# Crowd Behavior Simulation With Emotional Contagion in Unexpected Multihazard Situations

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***Abstract*—Numerous research efforts have been conducted to simulate the crowd movements, while relatively few of them are specifically focused on multihazard situations. In this paper, we propose a novel crowd simulation method by modeling the generation and contagion of panic emotion under multihazard circumstances. In order to depict the effect from hazards and other agents to crowd movement, we first classify hazards into different types (transient and persistent, concurrent and nonconcurrent, and static and dynamic) based on their inherent characteristics. Second, we introduce the concept of perilous field for each hazard and further transform the critical level of the field to its invoked-panic emotion. After that, we propose an emotional contagion model to simulate the evolving process of panic emotion caused by multiple hazards. Finally, we introduce an emotional reciprocal velocity obstacles (RVOs) model to simulate the crowd behaviors by augmenting the traditional RVO model with emotional contagion, which for the first time combines the emotional impact and local avoidance together. Our experimental results demonstrate that the overall approach is robust, can better generate realistic crowds and the panic emotion dynamics in a crowd. Furthermore, it is recommended that our method can be applied to various complex multihazard environments.**

***Index Terms*—Crowd simulation, emotional contagion, emotional reciprocal velocity obstacles (ERVOs), multihazard.**

## I. Introduction

THE ADVANCES in the study of typical crowd behaviors (such as stampede incidents and terrorist attacks) in various domains, including psychology, security management, and computer science, have pointed out that simulating both sentimental state evolution and decision-making of a crowd under different circumstances is an efficient way to show inherent laws of nature [1]. This problem has been considered as a system that as a class of multi-input multioutput systems in the nonstrict feedback structure [2]. As a result, it is important to accurately model both simulation environment and emotional contagion among individuals for realistic crowd simulation.

Recent research efforts of crowd simulation in emergency circumstances have been mostly focused on those situations where there is only one hazard in the area of interest [3]–[9]. However, in some real-world cases, multiple hazards may occur in the same area over a period of time, such as the two sequential bombing attacks in Boston, MA, USA, in 2013. Traditional crowd simulation algorithms with a single hazard in the scenario cannot be applied to these cases directly because of the following reasons.

1) A multihazard scenario, including different types of hazards, different critical levels of hazards, dynamic changes of hazards, various evacuation strategies, and so on, is more complex than the case with a single hazard. The traditional single-hazard models are very difficult to handle all the above factors in a unified way.
2) The emotional contagion in multihazard environment is a complex combining process of emotional spreading, concerning both direct effects from hazards and indirect effects from neighboring individuals. However, the existing emotional contagion models are mainly designed for single-hazard scenes and cannot be applied to multihazard scenes directly.
3) Traditional multiagent navigation algorithms, like reciprocal velocity obstacles (RVO) [8], have not considered the emotion of individuals, which means they are short of the mechanism to deal with the conflict between obstacle avoidance and panic escaping. Therefore, the simulation results under multihazard circumstance by these algorithms appear less realistic.

In order to tackle the above challenges, in this paper, we propose a novel multihazard scene model to describe different effects of various types of hazards, which is mainly applied to fire and explosion situations. In this model, the hazards are classified into six different types according to three kinds of inherent attributes: 1) durations; 2) time of occurrence; and 3) dynamics. Based on the definitions of these hazards, we further propose the concept of perilous field and a conversion function to map the criticality of the perilous field to

Manuscript received January 19, 2018; revised May 12, 2018 and August 15, 2018; accepted February 3, 2019. Date of publication March 14, 2019; date of current version February 17, 2021. This work was supported by the National Natural Science Foundation of China under Grant 61672469, Grant 61772474, Grant 61822701, and Grant 61872324. This paper was recommended by Associate Editor W.-K. V. Chan. *(Corresponding author: Pei Lv.)*

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Digital Object Identifier 10.1109/TSMC.2019.2899047

the emotion of individuals. It is noteworthy that emotion in this paper mainly refers to the panic mood of individuals in emergency situations.

In order to depict the complex process of panic spreading, we put forward a new emotional contagion model specially designed for multihazard situations by combining panic emotions from different hazards and individuals. Finally, an emotional RVOs (ERVOs) model, inspired from the traditional RVO model, is proposed to drive the crowd movement. Different from the existing RVO model, the ERVO model integrates the emotional effect into velocity decision for the first time.

The contributions of this paper are as follows.

1) We propose a novel multihazard scene model for the description of emergency fire and explosion situations, containing six different types of hazards with their dynamic changing process and a unified criticality conversion function.
2) We propose a new emotional contagion model in multihazard scenarios, which combines different emotional effects from hazards and individuals in a crowd.
3) We propose a novel crowd behavior simulation method, the ERVO to simulate how people under a panic mode choose their paths to safe places or planned goals in a realistic way.

The rest of this paper are organized as follows. Background and related work are reviewed in Section II. The overview of this paper is introduced in Section III. The definition of multiple types of hazards and emergency scenes are described in Section IV. The emotional contagion process is explained in detail in Section V. The simulation method of crowd movement is described in Section VI. Our experiments are presented in Section VII. Finally, this paper is concluded in Section VIII.

## II. Related Work

Although numerous research efforts have been conducted to simulate crowd movements, relatively little literature has been specifically focused on emergency evacuation simulation involved with multiple hazards. In this section, we will mainly review recent works that are clearly related to this paper. For more comprehensive review on crowd simulation techniques, please refer to [10].

### A. Crowd Evacuation With Social or Physical Model

One kind of important crowd movement scenarios is to simulate the emergency evacuation. Helbing *et al.* [3] employed the social force model, combined with social psychology and physics models for the first time, to describe the panic behavior in evacuation. After that, the lattice gas model [11], multigrid model [12], agent-based model [5], virtual hindrance model [13], etc., have also been proposed to describe the dynamical behaviors of the emergency crowd. The commonness among these methods is that they choose some typical characteristics of the crowd first, and then use corresponding models to describe different evacuation behaviors. Other studies considering more factors in crowd evacuation process, Narain *et al.* [4] simulated the clustering behaviors of a high density crowd in a combined macro–micro perspective. Funge *et al.* [14] put forward a cognitive model to direct autonomous characters to perform specific tasks, which outperforms many traditional behaviors models. Durupinar *et al.* [15] analyzed the impact of psychological factors on the crowd movement from the perspective of social psychology. Lai *et al.* [16] aimed at a problem of adaptive quantized control for a class of uncertain nonlinear systems preceded by asymmetric actuator backlash, which is similar with our motion analysis with agents in unexpected situations. Wang *et al.* [17] proposed a semantic-level crowd evaluation metric, which analyze the semantic information between real and simulated data. Başak *et al.* [18] validated and optimize crowd simulation by using a data-driven approach, which proves the parameters learned from the real videos can better represent the common traits of incidents when simulation. Oğuz *et al.* [1] used continuous dynamic model, to simulate the movements of agents in outdoor emergency situations successfully. In this paper, our crowd behavior model mainly focuses on the micro-level behavior simulation. According to different multihazard environments, we divide the crowd movement into various cases and design crowd behaviors for each case specially.

### B. Crowd Simulation With Psychological Model

In the real world, emotional state of an individual plays a vital role in his/her decision-making, which fundamentally determines his/her movements at each time step [19], [20]. Therefore, many recent works start to consider the psychological factors of agents, especially during the simulating process of crowd movement [21]. Belkaid *et al.* [22] stressed the important role that emotional modulation plays on behavior organization by analyzing the relationships between emotion and cognition. Bosse *et al.* [23] proposed the absorption model based on the heat dissipation theory in thermodynamic, which embodies the role of authority figures in the process of emotional contagion. Tsai *et al.* [24] devised a multiagent evacuation simulation tool ESCAPES, where an agent will accept the emotion of other agents who has the strongest mood or has special identity. Minh *et al.* [25] proposed an agent-based evacuation model by considering emotion propagation among individuals to make the simulation more realistic. Lhommet *et al.* [26] also proposed a computational model of emotional contagion based on individual personality and relationships. Durupinar *et al.* [15] created a system that enables the specification of different crowd types ranging from audiences to mobs based on a computational mapping from the OCEAN personality traits to emotional contagion. Tsai *et al.* [27] combined the dynamics-based and epidemiological-based models to describe the dynamics of emotional spreading from the perspective of social psychology. Fu *et al.* [28] used a modified SIR model, originally proposed in [29], to model the emotion evolving in the process of emergency crowd movement. The work in [30] proposes a stress model to realize the interactive simulation of dynamic crowd behaviors. Although stress is similar to our panic emotion in terms of the impact on crowd behaviors, there are still some inherent differences. For one certain crowd scene, they mainly model one type of stress in it and the stress of external environment on individuals. The mutual influence impact among different individuals is ignored. In addition, their model only focuses on the changes of individuals' velocities caused by the magnitude of stress. By contrast, in this paper, the emotional state of agents in emergency situations is mainly the panic emotion. Due to different emotional spreading and reception for various agents, we analyze the emotional contagion by involving the personality factors. Since the panic effect is not only coming from various hazards but also from neighboring individuals, a new micro-continuous emotion contagion model is designed.

