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A path planning approach for crowd evacuation in buildings based on improved artificial bee colony algorithm

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ABSTRACT

This paper proposes a new path planning approach for emergency evacuation simulation. This technique combines the Extended Social Force Model (ESFM) and the Improved Artificial Bee Colony (IABC) algorithm to enhance the visual realism and improve the efficiency of crowd evacuation. In the ESFM, we introduce a visual parameter to the original SFM and obtain the anisotropic psychological force rather than the isotropic one in the SFM so as to better fit crowd behaviors, such as long-range obstacle avoidance and self-organizing group formation. In addition, the IABC algorithm is proposed to improve the evacuation efficiency and provide support for building design and evacuation management by employing the strategies of grouping and exit selection. The algorithm uses the evacuation time of the individuals as the evaluation metric. If an exit is overcrowded and congested, the individuals will assess the degree of congestion, estimate the time needed to escape, and determine whether to select a farther exit for escape. By selecting the optimal exit and avoiding congestion, the evacuation efficiency can be improved. We have simulated the crowd evacuation with our new path planning approach via a crowd evacuation simulation system. The results show the effectiveness of our method.
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1. Introduction

Effectively organizing evacuation routes inside buildings, particularly densely populated buildings such as universities or schools, is always an important matter. One of the most frequent causes of this type of behavior is an emergency evacuation due to fire in a building. In such a situation, a large number of people must evacuate from a closed area that has a small number of fixed exits. When life-threatening disasters, such as fires, occur in crowded public buildings, congestion and jams are often triggered during crowd evacuation. Moreover, crowd stampedes in these situations may lead to fatalities. Thus, studies have explored the behavioral characteristics and motion laws of crowd evacuation to improve the rationality of architectural design, enhance safety management, and prevent or reduce fatalities under various emergency situations [1,3]. The current study can provide a theoretical basis and technical support for architectural design and emergency management.

The emergency evacuation of a large-scale crowd is a complex process. Real-world experiments on crowd evacuation are dedicated to several targets and are rich in data information. However, these experiments are hindered by various drawbacks, such as high cost, staff security problems, and so on [2,3]. Computer simulation has become the main measure to analyze the evacuation process and evaluate the evacuation efficiency [4]. This approach can cover the relevant influences in a uniform and comprehensive manner, provide useful information regarding the dynamics and time evolution, and be built up from intuitive and comprehensible basic assumptions and rules. As such, computer simulation has become the primary method for studying emergency evacuation.

The time it takes individuals to reach safety is affected by various factors, each of which must be understood to conduct successful evacuations [5]. How to analyze the influence on evacuation time of various circumstances is an important topic of crowd evacuation [6]. For example, the movement speed of evacuees may be affected by obstacles, exit widths, or increasing numbers of individuals [6,7]. A recent work has studied how stress or motivation levels affect the exit route selections in virtual crowd evacuations [8].

The behavior of animals in a swarm used to be considered a magical phenomenon. The individual animals in a swarm, flock, or school of animals follow rules that help the group. These rules help them stay together as a unit. Swarm behavior becomes swarm

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intelligence when a group can use it to collectively solve a problem in a manner that the individuals within the group cannot. Bees use swarm intelligence to discover new nest sites. Ants use it to find the shortest route to a food source. Swarm intelligence also plays a key role, if often an unsuspected one, in many aspects of human society, such as the working of the Internet and the functioning of cities [9]. Numerous studies have been successfully conducted using swarm intelligence techniques to solve path planning problems; these techniques include Ant Colony Optimization (ACO) [10] and Particle Swarm Optimization (PSO) [11].

The Artificial Bee Colony (ABC) algorithm is a new population-based algorithm that can find the global optimization solution, is simple and flexible, and uses few control parameters. Using a large set of unconstrained test functions, Karaboga et al. found that the ABC algorithm performs better than or at the same level as other evolutionary approaches, including Genetic Algorithm (GA), Differential Evolution (DE), PSO and Evolution Strategies (ES) [12]. However, few researchers have applied the ABC algorithm to crowd evacuation simulation because complex circumstances (e.g., obstacles, exit selection, congestion, and increasing numbers of evacuees) should be considered, which may lead to the critical decline of the evacuation efficiency.

Significant research interest is being received by the emerging application of computer simulation in psychosocial studies, which has been proposed as an effective approach for modeling crowd dynamics in emergency situations [5,6,8,13,14]. Helbing and Molnar proposed the SFM based on the Newtonian mechanics equation [13] to simulate human behavior. This model can effectively generate various phenomena, such as 'faster-is-slower' and arched phenomena at the exit. Bode et al. examined the evacuation time differences between the movement of independent individuals and individuals in groups, explained their findings, and discussed their implications [6]. Golas et al. exploited the insight that exact collision avoidance is unnecessary among the agents at large distances, and they proposed a novel algorithm for extending existing collision avoidance algorithms to perform approximate, long-range collision avoidance [14]. However, these methods can only compute the isotropic forces among individuals and obstacles, which do not fit the crowd behaviors in real situations.

To address the problems mentioned above, we propose a path planning method based on the ESFM and the IABC algorithm. Our method is performed in three steps as shown in Fig. 1. In the first step, the initial parameters of the crowd and environment are set. The second step shows the process of crowd evacuation. This process is divided into two layers: the upper layer is the IABC algorithm-based path planning, and the lower layer is the ESFM-based crowd motion. In the IABC algorithm, we employ the strategies of exit selection to avoid the congestion of some exits while other exits are relatively idle to reduce the exit bottleneck problem for crowd evacuation. Furthermore, we introduce visual parameters to construct ESFM for driving the individuals moving to the exit selected by IABC. In this model, visual realism crowd behaviors, such as long-range obstacle avoidance and self-organizing group formation, can be obtained. In the third step, the evacuation results are visualized on our simulation platform.

The main contributions of this paper are as follows:

(1) To improve the evacuation efficiency, we present the IABC by employing the strategies of grouping and exit selection. The model can provide a baseline for comparison in building design.
(2) To enhance the visual realism of crowd evacuation, we construct the ESFM by adding a visual parameter to the original SFM. The model can simulate more realistic crowd behaviors, such as long-range obstacle avoidance and self-organizing group formation.
(3) We simulate crowd evacuation via our new path planning algorithm, which couples the ESFM and the IABC algorithm.

The paper is organized as follows. Section 2 describes the related work on SFM and path planning algorithms based on swarm intelligence. Section 3 proposes the ESFM with the visual parameter. Section 4 describes the dynamic path planning algorithm based on ABC. Section 5 performs simulation experiments to show the efficiency of the approach proposed in this paper. Conclusions and future research focus are described in Section 6.

2. Related work

2.1. SFM

In the evacuation process, crowd motion is a complex physical process. Its dynamic adjustments are directly or indirectly restricted by many factors. Interactions among the crowd and the psychological states of individuals are important factors influencing the crowd motion. These factors will contribute to typical characteristics in crowd evacuation, including:

(1) **Clogging Phenomenon**: In emergency situations, individuals may react irrationally and move at a higher speed than normal. This feature will contribute to pushing, congestion at points of egress, and even crowd stampedes with resultant fatalities.
(2) **Mass Behavior**: In emergency situations, panic tends to generate and diffuse more easily than in conventional evacuation, suggesting the occurrence of higher "*contagion.*" This phenomenon will contribute to several non-adaptive crowd behaviors [15]. When the crowd is very large, dissemination of information is limited by time and space. Decisions are made instantly by individuals with a lack of information, leading to "*herding*" [16,17]. That is, people demonstrate a tendency to do

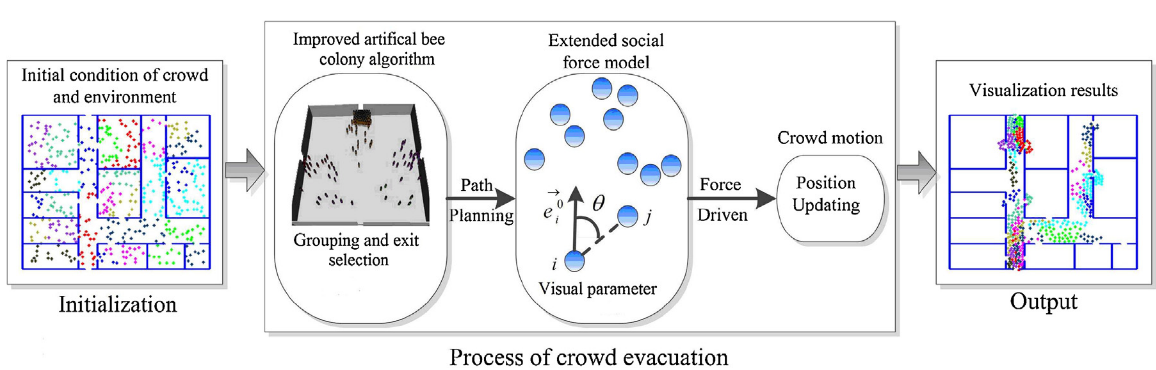


Fig. 1. The framework of our method.

what other people do. Likewise, people's emotions are easily affected by other people's panic.

(3) **Grouping Behavior**: In the evacuation of large-scale crowds, individuals tend to form a group with other people, and these groups usually have a social relationship among themselves, such as family members, friends, and so on. Although group formation can sometimes help in quickly finding the exit, it does not necessarily speed up the evacuation speed. Generally, some nonlinear characteristics emerge when individuals within a group interact with each other [18]. Meanwhile, a variety of collective phenomena, such as conflict, convergence, balance and imbalance, and the orientation and exclusion of groups, can also be produced by the behavioral characteristics of individuals in crowds [19,20].

Force-based modeling, which was proposed by Helbing and Molnár [13,21], was originally derived from human social force studies. This model solves Newton's equation to determine the position of each individual by considering repulsive interactions, friction forces, dissipation, and fluctuations. Particularly adapted for pedestrian traffic simulations, this model is based on the finding that individual conduct does not result directly from the surrounding environment but is dependent on individual motivation, which influences decision-making [22].

