Based on Emergency Evacuation of Improved Artificial Fish Swarm Algorithm

Qingrong Wang[1,a] and Yan Yang[1,b]

[1]School of electronics & information Engineering Lanzhou jiaotong University Lanzhou,China
a. 329046272@qq.com, b. 1224900570@qq.com

Keywords: Artificial fish swarm algorithm(AFSA), cluster analysis, weight strategy, global optimal solution, the path planning.

Abstract: With the increase of group activities and the frequent occurrence of accidents, there are often significant hidden dangers in crowded places.Therefore, it is of great practical significance to evacuate from dangerous places to ensure the safety of the crowd.Cluster analysis and weighting strategies are used to optimize the artificial fish school algorithm, thereby establishing a hybrid algorithm evacuation model.The model of the improved artificial fish school algorithm uses the evacuation time of the crowd to the exit as the evaluation standard of the fitness function to carry out the simulation of crowd path planning.Through model analysis, it is concluded that the behavior selected by the improved artificial fish school algorithm, namely the mixed artificial fish school evacuation model, is feasible and effective as a relevant factor influencing crowd evacuation path planning.

1. Introduction

With the increase of group activities and the frequent occurrence of accidents, there are often significant risks and hidden dangers in crowded places.By studying the path planning in emergency evacuation, we can make reasonable planning for crowd evacuation. The artificial fish swarm algorithm (AFSA) swarm intelligence algorithm proposed by Chinese scholar Li Xiaolei is inspired by the movement behavior of artificial fish[1].These coordinates are called the state of each artificial fish, and behavior includes foraging, gathering, following, moving, and assessing[2].In terms of global search performance, AFSA still has problems such as low convergence accuracy and slow convergence speed in later period. The work to improve AFSA mainly focuses on the parameter optimization of AFSA[3].Wang cuiru improved AFSA by adding the global optimal value through jumping behavior. In 2008, Wang Lianguo proposed to move the coordinates of autofocus directly and gradually to the sub-optimal position to reduce the visual range and step size of a single artificial fish. In literature 4, Zhu Xuhui et al. changed and adjusted foraging behavior and artificial fish step size[4].In 2018, Xian Sidong enhanced the ability of fish swarm algorithm to jump out of local optimal solution by expanding the selection range of random states[5].

However, the optimization method of initial value has not been paid enough attention. AFSA algorithm starts from a series of randomly distributed artificial fish, and the convergence speed is slow, which makes it easy to fall into the local optimal. In 2015, Wu Changyou et al. proposed the method for the generation of initial artificial fish stocks and introduced the mutation strategy at the same time, and introduced the adaptive moving step size into the foraging behavior, clustering behavior and tail-chasing behavior of the optimization algorithm[6].In reference 7, Liu Donglin et al. used chaos transformation to initialize the position of a shoal[7].In reference 8, Zhang Xiaobo et al. introduced Logistic chaotic sequence with uniform distribution in 2019, so that the field of vision and step size of artificial fish could be adjusted adaptively according to the changes of population diversity[8].These methods either make the algorithm lose the randomness of the initial state or make the algorithm inefficient.Among them, AFSA parameter has a large allowable range and strong robustness, which does not require a strict mechanism model of the problem, or even an accurate description of the problem, so that its application scope can be extended and it can be applied in many fields.

In this paper, the artificial fish swarm algorithm is improved, and the difference strategy and the optimal information feedback strategy are used to optimize the artificial fish swarm algorithm, and the visual range of artificial fish is dynamically adjusted.In the search, the crowding degree factor is restricted to restrict the flow of people, and the inertia speed factor is introduced to complete the iteration considering that the follow-up behavior in the later stage is prone to local optimization. The evacuation time is used as the evaluation criterion of fitness function to simulate the evacuation model of the optimal hybrid algorithm. In order to simulate the crowd emergency evacuation more realistic, should not only from the perspective of stream of people to study, researchers, and personalized features, in the optimization of the social force model and hybrid artificial fish crowd evacuation model based on the clustering analysis by introducing, achieve the initial state of randomness and the distribution of the uniform distribution, analysis of the improved model in a variety of scenarios.The results show that the behavior selected by the improved artificial fish swarm algorithm, namely the mixed artificial fish swarm evacuation model, is effective as a relevant factor affecting the evacuation path planning.

2. Improvement Strategy

2.1. Distance Factor

The In order to solve the randomness of the initial state, an improved clustering analysis method is proposed. The distance factor is introduced into the clustering method, and the population simulation is analyzed by controlling the randomness and uniform distribution of individual states.The initial value is simulated and compared.

$$dist = S_k \sqrt{\frac{1}{n}} \tag{1}$$

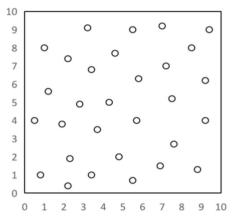

Figure 1: Uniformly distributed AFSA.