### C. Crowd Path Planning

Generally, path planning can be regarded as the multiobjective optimization [31] and local information interaction [32], [33] problems. In the process of crowd evacuation, an individual's action decision [34]–[40] is dependent on the evacuating directions of nearby agents, the locations of hazards, and the obstacles in the scene.

Some researches develop a variety of methods to avoid the collision problem through the calculation of possible positions of individuals at the next time step [41], [42]. On the premise of collision avoidance, Kluge and Prassler [43] used a local obstacle avoidance approach, combined with individual's emotion states to calculate the movements of agents iteratively. Van den Berg *et al.* [8] proposed the well-known RVOs model to drive the multiagent navigation without collision. Concretely, the reactive behavior of one agent at each time step depends on the behaviors of all the other agents. In their method, a collision-avoidance velocity for each agent is chosen by taking into account the positions and reciprocal velocities of all agents in the scenario. By constructing visual trees, Belkhouche [44] proposed a shortest path without conflict. Guy *et al.* [9] proposed an optimization method for collision avoidance on the basis of the RVO model for real-time simulation of large-scale crowd movement. In addition, they also proposed an energy-saving simulation method with the minimum energy consumption as the guidelines [45]. Furthermore, a series of path planning and navigation algorithms [46]–[49] are also described in mass population under complex background. In this paper, we enhance the traditional RVO model with emotional contagion in multihazard circumstances. Panic is used to describe the emotional state of each agent, which is changed dynamically and affect the behaviors of individuals.

## III. System Overview

As shown in Fig. 1, the main methodology of this paper is divided into three parts: 1) multihazard environment modeling in Section IV; 2) emotional contagion process under multihazard situations in Section V; and 3) crowd behavior simulation based on ERVO in Section VI.

Specifically, in order to simulate the crowd behavior in multihazard situations realistically, we analyze different types of hazards according to their properties, the time of occurrence and duration. After that, we propose a perilous field consisting of multiple hazards and define a conversion function to map the intensity of danger to panic emotion. Besides the direct effects from hazards, panic propagations also exist among different agents in emergency scenes. So we build an emotional contagion model (ECM) to handle the above cases. The ECM computes the panic emotion of each agent in the dangerous field according to the distance between this agent and the hazards using the above conversion function. At the same time, the ECM accumulates the contagious panic emotion from other agents to obtain the final emotion of each agent. To realize multiagent navigation with panic emotion under multihazard situations, we propose an ERVO model to simulate the crowd behaviors. The major contribution of ERVO is a new mechanism of velocity decision by integrating both traditional RVO and panic emotion.

## IV. Multihazard Environment Modeling

The characteristics of complexity, interactivity, and time-varying make crowd behavior simulation challenging, especially in multihazard environments. In order to achieve realistic simulation results, we first need to model multihazard simulation environment quantitatively.

According to their durations, we divide hazards into two different types: 1) transient and 2) persistent. The former only lasts for a moment, while the latter lasts for relatively long time. Both of them would cause drastic changes to the psychological state of a crowd, and individuals in the dangerous area would respond immediately. The difference between them is that a transient hazard only threats those individuals at the time when it is happening. Once it disappears, the threat will also disappear immediately. By contrast, a persistent hazard will continue to impact those individuals in the dangerous area during its existence.

According to their generation time, we divide hazards into concurrent and nonconcurrent. Specifically, when some hazards occur concurrently, their influences on neighboring agents can be treated as a single one. These influences should be accumulated together. For nonconcurrent hazards, we need to consider the status of the crowd each time when a new hazard happens. If an agent has already been affected by other hazards before or has its own emotion, the new effect needs to be accumulated.

More importantly, the static and dynamic characteristics of hazards also play vital effects on the crowd movement in complex situations. Based on this fact, we classify the hazards with fixed position and influence radius as static ones. Other cases, such as fixed position with variable influence radius and variable position with fixed or variable influence radius are regarded as dynamic hazards. For dynamic hazards, they may have different states over the time, which determine their position and area of influence dynamically.

The above six basic types of hazards have obviously different impacts on the crowd movement. Realistic multihazard scenarios usually consist of these basic types and their combinations.

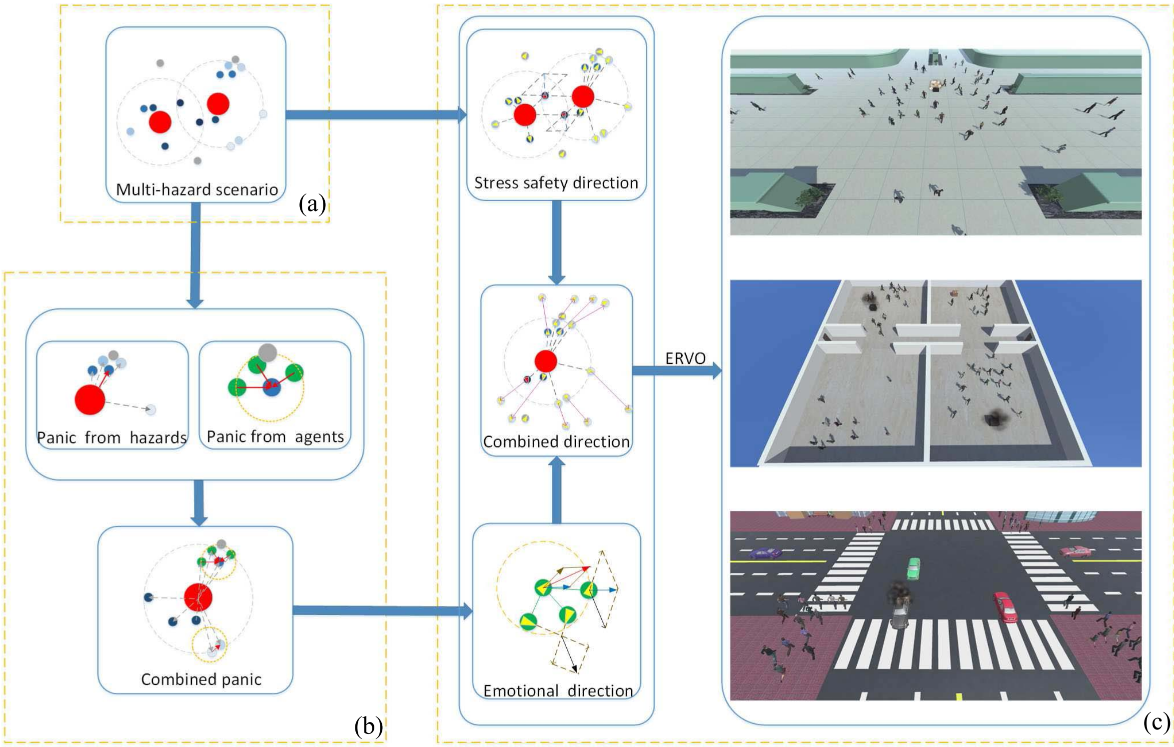



Fig. 1. Framework of crowd behavior simulation in multihazard situations, consisting of three parts. (a) Estimation of crowd panic in multihazard environment. (b) Panic propagation in emergency situation. (c) Impact on crowd movement from panic emotion. The red solid circle represents the hazard in our circumstance, different blue solid circles in (a) represent agents with different panic emotion values. The darker the color, the greater the panic emotion. In (b), the panic emotion of one agent (blue solid circle) is affected by other agents (green solid circles) in its perceiving range. Stress safety directions, emotional directions, and combined directions of agents are annotated by yellow arrows shown in (c).

After analyzing these hazards qualitatively, we give quantitative descriptions for them. We first define a perilous field as the circular area with the hazard position as the center and a radius. Each agent is aware of the existence of hazards in the scene through self-perception or neighbor contagion. The influence of danger is limited in space: the farther the distance to the hazard, the weaker influence to the crowd. For different types of hazards, due to the uncertainty of their location and range, new perilous fields will be formed constantly along with the time. Defining the hazard position as $P_s$, for example, it can affect all agents in its perilous field with radius, defined as $r_s$, in the existence time, defined by $U$. If the diffusion velocity and diffusion time for the hazard is $\mathbf{v}_s$ and $t_s$, respectively, where $\mathbf{v}_s = \{\mathbf{v}_{s1}, \mathbf{v}_{s2}, \ldots, \mathbf{v}_{sn}\}$, $n \to \infty$ depicts all possible directions for the diffusion, the new hazard point $P'_s$ can be defined as follows:

$$\begin{aligned} P'_s &= P_s + t_s \cdot \mathbf{v}_s \\ &= \{P_s + t_s \cdot \mathbf{v}_{s1}, P_s + t_s \cdot \mathbf{v}_{s2}, \ldots, P_s + t_s \cdot \mathbf{v}_{sn}\}. \end{aligned} \tag{1}$$