This model was further applied and generalized to other simulation scenarios, such as densely populated crowds, simulation of pedestrian evolution, and escape panic. Given that the model can successfully simulate the dynamic characteristics of pedestrians, it has attracted the attention of many scholars who have attempted to improve the model [23,24,25].

The SFM as modified by Moussaïd et al. [26] joined the "small group" phenomenon in the population. Johansson et al. [27] used video capture analysis to modify SFM parameters to create a model that closely resembles crowd dynamics in a real evacuation scenario.

However, crowd evacuation is a complex process consisting of various human behaviors, such as evacuation motion and behavior reaction. Pure motion study refers to an estimation of an ideal situation. Although crowd motion is important, many other factors influence crowd dynamics in an evacuation, and the time spent on other behaviors is greater than evacuation behavior. Therefore, the physiological and psychological factors in large-scale crowd evacuation should be considered to conform to the real characteristics of social behaviors during crowd evacuation.

2.2. Path planning algorithm based on swarm intelligence

Researchers have proposed various methods to solve the path planning problem. The main requirement of optimal path planning is identification of a minimum length path from the starting node to the target node, together with a collision-free path. Two popular heuristic-based algorithms for shortest path computation are the Dijkstra and A* algorithms [28]. These two algorithms can successfully provide the optimal path for various path planning problems. However, these approaches are not suitable for path planning that faces multiple exit options.

In recent years, several novel swarm intelligence techniques have been gradually introduced into path planning, such as ACO algorithm [29], PSO algorithm [30], and ABC algorithm [31]. Research results on the path planning problem using these algorithms have emerged continually. At the same time, the integration of different methods [32,33] has rapidly developed.

The ACO algorithm is a swarm intelligence algorithm that has been extensively used in recent years [34]. Reshamwala et al. used the ACO algorithm to describe the various techniques for robot path planning, and they provided a brief comparison of the three techniques described in the paper [35]. Yao et al. proposed the Heterogeneous Feature Ant Colony Optimization (HFACO) algorithm to solve the robot path planning problem; their experimental results show that HFACO can find a better path more quickly than the classical ACO algorithms [36]. However, when the swarm scale is large, premature and stagnation phenomena tend to occur in ant colony algorithms, imposing restrictions on their further applications.

The PSO algorithm was introduced by Kennedy and Eberhart in 1995 [37]. Since then, the PSO algorithm has been successfully applied to many optimization problems. Researchers have used PSO to solve path planning problems from different perspectives. Multi-objective PSO with a self-adaptive mutation operation has been proposed [38] to solve the path planning problem in an environment with obstacles and danger sources. Mansoor Davoodi et al. [39] used two multi-objective path planning models to find a safe path by minimizing the energy consumption.

However, PSO suffers from premature convergence in the evolutionary process when dealing with complex problems, such as some real-world optimization problems, including path planning. PSO also depends on users to tune control parameters, such as inertia weight, social and cognitive coefficients, and velocity clamping, to achieve the required solution.

The ABC algorithm is a population-based algorithm that can find the global optimization solution, is simple and flexible, and uses few control parameters [40]. Compared with ACO, PSO, and other similar swarm intelligence techniques, ABC possesses attractive characteristics and has been proven to be more effective in many cases. ABC has been extensively used for various optimization problems; in most of these cases, ABC has been proven to have superior computational efficiency [41]. Furthermore, ABC does not use any gradient-based information. Rather, it incorporates a flexible and well-balanced mechanism to adapt to the global and local exploration and exploitation abilities within a short computation time [42]. Given its efficiency in handling large and complex search spaces, ABC has considerable potential for solving more complex path planning problems.

2.3. Motivations

Human crowds are rarely composed exclusively of unrelated and independently moving individuals. Rather, crowds often comprise many small social groups based on friendship or kinship [26]. Under normal circumstances, both model and experience show that pedestrian crowds are self-organized [9]. When a social group meets severe environmental threats, they usually show strong emotional behavior and prefer to move together [43]. The individuals within a crowd can also form groups to cope with the emergency even if they are not socially connected [44].

Small social groups based on kinship or friendships are ubiquitous in human crowds [26]. Therefore, it is necessary to study the interaction between social groups and crowd evacuation [43,44,45,46]. Ji and Gao proposed a Leader-Follower Model for crowd evacuation simulation [46]. A crowd includes several groups, with each group having a leader and some followers guided by the leader. Leaders are responsible for finding the evacuation path for their followers. The objective of their simulation is to show the effect of different numbers of leaders on the efficiency of evacuation. Vihas et al. proposed a Cellular Automaton model for crowd movement simulation by embedding the follow-the-leader technique as its fundamental driving mechanism [47].

In reality, when an emergency occurs, the individuals usually attempt to keep the distance closer and form self-organized small groups based on friendship or kinship. Most of them will choose the same exit and follow the leader who can first reach an exit. Therefore, the evacuation processes will appear to follow each other, going hand in hand with the phenomenon. As the evacuation time increases, the environment changes, and so does the escape exit congestion. At this time, individuals away from the leader will reselect their exit.

The grouping strategy is used in the algorithm. The individuals are grouped according to the selected exits and the distance between the exits and individuals. The grouping in the evacuation process is dynamic, i.e., according to the number of individuals within the group and the distance from the exits to adjust. The algorithm takes the group as the unit to carry on the selection of the leading bee, the individual role transformation, and the path evaluation. The optimal path information is transmitted in the same group.

3. ESFM

To effectively model the typical features of crowd dynamics in an evacuation scenario, we propose the ISFM, which introduces a visual impact factor.

3.1. SFM

According to the characteristics of collective behavior, Dirk Helbing established the SFM based on Newtonian mechanics [13]. Social force is the force that one individual obtains from the environment [including human and objects] instead of the physical force that directly applies to him or her. Based on different motivations of pedestrians and influences from the environment, three forces are exerted in the SFM: (1) the driving force, (2) the interaction force among human beings, and (3) the interaction force between individuals and obstacles.

The resultant force of these three forces affects pedestrians and contributes to acceleration. The internal driving force guides the individual to move toward the target. However, before bodily contact, the repulsive force forces individuals (in a crowd) to avoid contact and prevents them from colliding with one another. The interaction force between people and obstacles prevents individuals from colliding with obstacles. This stage can be interpreted by the classical Newton's second law. The expression is shown in Eq. (1):

$$m_i \frac{d\vec{v}_i(t)}{dt} = \vec{f}_i^0 + \sum_{j(\neq i)} \vec{f}_{ij} + \sum_{w} \vec{f}_{iw} + \vec{\xi}(t), \tag{1}$$

where m_i is the mass of pedestrian i and $\vec{v}_i(t)$ is the actual walking velocity. Eq. (1) shows that the motion of pedestrian i is affected by four types of force, namely, the driving force of pedestrian i $\vec{f}_i^0$, the interaction force between pedestrian i and other pedestrians $\sum_{j(\neq i)} \vec{f}_{ij}$, the interaction force between pedestrian i and obstacles $\sum_{w} \vec{f}_{iw}$, and the noise $\vec{\xi}(t)$. The position of pedestrian i changes under the interactions of four forces. m_i is the mass of pedestrian i, and $\vec{v}_i$ represents the actual velocity of pedestrian i.

$$\vec{f}_i^0 = m_i \frac{v_i^0(t)\vec{e}_i^0(t) - \vec{v}_i(t)}{\tau_i}. \tag{2}$$

Eq. (2) describes the driving force $\vec{f}_i^0$ of pedestrian i. During movement, pedestrian i constantly adjusts his actual velocity $\vec{v}_i(t)$ and intends to move toward the destination with a certain desired speed $v_i^0(t)$. τ_i is the characteristic time of pedestrian i. $\vec{e}_i^0(t)$ is a unit vector that shows the direction pointing from a pedestrian i to the destination.

$$\vec{v}_i(t) = \frac{d\vec{r}_i}{dt}, \tag{3}$$

The next equation represents the interaction force imposed on a pedestrian i by the other pedestrian j.

$$\vec{f}_{ij} = \vec{f}_{ij}^{Psy} + \vec{f}_{ij}^{Touch}. \tag{4}$$

The interaction force $\vec{f}_{ij}$ includes two parts. One is the psychological forces$\vec{f}_{ij}^{Psy}$in which a pedestrian i tends to keep a velocity-dependent distance from the other pedestrians j.

$$\vec{f}_{ij}^{Psy} = A_i \exp\left[\left(r_{ij} - d_{ij}\right)/B_i\right]\vec{n}_{ij}. \tag{5}$$

A_i and B_i are constants, where A_i represents the strength of the interaction force and B_i is the floating range of the repulsive force. r_i and r_j are the radii for pedestrian i and pedestrian j, respectively. $r_{ij} = r_i + r_j$ is the sum of their radii r_i and r_j. $d_{ij} = |\vec{r}_i - \vec{r}_j|$ denotes the distance between the pedestrians' centers of mass. $\vec{n}_{ij} = \frac{\vec{r}_i - \vec{r}_j}{d_{ij}}$ is the normalized vector pointing from pedestrian j to i. $\vec{r}_i$ and $\vec{r}_j$ represent the positions of pedestrians i and j, respectively.

