An outdoor large-scale crowd evacuation model based on improved PSO algorithm

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Abstract

Individual evacuation decisions are often characterized by the consideration of many factors in real life. Based on the specific problems in actual evacuation, this paper introduces the concept of individual actual information interaction range based on the classical particle swarm optimization algorithm, and proposes a PSO evacuation model based on visual distance. In the actual evacuation process, people will be more inclined to find the best individual in the field of vision, and there will be a certain trend in the evacuation process to follow the optimal individual. Specially, the visual range of the actual evacuation is reduced by the obstruction of the obstacle, so we set the obstacle obstruction area. By modeling and analyzing the improved particle swarm optimization algorithm, the results show that the improved PSO algorithm has better evacuation effect than the traditional particle swarm optimization algorithm.

Keywords

Outdoor crowd evacuation, PSO algorithm, visual range.

1. Introduction

The study of evacuation dynamics has been studied for decades, in the paper Pedestrian and Planning Design [1], which was of great significance to dynamic evacuation in 1971, J.Fruin proposed the relation curve between the average traveling speed of the population and the population density considering the concept of "service level" in highway traffic theory. In addition, Henderson's two papers [2] [3] proposed the probability distribution formula and related content of individual travel speed based on Maxwell-Boltzmann distribution. The crowd evacuation researchers in the 1990s proposed "social force models" [4], SIMULEX[5], Building Exdous [6]and so on. In recent years, most of the research on crowd evacuation is the evacuation of indoor scenes. For example, in response to the emergency evacuation model in the event of a fire in a shopping mall, there is almost no research on evacuating people from the disaster areas to emergency shelters after the occurrence of geological disasters.

In the current study of outdoor scene evacuation, researchers focus more on the optimization of evacuation paths or increase traffic efficiency. There is no research on the occurrence of escape disasters for each individual on the microscopic concept. Some researchers have discussed the emergency evacuation decision-making behavior of the group in the no-car road, and analyzed the factors including patience and tolerable distance, but did not take into account the influence of individuals in the actual traffic condition. The research on post-earthquake evacuation behavior pays little attention to the mutual influence between each person, and most existing studies do not take into account the differences and rules of each individual's evacuation behavior[7].

The application effect of swarm intelligence algorithm is gradually widely in recent years, and the model of the population evacuation based on the particle swarm optimization algorithm is beginning to get the attention of scholars. Izquierdo et al. first introduced the particle swarm optimization model into large-scale crowd evacuation modeling [8], and evaluated the behavior patterns of pedestrians during the evacuation process. Literature [9] proposed the concept of "injury threshold" and improved the classical particle swarm optimization model. Literature [10] constructed an intelligent model of NPSO (Neighborhood Particle Swarm Optimization) to simulate the evacuation process of ships. In order to solve the problem of mass evacuation after geological disaster,this paper presents the scope of information interaction that individuals can actually carry out. An improved particle swarm optimization algorithm based on this is proposed to simulate the large-scale outdoor evacuation problem in real scene, and to provide reference for the emergency plan after geological disaster.

2. PSO Algorithm

2.1 Algorithm Construction

The basic idea of the PSO algorithm originates from the simulation of the foraging behavior of the birds, and the bird group is optimized through the collective cooperation between the birds. The thought of the algorithm is embodied in the process that each individual determines the optimal solution through its own flight experience and flight experience of the companion. Applying the PSO algorithm to the study of large-scale crowd evacuation in outdoor is to analogize the shelter in the evacuation scene to the food source of the bird group foraging process, and classify the bird (also known as "particle") as a pedestrian. For each particle, there is a fitness value corresponding to it, and the fitness value can evaluate the particle's quality. In this paper, the fitness value is defined as the distance between the individual particle and the shelter. Particle i can update speed and position information by the following formula[11]:

$$V_{id} = \omega V_{id} + c_1 r_1 (P_{ibest} - X_{id}) + c_2 r_2 (P_{gbest} - X_{id}), \quad (1)$$

$$X_{id} = X_{id} + V_{id}. \quad (2)$$

Where V_{id} is the current velocity of particle i, X_{id} is the current location of particle i, P_{gbest} is the location of the particle with the highest fitness, P_{ibest} is the historical optimal position of particle i, ω is the inertia weight of velocity, c_1, c_2 is the learning factor of the particle. r_1, r_2 is a random function with a value between [0, 1] .

