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ORIGINAL ARTICLE

# A novel simulation framework based on information asymmetry to evaluate evacuation plan

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**Abstract** In this paper, we present a novel framework to simulate the crowd behavior under emergency situations in a confined space with multiple exits. In our work, we take the information asymmetry into consideration, which is used to model the different behaviors presented by pedestrians because of their different knowledge about the environment. We categorize the factors influencing the preferred velocity into two groups, the intrinsic and extrinsic factors, which are unified into a single space called influence space. At the same time, a finite state machine is employed to control the individual behavior. Different strategies are used to compute the preferred velocity in different states, so that our framework can produce the phenomena of decision change. Our experimental results prove that our framework can be employed to analyze the factors influencing the escape time, such as the number and location of exits, the density distribution of the crowd and so on. Thus it can be used to design and evaluate the evacuation plans.

**Keywords** Crowd simulation · Information asymmetry · Influence space · Emergency evacuation

## 1 Introduction

With the rising instances of extreme events, such as fires, earthquakes and terrorist attacks, the need for developing and evaluating emergency evacuation plans is becoming increasingly important. However, it is an extremely difficult task because the behavior of pedestrians under emergency conditions might be influenced by many factors, such as their familiarity with the environment, tendency of herding, compliance with the rules and so on. Additionally it is impractical to evaluate the effectiveness of an evacuation plan through actual field testing.

Using virtual agents to simulate the pedestrian behavior in extreme events, crowd simulation has been proved to be one of the most effective ways to design and evaluate evacuation plan. The fundamental work is to build a mathematical model to simulate various behaviors exhibited by pedestrians under emergency situations. Though various methods have been proposed for crowd simulation [8,9,14,27] and emergency simulation [18,20,25], simulating the crowd behavior under emergency situations is still an open question due to the complicated characteristics of escape panic. In order to achieve a good evacuation plan, the factors influencing the pedestrian behaviors should be taken into consideration as much as possible.

Unfortunately, some factors are ignored in the previous research and information asymmetry is one of the most important factors. Most of the previous works assume that all pedestrians have the same amount of knowledge about the environment, such as the location of all exits. Thus all pedestrians can determine their escape routes immediately when the extreme events occur. This situation is not common in the real scenario. Imagine a huge and complex shopping mall with multiple exits, the staff working in the mall has a greater chance to escape from the mall than customers when it catches fire. One important reason behind this fact is information asymmetry, which indicates that some people have more information than the others. Information asymmetry also influences the behavior of pedestrians. Individuals without the knowledge of exit positions tend to follow the crowd.

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And on the other hand, individuals who know the ways out may not conform to the crowd.

In this paper, we propose a novel simulation framework to model the behavior of crowd under emergency situations in a confined space with multiple exits. The escaping process is modeled as a dynamic decision-making process which takes the information asymmetry into consideration. Decision is made according to the pedestrian's own knowledge about the environment combined with the movements observed from his nearby pedestrians. These two factors are modeled as a unified *influence space* in our paper. Note that the decision made by pedestrian is not fixed, which means that pedestrian may re-choose the escape route to respond to the dynamically changing environment. Our framework can be employed to measure the effectiveness of an evacuation plan, such as the influence of the crowd size, the initial pedestrian distribution density or the layout of the environment on the escape time.

The remainder of this paper is organized as follows. Section 2 reviews the related work. Section 3 provides an overview of our simulation framework. The construction of influence space and the determination of preferred velocity are introduced in Sect. 4. Section 5 discusses the decision-making process during escape. Experimental results are presented in Sect. 6, and the paper is concluded in Sect. 7.