The other part is the physical forces$\vec{f}_{ij}^{Touch}$between a pedestrian i and the other pedestrian j.

$$\vec{f}_{ij}^{Touch} = g\left(r_{ij} - d_{ij}\right)\left(k\vec{n}_{ij} + \kappa \Delta v_{ji}^t \vec{t}_{ij}\right). \tag{6}$$

Eq. (6) describes the physical force that pedestrian j imposes on pedestrian i. The first part of the equation $g(x)$ is zero when the pedestrians do not touch each other and is otherwise equal to x. The second part represents the sum of the forward extrusion pressure and the tangential extrusion pressure. k and κ are constants, and $\vec{t}_{ij}$ is the tangential direction from pedestrian i to j. Δv_{ji}^t represents the tangential velocity difference between pedestrian i and j, which can be defined as

$$\Delta v_{ji}^t = \left(\vec{v}_j - \vec{v}_i\right) \cdot \vec{d}_{ij} \tag{7}$$

The interaction force between a pedestrian i and an obstacle w $\vec{f}_{iw}$is expressed as follows:

$$\vec{f}_{iw} = \vec{f}_{iw}^{Psy} + \vec{f}_{iw}^{Touch}, \tag{8}$$

$$\vec{f}_{iw}^{Psy} = A_i \exp\left[(r_i - d_{iw})/B_i\right]\vec{n}_{iw}, \tag{9}$$

$$\vec{f}_{iw}^{Touch} = g(r_i - d_{iw})\left(k\vec{n}_{iw} - \kappa\left(\vec{v}_i . \vec{t}_{iw}\right)\vec{t}_{iw}\right). \tag{10}$$

The parameters of Eqs. (8), (9) and (10) are similar to Eqs. (4), (5) and (6) except the other pedestrian j is replaced by an obstacle w. For simplicity, we will not describe it here in detail.

3.2. ESFM with a visual parameter

The time needed for evacuation is crucial for the safety or even for saving the lives of evacuees. Therefore, different parameters affecting the time needed for evacuation are elaborated in the literature. These parameters include the influence of infrastructural elements, e.g., obstacles, narrow passages, or staircases [48]. Studies on pedestrian flow in crowds under normal and emergency conditions [49] have helped in improving safety by reducing congestion at exits. The majority of the literature on evacuation time has focused on delayed evacuation either by pre-movement time (detection and reaction) or suboptimal flow caused by human behavior [51].

The importance of long-range vision was pointed out by Golas et al. in reference [14]. Long-range vision is critical to human navigation: in addition to avoiding nearby obstacles, the human visual system looks ahead to perform dynamic global planning and local navigation. By considering the distribution of other pedestrians and obstacles over a large distance, people can anticipate overcrowded regions and navigate around them, thereby finding an efficient, uncongested path to their goals. Most existing work addresses either global navigation around static obstacles or local avoidance of collisions with nearby pedestrians but often neglects the importance of long-range collision avoidance [14].

The psychological force in the original social force model is isotropic, that is, the repulsive force of the surrounding objects is the same, without considering the individual's visual limit. To maintain consistent individual behavior in the group and look ahead to perform dynamic global planning and local navigation, we extended the original SFM by adding a visual parameter, which is defined in Eq. (12).

$$\cos\theta = \vec{e_i}^0 \cdot \left(\vec{x_j} - \vec{x_i}\right) / |\vec{e_i}^0||\vec{x_j} - \vec{x_i}|, \tag{11}$$

$$\text{where} Vis = \lambda(1 + \cos\theta)/2 + (1 - \lambda)(1 - \cos\theta)/4, \tag{12}$$

$$\lambda = \begin{cases} 1, \theta \in [0, \pi/2] \\ 0, \theta \in (\pi/2, \pi] \end{cases}$$

As shown in Fig. 2(a), the individual suffered from repulsion impact as that of the visible objects is greater than that by the invisible object. When the object is visible, the influence of the objects in front of the individual is greater than the impact of the objects on both sides. When the object is invisible, the impact of the objects behind is greater than that of the objects on both sides of those behind.

Fig. 2(b) shows the angle between the expected direction and the object, in which $\vec{f_{ij}}$ is the repulsive force from object j to the individual i and θ is the angle between the desired direction of the movement of the individual i and the repulsive force from other objects. λ reflects the relative orientation between the locations of objects and individuals.

Bring Eq. (12) into Eq. (5), we get the new psychological forces$\vec{f}_{ij}^{psy}$between a pedestrians i and the other pedestrian j:

$$\vec{f}_{ij}^{psy} = A_i \exp[(r_{ij} - d_{ij})/B_i]\vec{n}_{ij} \cdot (\lambda(1 + \cos\theta) \\ /2 + (1 - \lambda)(1 - \cos\theta)/4). \tag{13}$$

Similarly, by putting Eq. (12) into formula (9), we get the new psychological forces$\vec{f}_{iw}^{psy}$between a pedestrian i and an obstacle w:

$$\vec{f}_{tw}^{psy} = A_i \exp[(r_i - d_{iw})/B_i]\vec{n}_{iw} \cdot (\lambda(1 + \cos\theta) \\ /2 + (1 - \lambda)(1 - \cos\theta)/4). \tag{14}$$

Compared with the conventional SFM, the ESFM enhances the visual realism of crowd evacuation by adding a visual parameter. The visual realism can be reflected in two aspects. Firstly, obstacle avoidance can be achieved in advance, which is closer to the realistic situation. Additionally, the anisotropic psychological force is computed in ESFM rather than the isotropic one, which can result in common self-organizing group formation in crowd evacuation.

Although we consider visual factors in the ESFM, little additional computational overhead is incurred because the force in the original SFM is extended by multiplying a coefficient in our model.

4. A path planning approach based on improved ABC algorithm

A key problem in crowd evacuation research is planning the path of crowd motion. Given the complexity and subtlety of crowd motion, path planning must consider the environmental constraints and interactions among individuals in a crowd.

4.1. ABC algorithm

The ABC algorithm, which was presented by Karaboga of Turkish Erciyes University in 2005 [50], is a non-numerical optimization algorithm based on the self-organization model and collective intelligence. It has three essential factors, namely, food source, employed bees, and unemployed bees. Unemployed bees are composed of two types of bees: onlookers and scouts. The employed bees have two basic self-organization patterns: recruitment to a nectar source and abandonment of a food source. The employed bees search for food around the food source and share the searched food source with the onlooker bees. Good food sources (higher quality or fitness) found by the employed bees are selected by onlooker bees with higher probability. Onlooker bees perform local search around the food source to find the optimal solution. Low-quality food sources will be abandoned, and the corresponding employed bees will change into scout bees. Scout bees randomly search for new food sources in the global space. When a scout bee finds a new food source, it will record the information of the food source and turn into an employed bee.

Simulations have revealed that knowledgeable bees (employed bees) do not need to identify or advertise themselves to the rest of the swarm to lead it successfully. Just a few informed individuals can lead a larger group of uninformed individuals by moving faster and in the appropriate direction. Guidance is achieved by way of a cascade effect, in which uniformed individuals align their direction with those of their neighbors. Even if only a few bees know their way, Reynolds' three rules, namely, avoidance, alignment, and attraction, ensure that the entire swarm moves in the direction taken by the knowledgeable bees (employed bees) [9].

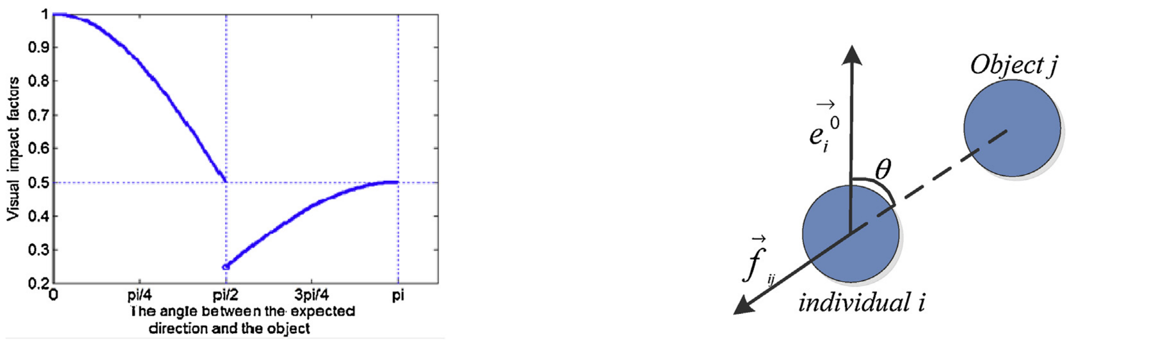
The ABC algorithm is described as follows.

Algorithm 1. ABC algorithm

Step 1: Initialize the solution space, the individual position, the maximum iteration number, the fitness function, and so on.
Step 2: Evaluate the fitness of each particle and sort the swarm in descending order according to the result.
Step 3: Select the top 50% of particles as employed foragers from the matrix obtained in Step 2.
Step 4: Compute the selected probability of each employed forager.
Step 5: Switch the roles of the remainders to scouts or onlookers.
Step 6: Update the position of each particle according to its current role.
Step 7: Return to Step 2 if the iterative condition is met; otherwise, exit the iterations.

A food source corresponds to a possible solution to the problem to be optimized. Its quality can be represented by the parameter named 'profitability.' The quantity of profitability determines the quality of a solution.

(1) Employed foragers are known as the leading bees, which correspond to a particular food source that they are currently exploiting.
(2) Unemployed foragers can be recruited by employed foragers as onlooker bees. Onlooker bees wait in the nest and decide on a food source to exploit by watching the waggle dance of employed bees. Employed bees should compute the probability



(a) Visual parameter (b) Angle between the expected direction and the object

Fig. 2. Visual parameter.

of each food source to be selected. Onlooker bees choose a food source according to the probability and update the position of the food source in the same manner as employed bees.

(3) Unemployed foragers can turn into scouts, which randomly search the environment surrounding the nest for a new food source to extend the global search ability of the algorithm. When a scout finds a new food source, it will record the information of the food source and turn into an employed bee.

Employed bees and onlooker bees update the position of a food source according to Eq. (15).

$$x_{ij} = x_{ij} + rand(-1, 1) \cdot (x_{kj} - x_{ij}). \tag{15}$$

The amount of nectar in a food source denotes the quality of the food source. This is calculated by Eq. (16).

$$fit_i = \frac{1}{1 + f_i}, \tag{16}$$

where f_i is the profitability of the food source i. The value of f_i is a combination of all factors that determine the quality of a food source, such as distance to the nest, nectar amount, and so on.

As the profitability of the food source increases, the probability of a food source preferred by an onlooker bee increases proportionally. The probability of the food source to be chosen can be expressed as

$$p_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j}. \tag{17}$$

In Eq. (17), fit_j represents the profitability of the jth food source, and SN is the total number of the food source.