The dangerous range $A_s$ after the diffusion forms a closed area consisting of $P_s$ as the source point and all points $P'_s$ as the boundary. Then we divide this area into two parts using a line between 1 and $(n/2)$, and this area can be expressed as the sum of integration of these two parts

$$A_s = \int_1^{\frac{n}{2}} (P_s + t_s \cdot \mathbf{v}_s) d_{\mathbf{v}_s} - \int_n^{\frac{n}{2}} (P_s + t_s \cdot \mathbf{v}_s) d_{\mathbf{v}_s}. \tag{2}$$

According to the above description, the dangerous impact on each agent is related to the dangerous range of hazard and the distance between the hazard and an agent. The farther the distance is, the smaller the impact, all points with the same distance from hazard share the same dangerous impact. In order to depict this symmetry and attenuation, which is inspired by the work in [1], a Gaussian distribution function is chosen to depict this procedure by the following equation:

$$\Gamma_s(P, t) = \begin{cases} \frac{1}{\sqrt{2\pi} \cdot r_s} e^{-\frac{(P-D_s)^2}{2{r_s}^2}} & \text{if } \|P - D_s\| < r_s \text{ and } t \in U \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

Here, $\Gamma_s(P, t)$ is the strength of danger at the position $P$ produced by hazard $s$ at time $t$. $U$ is the duration of hazard $s$. $D_s$ is the intersection position of line $PP_s$ and the hazard area $A_s$($D_s$ can be seen as the hazard position $P_s$ in static hazard situations), and $r_s$ is its influence radius. It is noteworthy that danger strength will be 1.0 if position $P$ is within the dangerous range $A_s$.

## V. Emotional Contagion Model Construction

The emotional contagion model under multihazard situations needs to consider the panic emotion invoked directly by the hazards, panic propagation among individuals, and panic attenuation. The final panic emotion of each agent can be obtained by summing up these three components.

### A. Emotional Impact From Multiple Hazards

In Section IV, we have defined the perilous field and the strength of danger of different hazards. Since the normalized value of the strength of danger is within the range [0, 1], which is the same as the property of emotional value [28], therefore, we adopt the strength of danger, perceived by the agent directly, as the panic value at the current position in the following equation:

$$E_i^h(P,t) = \sum_{s=1}^{n} \Gamma_s(P,t). \tag{4}$$

Here, $E_i^h(P,t)$ represents the panic value of agent $i$ affected by all the hazards $s$ at time $t$ and position $P$, where $n$ denotes the total number of hazards.

### B. Emotional Contagion Among Individuals

In real life, individuals escaping from the perilous field will carry panic emotion and propagate the panic continuously to infect other individuals within a certain distance when they are moving. Individuals who perceive this panic may also be affected by them, incorporate into their emotions and then pass them out. In addition, emotional contagion among different agents are totally different. The extent of emotional transmission among agents depend on their personalities, which affect their ability of expression and reception.

In order to depict the above process, we use the emotional contagion model proposed in [15], which incorporate a complex but easy-to-use psychological component into agents to simulate various crowd types. One personality model and two thresholds are used in this process. Specifically, OCEAN personality model [50] defines a 5-D vector $\langle \Psi^O, \Psi^C, \Psi^E, \Psi^A, \Psi^N \rangle$ to characterize the individuals' five kinds of personality: 1) openness; 2) conscientiousness; 3) extraversion; 4) agreeableness; and 5) neuroticism. Each dimension takes a value between $-1$ and 1. Moreover, personality can also affect the decision of agent in different situations. The two thresholds are expressiveness and susceptibility. Expressiveness correlated with extroversion, represents the ability to diffuse emotion. Susceptibility represents the minimum value of agent be affected by other agents. Taking agent $i$ and agent $j$ as an example, if the emotional value for agent $j$ at certain time is higher than its expressive force threshold, it will express the emotion to others. At the same time, if all emotions agent $i$ received exceeds its susceptibility threshold, agent $i$ can be affected by this emotion. The expressiveness threshold for agent $j$ and susceptibility threshold for agent $i$ are defined as follows:

$$e^{T_j} \sim N\left(0.5 - 0.5\psi_j^E, \left(\left(0.5 - 0.5\psi_j^E\right)/10\right)^2\right) \tag{5}$$

$$\mathrm{sus}T_i(t) \sim N\left(0.5 - 0.5\varepsilon_j, \left(\left(0.5 - 0.5\varepsilon_j\right)/10\right)^2\right) \tag{6}$$

where $N(.,.)$ represents a normal distribution with the former as a mean and the latter parameter as a standard deviation, the empathy value $\varepsilon_i (\varepsilon_i \in [-1, 1])$ in (7) for agent $i$ can be described as follows [51]:

$$\varepsilon_i = 0.354\psi^O + 0.177\psi^C + 0.135\psi^E + 0.312\psi^A + 0.021\psi^N. \tag{7}$$

Then for the susceptible agent $i$, all effect caused by all agent $j$ who is expressive and in the perceived range of it at time $t$ can be computed by the following equation:

$$E_i^c(P,t) = \sum_{t'=t-k+1}^{t} \sum_{j=1}^{n} d_i(t') E_j^{c'}(P_j, t') \tag{8}$$

where $d_i(t') \sim N(0.1, 0.0001)$ represents the dose values which agent $i$ accepted from agent $j$ at time $t'$ and $E_j^{c'}(P_j, t')$ is the panic emotion of agent $j$ within the perceiving range of agent $i$ at time $t'$. The value of $k$ is set as 10 based on [15], which means the emotional accumulation of agent $i$ at time $t$ is determined by the emotional values in the last ten consecutive time steps.

### C. Emotion Combination

Based on the documented observations [15], the panic emotion of individuals will decay over time gradually until to the normal state. So we define an emotional attenuation function to describe this process, where a parameter $\eta$ is the emotional decay rate. For agent $i$ at time step $t$, its new panic can be computed as follows:

$$E_i^d(P,t) = E_i\left(P^{\mathrm{pre}}, t-1\right) \cdot \eta \quad \eta \in (0, 1]. \tag{9}$$

As mentioned at the beginning of this section, the final panic emotion of each agent can be obtained by combining all above three components. Considering (4), (8), and (9), the incremental panic of the agent $i$, who is at the position $P$ and at time $t$, can be computed by (10). With this incremental value, we can obtain the panic emotion by (11). It is noteworthy that the emotional value $E_i(P,t)$ needs to be normalized after update

$$\Delta E_i(P,t) = E_i^h(P,t) + E_i^c(P,t) - E_i^d(P,t) \tag{10}$$

$$E_i(P,t) = E_i\left(P^{\mathrm{pre}}, t-1\right) + \Delta E_i(P,t). \tag{11}$$

## VI. Emotional Reciprocal Velocity Obstacle

After the panic of each agent in a multihazard environment is computed during evacuation, the stressful behaviors of these agents affected by the panic emotion can be determined. The location and moving direction of an agent are denoted as $P$ and $\vec{V}$, respectively. When the agent has perceived the impact from a hazard $s$ at location $P_s$, it will try to follow the *stress safety direction* $\overrightarrow{P_s P}$ to escape from the hazard instinctively. By contrast, those agents who are not within the impacted area of any hazard, will follow their original moving directions. If an agent is affected by multiple hazards, then all the stress safety directions of interest will be the result of a weighted sum. So, the stress safety direction of an agent in multihazard situations can be described by the following equation:

$$\overrightarrow{V_i^s}(P,t) = \begin{cases} \sum_{s=0}^{n-1} \Gamma_s(P,t) \cdot \overrightarrow{P_s P} & \text{if } \|P - P_s\| < r_s \text{ and } t \in U \\ \vec{V} & \text{otherwise.} \end{cases} \tag{12}$$

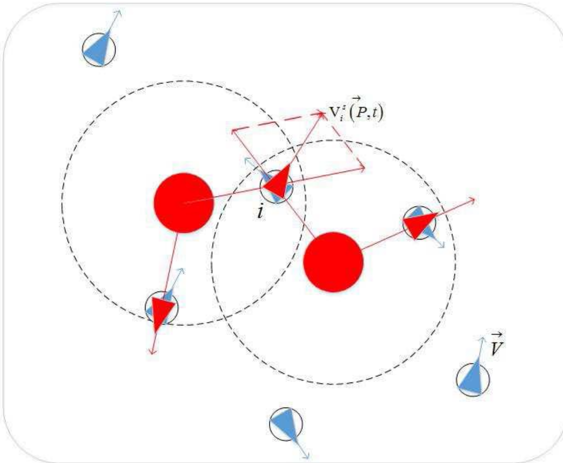



Fig. 2. Stress safety direction invoked by hazards. Red solid circles represent hazards and dotted circles are the perilous fields of the hazards. The original directions of agents are represented by blue triangles, while the stress safety directions of affected agents are denoted by red triangles.

Here, $\overrightarrow{V_i^s(P,t)}$ is defined as the *safety evacuation direction* for agent $i$ at the position $P$ and time $t$. $U$ is the duration of hazard $s$. Fig. 2 shows different safety evacuation directions chosen by a group of individuals.

