situation awareness and agent attributes, which are designed to be scenario independent and extensible.

Situation Awareness

Situation awareness defines an agent's awareness of the current status and the past occurrences in the virtual world. An agent is endowed with the abilities to sense the environment, detect happenings in real time, as well as reason about the surroundings and keep significant occurrences in memory. Specifically, situation awareness is achieved through sensing, reasoning, and memory.

Sensing. An agent obtains sensory information by constantly executing some range queries to the *virtual world database*. The queries will search for all possible happenings within agent's surrounding area, which may include external events, significant objects, and relevant people. For an urban evacuation scenario (our initial test case), the sensory information may include:

- External events: sales, threat.
- Significant objects: shop, exit.
- Relevant people: family members, acquaintances, leaders, and casualties.

Reasoning. Based on the explicit sensing of the virtual world, an agent may infer some implicit knowledge about the current status or situation via some reasoning mechanisms. Some implicit situation variables can be derived accordingly. Examples of such situation variables may be the threat level (tl) and the in-danger duration (idd) that an agent experiences at any given time. The reasoning mechanisms are generally based on the observations about spatial and temporal relationships with the perceived environment and states of other agents. For instance, an agent will either observe its physical distance to the threat or monitor other agents' emotional status (e.g., panic) to determine the current tl.

Memory. An agent also needs to keep a short-term working memory about the past occurrences. The working memory contains a list of physical objects and events an agent has visited or encountered. The incorporation of working memory can enable the agent to make decision based on both the current state and the previous memory. This is useful for agent to avoid processing the same sensory information repeatedly. For example, an agent will not visit the same attraction place (e.g., ticket booth and shop) again, if she/he remembers that the place has just been visited a few minutes ago.

Name	Description	Determining characteristic type
KL_i	Knowledge level of agent *i*	Role
AR_i	Attraction tendency of agent *i*	Role
TV_i	Threat vulnerability of agent *i*	Age group
TP_i	Time pressure susceptibility of agent *i*	Age group
RT_i	Relationship type of agent *i*	Social relationship
GID_i	Group ID of agent *i*	Social relationship
AT_i	Altruism level of agent *i*	Personality
AV_i	Avoidance level of agent *i*	Personality

Table 1. List of characteristic constants

Agent Attributes

Agent attributes are an agent's internal parameters that directly affect the decision making process and behavior execution. The attributes are either static or dynamic. The static attributes are an agent's characteristic constants, which delineate the agent's intrinsic characteristics in the long term. The dynamic attributes include an agent's physiological, emotional, and social group attributes. These attributes are influenced by situation awareness and interrelate with each other. The values of dynamic attributes are tuned and processed in real time. The physiological and emotional attributes contribute to the individual level behavior in our framework, while the social group attributes contribute to the group level behavior in the framework.

Characteristic Constants

The characteristic constants are defined as constant parameters that delineate an agent's long-term characteristics, which are unlikely to be altered in the simulation time. These constants are used to regulate the values of an agent's dynamic attributes. Table 1 shows the list of characteristic constants used in our model. Except for RT_i and GID_i, the values of the characteristics constants are defined in the range of [0, 1] and are set randomly within the confined range depending on the agent's characteristics types. The agent's characteristics types define the agent's affiliation to certain group of people, who have some similar characteristics (e.g., role, age group, social relationship, and personality). The inclusion of characteristic constants is useful to accommodate individual differences in our model. For example, the agents with higher threat vulnerability value will become less panic compared to others, while facing the same emergency situation. One example of rules to set agent's characteristics constants is as follows:

$$\text{If an agent's age group} = \textit{child}, \text{ then } TV_i \in [0.8, 1], \quad TP_i \in [0.8, 1]$$

The TV_i and TP_i of a child agent are set to high value to reflect that such agent is more vulnerable to the threat and less susceptible to the time pressure.

Dynamic Attributes

Physiological Attributes. The physiological attributes dictate an agent's physiological abilities to collect and process the sensory information and carry out actions. Four important physiological attributes are identified in our model, namely health level, energy level, sensing range and walking speed.

(i) *Health level* (hl): The health level of an agent is in the range of [0,100]. In normal situation, the health level of every agent is set to $hl_{max} = 100$ by default. Upon occurrence of a threat, the health level will be set differently based on a linear relationship to the threat distance. The decrease of the health level will limit an agent's locomotive abilities to execute behaviors.

(ii) *Energy level* (el): The energy level is in the range of [0,100]. In normal situation, the energy level of every agent is set to $el_{max} = 100$ by default. The energy level is different from the health level, as the energy level is changed adaptively based on the elapsed time in danger. The longer the time the agent is in danger, the lower the energy level the agent has. It also depends on the time pressure susceptibility defined in agent's characteristic constants. Similar to the health level, the decrease of the energy level will also affect an agent's locomotive abilities as time elapses.

