Modified ACO Evacuation Model Based On Evacuation Entropy

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Abstract. Since the existing crowd evacuation model for path optimization problems seldom considers the degree of confusion in the crowd movement, a modified Ant Colony Optimization (ACO) evacuation model based on evacuation entropy is constructed in this paper. Evacuation entropy reflects the degree of crowd confusion. It is used to modify the heuristic function of traditional ACO and is taken as the metric of the local pheromone updating strategy. This study is modeled by grid method and the simulation results show that the introduction of evacuation entropy greatly improves the convergence rate. The simulation of the optimal path takes the degree of chaos and the length of the crowd movement into account. It is of great practical significance to study how to plan reasonable evacuation routes.

1. Introduction
With the development of urban construction, the internal structure of large public places presents the characteristics of high complexity and small spacing. In an emergency, it is likely that casualties will occur due to untimely evacuation. In order to minimize such tragedies, more and more attention has been paid to public safety. It has become an important safety measure to design the optimal evacuation route according to the complex internal building structure. Accordingly more and more researchers are committed to constructing evacuation models to design a reasonable evacuation route to guide people to flee in time and effectively.

At present, the emergency evacuation model can be divided into macroscopic evacuation model [1], mesoscopic evacuation model [2] and microscopic evacuation model [3]. The microscopic evacuation model is widely studied because it can fully describe the movement state of evacuation individuals, among which cellular automata model [4], social force model [5] and lattice gas model [6] are most widely used. However, these models only consider the individual evacuation state from a micro perspective, ignoring the cooperation among individuals. In order to truly reflect the behavior characteristics of crowd evacuation, many scholars have applied ACO to the path optimization of crowd evacuation. ACO is derived from the ant foraging behavior [7], and its clustering is very similar to the herd of people [8]. ACO is used to find an optimal evacuation path accurately, which greatly shortens the escape time and provides valuable rescue opportunities for rescuers. However, ACO is easy to fall into local optimum and converges slowly [9], so many researchers are committed to improving ACO to speed up the convergence and increase the diversity of the solution. Zheng et al. [10] added the human density factor into the heuristic function of ACO, and improved its convergence rate by dynamically adjusting the pheromone intensity. Liu et al. [11] proposed an improved quantum ant colony algorithm (QACA) for exhaustive optimization of the evacuation path that people can...
evacuate from hazardous areas to safe areas. Wang et al. [12] established CA evacuation model based on improved ACO to describe the evacuation behavior such as retrograde, bypass, obstacle avoidance and crowd following. Fang et al. [13] proposed a multi-objective optimization approach to solve the evacuation routing problem, which involved three objectives such as minimization of total evacuation time, minimization of total evacuation distance and minimal cumulative congestion degrees in an evacuation process.

However, the above improved ACO evacuation models don’t take the impact of crowd chaos on evacuation into account. In the actual evacuation environment, people often escape blindly due to crowd chaos, and miss the best chance of rescue because of the death or injury caused by the collision. Wei et al. [14] proposed the concept of evacuation entropy reflecting the degree of crowd movement disorder quantitatively which is based on information entropy. Therefore, in this paper, to make the evacuation model closer to reality, the heuristic function is modified by the evacuation entropy and the evacuation entropy is used as a measure of the local pheromone updating strategy.

2. Modified ACO evacuation model based on evacuation entropy

In the process of simulating crowd evacuation, the traditional ACO only determines the next path according to the pheromone content and the heuristic information (the reciprocal of distance) of each path. It doesn’t consider whether the next path is chaotic. In actual evacuation scenarios, the probability of trampling accident casualties caused by chaos is much higher than the death rate due to hazards during evacuation. In addition, the traditional ACO is easy to fall into the local optimum. By adding the concept of evacuation entropy, the degree of crowd chaos can be considered. Evacuees no longer only consider the residual pheromone and the geometric distance between nodes when choosing the next node. This can increase the diversity of solutions and avoid falling into local optimum. The modified ACO evacuation model based on evacuation entropy constructed in this paper mainly includes the following three aspects. 1) Grid evacuation environment is built. 2) Evacuation entropy is introduced to modify heuristic function. 3) Evacuation entropy is used as a measure of the local pheromone updating strategy.