Besides the direct emotional impact from hazards, the contagious panic emotion received from its neighbors may also alter agents' original moving directions. As mentioned in [3], we assume the probability of agent $i$ following its original direction is $p_i$ and the probability $1 - p_i$ to follow the others' directions. Thus, the new direction can be defined as the addition of these two direction vectors. In this paper, the probability $p_i$ is equal to the panic value $E_i(P, t)$ of agent $i$. The updated moving direction of agent $i$ at time $t$ is defined as follows:

$$\overrightarrow{V_i^c(P,t)} = E_i(P,t)\,\overrightarrow{V_i^s(P,t)} + (1 - E_i(P,t)) \sum_{j \in R(i)} \overrightarrow{V_j^c(P_j,t)}. \tag{13}$$

Here, $\overrightarrow{V_i^c(P,t)}$ represents the moving direction of agent $i$ who is at the position $P$ at time $t$. $\sum_{j \in R(i)} \overrightarrow{V_j^c(P_j,t)}$ is the combined moving directions of those agents who are in the emotional perception range of agent $i$. $R(i)$ denotes neighboring agents within the perception range of agent $i$. When the agent is going to change its direction, we assume the magnitude of its velocity will remain. In other words, the velocity module of the agent at that time should be $\mathbf{V}_i^c$.

In (13), the moving direction of agent $i$ is only influenced by panic emotion. However, in the actual crowd movement, the final direction of an agent is also influenced by its planned targets and other neighboring moving agents. In other words, the local obstacle avoidance and global path planning for agents also need to be considered. The RVO model [8] is an efficient and safe multiobject automatic navigation algorithm. However, during the obstacle avoidance, the RVO model focuses on the position and velocity of the current agent and other agents [refer to (14)], but does not take into account the emotional impact on speed selection invoked by surrounding obstacles and existing hazards. In (14), $\mathrm{RVO}_j^i(\mathbf{V}_j, \mathbf{V}_i, \alpha_j^i)$ is the collision area for agent $i$ caused by agent $j$ [illustrated in the gray area around the white circle of Fig. 3 (RVO)], which means that agent $i$ and agent $j$ will collide with each other once the velocity of agent $i$ fall into this area. $\mathbf{V}_i$ and $\mathbf{V}_j$ represent the velocity for agent $i$ and agent (or hazard) $j$. $\alpha_j^i$ is the effort chosen by agent $i$ to avoid the collision with agent (or hazard) $j$, which is implicitly assumed to $(1/2)$ in the original RVO model. For more details of the RVO model, please refer to [8]

$$\mathrm{RVO}_j^i\left(\mathbf{V}_j, \mathbf{V}_i, \alpha_j^i\right) = \left\{\mathbf{V}_i' \middle| \frac{1}{\alpha_j^i}\mathbf{V}_i' + \left(1 - \frac{1}{\alpha_j^i}\right)\mathbf{V}_i \in \mathrm{VO}_j^i\left(\mathbf{V}_j\right)\right\}. \tag{14}$$

Inspired by the RVO model, we propose a new ERVO model by integrating emotional contagion into crowd movement planning. This new model constructs a new collision area [shown by the gray triangle areas in Fig. 3 (ERVO)] by considering the current velocity $\mathbf{V}_i$ and the updated velocity $\mathbf{V}_i^c$ of the agent, and also the velocity $\mathbf{V}_j$ as described in (15). The effort made by agent $i$ to avoid collision with agent (or hazard) $j$ is defined as follows:

$$\begin{aligned}\mathrm{ERVO}_j^i\left(\mathbf{V}_j, \mathbf{V}_i, \mathbf{V}_i^c, \alpha_j^i\right) = \Bigg\{\mathbf{V}_i' \Big| &\frac{1}{\alpha_j^i}\left(\mathbf{V}_i' + \mathbf{V}_i^c\right) \\ &+ \left(1 - \frac{1}{\alpha_j^i}\right)\mathbf{V}_i \in \mathrm{VO}_j^i\left(\mathbf{V}_j\right)\Bigg\}\end{aligned} \tag{15}$$

$$\alpha_j^i = \frac{E_j(P,t)}{E_i(P,t) + E_j(P,t)}. \tag{16}$$

During the crowd simulation, for agent $i$, if $\mathbf{V}_i$ is outside of the ERVO of agent (or hazard) $j$, both of them will never collide. The ERVO model can be used to navigate a large number of agents in a complex multihazard scenario. For each agent $i$ in the scene, it has a current position $P$, a current velocity $\mathbf{V}_i$, an updated velocity $\mathbf{V}_i^c$, a current panic emotion $E_i(P, t)$, and a goal location $G_i$. For a hazard $s$, it has position $P_s$ and duration $t$. For obstacle $o$, it has current position $P_o$ and velocity $\mathbf{V}_o$. Static obstacles have zero velocity in particular. In our experiments, we choose a small time step $\Delta t$ to simulate crowd behaviors. Within this time step, we select a new velocity for each object independently and update its position according to the surrounding environment until all of the agents have reached the safe area or their goals.

## VII. Experimental Results

We run a diverse set of crowd simulations in multihazard situations, all experiments are realized by using C++ in the Visual Studio and Unity 3-D platform. Our experimental results show that our method can soundly generate realistic movement as well as panic emotion dynamics in a crowd. In Section VII-A, we simulate crowd behaviors in four different outdoor multihazard scenes. In Section VII-B, we analyze the importance of our emotional contagion mechanism and different influence in different scenarios. Then the emotional contagion model is proved to be more suitable for our multihazard situations in Section VII-C. Furthermore, we validate the realism of our simulation results by comparing them with

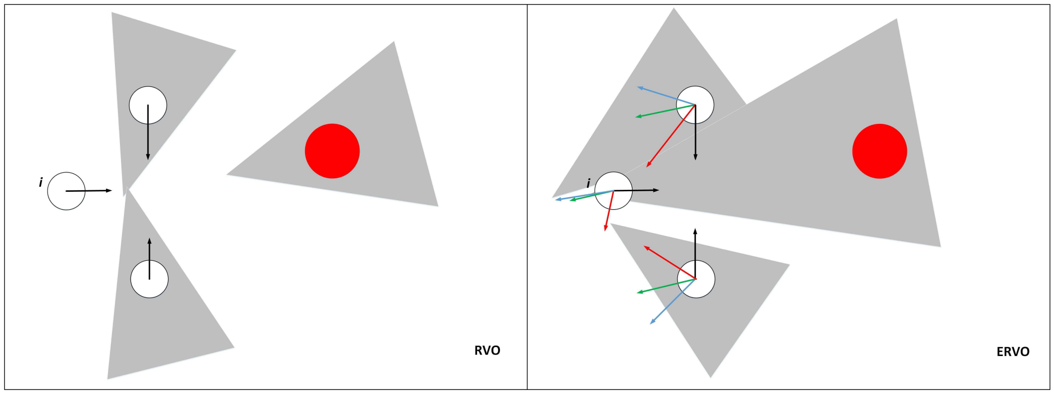



Fig. 3. Collision area computed by the traditional RVO model and our ERVO model for agent *i*. Gray triangle areas around white circles and red solid circles represent the collision areas caused by agents and hazards, respectively. The black, blue, green, and red arrows are separately the original direction, stress safety direction, emotional contagion direction, and final direction of one agent. The emotional contagion direction of an agent is determined by combining its safety stress direction with those of its neighbors. The final direction is determined by combining its original direction and emotional contagion direction.

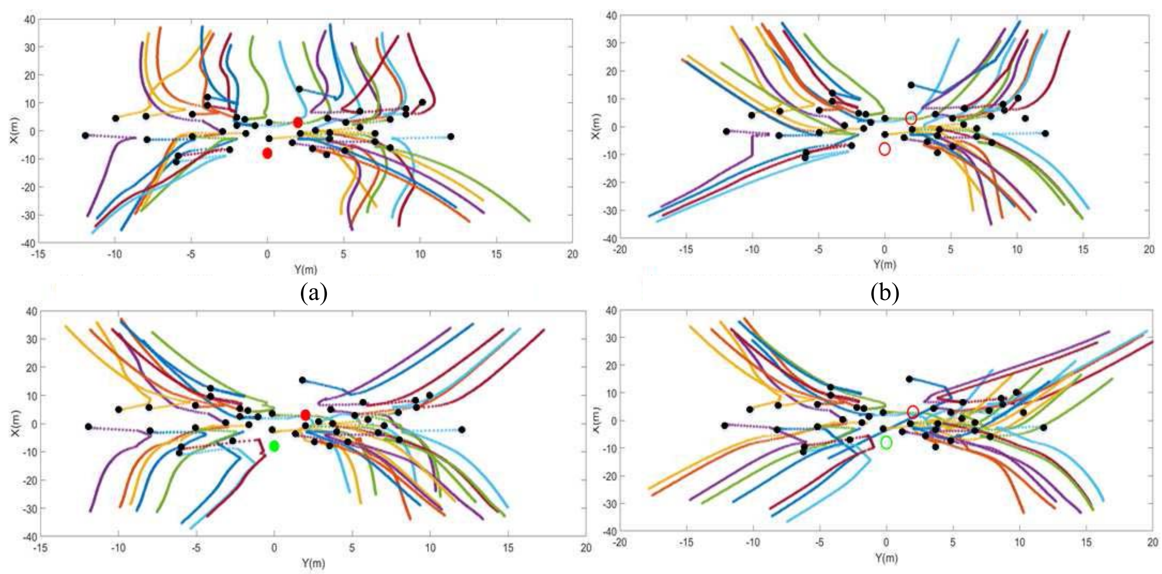



Fig. 4. Movement trajectories of forty agents in different types of hazard scenarios. In each scenario, black points represent the initial positions of all agents, the lines drawn by different colors are used to depict different paths of agents, while trajectories for the same agent use the same color in different conditions. In addition, the red solid and hollow circles represent persistent and transient hazard positions, respectively. While the green one represent the positions of the second hazards in the concurrent conditions. Persistent hazards occur at the (a) same time and (c) different moments. Transient hazards occur at the (b) same time and (d) different moments.

the crowd movement in real world in Section VII-D and the effectiveness of our method in different virtual environments in Section VII-E.