4.2. IABC algorithm

To improve the optimization efficiency of the ABC algorithm, we divide the original single population into multiple populations and run the ABC algorithm.

Major improvements are as follows. First, we define the selected probability$p_{grp,\varepsilon_i}$for the number ε_i leading bee in the grpgroup as

$$p_{grp,\varepsilon_i} = \frac{fit_{grp,\varepsilon_i}}{\sum_{j=1}^{N_{grp}} fit_{grp,\varepsilon_j}}, \tag{18}$$

where fit_{grp,ε_i} is the fitness of the number ε_i leading bee in the grp group and N_{grp} is the number of leading bees in the grp group. Then, in Step 3, after the leading bees are selected, the population is divided into several groups according to the location of the particle population. In Step 4, Eq. (18) replaces Eq. (17). In Steps 5 and 6, roles are switched to scouts or onlookers, and the position of each particle is updated based on its current role within each group. The grouping strategy can accelerate the convergence speed and improve search precision.

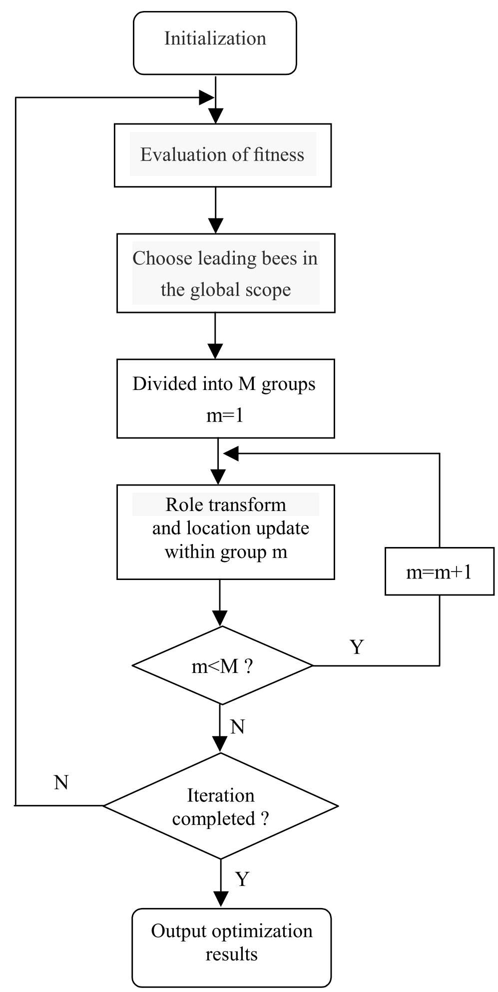


Fig. 3. IABC algorithm flow chart.

The flow chart of the IABC algorithm is shown in Fig. 3, where m is the count of the group and M is the total number of groups.

The IABC algorithm has two layers of interactive mechanism: between groups and internal groups. When the leading bees are selected, the groups interact with one another, and better solutions

Table 1
Parameters of crowd evacuation and ABC algorithm.

Parameters of the crowd to be evacuated	Parameters for ABC algorithm
Exit	Food source
Hazard or obstacle	Abandoned food source (Profitability of hazard equal to 0)
1/Evacuation time	Fitness of food source
Leaders of the group	Employed bees
Other individuals in the crowd	Onlooker bees and scout bees

We combine the ESFM and the IABC algorithm for path planning of crowd evacuation simulation. The combined algorithm is as follows.

are determined in the global scope to prevent the algorithm from falling into a local optimum. Onlooker search optimization is performed only within the group, and the optimum solution is selected in the group to which they belong and continue the search for sources in the vicinity of to ensure the convergence of the algorithm to the multiple global optimal solutions. The improved algorithm uses a parallel search mechanism and collaborative interaction between groups, within the scope of global multimode optimization, which deals with the optimization tasks to find all or most of the multiple solutions of a problem. Although the characteristics of the global swarm are maintained, it expands the multimode search ability of the algorithms and improves the optimization efficiency.

The IABC algorithm and the original ABC algorithm are compared in terms of a set of test functions and the experiments. The comparative results are presented in Sections 5.1 and 5.2. More details regarding the interaction mechanisms and information transfer between the bees can be found in our previous study [43,52].

4.3. IABC algorithm for crowd evacuation

Before the IABC algorithm is used to solve the path planning problem of crowd evacuation simulation in a building, we need to build a mapping between the ABC algorithm and the parameters in the path planning, as shown in Table 1.

Algorithm 2. Path planning algorithm for crowd evacuation based on the IABC algorithm

Step 1: Initialize the number and position of the individuals, the number of iterations, and the related parameters.
Step 2: Evaluate the fitness value of each individual and sort the swarm in descending order according to the result.
Step 3: Select the top 50% of individuals as the lead bees from the matrix obtained in Step 2.
The individuals are grouped according to the selected exits and the distances between the exits and individuals.
Step 4: Compute the selected probability of each lead bee.
Step 5: Switch the roles of the remainders to scouts or onlookers in each group.
Step 6: Update the individuals' positions according to their roles in each group.
Step 7: Driven by the ESFM, the individuals move toward the exits.
Step 8: Return to Step 2 if the iterative condition is met; otherwise, exit the iterations and output the result.

In the following, we introduce the fitness function in Step 4 of the algorithm.

In the evacuation process, people often must choose between more than one exit. In this case, the nearest exit is generally preferred. However, if the exit is overcrowded and congested, individuals will assess based on the degree of congestion, estimate the time needed to escape, and determine whether choosing a farther exit to escape would be more favorable. In the original ABC algorithm, the fitness function is used to comprehensively evaluate the abundance of honey in the nectar source and the cost of extracting the honey, so as to guide the bee to make the decision and select the suitable nectar source. The congestion and evacuation time has been regarded as the critical evaluation metric when the dynamic route selection of building evacuation is modeled [51]. Similarly, application of the original ABC algorithm to crowd evacuation should consider the impact of the congestion and evacuation time. In our IABC algorithm, the fitness function is used to comprehensively evaluate the degree of congestion at the exit and the distance that the individual moves to the exit so that the leader can make decisions and choose the appropriate exit. Having the shortest time to escape is the primary basis for people to choose an exit. Therefore, this study regards evacuation time as the fitness function evaluation criterion.

The fitness function is expressed as the time to reach an exit as follows:

Function 1: Fitness function

```
Begin
  For (i=0; i<dnum; i++)
    s=dist/2*width[i];
    p=pnum/s;
    If (p>∂*C_ρ)
      Then
        t=selectnum[i]/(β * size[i]/radius);
      Else
        t=dist/(γ * v_0);
    End if
  End for
End
```

where dnum is the number of gates that can be selected; S is the congestion area; pnum is the number of individuals in S; C_ρ is the density threshold; selectnum[i] is the number of individuals who select the i-th door; size[i] is the width of the door i; width[i] is the width of the path to the i-th door; radius is the radius of the individual; dist[i] is the distance between the individual and the door i; v_0 is the desired speed of the individual; and ∂, β, and γ are the adjustment coefficients. When the selected area density is greater than the threshold value, serious congestion will occur.

The fitness function is used to approximate the evacuation time for each individual. In this study, people select the exits with the least evacuation time. The individuals with smaller evacuation time (fitness function) are selected as the leaders of groups (as described in Steps 2 and 3 of Algorithm 2). The other individuals in the group will follow the leader during evacuation. The fitness function considers not only the optional exit from the current state, the gate width, and other static information but also exit crowding, individual velocity, and other dynamic information. The algorithm prejudges the escape time needed on crowded paths or smooth cases and selects the shortest time-consuming path; this strategy is consistent with the dynamic path finding feature during crowd evacuation. In this case, the evacuation time is the ratio of the number of individuals who select the gate and the gate width; otherwise, the evacuation time is the time by normal movement to the target gate.

5. Simulation experiments

To illustrate the performance efficiency of the proposed simulation model and algorithm for crowd evacuation, we perform the following test in the following sections:

(1) Test for the IABC algorithm by four sets of test functions;
(2) Simulation of the IABC algorithm and the comparison with the other swarm intelligence algorithms;
(3) Comparison with the captured surveillance video.

5.1. Test for the IABC algorithm

To verify the performance of the IABC algorithm, we compare our IABC algorithm with the original ABC algorithm and the IF-ABC (Internal Feedback based ABC) algorithm [53] on four sets of test functions (Griewank function, Rastrigin function, Sphere function and Rosenbrock function). Different to the original ABC which uses the roulette selection strategy, IF-ABC uses internal feedback information to improve convergence rate. The Griewank function and Rastrigin function are complex multi-mode functions, while the Sphere function and Rosenbrock function are single-mode functions. These functions are standard benchmark functions for optimization problems, and they are widely used for testing the performance of intelligent algorithms [12,40,50]. We set the initial population size of the algorithms as 100, the iteration number as 1000, and the fitness threshold as 50. Given that the algorithm is stochastic, we run two simulations of each algorithm and show the mean error curves. Fig. 4 illustrates the distribution of results under noise.

In Fig. 4, the mean error is computed as follows. In iteration step i, we compute the error err_i between the computed near-optimal solution and the optimal solution of the benchmark function. The average error of step i is then computed as the average error of all previous steps as $\sum_{j=1}^{i} err_j/i$. The analysis implies that our proposed IABC algorithm is more effective to improve convergence rate than the original ABC and the IF-ABC.