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(iii) *Sensing range* (sr): The sensing range defines the radius of an agent's local sensor for detecting stimuli from environment. Agents are assumed to be endowed with the similar sensing ability in normal situation. However, the sensing ability will diminish in emergency situation depending on an agent's health level, energy level and intensity of panic. Less or inaccurate sensory information will be obtained once the sensing range drops.

(iv) *Walking speed* (ws): The walking speed determines an agent's locomotive absolute speed value in the simulation. The walking speed will be affected by both health level and energy level of the agent.

Emotional Attributes. In virtual reality, emotion modeling is often applied to embodied entities for generating a variety of facial and body expressions, speech intonation and animation effects. In behavior modeling, emotion also plays a vital role on the decision making process to deal with competing motivations. For example, when there are competing choices (such as, going to a shop or continue wandering), emotional attributes (e.g., attraction intensity) may be used to facilitate the selection of a course of action. The people, who have greater attraction intensity (e.g., visitors), may choose to go to the shop, while others may simply resume their previous behaviors. In our current implementation for the urban evacuation scenario, two emotional attributes are identified: *attraction* (for normal situation) and *panic* (for emergency situation). The model may be extended with more emotional attributes in the future as required by new scenarios.

(i) *Attraction intensity* (I_a): The attraction intensity is used to model how likely an agent can be attracted by some attraction objects or events during normal situation. The value of attraction intensity is determined by several inputs obtained from situation awareness (e.g., the attraction object/event's own attraction level and the memory of previously visited objects) and is regulated by the agent's characteristic constants (e.g., attraction tendency).

(ii) *Panic intensity* (I_p): The panic intensity is used to model the instant fear level of an agent in emergency situation and it will affect the agent's decision making. Similar to the attraction intensity, the value of panic intensity is determined by several inputs obtained from situation awareness (e.g., the agent's perception on current tl, in-danger time duration, and detection of relevant people) and is regulated by the agent's characteristic constants (e.g., threat vulnerability and time pressure susceptibility).

Social Group Attributes. In our behavior model, modeling of the social relationship influence on the crowd behaviors is a major research issue. In psychology literature, Bowlby[18–20] has proposed a well-known ethological theory (i.e., social attachment theory) to dictate affiliative responses of crowd under threatening situation. Bowlby claimed that proximity seeking to familiar persons (also known as *attachment figures* in social attachment theory) rather than fleeing alone is a more typical response to threats and emergency. Different coping strategies are therefore developed based on the availability and viability of attachment figures.[21] In our model, we try to simulate such social interaction.

To classify different social groups, social tie is a determining factor to delineate different levels of social relationship to other agents. The agent will associate with other agents according to differentiated social ties (e.g., strong tie with kinship and normal tie with friend, colleague, and schoolmate). The social attachment theory mentioned above generally applies to the social groups with strong ties. For the social groups with normal ties, our model simulates the opinion consensus time. The social group with normal ties will take a period of time to make consensus on opinions in the presence of emergency. The leaders and followers are another important type of social groups, which emerge dynamically. Both gathered groups and individuals may choose to follow some well-trained leader(s) to find an escape path. Besides, the altruism behaviors of agents will also form one type of dynamic groups (helping and helped persons).

Based on the above discussion, the agents involved with social groups can be classified into four types: group agents with strong ties, group agents with normal ties, individual agents as leaders, and followers and

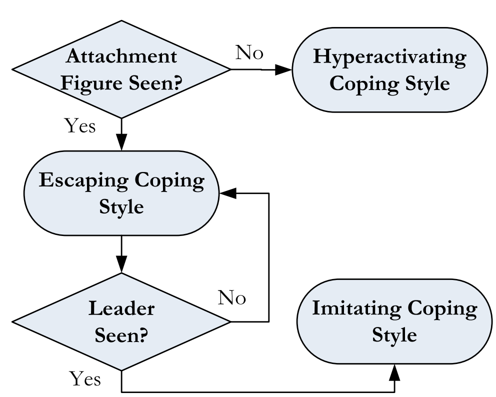

Figure 3. Coping style transitions for strong-tie agents during emergency.

individual agents with altruism. Different types of agents will have different social coping style (social group attributes in our model) and social interactions. Figure 3 illustrates one example of the transitions between different social coping styles for group agents with strong ties in emergency situation. In Figure 3, the hyperactivating coping style refers to an agent's social state of constantly searching for attachment figure. The escaping coping style refers to an agent's social state of escaping as a group from dangerous area. The imitating coping style refers to an agent's social state of imitating and following a leader's behaviors. When emergency happens, the agent with strong tie will search for its attachment figures until it finds one. The agent who has found its attachment figures will then try to escape together. On the way of escaping, if the agent finds some leaders, it will follow the leader's route.