2.1. Building grid evacuation environment

The evacuation environment is modeled by grid method, and the evacuation space is discretized into a uniform grid. The evacuation process is completed from the starting point to the safety exit. The feasible grids of the evacuees are all the grids except the ones occupied by obstacles. The reasons for modeling by grid method are as follows. First, it is convenient for computer storage, calculation and operation [15], which greatly improves the path search efficiency and makes the path search result clearer. Second, the grid method can better simulate the escape direction of the individual during the evacuation process. Third, the grid method can be combined with the calculation of evacuation entropy. When there are no obstacles in the surrounding grid, the movement direction of the evacuee is shown in figure 1.

![Figure 1. The movement direction of the evacuee.](image)

It can be seen from figure 1 that when there are no obstacles around the individual, it will choose 8 directions randomly according to a certain probability.

2.2. Modification of heuristic function

The traditional ACO only considers the distance between two nodes when defining the heuristic function, but doesn’t consider the trampling phenomenon caused by the crowd chaos frequently occurring in the real evacuation environment. When the crowd is too confused, the speed and time of
evacuees will be greatly affected. In order to simulate the actual evacuation scenario as real as possible, it is necessary to introduce the degree of crowd chaos to modify the heuristic function.

2.2.1. State transition probability and heuristic function of ACO. At the initial time of evacuation, it is assumed that the pheromone content on each path is the same, that is, \( \tau_{ij} = A_0 \) (where \( A_0 \) is a constant). The probability of the evacuee from node \( i \) to node \( j \) is shown by formula (1) \[16\].

\[
p^k_{ij}(t) = \begin{cases} 
\frac{\tau_{ij}^\alpha(t)\eta_{ij}^\beta(t)}{\sum_{s \notin tabu} \tau_{is}^\alpha(t)\eta_{is}^\beta(t)}, & j \notin tabu \\
0, & otherwise 
\end{cases}
\]

Where \( \tau_{ij}(t) \) is the residual pheromone on the path \( ij \) at time \( t \), \( \beta \) indicates the relative importance of heuristic information, \( \alpha \) represents the relative importance of pheromone on path \( ij \). \( tabu \) is a taboo table that records the path the evacuee has taken in this loop. \( \eta_{ij}(t) \) indicates visibility, usually expressed by the heuristic function \( \eta_{ij}(t) = \frac{1}{d_{ij}} \), \( d_{ij} \) is the geometric distance from node \( i \) to node \( j \).

2.2.2. Evacuation entropy model. The concept of information entropy was first proposed by Shannon, which is used to describe the uncertainty of the source \[17\]. Wei et al. \[14\] introduced the information entropy into the crowd evacuation model, and proposed the evacuation entropy model to measure the degree of chaos in the crowd. He dispersed the evacuation space into a uniform grid. In each grid, the evacuees had 8 speed directions. \( V_{\text{max}} \) represented the maximum walking speed of evacuees. \([0, V_{\text{max}}]\) was divided into eight intervals. The velocity direction entropy value \( E_{n1} \), speed entropy value \( E_{n2} \) and total evacuation entropy value \( E_n \) of the group are calculated by formula (2)-(6).

\[
E_{n1} = -\sum_{i=1}^{8} \frac{n_i}{N} \log \frac{n_i}{N} 
\]

\[
E_{n2} = -\sum_{j=1}^{8} \frac{m_j}{N} \log \frac{m_j}{N} 
\]

\[
i = 1, 2, 3, \ldots, 8
\]

\[
j = 1, 2, 3, \ldots, 8
\]

\[
E_n = \sum_{i=1}^{2} \alpha_i E_{ni}
\]

Where \( n_i \) is the number of evacuees in each velocity direction interval, \( m_j \) is the number of evacuees in each speed interval, \( N \) is the total number of evacuees in the grid, \( \alpha_i \) represents weight coefficient, and generally sets \( \alpha_1 = \alpha_2 = 0.5 \).