The classical particle swarm optimization (PSO) algorithm can be applied to the crowd evacuation dynamics model and has achieved good results, but there are still many shortcomings that need to be improved. For example, the update of particle position in the particle swarm algorithm is mainly determined by the position of the global optimal particle, but in the case of actual evacuation, it's difficult or even impossible to exchange information with the optimal particle. Therefore, we introduce the concept of individual actual information interaction range and propose an improved particle swarm optimization algorithm. The individual actual information interaction range refers to the longest distance range that an individual can bear within the range of maximum perception and information exchange. By setting the individual actual information interaction range, the process of evacuation simulation can be made closer to reality.

2.2 Improved PSO Algorithm

In order to be closer to the actual evacuation scenario, the concept of the actual information interaction range of individuals is added to the algorithm. Fig.1 shows the schematic diagram of the actual range of individual information interaction and the microscopic schematic diagram.

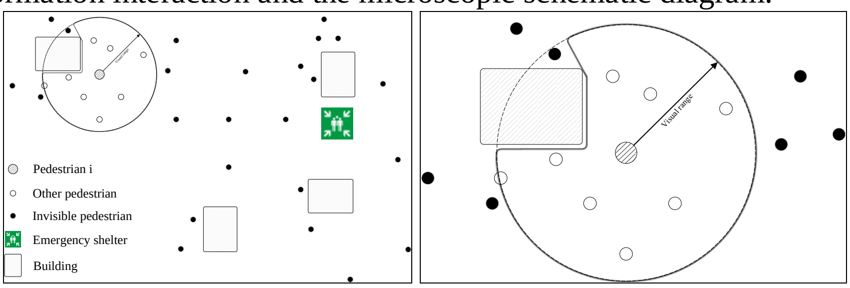


Fig.1 Schematic diagram of individual actual information interaction range

In particular, the scope of the individual's vision is affected by the surrounding environment, such as obstacles obstructing the field of vision. According to this reality, it is concluded that the scope of individual vision is irregular in most cases. We define the visual field radius of pedestrian i (shown as the shadow spot of Fig.2) under no building shelter is r, and there are multiple pedestrians in the circular range with radius r (shown as the white spots in Fig.2). By calculating the fitness of other pedestrians in the circular field of view, the local optimal pedestrian position can be obtained (shown as the red spot in Fig.2). Meanwhile, when there is a building block around the pedestrian i, first we need remove the area blocked by the building, and then calculate the fitness value of other pedestrians in the area to obtain the local optimal pedestrian position.

Considering the concept of individual actual information interaction range, we need to improve the particle swarm optimization algorithm. Since the local optimal model can replace the global optimal model in the classical PSO optimization model, we only consider the local optimal model, and do not consider the global optimal model. The improved PSO model considering local optimum is defined as:

$$V_{id} = \omega V_{id} + c_1 r_1 (P_{ibest} - X_{id}) + c_3 r_3 (P_{nbest} - X_{id}) \tag{3}$$

$$X_{id} = X_{id} + V_{id} \,. \tag{4}$$

Compared with the classical PSO algorithm, the improved PSO model removes the global optimal model and adds the local optimal model. P_{nbest} represents the position of the pedestrian with the highest fitness value in the actual field of view, c_3 and r_3 are the weights and random functions of the local optimum respectively.

3. Experiments

3.1 Evacuation Scene

The evacuation scene is selected from a real road network environment of a section of Wenchuan County, Sichuan Province, which is a high-risk area in China, and is implemented on the Netlogo platform. In order to ensure the reliability of the experiment to the greatest extent possible, we have made the following assumptions:(i) the population structure is fixed, and the individual differences, such as casualties, movement speed differences, etc. are not considered; (ii) the communication is in good condition, and the principle of walking evacuation is adopted. (iii) The shelters choose large urban open spaces without population restrictions.