## 2 Related work

### 2.1 Crowd simulation

Various methods have been proposed for crowd simulation [8,9,14] and emergency simulation [18,20], from the cellular automate technique [24] to continuum methods like the fluid [26] or gas particles [15]. These works focus on building a mathematical model to simulate various behaviors under specified conditions. For example, Kim et al. [13] combine velocity-based collision-avoidance algorithms with external physical forces, which is capable of modeling both physical forces and interactions between agents and obstacles, while also allowing the agents to anticipate and avoid upcoming collisions during local navigation. Ninomiya et al. [16] present a planning framework that satisfies multiple spatial constraints imposed on the path. It introduces two hybrid environment representations that balance computational efficiency and search space density to provide a minimal, yet sufficient, discretization of the search graph for constraint-aware navigation. In order to accelerate calculation, Papageorgiou and Platis [17] present a simplification algorithm, which performs edge collapses on manifold triangular meshes driven by a quadric error metric implemented on GPU.

### 2.2 Evacuation simulation

An extensive body of literature involving simulation for evacuation planning [2,4,10] and disaster response [7,22,30] have been proposed in recent years. Studies of indoor building evacuation specially deal with the safety design and guiding measures to make a reasonable evacuation plan.

The layout of facility is important to the design of an evacuation plan. A specially designed prototype [29] is presented to simulate a concert venue setting which is highly configurable allowing for user definition of concert venues with any arrangement of seats, pathways, stages, exits in a fire disaster. A methodology [28] is presented to evaluate evacuation safety versus productivity concurrently for various, widely known manufacturing layouts. Camillen et al. [6] implement simulation of people visiting and evacuating a museum, which offers an excellent test environment for simulating a collective behavior emerging from local movements in a closed space.

Another important factor has to be considered in the evacuation simulation is the location of exits. A framework is presented in [1] to develop an optimal evacuation plan for large-scale pedestrian facilities with multiple exit gates and gives evacuees instructions in terms of the optimal exit gates.

A study about human responses to the direction information like signs, moving crowd and memorized information when choosing exit routes is proposed [4]. Pelechano and Badler [19] notice that agents may take different roles such as trained personnel, leaders and followers. And they can communicate knowledge about the buildings during evacuation. Braun et al. [5] present a model for studying the impact of individual agents characteristics in emergent groups using the physically based model of crowd simulation. Sagun et al. [23] aim to enhance safety through improved design of the built environment by investigating issues associated with emergencies and evacuations and to establish new building design guidelines. Kamkarian and Hexmoor [12] focuses on designing a tool for guiding a group of people out of a public building when they are faced with dangerous situations that require immediate evacuation.

## 3 Framework overview

We first introduce the notations used in our paper. Each pedestrian $i$ is modeled as a cylinder in 3D space with the following common attributes $\{p_i, r_i, \mathbf{v}_i, \mathbf{v}_i^p\}$, indicating the current position, radius of representative cylinder, current velocity and preferred velocity respectively. Additionally, $r_{ij} = r_i + r_j$ is the combined radius of pedestrian $i$ and $j$, $\mathbf{p}_{ij} = p_i - p_j$ is the displacement vector, $p_{ij}$ is the distance between $i$ and $j$, and $\mathbf{v}_{ij} = \mathbf{v}_i - \mathbf{v}_j$ is the relative velocity, Further norm(.) is the normalization function and $\|\mathbf{v}\|$ denotes the length of vector $\mathbf{v}$.

Among all these above-mentioned variables, the preferred velocity $\mathbf{v}_i^p$ is the most important one because it reflects the decision made by the pedestrian. In our paper, we categorize the factors influencing $\mathbf{v}_i^p$ into the following two types:

1. Extrinsic information: it represents the information that a pedestrian continuously extracts from the surrounding environment, such as the crowd moving direction, exit signs, evacuation instructions and so on. Because of the similarity of the surrounding environment for the nearby pedestrians, the extrinsic information tends to make pedestrians coordinate collectively and follow a similar path to escape.
2. Intrinsic information: it is employed to model a pedestrian's prior knowledge about the exit locations. Note that we do not assume that all pedestrians know the exit locations. Thus all pedestrians can be divided into two groups named awareness and ignorance according to whether they have this kind of knowledge or not.