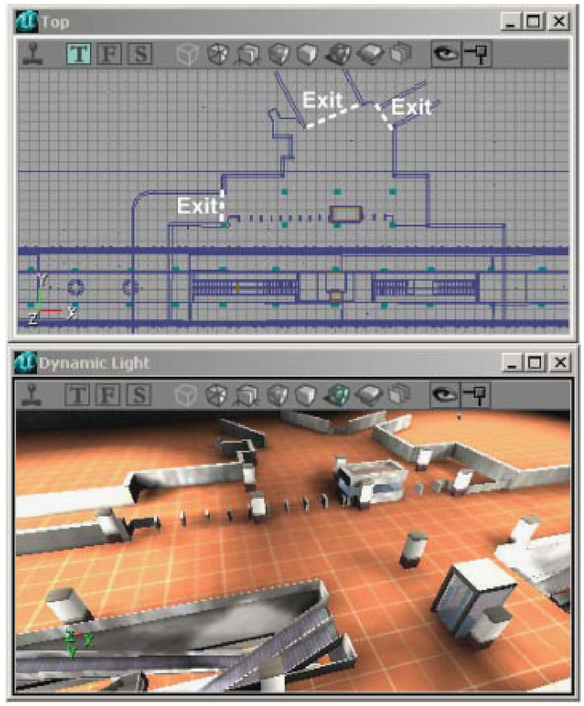

Figure 4. Top-down layout and 3D view of 1st story in the reconstructed train station.

Case Study

In this section, we give a case study to demonstrate the effectiveness of our behavior model in producing realistic and robust human behaviors in crowd simulation. Our initial scenario is targeted at a case of emergency evacuation in an urban terrain. The testing environment is constructed as a public transportation system and human behaviors in normal and emergency situations are modeled.

Environment configuration: We create the testing environment by reconstructing a train station in Singapore. The train station is a three-story underground transportation building connected by escalators and lifts. Figure 4 shows the top-down layout and 3D view of the first story in the reconstructed train station. The area is approximately 2400 m^2 and there are three different exits, as indicated in Figure 4, which connect to main roads and shopping malls. The station is usually used by hundreds of people daily at any given time.

Crowd initialization: To exhibit individual differences and crowd variety, the crowd population is initialized based on the agent's characteristics types of role, age group, social relationship, and personality in our scenario. An individual agent can be initialized as staff, civilian, or tourist based on its role; child, adult, or elderly based on its age group; strong tie, normal tie, or

Figure 5. Three-dimensional screenshots. (a) Before the time that the threat happens. (b) At the immediate time that the threat happens. (c) At the time that the agents escape.

individual based on its social relationship; and altruist, common person, or avoidantist based on its personality. According to the assigned characteristics types of agent, the characteristic constants defined in our behavior model will be set accordingly.

Behaviors repository: To take into account of both normal and emergency situations, eleven types of agent's behaviors are identified and implemented in our behaviors repository. They include: *wander*, *flock*, *evade*, *lead*, *follow*, *seek*, *individual escape*, *group escape*, *idle*, *help*, and *run aimlessly*. In normal situation, people *wander* individually or *flock* as a group. The staff (e.g., the security personal) *wander* around and look after the station. When emergency happens (e.g., a bomb is detonated), people surrounding the threat area, who are still able to move, start to *evade* from the spot. The staff *lead* others to exits. Normal people (e.g., civilian and tourist), who are near a staff, *follow* the staff. Others just *escape individually* or *escape as a group*. If a person cannot see her/his family members, she/he tries to *seek to* the family members before escaping. A group of friends may become *idle* for a while to make consensus about escaping strategy. Some altruistic people may *help* the injured people. Some of people (e.g., child and elderly) may become panic. They may *run aimlessly* or are simply *idle* for a short period of time.

Visualization Results

Based on our behavior model and testing scenario, our agent-based crowd simulation architecture is implemented. The simulation results are visualized in both the 3D unreal tournament game engine and the Java 2D display panel. Unlike other crowd simulation systems, our simulation focuses more on the observations on various agent behaviors rather than the global patterns of the crowd. Figure 5 shows the 3D screenshots from unreal tournament engine, which are captured (a) before the time that the threat happens, (b) at the immediate time that the threat happens, and (c) at the time that the agents escape. It can be observed in Figure 5(a) that groups of agents are coming in and out of the ticket booth area of the station during normal situation. In Figure 5(b), a threat has been dynamically generated. Some of the agents near the threat are getting injured and some of them are trying to escape. In Figure 5(c), a group of agents are escaping together towards the exit area after the threat has been detected. Figure 6 captures the 2D visualization results with the crowd size of 64. In the original 2D display, different agents are distinguished by colors. In Figure 6, for demonstration