The evacuation scene is shown in Fig.2. The blue strips in the figure represent rivers, in particular pedestrians cannot cross rivers. The green area represents the refuge, the gray area represents the building, and pedestrians avoid obstacles during the evacuation process.

Fig.2 Evacuation scene sketch map

3.2 Application of Improved PSO Model in Evacuation

Since the individual cannot know whether other individuals whose distance is too far is a global optimal solution under actual circumstances, the local optimal solution is an important factor affecting the individual behavior except for his own experience. The main object of this paper is the influence of the weight of the local optimal solution on the overall evacuation efficiency. The weight coefficient

c_1 in formula (3) is set to 0.1, and the weight coefficient is determined according to the following formula[12]:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{k_{max}} \times k_n \tag{3}$$

ω_{max} and ω_{min} represent the maximum and minimum values of the weight, k_n is the current number of iterations, and k_{max} is the maximum number of iterations. As k_n increases, it gradually decreases linearly from 0.9 to 0.4.

In this study, ω was set to a linear decrease from 0.9 to 0.4, so that each individual of the improved post-earthquake evacuation model moved in a larger area at the beginning and moved faster to the emergency shelter. As the ω gradually decreases and the individual speed slows down, the individual is prevented from being affected by other factors to move in the opposite direction of the emergency refuge to increase the overall evacuation time. Considering the road traffic situation after the earthquake, the speed of the individual in the disaster area has an upper limit. This paper defines V_{max}=1.7m/s, $V_i \leq V_{max}$. In the model, 500 individuals will be randomly distributed in the region, and the initial velocity of each individual will be randomly selected within the interval [-1.7 m/s, 1.7 m/s]. Fig.3 is individual positions in simulation experiments at the 0th minute, the 3rd minute, the 6th minute and the 8th minute respectively.

a. b.

c. d.

Fig.3 Evacuation simulation map using improved PSO model

4. Experimental Results and Analysis

4.1 Influence of Local Optimal Weight on Evacuation Time

The weight is set to 0.1, and we take the average of the results of 10 simulation experiments to avoid the special situation randomly generated during the experiment, for example, the 500 individuals randomly generated in the experimental simulation are too concentrated or too remote. Fig.4 shows the relationship between the overall evacuation time and the local optimal weight. Fig.5 shows the variation of the number of people who did not enter the emergency shelter when the local optimal weights were 0.1 and 0.5 respectively.

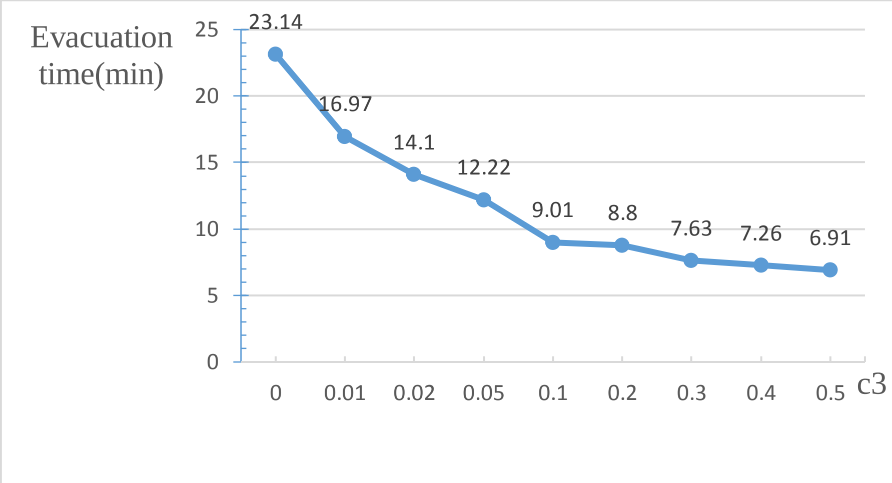
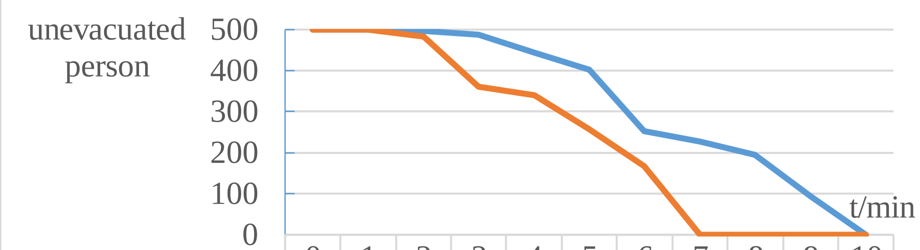