### A. Crowd Simulation Under Different Multihazard Scenarios

As discussed before, different hazard types have various effects on crowd movement. We simulate emergency behaviors in a crowd with the following two-hazard situations.

1) Persistent hazards occur at the same time.
2) Transient hazards occur at the same time.
3) Persistent hazards occur at different moments.
4) Transient hazards occur at different moments.

All simulations run in open field, and each simulation involves 40 agents. The persistent hazards and transient hazards are represented by fire and explosion, respectively. The time step is set to 0.25 s and other parameters in our system are set experimentally: the influence radius $r_s = 10$ m, emotional decay parameter $\eta = 0.01$, the personality parameters $\Psi^O$, $\Psi^C$, $\Psi^E$, $\Psi^A$, and $\Psi^N$ are set to random numbers between $-1$ and 1 to simplify depicting different agents, and the perceived scope is set to 4 m for all agents.

Path flow maps for all agents are used to depict the crowd movement differences among this four conditions. As illustrated in Fig. 4, the black points are the original positions of all agents, lines of different colors are used to depict different paths of agents, while trace flows for the same agent indicated by the same color in four conditions, the red solid and hollow circles represent persistent and transient hazard positions in our scenarios, respectively. While the second hazards occur in the concurrent conditions draw by green.

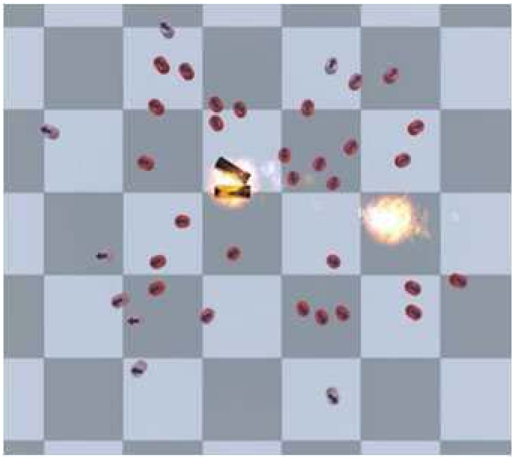


Fig. 5. One snapshot in the condition of persistent hazards occur at the same time, where the cylinders are used to depict agents, different colors represent different panic values of them, the darker the color is, the larger its panic value.

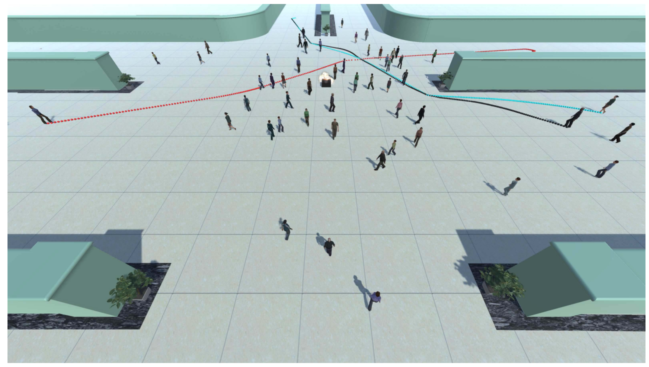
If two hazards occur at the same time as shown in Fig. 4(a) and (b). Agents around these two hazards will change their routes to be distant far away from them. When compared with the transient condition, based on the persistent effect from hazards, more emotional contagion lead to jittery for many paths of agents [shown in Fig. 4(a)], while trajectory for the agents in transient conditions are smoother owing to the disappearance of hazards in this scenario [shown in Fig. 4(b)].

If two hazards occur at different moments, as shown in Fig. 4(c) and (d). When the first hazard occurs, agents in the perilous field of this hazard will change their movement direction far away from it, while other agents keep the original movement. When the second hazard occurs, if the first one does not disappear, agents will escape away from both of the two hazards [shown in Fig. 4(c)]. By contrast, some agents' path may move to or pass through the area where the first hazard disappeared [shown in Fig. 4(d)].

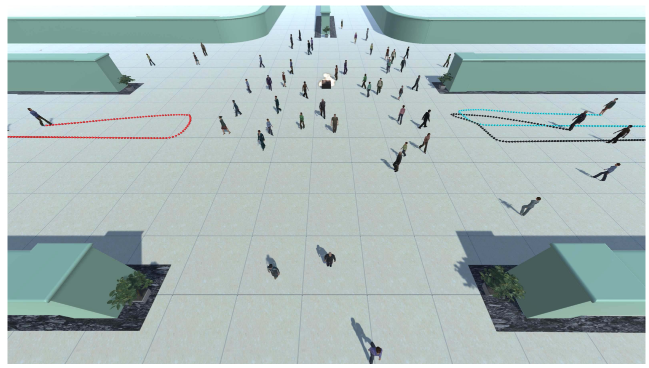
In addition to that the panic emotion changes of agents are also important during this procedure. Fig. 5 illustrates a snapshot in the condition of persistent hazards occur at the same time, where we use a cylinder to represent an agent and visualize its panic value using different colors. Despite those two dead agents drawn by the black cylinders, the white, light red, red, dark red, and red black are used to represent $E_i = 0$, $E_i \in (0, 0.3]$, $E_i \in (0.3, 0.5]$, $E_i \in (0.5, 0.7]$, and $E_i \in (0.7, 1.0]$, respectively. The larger the panic value is, the darker its color. For more dynamic simulation details in different multihazard conditions, we refer readers to the supplementary video.

### B. Analysis of Emotional Contagion

In order to validate the effectiveness of the emotional contagion in our method, we run crowd simulations in a scene with and without this mechanism, respectively. Fig. 6 shows the moving trajectories of three selected agents in the situation with one transient hazard. Agents with emotional contagion will adjust their moving directions to escape away from the hazard even when they have not reached the nearby region of the hazard. In contrast, agents without emotional contagion will keep moving along the original planned directions. The trajectory of one agent is illustrated by one colorful line. From these results, we can infer that the crowd movement in a hazard environment is affected by the panic emotion significantly.



(a)



(b)

Fig. 6. Comparison of crowd movements with and without emotional contagion. (a) Without emotional contagion model. (b) With emotional contagion model.

In the previous section, we have discussed the effect of emotional propagation on crowd movement qualitatively. Here, we mainly focus on the change of panic emotion of each agent during the crowd evacuation, especially when persistent/transient hazards occur at the same time. From Fig. 7, we can see that the panic emotion value will increase to the maximum when a persistent hazard happens. The reason is that although the agent is moving far away from the hazard, the agent is still in the perilous field and the panic value is accumulated. When agents are out of the perilous field, their panic values will decay and reach to a similar low level due to the effect of emotion contagion. For a transient hazard, the panic emotion will reach to the maximum immediately when the hazard occurs, then it will decrease gradually.

### C. Comparisons With Another Emotional Contagion Model

In order to validate the effectiveness of our emotional contagion model among agents, we compare our simulation results to an agent-based emotional contagion model proposed in [52]. Same personality and original state are chosen for 50 agents in this two models, then the overall difference caused by emotional contagion can be caught. After bomb occurs, agents may

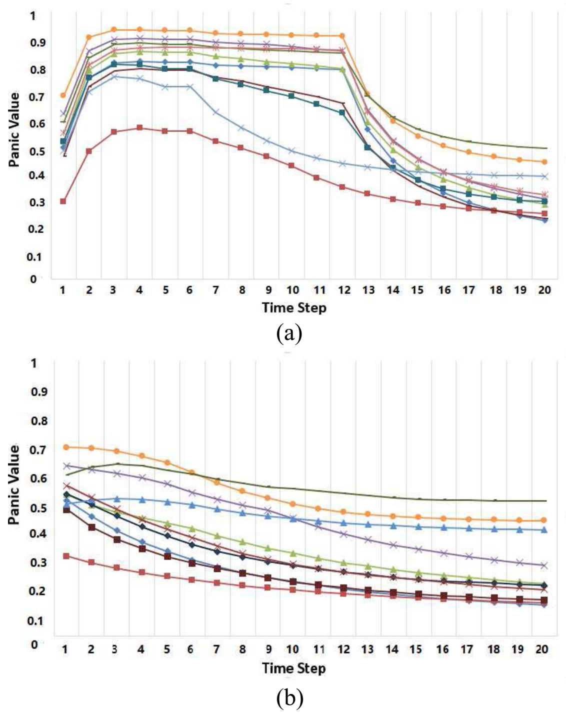



Fig. 7. Panic emotion changes in a crowd in different situations. The simulation contains 15 agents and each colored line represents the panic emotion of one agent in the scene. Panic changes caused by (a) persistent hazards and (b) transient hazards.