As illustrated in Eq. (1), $\mathbf{v}_i^p$ is decoupled to its direction $\mathbf{e}_i^p$ and magnitude $v_i^p$, which will be solved separately.

$$\mathbf{v}_i^p = v_i^p \cdot \mathbf{e}_i^p \tag{1}$$

In order to determine $\mathbf{e}_i^p$, an *influence space* $\Phi_i$ is constructed for each pedestrian. As mentioned above, all the factors influencing $\mathbf{v}_i^p$ are divided into extrinsic and intrinsic information. Thus, the influence space is built from two parts. The first part $E_i$ is used to model the extrinsic information including the influence from nearby pedestrians, exit signs and evacuation instructions. The second part $I_i$ is employed to model the intrinsic information. These two parts are combined together by a combination weight $\alpha_i$ to determine $\mathbf{e}_i^p$ (see Sect. 4 for more details).

The computation of $v_i^p$ is much simpler than $\mathbf{e}_i^p$. For the members in the $awareness$ group, their preferred speed $v^p$ is set to the maximum speed $v_{\max}$ they can reach because they do not need to observe the movement of the crowd. On the other hand, $v_i^p$ for a member in the $ignorance$ group is set to the average speed of his neighbors.

The behavior of pedestrians under emergency situation is controlled by a finite state machine with five states which will be explained in Sect. 5. The core operation in each state is to determine the preferred velocity $\mathbf{v}_i^p$ under different conditions.

## 4 Influence space

In this section, we will discuss the details about solving $\mathbf{e}_i^p$, which is represented by Eq. (2), from the influence space.

$$\mathbf{e}_i^p = \alpha_i \cdot \mathbf{e}_i^E + (1 - \alpha_i) \cdot \mathbf{e}_i^I \tag{2}$$

where $\mathbf{e}_i^E$ and $\mathbf{e}_i^I$ are two normalized vectors derived from the extrinsic and intrinsic information respectively, and $\alpha_i \in [0, 1]$ is the combination weight.

### 4.1 Computation of $\mathbf{e}_i^E$

Empirical study [3] indicates that crowds maintain local interaction only with a few number of neighbors based on topological distance, rather than with all the neighbors within a fixed metric distance, especially in the emergency case. Motivated by this fact, a neighborhood $\Psi_i$ is constructed for each pedestrian $i$, which contains $N$ pairs of relative position and velocity, as shown in Eq. (3).

$$\Psi_i = \{(\mathbf{p}_{i1}, \mathbf{v}_{i1}), \ldots, (\mathbf{p}_{iN}, \mathbf{v}_{iN})\} \tag{3}$$

According to [3], the value of $N$ is 6 or 7.

In our paper, the construction of neighborhood $\Psi_i$ also has to satisfy the following conditions:

– If pedestrian $j$ is neighbor of $i$, their distance must satisfy $p_{ij} < R$, where $R$ is a user-defined constant indicating the maximum visual range.
– If there exists obstacles like walls between $i$ and $j$, then $p_{ij} = \infty$.
– If the number of neighbors $N'$ satisfying the above two conditions is larger than $N$, then the $N$ nearest neighbors are employed to construct $\Psi_i$. On the other hand, if $N' < N$, then we use the $N'$ neighbors' information plus $N - N'$ pairs of (0, 0) to construct $\Psi_i$.

A $3 \times N$ matrix $M_i$ is constructed for each pedestrian $i$ to represent the influence from his neighborhood $\Psi_i$. This matrix can be formulated as:

$$M_i = [\mathbf{y}_{i1}, \ldots, \mathbf{y}_{iN}] \tag{4}$$

where

$$\mathbf{y}_{ij} = w_{ij} \cdot \mathrm{norm}(\mathbf{p}_{ji}) \tag{5}$$

where $w_{ij}$ is a weight as illustrated in Eq. (6).

$$\begin{cases} w_{ij} = g_j \cdot w_{D(i,j)} \cdot w_{V(i,j)} \cdot w_{P(i,j)} \\ w_{D(i,j)} = \dfrac{A}{\|p_{ij} - r_{ij}\|} \\ w_{V(i,j)} = e^{-\dfrac{\|\mathbf{v}_j - \bar{\mathbf{v}}\|}{B}} \\ w_{P(i,j)} = e^{-\dfrac{\|\mathrm{norm}(\mathbf{p}_{ji}) - \mathrm{norm}(\bar{\mathbf{v}})\|}{C}} \end{cases} \tag{6}$$

where $A$, $B$ and $C$ are three constants used to adjust the contributions of $w_{D(i,j)}$, $w_{V(i,j)}$ and $w_{P(i,j)}$ to $w_{ij}$.