5.2. Comparison with A* algorithms with regards to the computational time

We conduct experiments on the computational time to compare our IABC algorithm with the A* algorithm. The computational time is closely related to the scene and the number of individuals. Both of the algorithms are tested in two scenarios (teaching building room and teaching building hall). The teaching building room is a complex scenario with a size of 30 m × 30 m and two exits (shown in Fig. 5(a)). The teaching building hall is a simple scenario with a size of 20 m × 30 m and three exits (shown in Fig. 5(b). The diameter of individuals r is 0.25 m. To run the A* algorithm, we divide the scenarios into grids, and the length of each grid is set equal to the diameter of the individual. In addition, we set the number of iterations to 2000 for our IABC algorithm. The computer we used

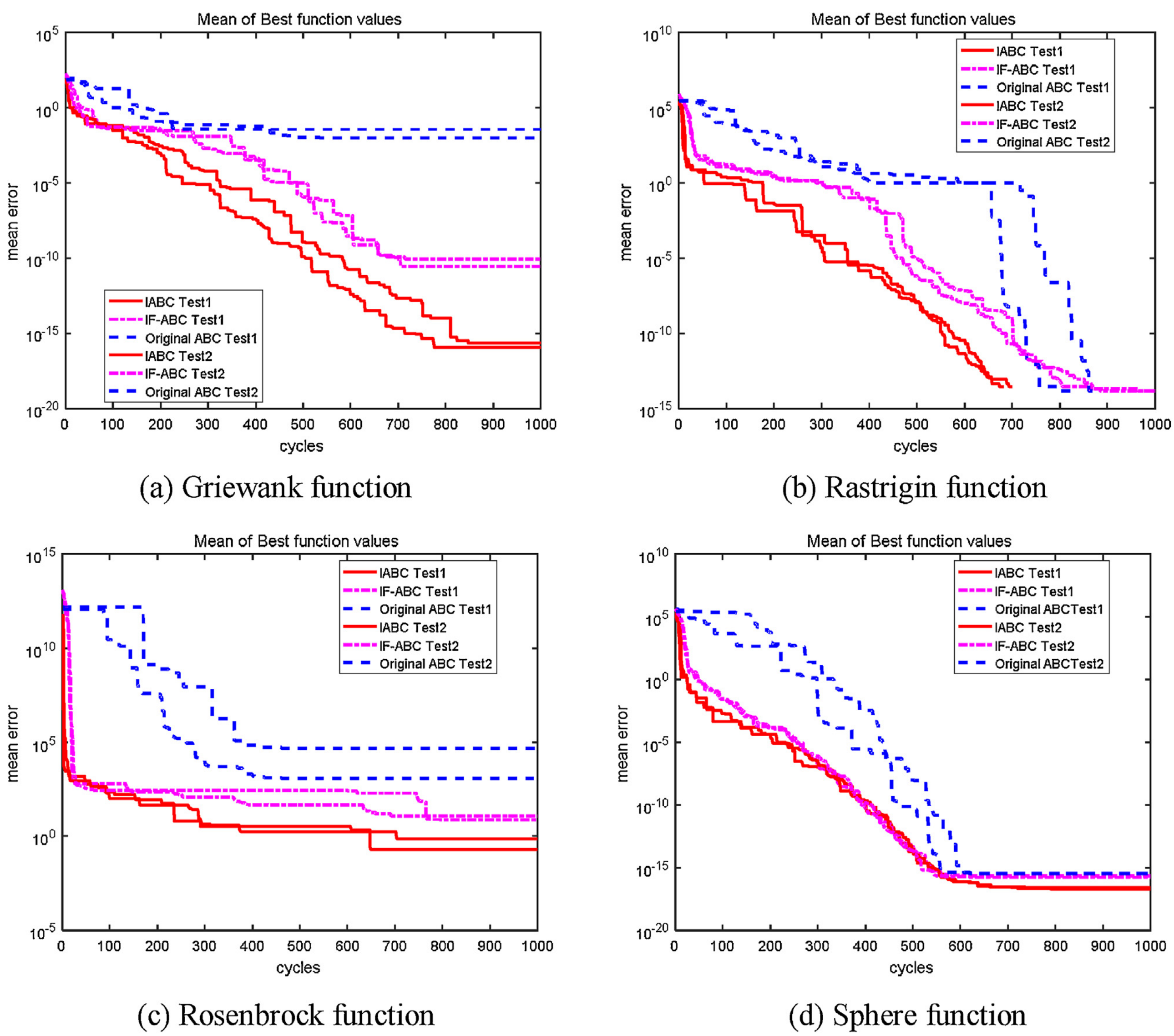


Fig. 4. Mean error comparison of three algorithms.

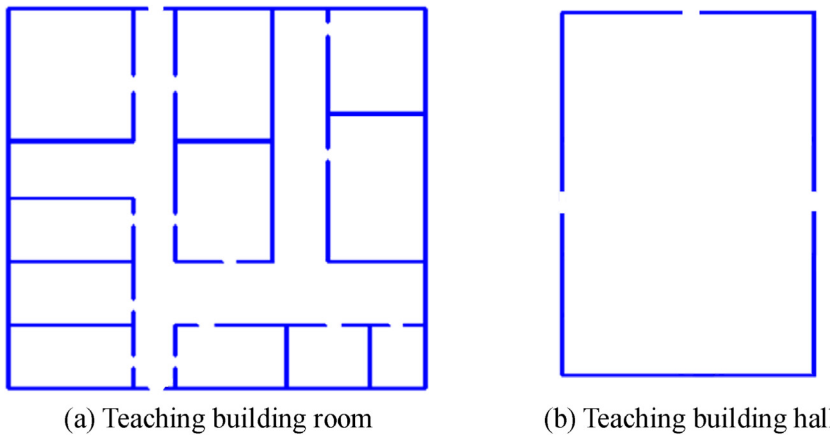


Fig. 5. Scenario of teaching building room and teaching building hall.

was equipped with a Core i7 processor and 16 GB of RAM. Fig. 6(a) and (b) shows the average computational time in accordance with the incremental population size, which varies from 25 to 350 with an interval of 25.

As shown in Fig. 6(a), the computational time is close when the population size is less than 100. However, when the size rises, the computational time of the IABC algorithm is less than that of the A* algorithm. As we also can see from Fig. 6(b), A* performs better than our IABC when the population size is small. However, when the size is larger than 200, IABC performs better. In summary, the A* algorithm is not suitable for complex scenes and cases with large population sizes. The proposed IABC algorithm can greatly improve the computational efficiency in cases of complex scenes and large population sizes.

5.3. Simulation and comparison with swarm intelligence algorithms

The simulation is carried out in the teaching building scene, and the parameters are set as follows. The number of individuals n is 500, and the individual radius r is 0.25 m. Moreover, the individual quality m is 80 kg, and the desired individual movement speed is $v_i^0 = 0.8\text{ms}^{-1}$. The SFM parameters are $k = 1.2 \times 10^5 \text{kg s}^{-2}$, $\kappa = 2.4 \times 10^5 \text{kg m}^{-1} \text{s}^{-1}$, $A = 2000$N, $B = 0.08$m, $C = 2000$N, $D = 0.05$m, and $\alpha = 0.7$. We execute the algorithm to generate the motion paths. The evacuation effects are shown in Fig. 7.

Fig. 7(a) shows the initialization state. A total of 500 individuals were randomly distributed in the scene; the color codings of individuals indicate that they belong to different groups. Fig. 7(b) is the state of movement of the crowd when $t = 17$ s. As shown in Fig. 7(b), when the evacuation began, no serious congestion occurred in the two exits, and individuals chose to escape from the nearest exit. Fig. 7(c) shows the motion state of the population when $t = 46$ s. Among them, the individuals colored sky blue and purple assess that the congestion is higher at the lower exit. Therefore, they select the upper exit, which is more distant but less crowded, to reduce the evacuation time. When $t = 73$ s, the evacuation state is as shown in Fig. 7(d). As described, the follow-up group selects the exit expected to take the least time to evacuate. Fig. 7(e) and (f) shows that the final evacuation of the two outlets were completed almost simultaneously.

To illustrate the effectiveness of the proposed method, we compare it with two classical swarm intelligence algorithms, namely, the ACO algorithm and PSO algorithm. The evacuation status of the ACO and PSO algorithms is shown in Figs. 8 and 9, respectively.

Fig. 8(a) shows the evacuation state when $t = 5$ s. At the beginning, individuals randomly selected exits, and the numbers of individuals at two exits were nearly the same. After some time, due to the advantages of distance, the lower exit evacuates more individuals and produces more pheromones. Based on the positive feedback mechanism of the ACO algorithm, the following individuals with larger proportion selected the lower exit to escape, as

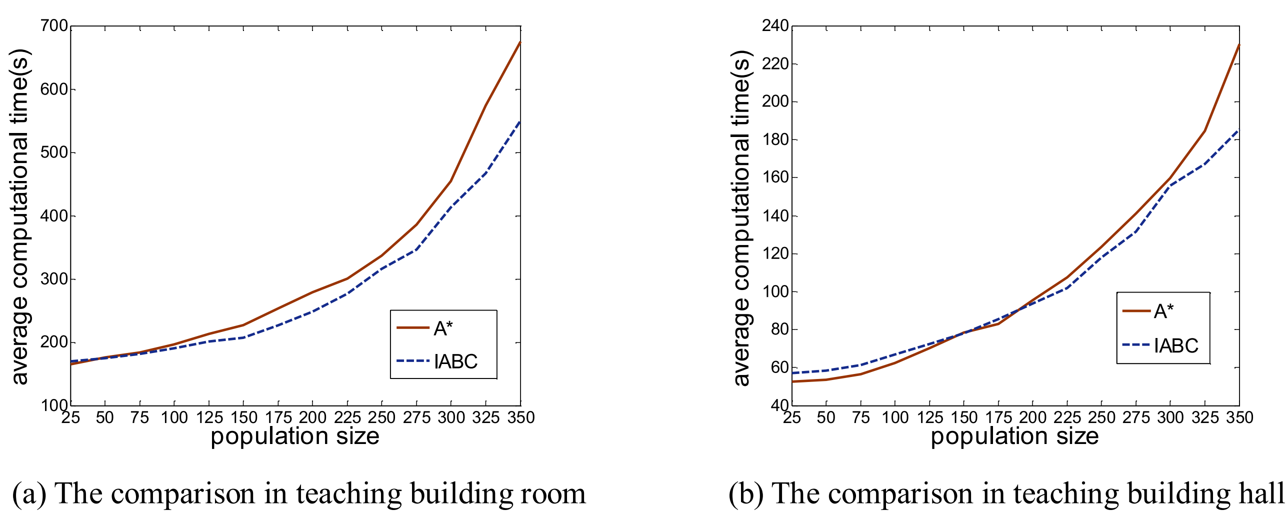


Fig. 6. Average computational time of A* and IABC.

