Evacuation Entropy Path Planning Model Based on Hybrid Ant Colony-Artificial Fish Swarm Algorithms

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Abstract. The artificial fish swarm algorithm is introduced to construct the evacuation entropy path planning model of hybrid ant colony-artificial fish swarm algorithm to improve the convergence speed of the model. In the early stage of the model, the advantage of artificial fish swarm algorithm is used to search the optimal solution quickly and generate the initial solution. In the later stage of the model, the strong positive feedback mechanism of ant colony algorithm is used to quickly iterate out the optimal path. At the same time, the crowding factor of artificial fish swarm algorithm is introduced to update local pheromones adaptively combined with evacuation entropy. The simulation results show that the hybrid ant colony-artificial fish swarm algorithm has fast convergence speed and can avoid falling into local optimum.

1. Introduction

With the in-depth development of urban construction, the internal structure of public places is extremely complex and the flow of people is large. Once an emergency occurs, it is easy to cause group crowding and trampling accidents due to chaos. It has become an important research topic at home and abroad to study the behavior characteristics of evacuated people in emergency situations and establish a set of perfect and reasonable evacuation path planning model to guide the safe and rapid evacuation of the crowds.

Imanishi, M et al. [1] analyzed the actions of evacuees during three consecutive evacuation exercises in theatre, clarified the route selection mechanism of evacuees in auditorium, and obtained a set of data sets to simulate the whole evacuation process. Lujak, Marin et al. [2] thought it is not enough to find the shortest evacuation route, and other relevant characteristics should be taken into account to make the evacuation route safe enough. Hong et al. [3] studied the problem of path planning for constrained spatial evacuation in three-dimensional scenarios. Aiming at maximizing the utilization of evacuation exit, a three-stage heuristic routing network construction method based on minimum weighted set coverage was proposed and applied to evacuation in a typical constrained spatial scenario-underground. The results showed that this method can improve the utilization rate of escape exit. Han et al. [4] proposed an extended route selection model based on available evacuation route set to simulate how pedestrians choose appropriate route according to the evacuation situation in emergency situations. The experimental results showed that the extended model can effectively reproduce crowd behavior in emergency situations and help to analyze emergency evacuation scenarios. Liu et al. [5] established hexagonal grid map for fire evacuation scenarios, and proposed the shortest path considering real-time fire diffusion based on improved ant colony algorithm. The results showed that the established model can avoid pedestrians blindly entering dangerous areas.

However, the above-mentioned models don’t take into account the impact of population chaos on population path selection, and the convergence speed of the model is slow. Therefore, this paper constructs an evacuation entropy path planning model based on hybrid ant colony-artificial fish swarm algorithm, and uses the advantage of fast search for better solution in the early stage of artificial fish swarm algorithm to determine the initial solution of the model, which makes up for the shortcoming of slow convergence in the early stage of ant colony algorithm.

2. Establishment of Evacuation Entropy Path Planning Model Based on Hybrid Ant Colony-Artificial Fish Swarm Algorithms

The hybrid ant colony-artificial fish swarm algorithm constructs in this paper mainly uses artificial fish swarm algorithm to determine the initial solution in the early stage, and uses ant colony algorithm to quickly iterate out the optimal path in the later stage.

2.1 Determination of Initial Solution

At the initial time of the ant colony algorithm, in the process of evacuation from the starting point to the exit, the pheromone content of each path is constant. The movement of evacuated individuals has great randomness, which leads to long time-consuming in the early stage of evacuation. The quality of the solution obtained by the search is not high. Therefore, this paper uses the advantages of artificial fish swarm algorithm, such as fast search speed in the early stage and easy to obtain better solution, to determine the initial solution in the early stage, as the inspiration of the later ant colony algorithm.

The key to determine the initial solution is how to set the end condition of artificial fish swarm algorithm, which becomes the signal of the ant colony algorithm to start iteration. The main design ideas of this paper are as follows: (1) Setting the position of the export as the optimal state x_{best} , and the food concentration as the geometric length of from the current position x_i of each artificial fish to the exit. The shorter the geometric length is, the higher the food concentration is, that is $Y_{best} = 0$. (2) Take (x_{best}, Y_{best}) as the initial value of the bulletin board. (3) Each artificial fish carries out foraging behavior, clustering behavior and tail-chasing behavior separately. After each behavior, it updates its own state and compares it with the value on the bulletin board. If the value of the final state of an artificial fish equals the optimal value on the bulletin board, the artificial fish will stop foraging. Only when all artificial fish stop foraging within a limited number of iterations can the initial solution of artificial fish swarm algorithm be determined. (4) If the maximum number of iterations $Gen\max$ is reached, the remaining artificial fish fails to find the optimal state, the algorithm is set to terminate. The path of all artificial fish is recorded, the pheromone updating of ant colony algorithm is enabled, and the ant colony algorithm is modified by the evacuation entropy.