- $w_{D(i,j)}$: this term indicates that the influence of $j$ on $i$ will decrease with the increase of their distance.
- $w_{V(i,j)}$: this term indicates that if $j$ has higher conformity with the crowd, $j$ will have a greater influence on $i$.
- $w_{P(i,j)}$: this term indicates that the crowd in front of $i$ has greater impact on it than the crowd behind [11].

In our paper, the influence of evacuation instructions is modeled as following the pedestrians who know the exit locations. During the process of evacuation, these persons will have extra influence on the crowd by instructing the evacuation routes to the pedestrians in their neighborhood. This extra influence is represented by the parameter $g_j$ in Eq. (6). For pedestrian $j$ in the *ignorance* group, $g_j$ equals to 1, thus he has no extra influence on his neighborhood. Likewise for pedestrian in the *awareness* group, $g_j$ is bigger than 1.

According to the above descriptions, matrix $M_i$ contains the influence of the nearby pedestrians and evacuation instructions on pedestrian $i$. The normalized eigenvector $\mathbf{e}_i^M$ corresponding to the maximum eigenvalue of $M_i$ will be solved, which is involved in the determination of $\mathbf{e}_i^E$ later.

The influence of exit signs is modeled as a normalized vector $\mathbf{e}_i^s$ which points to the identical direction as the exit signs. Note the fact that the exit signs are not everywhere inside the environment. Thus $\mathbf{e}_i^s$ is effective only when the distance between exit sign and pedestrian $i$ is smaller than the maximum visual range $R$.

$\mathbf{e}_i^E$ is chosen from either $\mathbf{e}_i^M$ or $\mathbf{e}_i^s$ by Algorithm 1. Note that if the angle between $\mathbf{e}_i^M$ and $\mathbf{e}_i^s$ is smaller than 90° (line 4), which indicates that $\mathbf{e}_i^M$ and $\mathbf{e}_i^s$ roughly point to the same direction, $\mathbf{e}_i^M$ is used as $\mathbf{e}_i^E$. Otherwise a random number $t$ is generated (line 7) and compared with a constant $T_i$ (line 8) to determine $\mathbf{e}_i^E$. Here $T_i$ is used to model the tendency that pedestrian $i$ will follow the movement of crowd instead of the exit signs when they provide conflicted information.

**Algorithm 1** Determination of $\mathbf{e}_i^E$.

1: **if** no exit signs inside maximum visual range of $i$ **then**
2: $\quad \mathbf{e}_i^E = \mathbf{e}_i^M$
3: **else**
4: $\quad$ **if** $\mathbf{e}_i^M \cdot \mathbf{e}_i^s > 0$ **then**
5: $\quad\quad \mathbf{e}_i^E = \mathbf{e}_i^M$
6: $\quad$ **else**
7: $\quad\quad$ Generate a random number $t \in (0, 1)$
8: $\quad\quad$ **if** $t > T_i$ **then**
9: $\quad\quad\quad \mathbf{e}_i^E = \mathbf{e}_i^M$
10: $\quad\quad$ **else**
11: $\quad\quad\quad \mathbf{e}_i^E = \mathbf{e}_i^s$
12: $\quad\quad$ **end if**
13: $\quad$ **end if**
14: **end if**

## 4.2 Computation of $\mathbf{e}_i^I$

For the members in the *awareness* group, the navigation mesh method [21] is employed to plan their routes. The only problem needed to solve here is to choose one out of the multiple exits. The simplest solution is to choose the closest exit, but this solution is too idealistic in reality due to the following facts: (1) closest exit is a mathematical concept. It might be not easy for a pedestrian to determine which exit is the closest one. (2) Choosing the closest exit is the most reasonable decision. But in emergency situations, pedestrian has to make a decision as soon as possible. Under such situation, pedestrian is not always capable of making the most reasonable decision.

