Modeling and Simulation of Evacuation Based on Bat Algorithm

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Abstract. The safe and orderly evacuation of crowds is a hot topic at home and abroad. To solve the problem of low evacuation efficiency of evacuation model based on PSO, this paper constructed a crowd evacuation model based on Bat Algorithm (BA). This model selected the new swarm intelligence algorithm Bat Algorithm and comprehensively considered obstacle avoidance. Specifically, firstly, the principle of BA and its feasibility for evacuation was introduced. Then, BA was used to update the crowd movement, the obstacle avoidance mechanism was established by using the cost function, and the crowd evacuation model based on BA was constructed. Finally, the evacuation path, evacuation efficiency and degree of chaos of this model and PSO-based evacuation model were compared and analyzed. The degree of chaos is represented by the value of evacuation entropy. Simulation results show that this model can effectively improve the evacuation efficiency and reduce the degree of chaos in the evacuation process.

1. Introduction
Research on crowd evacuation in emergencies can provide effective evacuation strategies and improve public safety, which is of great research significance. According to the description scale of the model, evacuation model can be divided into macroscopic model, mesoscopic model and microscopic model [1]. In the early stage, macroscopic evacuation model was the main one, which paid attention to the overall behavior characteristics. The representative models included Fluid Dynamics Model [2] and Network Model [3]. Mesoscopic evacuation model classifies the crowd and studies the behavior rules of each class of people, both of which lack the description and expression of evacuation individuals. In recent years, researches at home and abroad have focused on micro evacuation models, which can describe each evacuation individual well and fully express the heterogeneity and interaction between individuals. Cellular Automaton Model [4] and Social Force Model [5] are the representative models.

With the development of artificial intelligence and bionics, some scholars began to use swarm intelligence to model crowd evacuation in recent years. Swarm intelligence simulates intelligent groups with self-organizing behaviors in nature. Classical algorithms include Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) [6]. New algorithms include Artificial Fish-swarm Algorithm (AF) [7], Artificial Bee Colony Algorithm (ABC) [8], Bat Algorithm (BA) [9], etc. Among them, PSO and ACO have been more mature in the application of evacuation modeling, and some new algorithms have begun to be applied in evacuation modeling. Zheng et al. [10] introduced local population density and injury threshold to establish a new PSO evacuation model. Hajjem et al. [11] used ant colony algorithm to build a real-time evacuation guidance system. Liu et al. [12] added grouping and multi-exit selection strategies into the artificial bee colony algorithm, combined with the expansion of social force model, to improve the evacuation efficiency.
Among them, the most commonly used one is the PSO-based evacuation model, but this model is prone to fall into the local optimization, leading to the gathering and wandering of crowds and affecting the evacuation efficiency. In this paper, a new intelligent algorithm Bat Algorithm is adopted for crowd evacuation modeling. BA has been successfully applied to production scheduling, classification and other problems at present [13,14], but there is little literature on the establishment of crowd evacuation model based on it. Compared with PSO and other algorithms, BA has more advantages in both accuracy and convergence speed [15]. In this paper, BA was used for evacuation modeling and simulation, and compared with the basic PSO evacuation model, it was found that this model could reduce the wandering of crowds, reduce the degree of chaos in the evacuation process, and effectively improve the evacuation efficiency.

2. Basic bat algorithm and its feasibility analysis for evacuation

Bat Algorithm [9] was proposed by Yang from Cambridge University in 2010, which simulated bats detect prey by echolocation. It is an optimization algorithm that combines echolocation with the objective function to be optimized, and it is also a new artificial intelligence algorithm. Its pseudo code is shown in figure 1.

- **Initialize bat population xi and vi, frequency fi, pulse rates ri and loudness Ai**
- **while (i < Max number of iterations)**
  - Find the global optimum x* using fitness
  - Update velocity and position xi(t+1) [equations (1) to (3)]
    - if (rand > ri)
      - Generate a local solution xi(t+1) around global optimum x* [equations (4)]
    - end if
  - Calculate the fitness f(xi(t+1))
    - if (rand < Ai & f(xi(t+1)) < f(xi history optimum))
      - Update f(xi history optimum)
      - Increase ri and reduce Ai [equations (5) to (6)]
    - end if
- **end while**

Figure 1. Pseudo code of BA

1. **position update**

Bat Algorithm controls the update of velocity and position by adjusting frequency and searching for the global optimal bat. The formula is as follows.

\[ f_i = f_{min} + (f_{max} - f_{min})\beta, \]  
\[ v_i^{t+1} = v_i^t + (x_i^t - x^*)f_i, \]  
\[ x_i^{t+1} = x_i^t + v_i^{t+1}, \]

where, \( f_i \) is the pulse frequency of bat i. \( x_i \) is the position of bat i. \( v_i \) is the velocity of bat i. \( f_{max}, f_{min} \) as the maximum and minimum frequency is constant. \( \beta \) denotes random function with the value between [0,1]. \( x^* \) is the position of the bat with the best fitness in the whole space.