2.2.3. Modifying heuristic function with evacuation entropy. According to the evacuation entropy model, the value of evacuation entropy can quantitatively reflect the degree of crowd chaos. The larger the evacuation entropy value, the more chaotic the crowd is. The evacuees will be hard to pass and the evacuation time will be longer. The evacuation entropy is abstracted as the entropy distance of evacuation. It means that the degree of confusion influences the evacuation velocity and time to a certain extent, similar to the actual geometric distance elongation. Based on the evacuation entropy, the formula of heuristic function is shown in formula (7) and (8).

\[
D_{ij}(t) = d_{ij}(t)E_n(t)
\]
\[ \eta_{ij}(t) = \frac{1}{D_{ij}(t)} = \frac{1}{d_{ij}(t)E_n(t)} \] (8)

Where \( D_{ij}(t) \) is the modified length based on the evacuation entropy. The larger the evacuation entropy value is, the greater the modified length is. And the probability that the evacuees choose this path will decrease.

2.3. Integration of global pheromone and local pheromone updating mode

Traditional ACO only updates global pheromones, but it may fall into local optimum because of too high local pheromones. In this paper, the evacuation entropy is introduced as a measure of the updating strategy to update the local pheromone in real time. The modified ACO combines global pheromone updating with local pheromone updating to avoid ACO falling into local optimum.

2.3.1. Global pheromone updating mode. When the ant colony completes an iteration from the starting point to the exit, the pheromone remaining on the path will evaporate over time. \( \rho(t)(0 < \rho(t) < 1) \) represents the pheromone volatilization function. \( 1 - \rho(t) \) represents the residual pheromone ratio. In the next iteration, the pheromone on the path needs to be updated globally. The updating method is shown by formula (9)-(12) [10].

\[
\tau_{ij}(t+1) = (1 - \rho(t))\tau_{ij}(t) + \Delta\tau_{ij}(t)
\] (9)

\[
\Delta\tau_{ij}(t) = \sum_{k=1}^{n} \tau_{ij}^k(t)
\] (10)

\[
\tau_{ij}^k = \begin{cases} 
\frac{Q}{L_k}, & \text{if the individual } k \text{ passes through the path } ij \text{ in the loop} \\
0, & \text{else}
\end{cases}
\]

\[
\rho(t) = \begin{cases} 
0.95\rho(t-1), & \text{if } 0.95\rho(t-1) > p_{\text{min}} \\
p_{\text{min}}, & \text{else}
\end{cases}
\] (11)

Where \( \Delta\tau_{ij}(t) \) indicates the increment of the pheromone on the path \( ij \) after the end of the loop, \( \tau_{ij}^k \) represents the amount of pheromone left on the path \( ij \) after the individual \( k \) completes the search, \( Q \) is the pheromone intensity, \( L_k \) represents the sum of the path lengths of individual \( k \) in this cycle.

2.3.2. Modification of local pheromone updating mode. Traditional ACO updates the pheromone globally after an iteration. However, if the local pheromone is too high, the ant tends to choose the path with higher pheromone concentration, even if another better path appears. Similar to the real evacuation environment, the trampling events may occur due to local path chaos. Evacuation entropy can be introduced as a measure of local pheromone updating strategy. The attraction of pheromones to evacuee can be reduced by updating local pheromones. The local pheromone updating is shown in formula (13) and (14).

\[
\tau_{ij}(t+1) = (1 - \varepsilon)\tau_{ij}(t) + \varepsilon\tau_0 \quad E_n \geq E_n(n \in 1,2,\cdots 8)
\] (13)

\[
E_n = \frac{\sum_{i=1}^{n} E_{ij}}{n}
\] (14)

Where \( \varepsilon \) is a local pheromone volatilization factor, \( \tau_0 \) is a constant, \( E_n \) is the average evacuation entropy of 8 feasible areas around evacuees. When the evacuation entropy value of the evacuation area is greater than the average evacuation entropy value, the evacuation area is more chaotic. It is necessary to update the local pheromones.
2.4. Algorithm flow chart

In this paper, by introducing the evacuation entropy model to modify ACO for crowd evacuation, the overall workflow of the algorithm is described as follows.