In our paper, we propose a simple mathematical model to solve the exit choosing problem. Considering a facility with $X$ exits, a pedestrian in the *awareness* group knows the location of $M$ exits ($1 \le M \le X$). The distances from these $M$ exits to his current location are $L_1, L_2, \ldots, L_M$ respectively. The probability $P_k$ of choosing exit $k$ can be computed by Eq. (7), which indicates that the closer exit will have a higher chance to be selected.

$$P_k = \frac{f(k)}{\sum_{i=1}^{M} f(i)} \quad \text{where} \quad f(k) = \frac{1}{L_k} \tag{7}$$

In order to choose one exit, the range [0, 1) is divided into $M$ intervals $[I_0, I_1), [I_1, I_2), \ldots [I_{M-1}, I_M)$, where $I_k = \sum_{i=1}^{k} P_i, k = 1, 2..., M$ and $I_0 = 0$. Then a random number $t \in [0, 1)$ is generated and exit $m$ is chosen if $t$ falls in the interval $[I_{m-1}, I_m)$.

For the members in the *ignorance* group, we simply give them a random direction.

## 4.3 Computation of $\mathbf{v}_i$

After $\mathbf{e}_i^E$ and $\mathbf{e}_i^I$ are achieved, they can be combined together to compute the direction of the preferred velocity $\mathbf{e}_i^p$ by Eq. (2). The combination weight $\alpha$ in Eq. (2) is determined by the following way.

- For the members in the *awareness* group, we set $\alpha$ to zero, indicating that these pedestrians always trust their own knowledge and ignore the movement of crowd and exit signs.
- For the members in the *ignorance* group, $\alpha_i$ obeys the Gaussian distribution $G(\mu, \sigma^2)$ where $\mu$ is the average tendency that a pedestrian will follow the information extracted from the extrinsic factors instead of finding his own path. If $\mathbf{e}_i^M$ is selected as $\mathbf{e}_i^E$ by Algorithm 1, $\alpha_i$ will be modulated by multiplying a factor $\frac{N'}{N}$ where $N$ and $N'$ are defined in Sect. 4.1. This factor is employed to simulate the phenomena that if more pedestrians are in

the neighborhood of pedestrian $i$, he has a greater chance to follow the movement of crowd instead of finding the way out by himself.

Then the preferred velocity $\mathbf{v}_i^p$ can be computed by Eq. (1). Note that $\mathbf{v}_i^p$ is employed to reflect the decision made by pedestrian $i$, but when he carries out this decision, he must be constrained by many other conditions such as obstacles, collision avoidance. In our framework, the Reciprocal Velocity Obstacles method [27] is employed to compute $\mathbf{v}_i$ from $\mathbf{v}_i^p$.

## 5 Decision-making process

In our framework, we employ a finite state machine as demonstrated in Fig. 1 to control the behavior of the pedestrians. The computation of $\mathbf{e}_i^p$ is slightly different in each state. We will discuss all these details in this section.

### 5.1 State INIT

In this state, every pedestrian gets a random velocity to make him wandering in the confined space. When an emergency happens, the $awareness$ group members directly enter the *ESCAPE* state (transition ① in Fig. 1) and the $ignorance$ group members enter the *CONFUSE* (transition ②) state.

### 5.2 State CONFUSE

Only the members of the $ignorance$ group can enter this state which lasts for a fixed and short time period $t_{\text{confuse}}$. During $t_{\text{confuse}}$, the preferred speed is set to zero to model the behavior of halting movement and observing surrounding environments. At the end of the state, preferred velocities are generated by the method described in Sect. 4 and the pedestrians enter the *ESCAPE* state (transition ③).