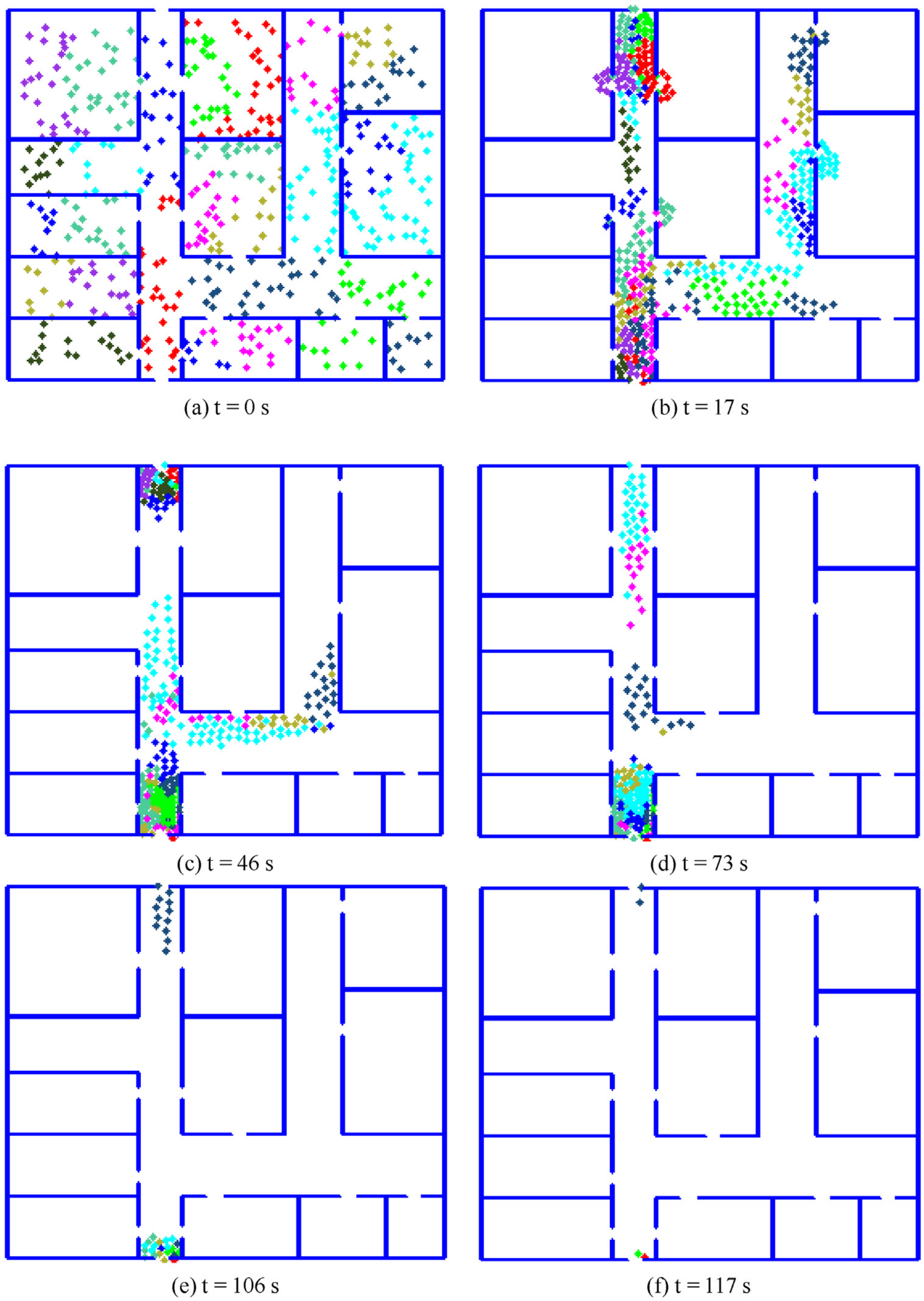


Fig. 7. Teaching building scene evacuation simulation of the IABC algorithm.

shown in Fig. 8(b) and (c). Fig. 8(d) shows the evacuation state when $t = 105$ s. As shown, the congestion at the lower exit is serious, whereas the crowd at the upper exit is minimal. With the increase in the probability of the lower exit being selected, which results in serious congestion, the evacuation efficiency was significantly reduced.

Fig. 9(a) shows that, when $t = 17$ s, the crowd evacuation situations of the IABC algorithm proposed in this paper and the PSO algorithm are similar. The individual position is slightly behind in Fig. 7(b). Fig. 9(b) and (c) shows an evident "clogging" phenomenon in the lower exit, which is due to the unfettered movement of individuals in the PSO algorithm, which does not consider the effect of exit congestion. Fig. 9(d) shows that all subsequent individuals select the lower exit with shorter distance but are congested until the evacuation of the upper exit is completed. Many individuals remain congested at the lower exit. Finally, the evacuation is completed when $t = 126$ s. The entire evacuation process cannot effectively use the free exits, and the evacuation efficiency is lower than that in the proposed IABC algorithm.

Tables 2 and 3 show the mean and variance of the evacuation time in the two-exit scenario (shown in Fig. 7) with different numbers of individuals. Each algorithm and each situation were run 10 times. As shown in Table 2, the evacuation time increased when the number of individuals increased because exit congestion occurred in this situation. We compare our IABC algorithm with PSO, ACO, original ABC, and HABC (cooperative co-evolutionary artificial bee colony algorithm based on hierarchical communication model) [52]. Although IABC has higher evacuation efficiency

(a) t = 5 s (b) t = 25 s

(c) t = 68 s (d) t = 105 s

Fig. 8. Crowd evacuation simulation of the ACO algorithm.

Table 2
Mean evacuation time of different algorithms.

	Numberof individuals								
Time (s)	100	150	200	250	300	350	400	450	500
PSO	90.13	90.50	90.69	93.20	97.90	103.00	111.50	117.92	124.00
ACO	89.93	90.24	90.40	92.60	96.30	100.87	113.30	120.6	128.37
ABC	89.88	90.15	90.26	93.19	95.67	102.75	111.13	115.25	122.93
HABC	89.78	89.93	90.05	91.75	95.37	100.04	109.22	114.05	122.84
IABC	89.60	89.76	89.87	91.31	94.60	98.58	106.42	112.85	119.60

Table 3
Variance evacuation time of different algorithms.

	Number of individuals								
Time (s)	100	150	200	250	300	350	400	450	500
PSO	1.159	1.079	0.709	1.104	1.246	1.343	1.446	1.683	1.681
ACO	1.501	1.247	0.931	0.962	1.148	1.165	1.287	1.325	1.397
ABC	1.168	1.082	0.861	1.079	0.834	1.012	1.275	1.360	1.283
HABC	1.090	0.956	0.808	1.075	1.230	1.334	1.221	0.985	0.942
IABC	1.303	0.937	0.710	1.083	1.205	1.266	1.057	0.951	0.901

Table 4
Mean evacuation time of teaching building hall with 3 exits.

	Number of individuals								
Time (s)	100	150	200	250	300	350	400	450	500
PSO	42.42	45.66	49.75	54.24	60.59	68.41	77.34	87.75	99.39
ACO	41.52	44.68	47.24	50.28	54.86	62.3	70.21	79.75	93.78
IABC	32.48	33.39	34.71	36.69	39.57	43.51	48.45	54.25	65.2

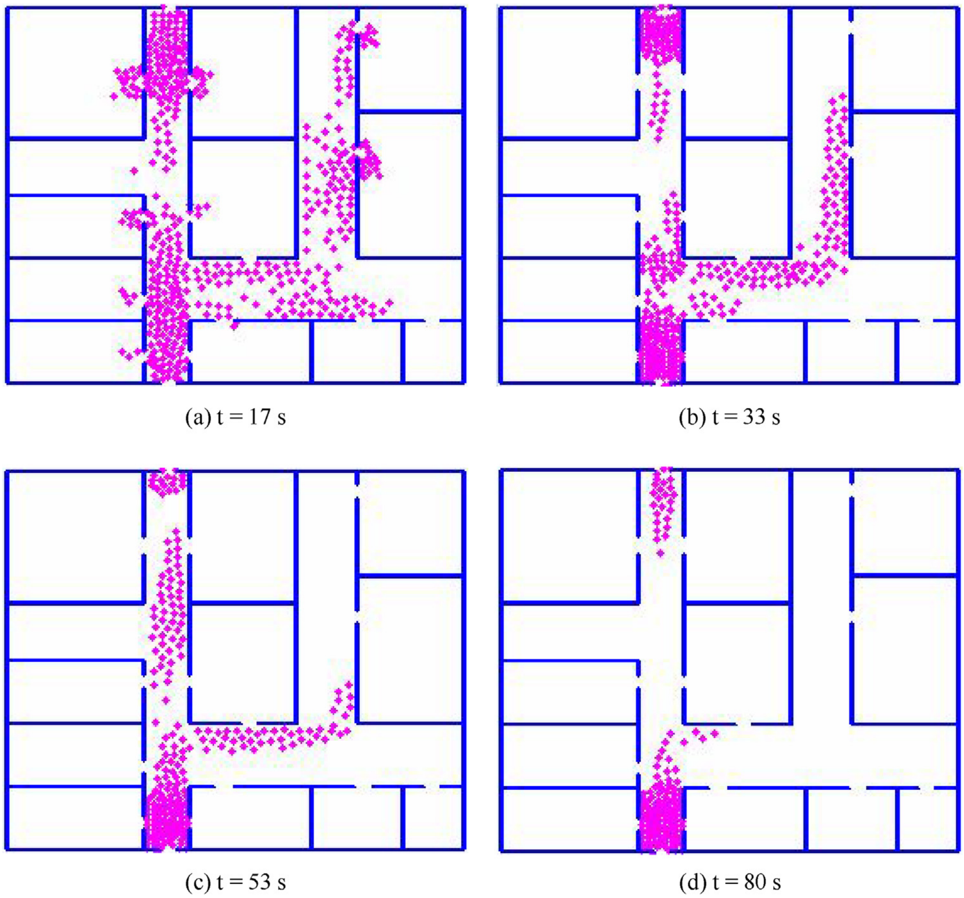


Fig. 9. Crowd evacuation simulation of the PSO algorithm.