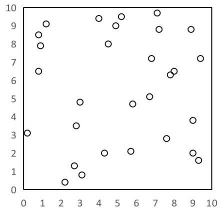

Figure 2: Randomly distributed AFSA.

2.2. Optimal Information Strategy

The template is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. You may note peculiarities. For example, the head margin in this template measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations.

In the improved artificial fish swarm mixing algorithm, the weight is ω introduced into formula (2) [9]:

$$\upsilon_i(t+1) = \omega\upsilon_i(t) + c_1 r_1(t+1)[x_i^{best}(t) - x_i(t)] + c_2 r_2(t+1)[B(t) - x_i(t)] \tag{2}$$

$$\omega = \frac{\omega_{start}(\omega_{start} - \omega_{end})(T_{\max} - t)}{T_{\max}} \tag{3}$$

$$Visual(t+1) = \omega \cdot Visual(t) \tag{4}$$

The information communication strategy search algorithm can effectively enable the fish to carry out information communication in the group, so as to effectively avoid the blind local search of artificial fish, so as to improve the convergence speed and field of vision of the algorithm, artificial fish can get the optimal value of the position of artificial fish state.

2.3. Crowding Factor

Each artificial fish tried to herd and follow in order to select a behavior that could improve the fitness value of the artificial fish[10,11]. After the artificial fish has performed two actions, if the fitness value does not increase, the foraging behavior is performed.If the foraging behavior does not improve the fitness of the artificial fish, the migration behavior is performed. The five basic parameters of artificial fish swarm algorithm directly affect the convergence performance of the algorithm[12].

The crowding factor δ is set to limit the size of artificial fish[13,14].The upper limits of the crowding factor $\delta_{\max}$ and lower limits of the crowding factor $\delta_{\min}$ are set to limit the $\delta_{\min}$ conditions under which $\delta < \delta_{\min}$ or $\delta > \delta_{\max}$ prohibit or prohibit clustering.

3. Based on Emergency Evacuation of Improved Artificial Fish Swarm Algorithm

3.1. Behaviors and Path Planning

Through the study of the improved swarm algorithm model, the foraging behavior of fish swarm is used to simulate the path planning problem, the inertia factor in particle swarm optimization algorithm is improved to improve the fish swarm algorithm, as the population in the later period of rapid path search, finally to prevent local optimization to introduce the difference factor, so that the solution is better. In addition, when studying the emergency evacuation problem, there are usually multiple exits in the limited space, so there are multiple locations with high food concentration, and the optimal solution can be obtained.

Table 1: Behavior and path planning table.

Foraging behavior	Path planning problem
Food place	Feasible solution
Particle velocity	Individual speed
Search speed	Path solving speed
Looking for food concentrations	solution method for model

3.2. The Evaluation Criterion

The effect of crowding and evacuation time should also be considered in the application of the improved algorithm in crowd evacuation. In the improved algorithm, the fitness function is used to comprehensively evaluate the degree of exit congestion and the distance of the individual moving to the exit, so that the leader can make a decision and choose the appropriate exit. The main reason people choose to escape is that it takes the shortest time to escape. Therefore, evacuation time was used as the evaluation criterion of fitness function in this study. The fitness function is expressed as the time to reach the exit:

$$t_i = \begin{cases} \dfrac{nnum_i}{\beta \cdot l_i / r}, \rho_i > \partial \cdot C_\rho \\ \dfrac{d_i}{\gamma \cdot \upsilon_0}, \rho_i \le \partial \cdot C_\rho \end{cases} \tag{5}$$

$$S = d_i / \sigma \cdot width \tag{6}$$

$$\rho_i = pnum / S \tag{7}$$

The number of exits is num, the area of the congestion area is S, and the number of individuals in the congestion area is $pnum$, which C_ρ represents the density threshold,Choose the number of individuals in gate i as $nnum_i$ .The width of the door is l_i ,the individual radius is r ,the distance between the individual and the exit is d_i ,The expected speed of the individual is expressed as υ_0 . α , β , γ is the adjustment coefficient.If $\rho_i \le \partial \cdot C_\rho$, represents severe crowding, then the evacuation time of the individual is the time of all advancing individuals at the exit.If $\rho_i > \partial \cdot C_\rho$,it is the movement time of the individual to the exit.

4. Experimental Simulation

In order to establish the evacuation model, all real scenarios of simulation Settings are accurately described, so that they are close enough to the real parameters obtained from previous sources. All the simulations did a good job of achieving the goal of qualitative analysis of evacuation plans, identifying bottlenecks, critical paths, and evaluating and comparing evacuation strategies. The experimental model of evacuation environment was established with the scene of 60 meters long and 70 meters wide.The evacuation situation was analyzed by setting different exits.

4.1. Barrier-free Scene

In this section, the experimental results of evacuation without any obstacles are measured. First consider the different arrangements for the exit doors in an environment of 200 people. The evacuation environment is 60 m×70 m, and the width of the door is 2 m, but it is difficult for four or more people to pass at the same time. The absence of a circle near the door means that the door has universal visibility, meaning that everyone knows the exit. The accessibility performance was measured under different conditions.