2. **local search**

If the pulse rate is low, random search is conducted near the global optimal bat. The formula of local search is as follows.

\[ x_i^{t+1} = x^* + \epsilon \Lambda^t, \]

where, \( \epsilon \) is a random function with the value between [0,1] and \( \Lambda^t \) is the average loudness of all bats at time t.

3. **pulse emission rate and loudness update**

Bats have low pulse emission rate and high loudness when they start hunting for prey, which facilitates extensive search. When prey is found, bats will increase pulse emission rate and reduce loudness, so as to make better progress towards the target. Therefore, the formula of pulse rate and loudness update of bat algorithm is as follows.
\[ A_i^{t+1} = \alpha A_i^t, \]
\[ r_i^{t+1} = r_i^0 [1 - \exp(-\gamma t)], \]
where, \( A_i \) is the loudness of bat \( i \),\( r_i^0 \) is the maximum pulse rate of bat \( i \). \( \alpha \) and \( \gamma \) stand for the control parameters of loudness and pulse rate respectively, which are constants.

The final goal of the bat algorithm is to hunt prey, that is, to find the optimal solution, which is consistent with the goal of the population evacuation go toward the exit (optimal solution). The crowd is abstracted as bats, the exit position is abstracted as prey, and the echolocation of bats is simulated by lights, broadcasts or other forms, making it feasible to use the bat algorithm for crowd evacuation.

3. Evacuation model based on Bat Algorithm

In this paper, evacuation individuals are abstracted as circular particles, crowd position is updated based on bat algorithm. Then, we comprehensively consider obstacle avoidance factors, constructing a crowd evacuation model based on bat algorithm.

3.1 Crowd position update based on BA

Since the bat algorithm is only interested in the position of prey, namely optimal solution, and doesn’t care about the flight path of bats, it is inconsistent with evacuation. In the actual evacuation, it is impossible for people to jump directly to the position near global optimal, so this paper makes some changes to bat algorithm to adapt to the crowd evacuation. The specific steps are shown in figure 2.

In pseudo code, the main change between bat algorithm for evacuation and basic bat algorithm lies in the local search part, this change makes the model more close to the reality of evacuation. At the same time, in the process of crowd evacuation, local search is added to simulate the extensive random search of bats, makes the evacuees have a higher probability to perceive the position of the exit and then move towards the exit, which improve the efficiency of evacuation. The formula is as follows.

\[ s_{x_i}^{t+1} = x_i^{t+1} + \epsilon A^t, \]
where the meaning of \( \epsilon \) and \( A^t \) are the same as formula (4).

The fitness selected in this paper reflects the good or bad position of evacuation individuals in evacuation space. It is affected by the position of exit and obstacles. The influence of the obstacle can be expressed by the cost function as follows [16].

\[ \text{cost}(p, q) = \exp \left( -\left( \frac{(p_x - q_x)^2}{(\sigma_{px} + \sigma_{qx})^2} + \frac{(p_y - q_y)^2}{(\sigma_{py} + \sigma_{qy})^2} \right) \right), \]
where, \((p_x, p_y)\) is the position of particle \(p\), \((q_x, q_y)\) is the position of obstacle \(q\), the obstacle maybe dynamic obstacles, like other evacuation individuals, or static obstacles, like walls or square columns, etc. \((\sigma_{px}, \sigma_{py})\) is the size of particle \(p\). \((\sigma_{qx}, \sigma_{qy})\) is the coverage area of the obstacle \(q\).  

Then, the cost function is used to represent the fitness \(F_{obj}(p)\) as follows [16].

\[
F_{obj}(p) = C_{obs} \times \max_{o \in O}(\text{cost}(p, o)) + \frac{1}{\text{cost}(p, g)},
\]

where, \(O\) represents all dynamic obstacles and static obstacles. \(g\) represents the position of exit. \(C_{obs}\) represents the weight coefficient of obstacles, the larger \(C_{obs}\) is, the greater the influence of obstacles on the path selection of particles is.

### 3.2 Obstacle avoidance mechanism

Obstacle avoidance mechanism is mainly used to judge whether the next position of evacuees is occupied by obstacles or other evacuation individuals, and then take the next action. In this paper, the cost value calculated by formula (8) is used to determine whether there is a collision with an obstacle. The acceptable probability of next position is calculated as follows [16].

\[
\text{prob}(f) = 1 - \frac{f}{e^{-k}}
\]

where, \(f\) is the cost value of the target obstacle, including static obstacle and dynamic obstacle. \(k\) is the behavior constant, which expresses the strength of obstacle avoidance. \(k = 1\) is a boundary value, that is, when particles are tangent or intersecting with the obstacle, the acceptable probability of next position is 0 or less, effectively achieving the goal of obstacle avoidance.

The flow chart of this model is shown in figure 3.

![Figure 3. Flow chart of the evacuation model based on BA](image)
4. Simulation and analysis
In order to verify this model, we use matlab for simulation, and compared the results of this model and PSO evacuation model. PSO evacuation model is the most commonly used evacuation model based on swarm intelligence at present. By comparing with PSO evacuation model, the superiority of this model can be well verified.