### 5.3 State ESCAPE

This state occupies most of the time of the escaping process. For the pedestrians who have lost confidence in the decisions made before, they will enter state $HESITATE$ to reconsider the decisions (transition ④). In our paper, the phenomenon of lost confidence is modeled as $d_i^{\Delta t} < \epsilon$, where $d_i^{\Delta t}$ is the distance moved during a time period $\Delta t$ and $\epsilon$ is an user pre-defined threshold. Note that the members in the group $awareness$ always have more confidence in their decision than those in the group $ignorance$, thus we use a smaller value of $\epsilon$ for $awareness$ members in our implementation.

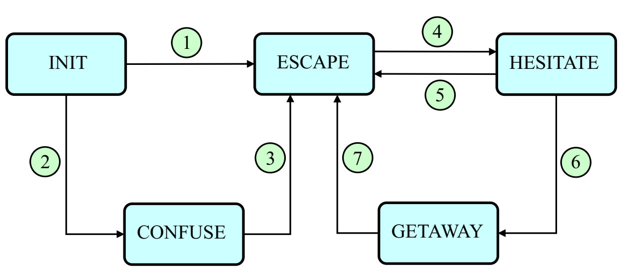


**Fig. 1** The finite state machine which is used to model the behavior of pedestrians

### 5.4 State HESITATE

Each pedestrian in the $HESITATE$ state will reconsider the decisions made before. Different mechanisms are employed for the $awareness$ and $ignorance$ group.

- For the $awareness$ group, its members will re-choose a route by the method described in Sect. 4.2. The only difference is that the probability $P$ for the current route will drop to half of its original probability. This mechanism is consistent with the phenomenon that if a pedestrian starts questioning his previous decision, he has a lower chance to stick to the old route. After a new route is determined, he will go back to the state *ESCAPE* (transition ⑤).
- For the $ignorance$ group, $\mathbf{e}_i^I$ is set to the opposite direction of $\mathbf{e}_i^M$, and then he enters the state $GETAWAY$ (transition ⑥).

### 5.5 State GETAWAY

Only members of the $ignorance$ group can enter this state which is designed to help the pedestrians to get away from the crowd. Like the state *CONFUSE*, it also lasts only for a fixed and short time period $t_{\text{getaway}}$. During this period, the combination weight $\alpha_i$ is set to 0 so that pedestrian $i$ will follow $\mathbf{e}_i^I$ to get rid of the influence from the crowd. After this period is over, the pedestrians will go back to the *ESCAPE* state (transition ⑦).

## 6 Experiments and discussions

We use a maze which is quite similar to the structure of the supermarket to test our simulation framework. Its layout is as illustrated in Fig. 2. Without further specification, the awareness ratio (the ratio of individuals who at least know the location of one exit) and the crowd size are fixed to 70 % and 400 respectively.

In reality, the decision-making process under emergency situations is influenced by so many factors, some of which are unmeasurable and unreproducible. Thus even when the same person faces an identical situation, he might make different decisions at different times. Based on this fact, if we