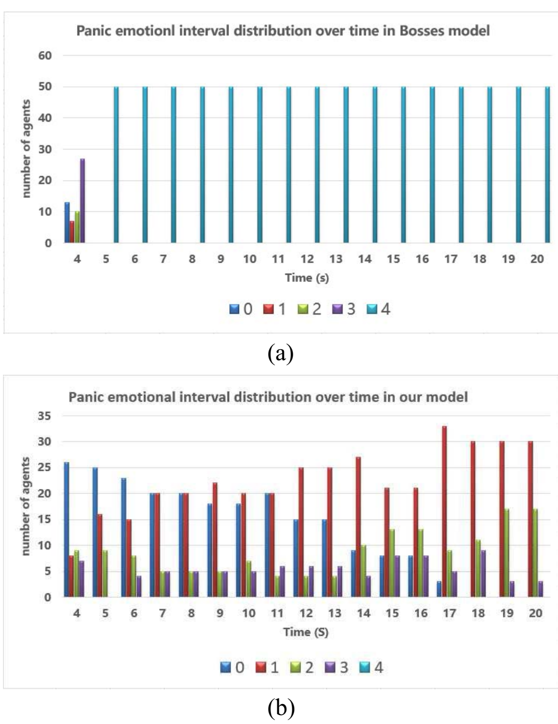



Fig. 8. Agent numbers in different panic emotional interval during the evacuation. Five panic emotion levels depicted by 0–4 with different colors, the higher this value, the higher the panic emotion. Panic emotional interval distribution over time in (a) model [52] and (b) our model.

have different panic emotions and movements in different time. The panic emotion of all agents and movements simulation results can be shown in Figs. 8 and 9.

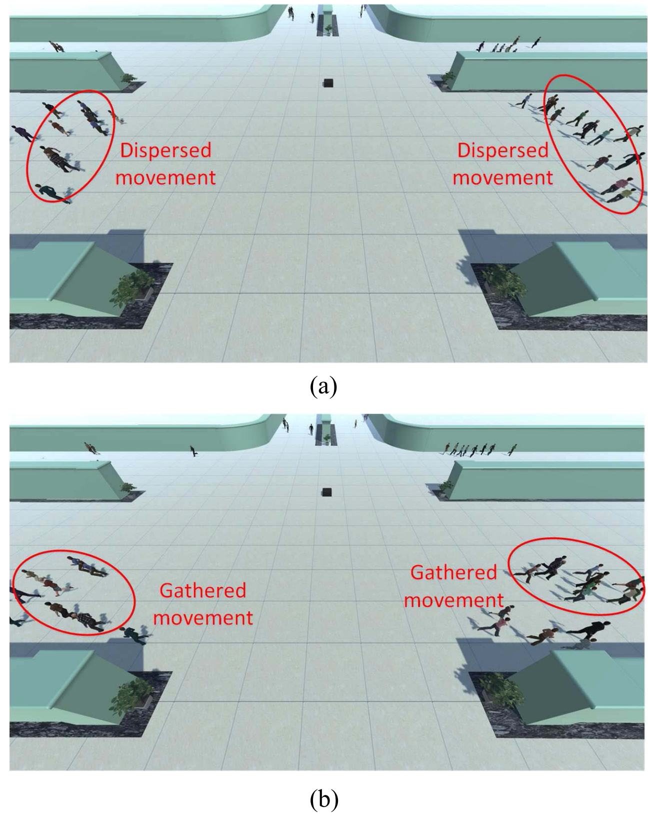



Fig. 9. Comparison of crowd movements with another emotional contagion model. (a) With our emotional contagion model. (b) With emotional contagion model proposed in [52].

In Fig. 8, the number of distribution of agents panic emotion is illustrated by five levels defined in Section VII-A, where 0 as the lowest panic emotion values 0 and level 5 represents the highest panic emotion values from 0.7 to 1.0. We choose the explosion time at 4 s as the start time, which can be seen that all agents have the high panic emotion almost the whole evacuation process when used emotional contagion model mentioned in [52], but in our model, the number of lower emotion levels decrease first and increase as the following, the higher level ones reverses. The reason of this phenomenon is that [52] considers all agents in the whole scenes once a hazard occurs, and does not take emotion decay into account. While in our emotional contagion model, each agent have a perception range as well as expressiveness and susceptibility to accept emotional contagion from others, and their panic emotion change along with the movement.

In addition, the simulation results in this two conditions shown in Fig. 9. The movement of agents after explosion in our model are more dispersed as labeled by red ellipses, while in another model, all agents behave toward an aggregation states. With considering the different emotion changes in this two models, lower panic emotion lead to a more independent movement direction [shown in Fig. 9(a)] instead of gathered movement based on stronger emotional contagion [shown in Fig. 9(b)]. In real world, panic emotions will decrease when the crowd are away from hazards. From the results of these two different models, where be seen that our emotional contagion

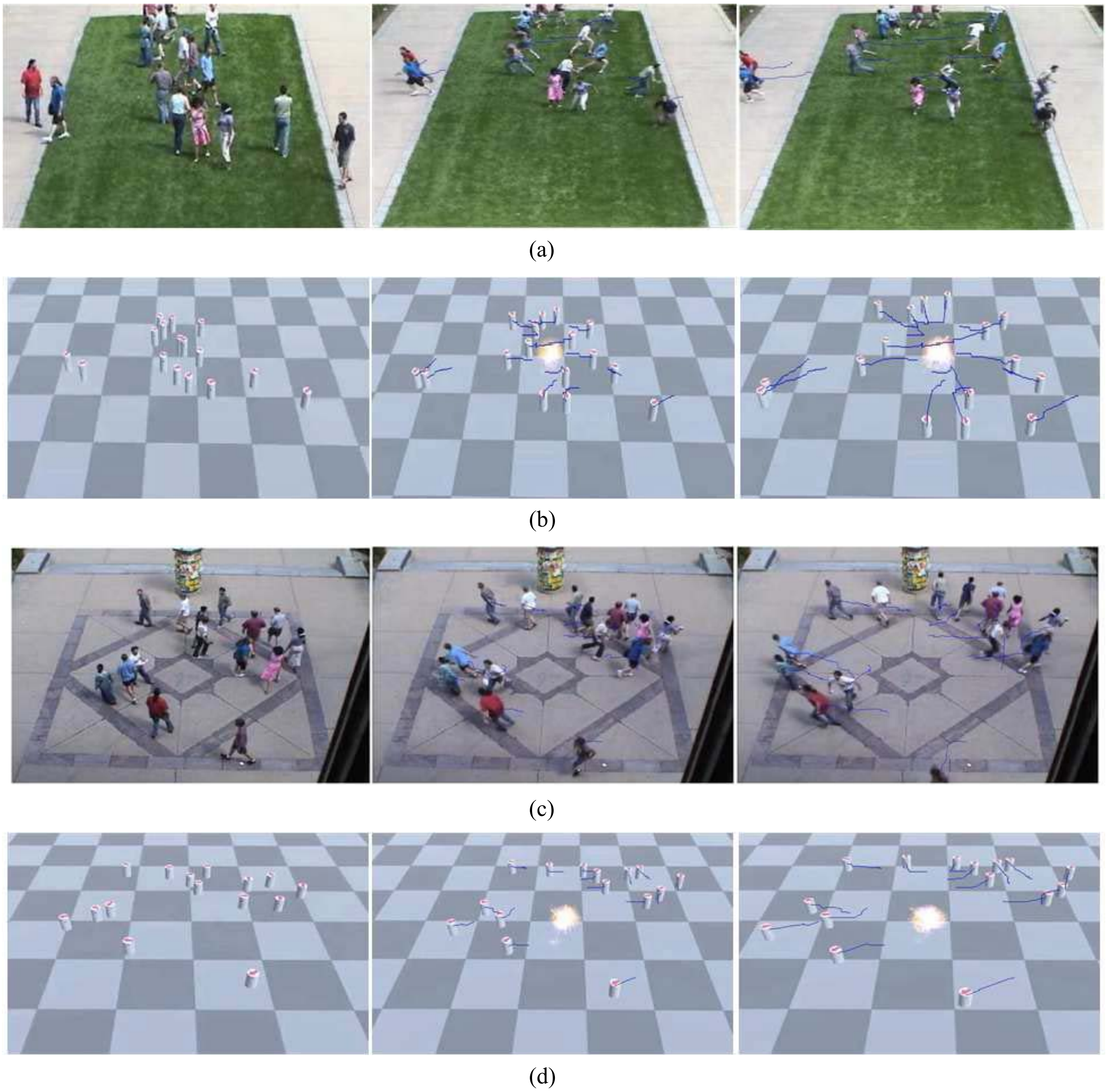


Fig. 10. Snapshots of ground-truth crowd evacuations on the outdoor ground and our corresponding simulation results. Three images from left to right is: initial random status, at the beginning of the evacuation, one moment in the evacuation. The movement trajectories for all agents are drawn by the blue lines. (a) and (c) Recorded video data (ground-truth). Our simulation (b) result [corresponding to (a)] and (d) result [corresponding to (c)].

model is more realistic and suitable to simulate the crowd movement in the multihazard situations.