2.2 Adaptive updating of local pheromones

The implementation of ant colony algorithm relies heavily on pheromone updating, and pheromone updating strategy can greatly affect the ant's path search behavior. However, the traditional ant colony algorithm does not take any constraints on pheromone updating strategy, which makes the algorithm very easy to fall into local optimum. In artificial fish swarm algorithm, this phenomenon does not occur, because the fish swarm will judge before swimming. If the destination of the movement is too crowded, the fish will find other areas with higher food concentration [6]. Therefore this paper uses the idea of artificial fish swarm algorithm for reference, introducing the crowding factor into ant colony algorithm, and integrating evacuation entropy as a measure of local pheromone updating strategy. The calculation formula of congestion degree is as follows [7]:

$$\delta(t) = \frac{2\tau_{ij}}{\sum_{j=1}^{8}\sum_{i=1}^{8}\tau_{ij}}, i、j \in allow_k \tag{1}$$

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After calculating the congestion degree, the criterion of congestion on this route should be worked out, that is, the threshold of congestion degree should be defined. The congestion threshold $\delta_{\max}$ is updated according to equation (2).

$$\delta_{\max}(t) = 1 - e^{-ct} \tag{2}$$

The congestion threshold is not a fixed value, but increases monotonously with time. In the early stage of the algorithm, the threshold of congestion degree is close to 0, and the residual pheromone is less. Ants randomly choose the moving path according to the probability of state transition. In the middle and late stage of the algorithm, with the accumulation of pheromones, the threshold of congestion degree plays a limiting role, avoiding the accumulation of pheromones in a certain region and falling into local optimum. At this time, if $\delta(t) > \delta_{\max}$ or entropy $E_n > 2\overline{E_n}$,the population in this area is crowded or confused, the local pheromone updating method should be carried out according to the following equation(3)-(7).

$$\begin{cases} \tau_{ij}(t+1) = (1-\delta(t))\tau_{ij}(t) + \delta(t)\tau_0, & \text{if } E_n > \overline{E_n}(n = 1,2,3,\cdots 8) \cup \delta(t) > \delta_{\max} \\ \tau_{ij}(t+1) = \tau_{ij}, \end{cases} \tag{3}$$

$$\overline{E_n} = \frac{\sum_{n=1}^{8} E_n}{n} \tag{4}$$

$$E_n = \sum_{i=1}^{2} \alpha_i E_{ni} \tag{5}$$

$$E_{n1} = -\sum_{i=1}^{8} \frac{n_i}{N} \log_2 \frac{n_i}{N} \tag{6}$$

$$E_{n2} = -\sum_{j=1}^{8} \frac{m_j}{N} \log_2 \frac{m_j}{N} \tag{7}$$

Where, E_{n1} is the velocity direction entropy, E_{n2} is the velocity magnitude entropy, n_i is the evacuee in a certain velocity direction within the grid, m_j is the evacuee in a certain velocity range within the grid, and N is the total number of evacuees in the grid. α_i is the weight coefficient, usually $\alpha_1 = \alpha_2 = 0.5$ [8].

3. Experimental simulation

The simulation scenario is set as a single outlet rectangular large public place, as shown in figure 1. The black part is the wall and the green part is the exit. The simulation experiment is based on the programmable software Netlogo developed by Northwestern University.

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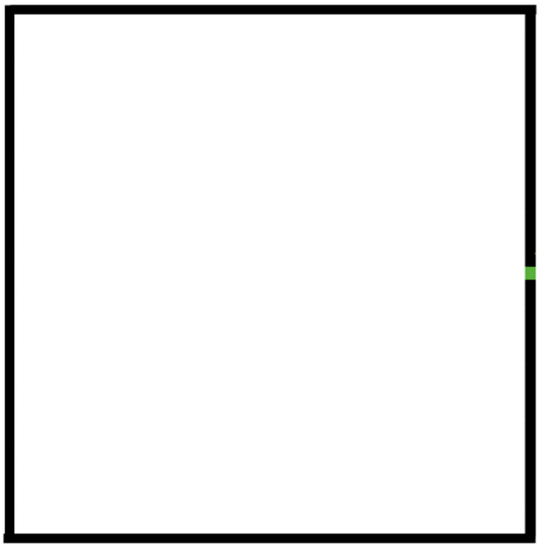

Figure 1. Evacuation Scene Map

The experimental simulation population is 100 people, among which 33.33% of the calm crowd, sensitive crowd and managerial crowd are randomly distributed in the evacuation scene. Among them, the black arrow marks the calm crowd, the red arrow marks the sensitive crowd, and the blue arrow marks the managerial crowd. Figure 2 is evacuation optimal path map. The red, black and blue lines in the evacuation scene are the change process from sensitive to calm to managed crowd under the guidance of residual pheromone and managed crowd.