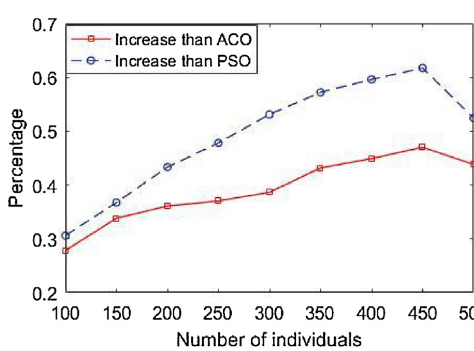


Fig. 10. The increased percentage of evacuation efficiency compared to the ACO and PSO algorithms.

than the other algorithms, the evacuation efficiency is not improved much. That is because the bottleneck problem of the exit gradually manifests (as shown in Fig. 9) as the population density increases. Thus, the time efficiency of our algorithm is offset when congestion occurs. To highlight the advantages of our algorithm, we select a scenario with more exits to alleviate congestion. Table 4 shows the comparison results in the teaching building hall scene (20 m x 30 m) with three exits. Fig. 10 shows the increased percentage of the evacuation efficiency compared to the ACO and PSO algorithms. As can be seen, our algorithm is more efficient than others in the situations with different numbers of individuals. Notably, the evacuation efficiency of our method is higher than that of ACO and PSO, up to 47% and 61.7%, respectively, when the number of pedestrian is set to 450. The percentage increases as the number of individuals rises until 450, and then it drops. This means that an excessive number of people can also cause congestion even if the number of exits increases, which leads to a decline in evacuation efficiency.

5.4. Comparison with the captured surveillance video and GSFM

To compare the ESFM with the real scene, the original SFM and other improved SFM algorithms (e.g. GSFM [25]), we use an unmanned aerial vehicle (UAV) to capture video of the campus road in Shandong Normal University after school (see Fig. 11(a)). As shown in the captured surveillance video, the crowd is composed of many small groups (each red circle represents a group in Fig. 11(a)). The distance within a group is small, and the distance between groups is large. In Fig. 11(b), (c) and (d), the crowd evacuation is generated by the original SFM, GSFM and ESFM on a 100-m $\times$ 30-m 3D scene. The other parameters are set the same as in Section 5.3. As we can see from Fig. 11(b), the crowd is evenly distributed and lacks the grouping phenomenon. In Fig. 11(c), some groups are formed. That is because that GSFM introduces some guided individual into the crowd artificially, and then effect of the group can be achieved since the crowd should follow the guided individual in a certain probability. However, the individuals within these groups are also evenly distributed which is not consistent with the actual phenomenon. Differently, the individuals in Fig. 11(d) form many small non-uniformly distributed groups, which is visually similar to the captured surveillance video intuitively.

To analyze the similarity quantitatively, we extract some parameters (e.g., the number of groups and the number of individuals in each group) from the captured surveillance video to capture the characterization of the small groups. We first extract the positions from the video and then transform them into world coordinates.

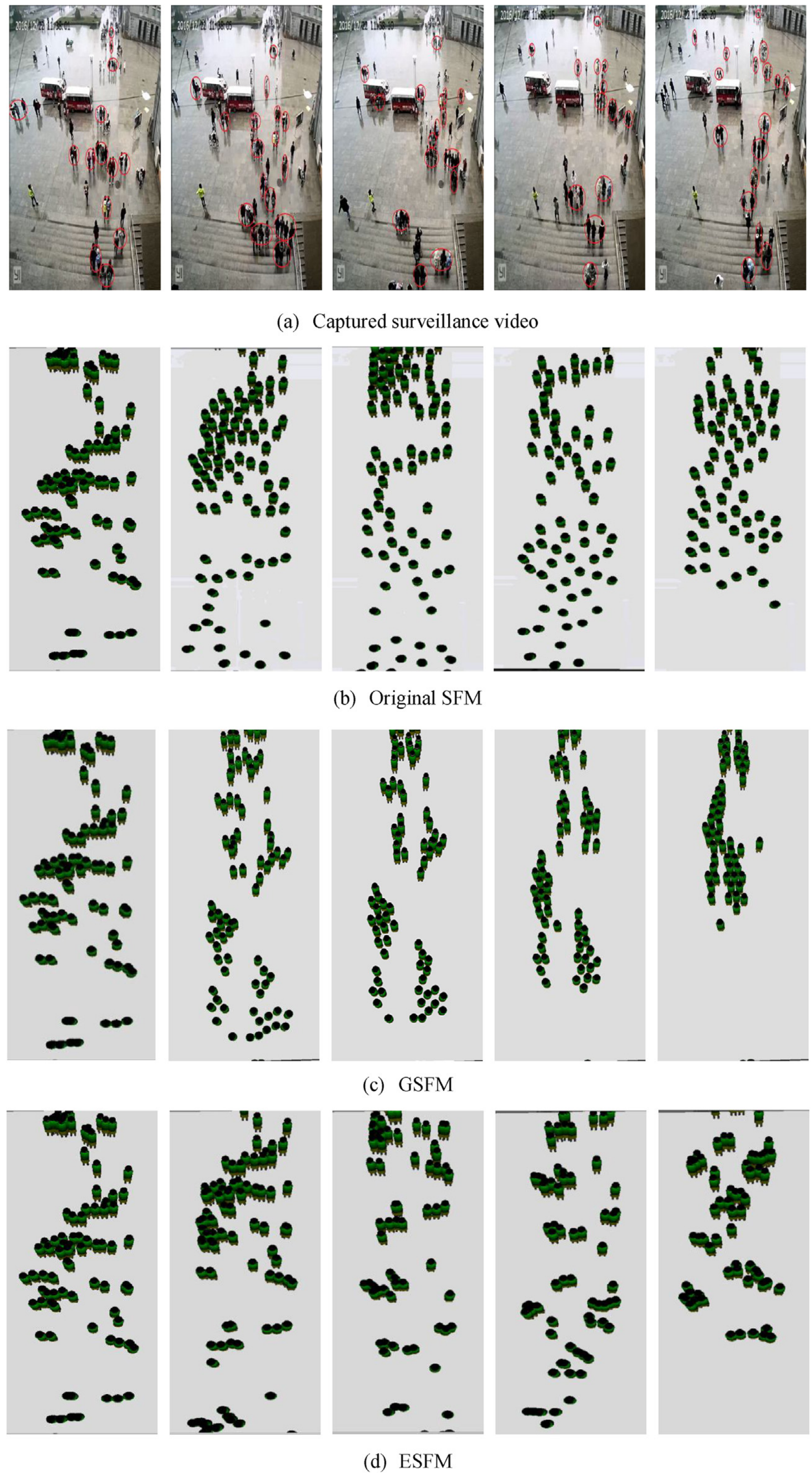
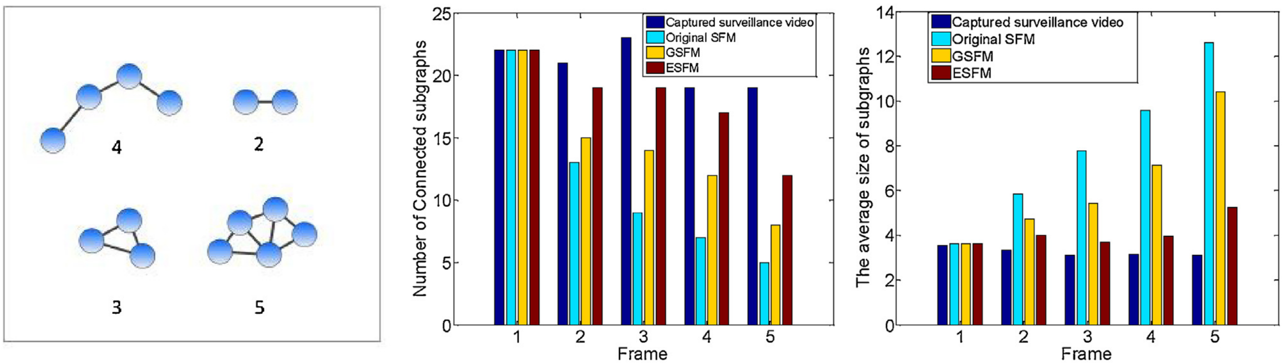


Fig. 11. Comparison among the captured surveillance video, the original SFM, GSFM and ESFM.

After the transition, these coordinates can be used to compare with the generated crowd evacuation. Thus, the generated crowd evacuation whose parameters have smaller difference to the captured surveillance video is thought to be more similar to the real video. To obtain the parameters of the crowd evacuation in Fig. 11(a)–(d) conveniently, we introduce the concept of graph connectivity. First, we create a graph where each vertex is an individual of the crowd. When the distance between two individuals is within a threshold (the width of two bodies, 2 m), they are linked by an edge. If two individuals are far away from each other, they cannot be connected with an edge. For any two vertices, they belong to one connected subgraph if they are linked by one or multiple edges. Therefore, the graph can be divided into a number of connected subgraphs. We use the number of connected subgraphs and the average size of connected subgraphs to quantify the self-organizing group formation of the crowd evacuation. In Fig. 12(a), an example of a graph with



(a) An example of subgraphs (b) The number of subgraphs (c) The average size of subgraphs

Fig. 12. Quantitative comparison of the captured surveillance video with the original SFM, GSFM and ESFM.