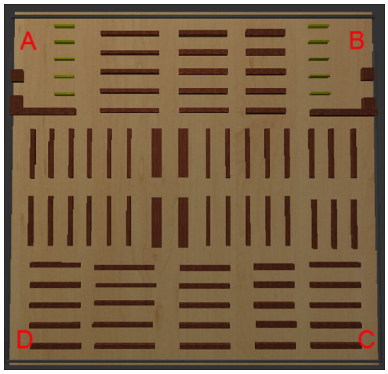


**Fig. 2** The layout of the maze demonstrating the confined space with four exits *A*, *B*, *C* and *D*

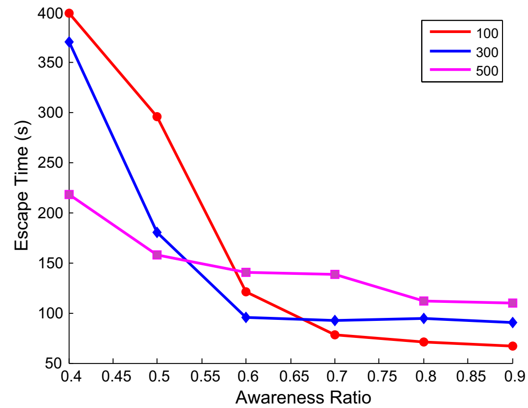


**Fig. 3** The influence of the awareness ratio and crowd size on escape time

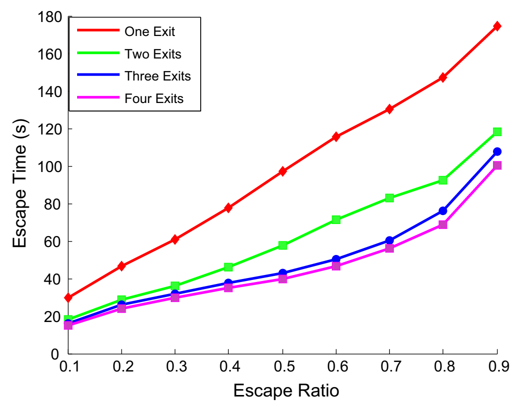


**Fig. 4** The influence of the number of exits on the escape time

run the simulation multiple times starting from the identical initial conditions, the results should have slight differences to reflect the randomness in people's decision-making process. On the other hand, the differences should not be too large because pedestrian's movements are largely influenced by the crowd, which makes the behavior of crowd less random than the individuals. Thus our first experiment is designed to prove that our simulation framework has the above properties. We run the simulation with the same initial conditions (500 pedestrians, one exit, awareness ratio 60 %) 50 times, and measure the mean time and its variance when the escape ratio reaches from 10 to 90 %. The experimental results are as shown in Table 1.

As shown in the third row of Table 1, the variances are always non-zero values, indicating that our framework will produce different simulation results under the same initial conditions. This satisfies our previous analysis on the randomness in the decision-making process. Also note that the variance is a fairly small value with regard to the mean escape time. Thus our framework can produce stable simulation results. In the remaining tests, all the escape time reported refers to the average escape time.

The second experiment is conducted to study the influence of awareness ratios on the escape time under different crowd sizes. The escape time is measured when the escape ratio reaches 80 %. The experimental results are as shown in Fig. 3, from which we can find the following facts: (1) when the crowd size is small, higher awareness ratio will largely reduce the escape time. (2) When the crowd size increases, the awareness ratio is still positively related to the escape time, but the appearance of congestions will neutralize the positive effects caused by high awareness ratio.

The third experiment is conducted to study the influence of the number of exits on the escape time. The experimental results in Fig. 4 suggest that the escape time is reduced with the increase of number of exits. But the relationship between the escape time and the number of exists is not linear. When the number of exits is larger than three, its influence on the escape time is not so significant. A direct application of this test is to answer questions such as "What is the minimum number of exits for a supermarket to guarantee that 90 % of individuals can escape from the extreme events in 300 s?".

The fourth experiment is conducted to study the influence of the exit locations and the crowd's initial density distribution on the escape time. In this experiment, we use two exits with two different configurations. One is to use exit a and c as illustrated in Fig. 2, and the other uses exit a and b. We also design two initial density distributions as illustrated in

**Table 1** Test on the stability and randomness of our simulation framework

| Escape ratio | 10 % | 20 % | 30 % | 40 % | 50 % | 60 % | 70 % | 80 % | 90 % |
|---|---|---|---|---|---|---|---|---|---|
| Mean time (s) | 29.253 | 45.565 | 60.024 | 75.902 | 94.873 | 111.532 | 125.739 | 142.455 | 170.077 |
| Variance (s) | 0.331 | 0.503 | 1.230 | 3.315 | 4.432 | 2.616 | 3.128 | 3.653 | 3.815 |