Fig.4 The relationship between local optimal weight and evacuation time



	0	1	2	3	4	5	6	7	8	9	10
c3=0.1	500	500	496	487	443	403	253	226	194	93	0
c3=0.5	500	500	483	361	339	257	167	0	0	0	0

Fig.5 The number of evacuees with different local optimal weights changes

It can be seen from Fig.4 that increasing the local optimal weight c_3 will greatly reduce the overall evacuation time, because the influence of individual optimal weight c_1 and random orientation ωV_{id} on the movement of individuals will gradually decrease as the local optimal weight c_3 increases. It effectively avoids the individual's no target movement in the disaster area and reduces the overall evacuation time. At the same time, it can be seen from the figure that the decrease of the overall evacuation time is relatively obvious when the value of the local optimal weight c_3 increases from 0 to 0.1, while the overall evacuation time decreases from 0.1 to 0.5. The reason why the local optimal weight c_3 is increased to a certain extent and the overall evacuation time cannot be effectively reduced is that there is an upper limit for the individual's moving speed, and the traffic capacity also limits the reduction of the overall evacuation time when the crowd is excessive. At the same time, it is worth noting that in the multiple simulation experiments, the value of c_3 will have a certain probability that it will fall into local optimum and cannot converge. This situation is reflected in the fact that in actual evacuation, it is too much to believe in the surrounding people, thus causing some people to concentrate on the distance. The location of the shelter is far away.

As can be seen from Fig.5, the local optimal weight c_3 has a value of 0.5. When the value is 0.1, the number of individuals not evacuated in the region decreases more rapidly. In addition, there is no significant difference in the number of individuals in the first two minutes of evacuation, because the distribution of individuals within the region is less likely to be concentrated around emergency shelters.

4.2 Influence of Regional Number on Evacuation Speed

The local optimal weight c_3 is 0 and 0.5, the individual optimal weight c_1 is set to 0.1, and the number of individuals with evacuation in the region is set in the [400, 1300] interval. Fig.6 shows that c_3 is 0 and 0.5. The effect of the increase in the number of individuals to be evacuated in the time zone on the evacuation time.

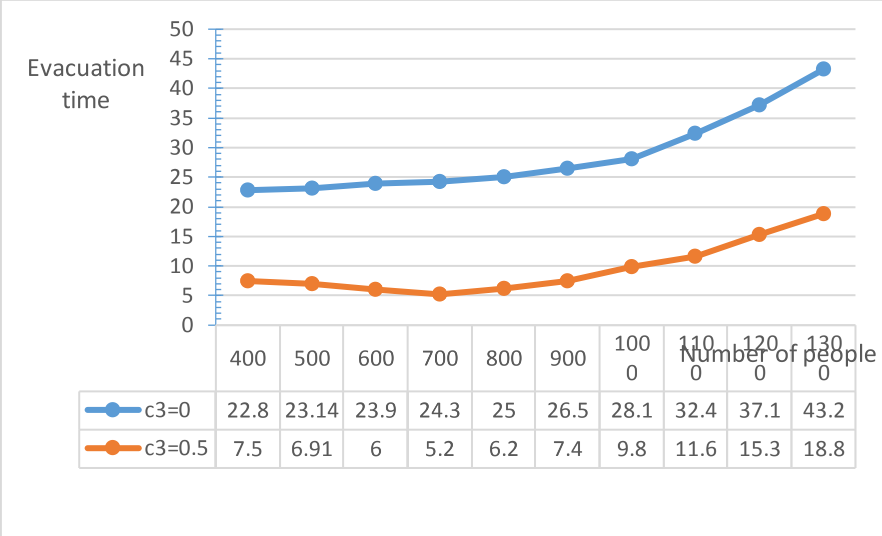


Fig.6 The relationship between the number of people and the evacuation time

It can be clearly seen in Fig.6 that the overall evacuation time when the value of c_3 is 0 is higher than the overall evacuation time when the value of c_3 is 0.5. In addition, when the value of c_3 is 0, the overall evacuation time increases with the increase of individuals in the region, especially when the number of individuals in the region increases to 1,100, and the increase rate becomes significantly larger. One reason is that traffic congestion is caused by an increase in the number of individuals, and the increase in the number of individuals without a target location greatly increases the overall evacuation time.