4 connected subgraphs is given. The numbers of vertices in each subgraph are 4, 2, 3 and 5, respectively. As a result, the average size of subgraphs is 3.5 in this example.

We compare each frame of the three videos mentioned in Fig. 11. In Fig. 12(b) and (c), and compare the number of connected subgraphs and the average size of subgraphs correspondingly. As we can see from Fig. 12(b), in the initial frame, all four videos have the same number of connected subgraphs. With the crowd moving, the number of connected subgraphs in the original SFM video and the GSFM video are 58.9% and 40.2% lower than the captured surveillance video on average respectively, while only 18.6% for the ESFM video. In Fig. 12(c), the average size of subgraphs of the videos is similar to the initial frame. As time passes, the size of subgraphs in the original SFM video and the GSFM are 184.1%, 108.7% higher than the captured surveillance video on average respectively, while only 33.3% for the ESFM video. Thus, the crowd motion of ESFM is more similar to that of the captured surveillance video.

Another example, shown in Fig. 13, is used to verify the effectiveness of our IABC algorithm. We captured video (see Fig. 13(a)) in a teaching building hall of Shandong Normal University when class was over. In Fig. 13(a), the crowd swarms around the entrance and the groups that select the left or right entrance are marked by red circles, and their movement directions are denoted with red arrows. The original SFM requires the setting of the goal position of each individual. In Fig. 13(b), the goal position is set as the top exit (the most commonly used exit) of the building. Clearly, all people move to the definite exit regardless of how crowded the exit is. The situation is improved in Fig. 13(c) and (d) where the nearest exit is selected or the guided individuals are followed in a certain probability. However, the top exits of both of the two scenario are still crowded. Neither of these cases can effectively use the exits to evacuate the crowd in a short period of time. Fig. 13(e) shows the simulation results using the proposed method. The people are automatically divided into different groups. Each group selects the most optimal exit for evacuation. For example, the two groups in red circles attempt to move to the nearest top exit first. Considering that the top exit becomes crowded, they reselect the exit (the left or right exit) by evaluating the evacuation time. The experimental results show that the combination of the ESFM and the IABC algorithm is the most effective approach. The simulation result of our approach also reflects the decision-making process of humans and is therefore closer to the real data captured by surveillance video.

Furthermore, we perform another quantitative comparison regarding velocity-density between the captured surveillance video, Seyfried's fundamental diagram [54] and our method. This comparison is also carried out in the teaching building scene. As we can see from Fig. 14, the pedestrian velocities via our method and in the captured surveillance video decrease when the density of the crowd increases. This phenomenon shows that the dependences of velocity-density are similar to the fundamental diagram of the literature [54]. However, when the density of pedestrians is higher than 1.0 p/m2, the crowd velocity of our method descends more quickly. That is mainly because the time spent on grouping increases as the density of pedestrians rises.

6. Conclusion

Economic development has prompted the emergence of large-scale public events, which attract large crowds. Such events pose significant challenges with respect to crowd management. This phenomenon has resulted in growing research interest in the simulation of crowd behavior to address security challenges and evacuation scenarios. Studies on the human behavior of crowd evacuation will contribute to the reasonable design of buildings and reinforcement of security management so as to prevent and reduce fatalities in emergency cases.

Inspired by the foraging behavior of bee colonies with self-organization in nature, this paper proposes a new path planning approach for emergency evacuation simulation. We learn dynamic adjustment of swarm activities according to nectar honey richness from the bee colony and map the reciprocal of the exit congestion degree with nectar honey richness. This means that, the more crowded the exit, the less honey the bees can gather in the ABC algorithm, and the lower the probability that the individuals choose the exit. We also combine the ESFM and the IABC algorithm to improve the efficiency of crowd evacuation.

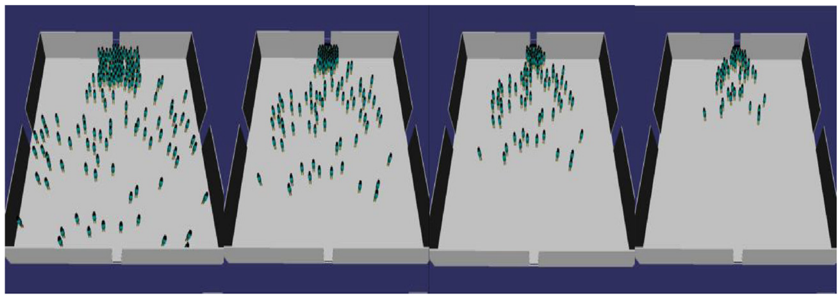
The following conclusions can be drawn from the simulation results:

(1) The proposed IABC algorithm can improve the evacuation efficiency by employing the strategies of grouping and exit selection.
(2) The extended SFM is able to simulate more realistic crowd behaviors by considering a visual parameter.

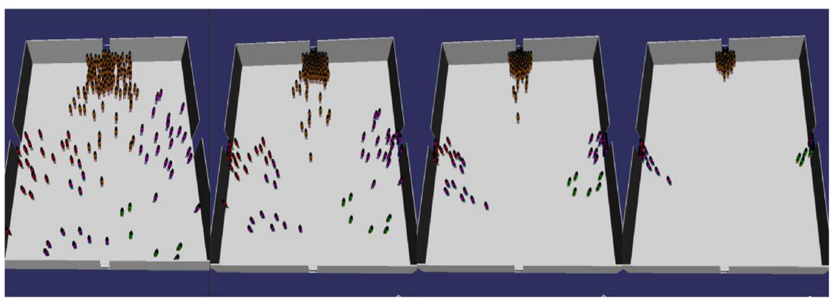
From the existing research and our simulation results, rational management strategies are helpful in expediting evacuation processes. The aim of this research is to develop an evacuation management system. Studies on the behavioral characteristics of crowd evacuation and motion laws will be researched on this system and contribute to the reasonable design of buildings and reinforcement of security management to prevent and reduce fatalities in emergency cases.

To achieve this goal, our research team studied the related issues from different aspects. We compared the proposed model with the video data captured on campus [55]. The results show that our pro-

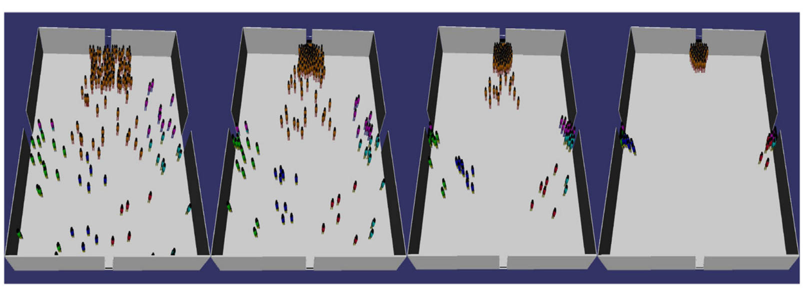
(a) Captured surveillance video



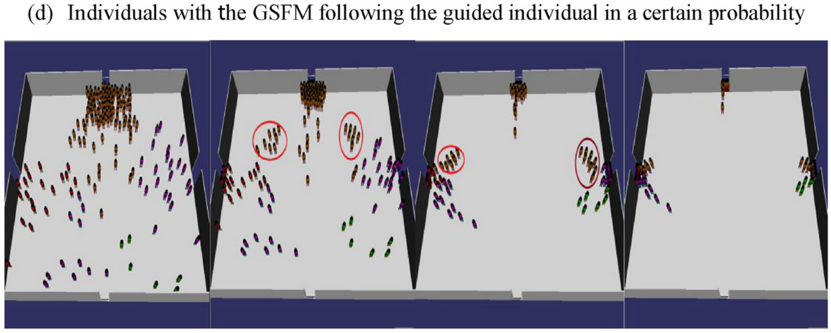
(b) Individuals with the original SFM selecting a definite exit by the IABC algorithm



(c) Individuals with the original SFM selecting the nearest exit by the IABC algorithm



(d) Individuals with the GSFM following the guided individual in a certain probability



(e) Combination of the ESFM and the IABC algorithm

Fig. 13. Simulation results of crowd evacuation with different methods.

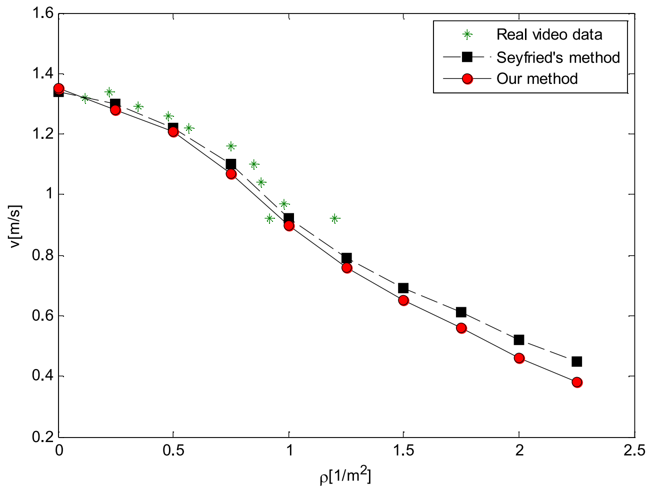


Fig. 14. Comparison of velocity-density.

posed grouping model and the improved social force model are consistent with real campus scenes. We also explored the impact of the location of the leader on the evacuation speed when moving in groups using the social model with the leader [25]. Furthermore, we believe that the simple swarm intelligence algorithm has limited efficiency in crowd evacuation issues. Therefore, we proposed a two-layer control mechanism framework with knowledge navigation [56]. We tested and compared the results of three models in two different scenarios to verify the role of the knowledge base and knowledge-based navigation. However, in this framework, we do not have a good solution to the problem of dynamically grouping crowd according to the exit congestion and their position. This article is exactly the solution to this problem.

Next, we intend to embed IABC algorithm into the framework of knowledge based navigation with two-layer control mechanism for grouping the population dynamically, and use the machine learning method to extract and update the path information, and combine the swarm intelligence algorithms to optimize the evacuation path to implement knowledge-based crowd evacuation navigation.

Acknowledgement

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