### D. Comparisons With Real-World Crowd Behaviors

In order to validate our approach, we also compare the simulation results with real-world crowd evacuation video. Two crowd evacuation video are chosen in this part, first one is chosen from the public available dataset of normal crowd videos from the University of Minnesota [53], which is designed to test the abnormal detection method originally. In this scene, movement details are used to verify the similarity between real-world crowd behaviors and our simulation results. Although no predefined goals are set in advance, agents can still be driven to escape in a realistic way by our method. Illustrated in Fig. 10, three images in each row are the crowd movement states at initial random conditions, at the beginning of the evacuation, one moment after the hazard occurs. The trajectories of agents are shown by the blue lines. From the trajectories we can find that movement trends of our simulation results are similar with that in real scenes. Furthermore, we also compare the trajectory length and the maximum speed of each agent from the moment when hazard occurs to the end of simulation, as shown in Tables I (comparison with the grassland scene) and II (comparison with the square scene), where can be seen that our mean trajectory length and mean maximum speed are close to the true video data. Thus, we can see both overall movement trend of the crowd and individuals' movement details in the crowd are similar to those in the recorded real-world crowd video. More animation comparison details can be found in the supplementary video.

TABLE I
COMPARISON BETWEEN OUR SIMULATION RESULT AND REAL GRASSLAND SCENE

| Agent ID | Trajectory length in simulation result (pixel) | Trajectory length in real video (pixel) | Maximum speed in simulation result (pixel/frame) | Maximum speed in real video (pixel/frame) |
|---|---|---|---|---|
| 1 | 111.8814 | 94.1773 | 6.0828 | 8.0156 |
| 2 | 121.1261 | 121.4284 | 5.5902 | 8.0000 |
| 3 | 117.4920 | 155.8467 | 5.8310 | 9.0000 |
| 4 | 106.193 | 89.5567 | 5.4083 | 9.8234 |
| 5 | 94.7727 | 50.7417 | 5.3852 | 6.2560 |
| 6 | 86.9983 | 32.9509 | 8.0623 | 6.5765 |
| 7 | 83.7936 | 60.6989 | 5.0000 | 3.6056 |
| 8 | 110.8647 | 110.0192 | 6.5192 | 11.5109 |
| 9 | 57.6991 | 61.0370 | 5.5227 | 9.8489 |
| 10 | 45.4759 | 42.4537 | 3.6401 | 7.5664 |
| 11 | 35.5255 | 39.0000 | 3.5355 | 8.5586 |
| 12 | 73.6405 | 42.2433 | 4.7170 | 5.3852 |
| 13 | 84.6207 | 81.6077 | 3.5355 | 9.0000 |
| 14 | 90.2147 | 98.1849 | 5.0000 | 10.0000 |
| 15 | 96.3887 | 116.4673 | 7.5000 | 10.0000 |
| 16 | 113.0668 | 128.4863 | 4.5277 | 13.5370 |
| mean | 95.3169 | 88.3267 | 5.3661 | 8.5405 |

TABLE II
COMPARISON BETWEEN OUR SIMULATION RESULT AND REAL SQUARE SCENE

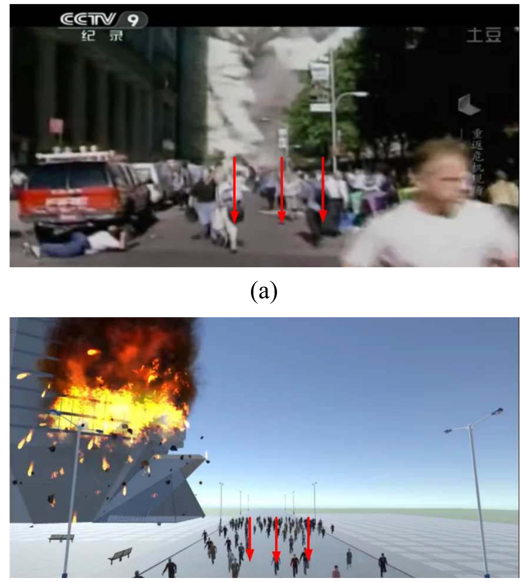
| Agent ID | Trajectory length in simulation result (pixel) | Trajectory length in real video (pixel) | Maximum speed in simulation result (pixel/frame) | Maximum speed in real video (pixel/frame) |
|---|---|---|---|---|
| 1 | 84.9795 | 93.1883 | 6.8007 | 5.5902 |
| 2 | 36.1059 | 49.7452 | 4.6098 | 4.5277 |
| 3 | 32.0000 | 56.9671 | 4.0000 | 3.5355 |
| 4 | 39.0000 | 70.1650 | 3.6056 | 7.1589 |
| 5 | 65.1402 | 121.4701 | 5.4083 | 9.7082 |
| 6 | 37.3852 | 64.8521 | 3.2016 | 6.5765 |
| 7 | 32.3006 | 66.2214 | 3.2016 | 3.6056 |
| 8 | 85.3429 | 135.1380 | 5.5902 | 9.5525 |
| 9 | 86.2274 | 80.3388 | 6.2650 | 6.1033 |
| 10 | 38.7559 | 88.4081 | 5.0249 | 6.0208 |
| 11 | 136.2666 | 83.5291 | 12.2577 | 6.5192 |
| 12 | 109.6164 | 120.4088 | 7.0711 | 9.0139 |
| 13 | 124.5751 | 69.5775 | 13.0096 | 13.2004 |
| 14 | 159.8465 | 152.3059 | 9.1788 | 10.5000 |
| 15 | 176.6732 | 191.3627 | 12.0934 | 8.0156 |
| mean | 82.9477 | 96.2452 | 6.7546 | 7.3086 |

The second one is the 911 terrorist attacks with two explosion, while when considering the camera shaking and crowd occlusion, movement details of agents cannot be obtained accurately, thus this scene is mainly used to verify the similarity of group movement trends between our simulation result and true situation. In this circumstance, two bombs occurred concurrent on the building, and all agents straight forward in the whole procedure. As shown in Fig. 11, the crowd movement directions are indicated by red arrows, more details can be found in the supplementary video.

### E. Applications in Different Scenarios

We apply our method to simulate crowd evacuation simulations in office building (Fig. 12) and crossroads (Fig. 13) with multiple hazards to check the effectiveness of our method.

In an office building, we numbered its four rooms as 1–4 from left to right and up to bottom. The corridor in the middle connects all these rooms together and there are no exits on both sides. At the beginning, 50 agents located in different rooms move randomly in Fig. 12(a). At the eighth frame, there are two bomb explosions in rooms 1 and 4 at the same time in Fig. 12(b). At the 64th frame, there is a fire in room 2 in Fig. 12(c). From the simulation results, we observe the following: when bomb explosions occur, in order to avoid the danger, agents in the rooms begin to move to rooms 2 and 3, respectively. When room 2 is on fire, the agents in or aiming to room 2 try to escape. At last, all of the agents move to the safe room 3 in Fig. 12(d).



(a)

(b)

Fig. 11. Snapshots of the true video and our simulation result of 911 scenario, where the red arrows represent the movement trends of crowd. (a) True video data (911 terrorist attacks). (b) Simulation result.

The crossroad scene contains 50 pedestrians and two noncurrent car bombs. When the simulation starts, agents cross the road freely in Fig. 13(a). At the 16th frame, one black car bomb explodes in Fig. 13(b) and another red car bomb explodes at the 24th frame as shown in Fig. 13(c). When the first car bomb occurs, the agents nearby evacuate immediately. Some agents affected by their neighbors move away from the black car bomb. Since the dangerous field of black car bomb is limited, the agents far away from it continue to move along their original paths. When the red car bomb occurs, these agents who are in the perilous field also begin to evacuate, while others just move in their original directions. Fig. 13(d) is the result at the end time (at the 60th frame). The animation details can be found in the supplementary video.