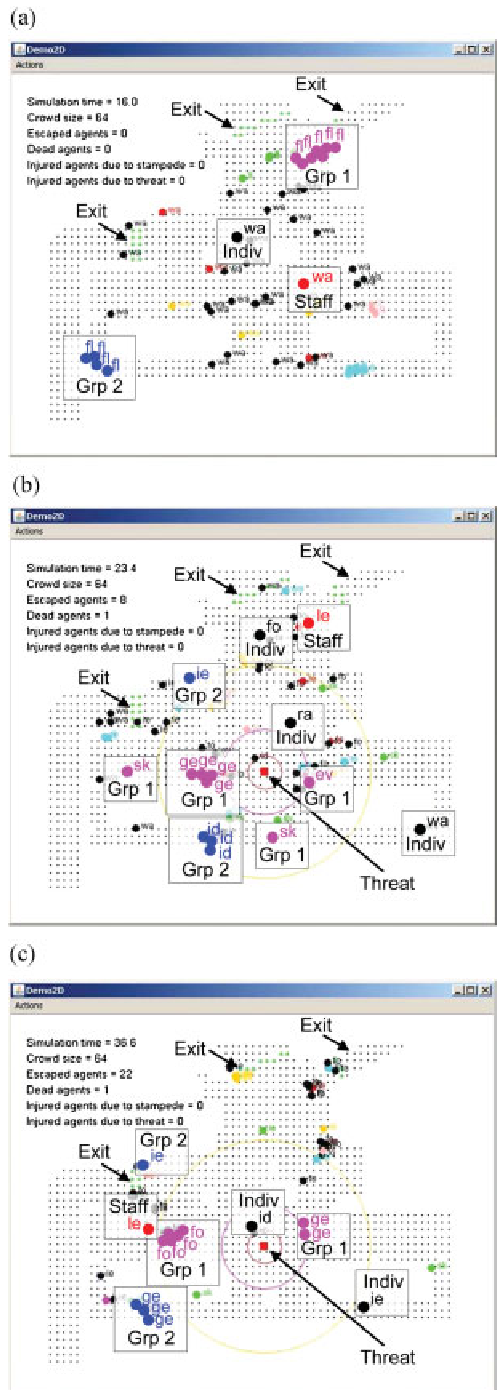

Figure 6. Two-dimensional screenshots. (a) At simulation time t = 16. (b) At simulation time t = 23.4. (c) At simulation time t = 36.6.

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purpose, we manually annotate and enlarge two groups of agents (group 1 for strong tie and group 2 for normal tie) and some individual agents. To show the behavior an agent is currently executing, a behavior index is displayed near each agent in the 2D visualization display. The behavior indexes for the 11 behaviors defined in the *behaviors repository* are: *wander* (wa), *flock* (fl), *evade* (ev), *lead* (le), *follow* (fo), *seek* (se), *individual escape* (ie), *group escape* (ge), *idle* (id), *help* (he), and *run aimlessly* (ra).

In Figure 6, it can be seen that, before the threat is generated (a), the individual agents are *wandering* individually and the group agents are *flocking* together. Staff agents are *wandering* to look after the station. Right after the threat is generated (b), the agents from the strong-tie group (group 1), who are separated from their group, are *seeking* to their *attachment figures*. Those, who are already together, are escaping together (i.e., performing *group escaping* behavior). The normal-tie group agents (group 2), who are close to others, are *idling* first to make consensus about the way of escaping; whereas the agent, who is separated from the group, is *escaping* individually. Some agents may become panic and *run aimlessly*. The agents far from the threat are not aware of the emergency and continue *wandering*. Some time after the threat is generated (c), most of the agents are escaping to the exits. They may *follow* the staff or *escape* by themselves. One individual agent is dead (*idle*) due to the explosion near the threat location.

Conclusion

The objective of our research is to develop a generic behavior modeling and simulation framework for crowd simulation, with focus on imitating real human's decision making process. To this end, a layered behavior modeling framework is designed to naturally reflect the pattern of human-like decision making process. The agent-based approach is adopted. Each agent in the model is endowed with the ability of situation awareness and can update its physiological, emotional, and social group attributes, which collectively influence the agent's behavioral decisions. The case study shows that our behavior model can adapt to user-defined scenario and generate realistic human behaviors in a crowd. We will continue to work on the proposed behavior model, which aims to be useful in different kinds of crowd simulation applications, such as military training, safety planning, and digital entertainment.

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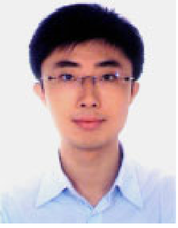

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