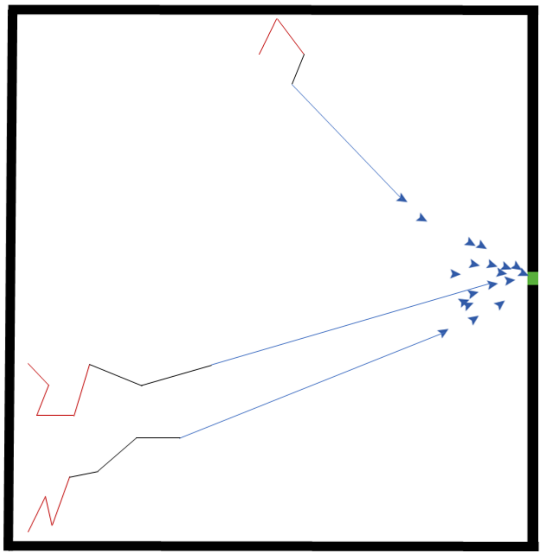

Figure 2. Evacuation Path Map

Figure 2 vividly shows the evacuation individual from sensitive state to calm state, and finally under the guidance of pheromone and management group, it is similar to the management group. It can be seen that the red line is more tortuous, the black line is in the middle of transition. Because of the impact of sensitive group, the black line will also have twists and turns. The blue line appears particularly straight extended to the exit in the best way. The three lines show the change of path shape caused by the change of crowd types. The path obtained is also the optimal path for sensitive people from the corresponding starting point to the exit.

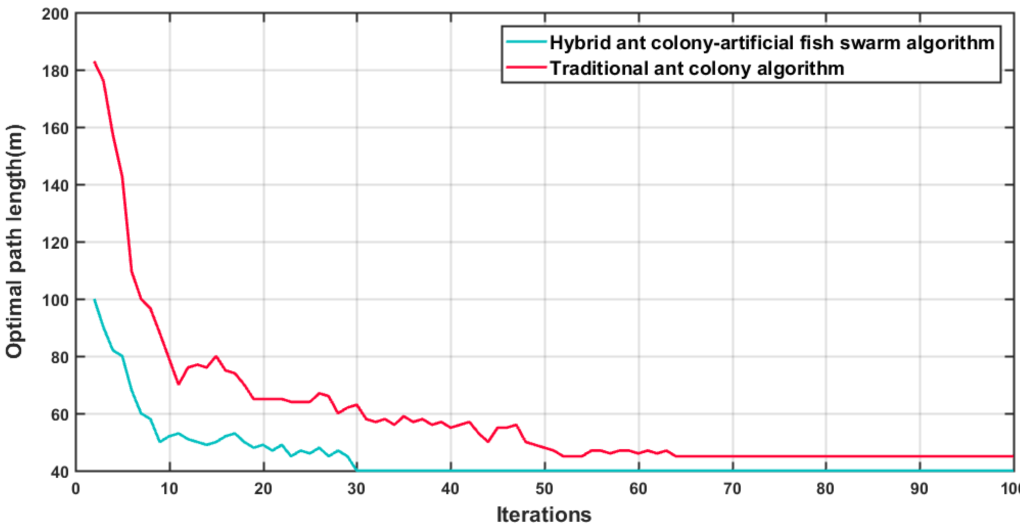

Figure 3. Convergence Curve of the Algorithms

From figure 3, it can be clearly seen that the convergence speed of hybrid ant colony-artificial fish swarm algorithm is very fast, and it has converged to the optimal value when iterating 35 times. In contrast, the traditional ant colony algorithm only finds the optimal path after 63 iterations, and the optimal path length obtained by the traditional ant colony-artificial fish swarm algorithm is obviously larger than that obtained by the hybrid ant colony-artificial fish swarm algorithm iterations. This shows that the traditional ant colony algorithm has fallen into the local situation. The global optimal path is not found by the partial optimal value. By contrast, it also reflects the strong superiority of the ant colony-artificial fish swarm algorithm constructed in this paper. A crowd evacuation path planning model is constructed by making rational use of the advantages of artificial fish swarm algorithm and ant colony algorithm. The convergence speed of the whole algorithm is improved.

4. Conclusion

In this paper, an evacuation entropy path planning model based on hybrid ant colony-artificial fish swarm algorithm is constructed. The initial solution of the model is determined by the artificial fish swarm algorithm, which makes up for the shortcoming of slow convergence in the early stage of the ant colony algorithm. The constructed model uses the strong positive feedback mechanism in the later stage of the ant colony algorithm to quickly optimize the optimal path. At the same time, the crowding factor of artificial fish swarm algorithm is introduced and the model is rebuilt to avoid the algorithm falling into local optimum. The paper provides theoretical help for the development and design of intelligent evacuation guidance system.

Acknowledgments

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