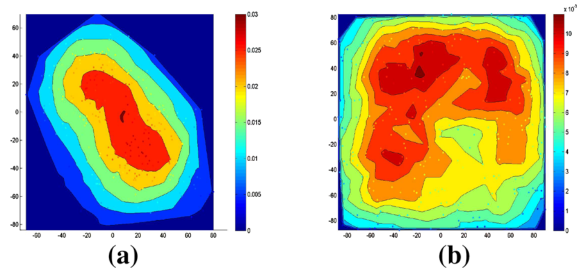


**Fig. 5** Initial density distributions of the crowd (*reddish* color indicates higher density). **a** Most of the pedestrians gather at some specified region. **b** Pedestrians distribute uniformly

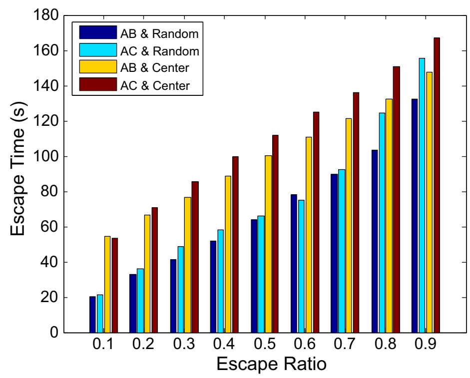


**Fig. 6** The influence of the distribution of exits and the population distribution on the escape time

Fig. 5. Together we have four combinations and the results are as shown in Fig. 6. It unveils the following facts: (1) the initial density distribution of crowd is significantly related to the escape time. In most cases, the escape time of uniformly distributed crowd is shorter than the crowd gathered at some regions. Consequently, making the crowd uniformly distribute in a supermarket is the best choice from the angle of safety. (2) The escape time of exits a, b is slightly shorter than exits a, c in most cases but the differences are not significant.

We also conduct an experiment to find out the relation between the locations of crowd gathered region and the escape time. In this experiment, $\frac{1}{3}$ individuals gather at four different places and the rest randomly distribute in the scene. The escape time is measured when the escape ratio reaches 80 %. The experimental results are as shown in Fig. 7. It can be seen that with the increase of distances between the high density pedestrians and exit, more escape time is required. But if the high density crowd is too close to the exit, the sudden congestions slow down the evacuation.

## 7 Conclusions and future work

In this paper, we propose a new framework to simulate the crowd behavior in a confined space with multiple exits under emergency conditions. We note that information asymmetry

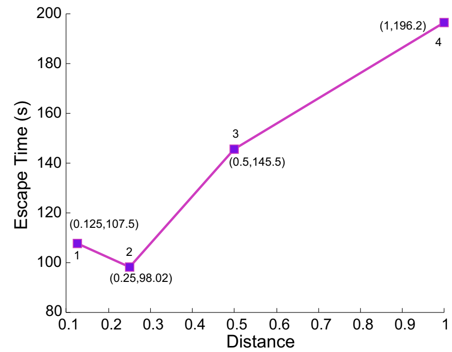


**Fig. 7** The influence of the distances $d$ between the high density pedestrians and exit on the escape time. The $X$ axis is the ratio between $d$ and the edge length of maze

plays an important role in such simulations because it causes different behavior of pedestrians. Based on this observation, we categorize the information into two types and propose a unified influence space to model them. Our experiments prove that the proposed framework can be employed to analyze the factors influencing the effectiveness of an evacuation plan.

A very challenging future work is to extend our framework to automatically design the evacuation plan. In order to fulfill this target, a mathematical model needs to be proposed to accurately describe the relationships between the influence factors and escape time. Another interesting future work is to implement our framework on a cluster to improve the efficiency and scalability of the system.

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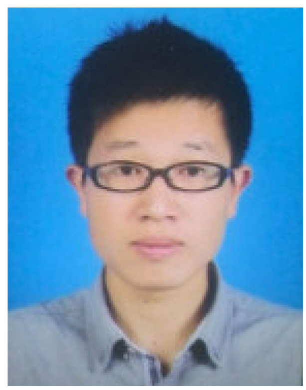

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