![Algorithm flow chart](image)

Figure 2. Overall workflow of the evacuation model.

3. Modified ACO evacuation model based on evacuation entropy

The simulation experiment scenario is set to 40m×40m single exit square room. In consideration of the evacuation scenes with obstacles, the room was set up with various sizes of rectangular obstacles. The starting point of the evacuees is set at the upper left corner of the room, and the exit is set at the lower right corner farthest from the starting point.

3.1. setting parameters

Setting up the grid map of 20*20. The length of each grid is 2m. The parameters of the model are set out in the references [16], and the specific parameters are shown in table 1.
Table 1. Formatting sections, subsections and subsubsections.

| parameters | α | β | Q | τ₀ | nAnt | V_{max} | ρ | p_{min} | ε | τ₀ |
|------------|---|---|---|----|------|---------|---|---------|---|----|
| value      | 1 | 10| 100| 20 | 50   | 1.5     | 0.5| 0.05    | 0.5| 10 |

3.2. Analysis of simulation data

Figure 3. The relationship between the number of iterations and the total value of evacuation entropy.

It can be seen from figure 3 that when the number of iterations is less than 80, the total value of evacuation entropy changes greatly. When the number of iterations is greater than 80, it tends to be stable. When the number of iterations is greater than 100, the total value of evacuation entropy changes very little. The simulation results show that concentration of pheromone is low, positive feedback is not strong at the beginning of the simulation. Evacuees can’t accurately choose the best path according to the residual pheromone. The speed and direction of the evacuees are relatively random and different. Evacuation situation is more chaotic, the total value of evacuation entropy is larger.

Figure 4 is a comparison of the geometric length of node 1 to the other 9 nodes and the modified length of the evacuation entropy. It shows evacuation entropy modifying length is larger than the geometric length in the most cases. The greater the length difference is, the more chaotic the crowd is at the forward node. When the modified length of evacuation entropy is less than the geometric length, the evacuation process is more orderly, which accelerates the whole evacuation process and makes the evacuees not only choose the shortest route. It can be seen from the comparative diagram of node length that the introduction of evacuation entropy modified heuristic function has a certain influence on the path selection of evacuees and makes them consider the degree of crowd confusion when choosing the path.

Figure 5. Comparison of Convergence Curve between traditional ACO and modified ACO based on evacuation Entropy.
In figure 5, compared with the traditional ACO, the speed of convergence of the modified ACO model based on evacuation entropy is greatly improved, but the optimal path length is increased. The results show that modified heuristic function and updating the local pheromone in real time speed up the whole convergence process and reduce the evacuation time. However, considering the degree of crowd confusion, evacuees will choose to abandon the shortest path and choose the optimal route because of the congestion and chaos in front of them in the evacuation process. The optimal route must be relatively orderly and not too long.

Figure 6 is the optimal path graph simulated. The black rectangular part is a variety of obstacles. The evacuees set out from the upper left corner of the room (red dot) to the lower right corner of the room (green dot) to complete the evacuation process. Evacuees will speed down when they bypass obstacles and avoid other individuals. Although the searched optimal path is not the shortest path, it takes the chaos of evacuation into account, which is of great significance to the study of actual evacuation. In the real evacuation environment, the shortest path can’t be pursued blindly. The optimal evacuation path planning should take the movement of the crowd into account.

4. Conclusion
In this paper, a modified ACO evacuation model based on evacuation entropy is constructed aiming at the influence of chaos on evacuation process. The evacuation entropy is introduced to modify the heuristic function and is used as a measure of the local pheromone updating strategy. Simulation results show that it can greatly improve the convergence rate and increase the diversity of solutions. The optimal path simulated takes the length of the path and the degree of crowd chaos into account, and provides a reference for the intelligent evacuation system.

However, this model does not consider the influence of individual physiological and psychological changes on path selection during evacuation. For example, individuals cannot rationally choose the path due to crowd panic. In addition, the occurrence of disability in the evacuation process will also affect the individual velocity and the value of evacuation entropy, thus affecting the selection probability of nodes. In the following research, the model will be improved based on the above two points, so that the evacuation model is closer to the real evacuation scenario.

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