4.1 Evacuation environment and parameter
In this paper, the evacuation scene is set as a two-dimensional rectangular area of 60m×40m with a single exit. The gray part around is the wall, and the red rectangle at the lower left corner is the exit. Some rectangular and circular obstacles are randomly placed in the scene. The evacuation number is set as 50 people.

The setting of parameters is shown in table 1. $S_{\text{max}}$ is the maximum step size of the evacuee's movement, and $R$ is the size of particles. $f_{\text{min}}$, $f_{\text{max}}$, $\alpha$, $\gamma$, $r_0^i$ are the parameters in the bat algorithm, which represent the minimum frequency, maximum frequency, loudness control parameter, pulse rate control parameter and maximum pulse rate respectively. $C_{\text{obs}}$ is the obstacle weight coefficient when calculating the fitness value, and $k$ is the behavior constant in the obstacle avoidance mechanism.

| PARAMETERS | $S_{\text{max}}$ | $R$ | $f_{\text{min}}$ | $f_{\text{max}}$ | $\alpha$ | $\gamma$ | $r_0^i$ | $C_{\text{obs}}$ | $k$ |
|------------|-----------------|-----|-----------------|-----------------|----------|----------|--------|----------------|-----|
| VALUE      | 1m              | 0.4m| 0               | 2               | 0.5      | 0.5      | 0.001  | 0.1            | 1   |

4.2 Comparison of evacuation results
In the comparison experiment, the initial position of the evacuation population in this model and the PSO model was set to be the same, and the average value of 500 groups was taken to reduce the impact of the randomness of the initial position. The results are shown in table 2. Then, one group data was selected to compare and analyze the changes in the evacuation path, evacuation efficiency and degree of chaos of the two models with the progress of time in the entire evacuation process.

|                      | average evacuation time | max evacuation time | average evacuation entropy value | max evacuation entropy value |
|----------------------|-------------------------|---------------------|----------------------------------|-----------------------------|
| BA-BASED             | 35.25                   | 70.65               | 2.24                             | 6.87                        |
| PSO-BASED            | 56.97                   | 115.30              | 2.28                             | 6.96                        |

Evacuation entropy expresses the inconsistency of velocity and direction between evacuation individuals. It can be used to characterize the chaos degree in evacuation process [17]. Table 2 shows that this model is superior to the PSO-based model in terms of both evacuation efficiency and degree of chaos. The average and the longest evacuation time decreased by 38.13% and 38.73% respectively, and the average and the maximum entropy value decreased by 1.45% and 1.25% respectively.

(a) BA-based evacuation model                                (b) PSO-based evacuation model

Figure 4. Evacuation path
Figure 4 shows the comparison figure of evacuation path between this model and PSO-based evacuation model, and the blue line are the evacuation path of evacuees. It can be clearly seen from the figure that the BA-based evacuation model constructed in this paper makes the crowd more orderly in the evacuation process. No matter the area is close to the exit or far away from the exit, the evacuees can move more firmly towards the target exit. In places where the evacuation crowd is sparse, this model reduces the phenomenon of wandering. In places where the crowd gathers, this model reduces the degree of crowd gathering to some extent and improves the evacuation efficiency.

Figure 5. The relationship between evacuation time and the number of evacuees who haven’t left

Figure 6. The relationship between evacuation time and total evacuation entropy value

As can be seen from figure 5, the number of evacuees who failed to evacuate in this model is always lower than that of PSO evacuation model, which proves that this model can quickly evacuate people and has higher evacuation efficiency. In addition, with the increase of evacuation time, the gap between the two models becomes larger and larger. This is because, compared with the PSO evacuation model, the BA evacuation model reduces the degree of crowd aggregation and congestion at the exit or obstacle corner and then reduces the evacuation time.

In order to calculate the value of evacuation entropy, this paper discretizes the evacuation space into uniform grids of 10m x 10m, calculates the evacuation entropy value in each grid, and then adds the evacuation entropy values of all grids to obtain the total entropy value. The change of the total entropy value over time is shown in figure 6. In figure 6, the total entropy value of this model is lower than that of PSO model in most of the time, which proves that this model is more orderly in the evacuation process. In the early stage of evacuation, the curves are relatively identical, the difference between the two models is not big. At this time, most evacuees are in the stage of searching for exits, and the degree of chaos is relatively high. In the middle and late stage of evacuation, the curve gap starts to widen. After perceiving the general direction of exit, evacuees based on BA evacuation model can move forward firmly towards the exit, and the evacuation process becomes more orderly.

5. Conclusion
The safe evacuation of the crowd in the event of an emergency is directly related to the safety of public life and property as well as the security capability of the site. In this paper, Bat Algorithm is applied to crowd evacuation modeling, and considering obstacle avoidance comprehensively, an evacuation model based on Bat Algorithm is construct. Through the comparative analysis with the PSO evacuation model, this model reduces the evacuation time by about 38% and the evacuation entropy by about 1.4%, improves the evacuation efficiency and reduces the degree of chaos in the evacuation process. However, this model does not take into account the impact of evacuation individual psychological factors, such as panic, and specific evacuation environment, such as fire, which can be further optimized later to make the model more consistent with the actual evacuation.
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