When the value of c_3 is 0.5, and the number of individuals increases from 400 to 700, the overall evacuation speed is not increased and there is a small decrease, but the overall evacuation time after 700 is significantly increased. When the number of individuals is small, there will be some individuals who have no other individuals in their visible range, which results in the inability to obtain local optimum and can only rely on individual optimal and random speed to move. When the individual density in the region increases to a certain extent, most individuals can obtain local optimal solutions and reduce untargeted movement. However, when the number of individuals in the region increases to 700, the speed of evacuation will increase with the increase of the number of individuals in the region.

4.3 Influence of the Number of Shelters on Evacuation Time

The local optimal weight c_3 is 0.5, the individual optimal weight c_1 is set to 0.1, and the number of individuals with evacuation in the region is set in the 500 interval. Fig.7 shows the effect of the number of emergency shelters in the region on the overall evacuation time.

As can be seen from the Fig.7, the increase in the number of emergency shelters will reduce the overall evacuation time, but when the number of emergency shelters in this area increases from two to three, the reduction in overall evacuation time becomes small. This shows that there is an optimal value for the number of emergency shelters in the area to balance the evacuation efficiency and resources consumed by emergency shelter settings.

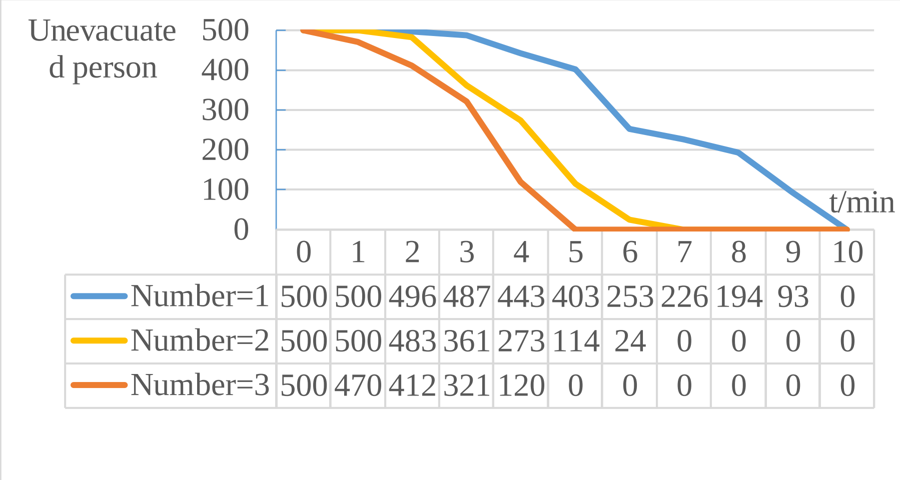


Fig.7 Relationship between the number of shelters and evacuation time

5. Conclusion

The research content of this paper is aimed at the outdoor evacuation after the occurrence of geological disasters. Combined with the ability of the population to obtain information after the disaster, an improved particle swarm optimization model based on the actual information interaction range is proposed. In the model, the global optimal part is removed according to the actual situation, and the local optimum within the actual information interaction range of the individual is added.

By changing the local optimal weight, when the number of individuals in the region does not exceed the road traffic capacity we find that the evacuation time will decrease with the increase of the local optimal weight. When changing the number of individuals in the region, we find that the more the number of individuals, the slower the evacuation time is. In addition, when the local optimal weight is large, a small increase in the number of individuals will reduce the evacuation time. Finally, by setting up different emergency shelters, we find that too many emergency shelters will not increase evacuation efficiency linearly when the number of individuals in the area is fixed.

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