## VIII. CONCLUSION

The crowd behavior simulation under multihazard environment is a very challenging problem, and the existing models with a single hazard cannot be applied to these cases directly. In this paper, we present a novel evacuation simulation method by modeling the generation and contagion of panic emotion under multihazard circumstances. First, we model multihazard environment by classifying the hazards into different types based on their inherent characteristics and introducing the concept of perilous field for a hazard. Then, we propose a novel emotion contagion model to simulate the panic emotion evolving process in these situations. Finally, we introduce an ERVOs model by augmenting the traditional RVO model with emotional contagion, which combines the panic emotion impact and local avoidance together for the first time. By comparing our simulation results with the ground-truth data and applying our algorithm in different virtual environments, our experimental results show that the overall approach

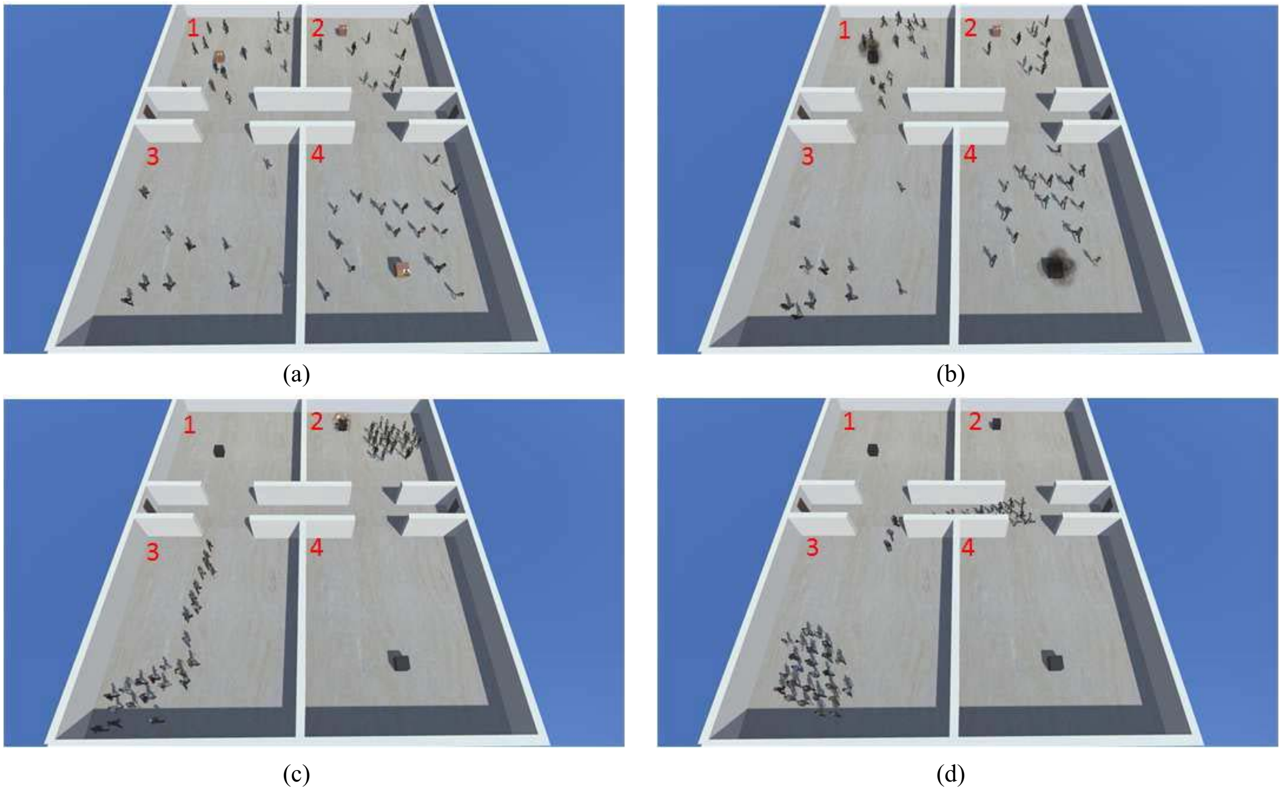



Fig. 12. Evacuation simulation result by our approach in an office building. (a) First frame. (b) Eighth frame. (c) 64th frame. (d) 120th frame.

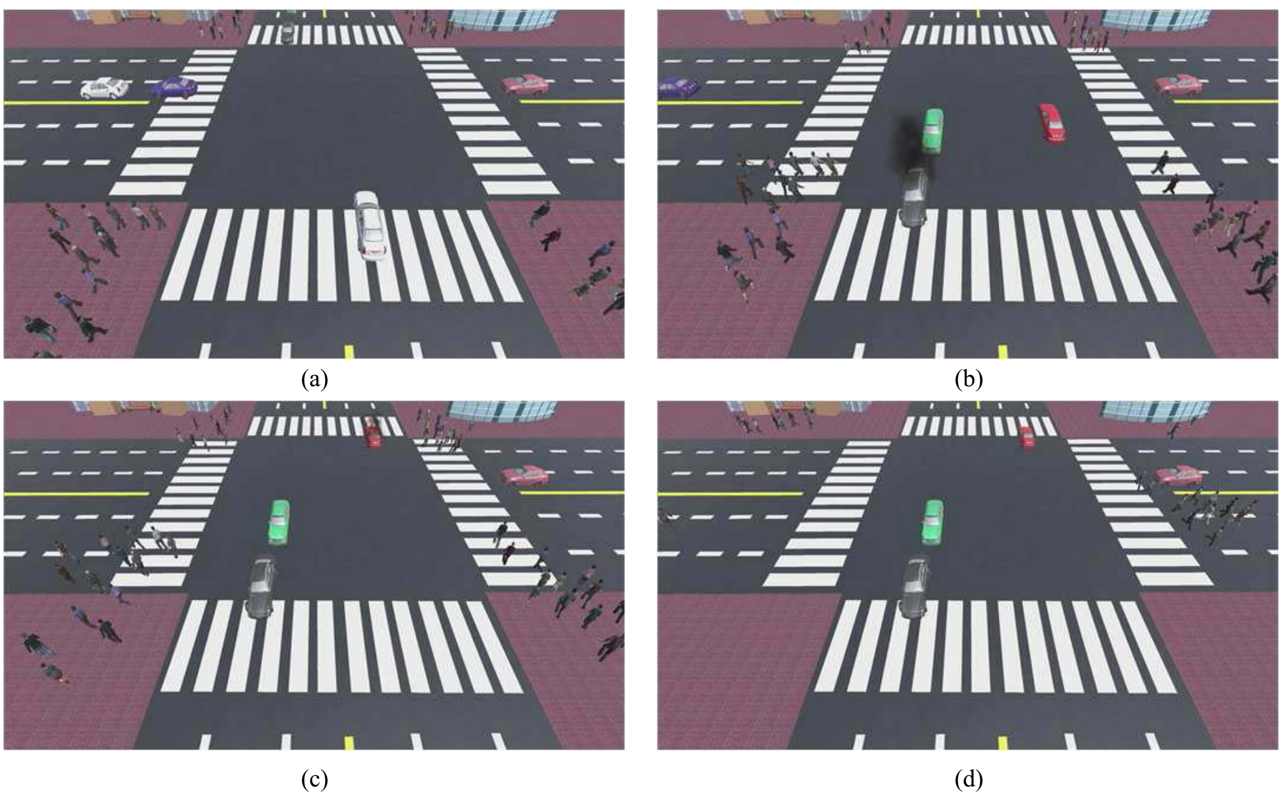



Fig. 13. Evacuation simulation result by our approach in a crossroad. (a) First frame. (b) 16th frame. (c) 24th frame. (d) 60th frame.

is robust and can better generate realistic crowds as well as the panic emotion dynamics in a crowd in various multihazard environments.

There are still several limitations in this paper. The first one is that our current method relies on some important assumptions, such as all agents in our scenario are treated equally in the face of hazards except the different personalities, thus they can perceive the danger level and be affected by the hazards once he/she enter into the influence radius of them. Besides that safe exits chosen in the simulation environment in advance, especially in the office building situations, where the doors are chosen as the sole exit for each room. In real world, this is not very common. So we need to improve the sensing capability of the agents in an unknown multihazard scenario. The second is, in spite of considering agents personalities, expressiveness, and susceptibility, diverse crowd movements are shown in our simulation results, many other complex personality traits and prior expertise may also affect the emotion changes and motion choices of each agent. In addition, the personality parameters in our emotional contagion model are set randomly to depict different agents, while it may not include all agents or some agents with special characters. Thus, more factors need to be considered. Furthermore, our method is sensitive to some key parameters, such as the strength of danger. In the future, we want to utilize a large number of surveillance video clips to calibrate and further improve our model.

## ACKNOWLEDGMENT

The authors would like to thank all the anonymous reviewers.

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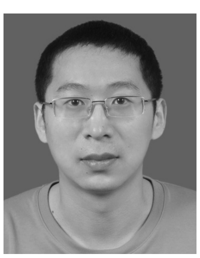

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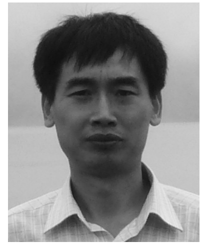

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