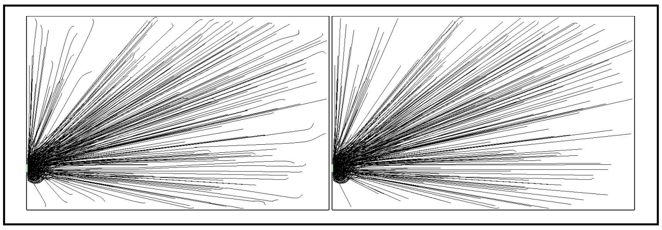

Figure 3: Comparison of group algorithm evacuation model simulation (1 exit)(a) Improved AFSA evacuation model simulation (b) AFSA evacuation model simulation

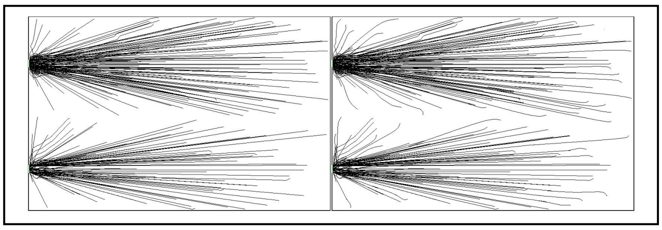

Figure 4: Simulation comparison of group algorithm evacuation model (2 exits)(a) Improved AFSA evacuation model simulation (b) AFSA evacuation model simulation

Table 2: Table type Styles.

The number of the export	Evacuation time of AFSA evacuation model (s)	Improved AFSA Evacuation time (s)
1	82.5	82.3
2	68.1	67.5
3	46.9	45.7

By improving the evacuation model of swarm algorithm, the evacuation model of 1 exit, 2 exit and 3 exit is simulated in the barrier-free plan.It can be seen from table 3 that the evacuation time of the improved artificial fish swarm evacuation model is less than that of the swarm algorithm evacuation model.

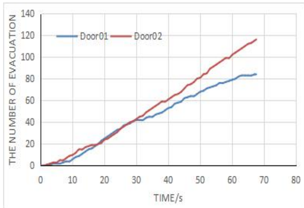

Figure 5: Relation diagram of exit evacuation when there are two exits.

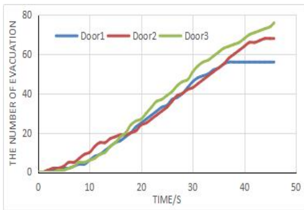

Figure 6: Relation diagram of evacuation at three exits.

As shown in the table 2, it is the comparison of evacuation time of three exits. It can be seen that the more exits there are in a single limited environment, the less evacuation time is needed.It can be seen that when the evacuation time of the two exits is close to each other, the relationship between the evacuation time of orange no. 2 and the number of people increases steadily. Therefore, exit no. 2 can evacuate relatively steadily. Figure 6 shows the relation between evacuation time of three exits and the number of evacuees, and describes the evacuation time of these three exits.It can be seen from figure 5 and figure 6 that the evacuation time and evacuation number of exit 1, which is on the same side as exit 2, have both decreased. Based on this, it is necessary to continue to study this problem.According to the three exits, the total evacuation time is 35, 42 and 45.7s respectively, it can be seen that the distance to the exit still has an impact on the evacuation situation.

4.2. Obstacle Scene

This is similar to the previous experiment, but with added obstacles. Unlike in previous cases, we did not take into account the obstacles in the environment, which shows how the presence of obstacles can create bottlenecks for evacuation and can be completely re-positioned, which is considered the best choice for emergency doors or normal exit doors. Therefore, it is necessary to identify these locations and bottlenecks, which may cause a lot of trouble in the emergency evacuation. Therefore, a simplified mall model is built in the model, and an obstacle store is set up in the model as a simple obstacle.

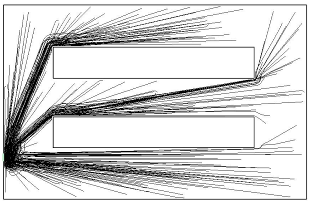

Figure 7: Simulation of mixed AFSA evacuation model (1 exit).

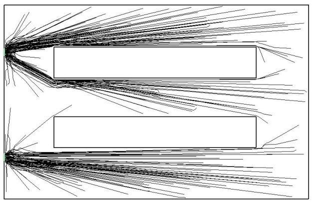

Figure 8: Simulation of mixed AFSA evacuation model (2 exits).

In the obstacle environment, three different exits are simulated, and it can be seen that in the obstacle simulation, the evacuation time decreases as the number of exits increases. In the improved fish swarm algorithm evacuation model, the evacuation time is still reduced despite the addition of obstacles in the case of obstacles. In the optimization simulation, the improved optimization model can accurately simulate the crowd evacuation, which is more in line with the actual situation, so as to choose a better path and reduce the evacuation time.

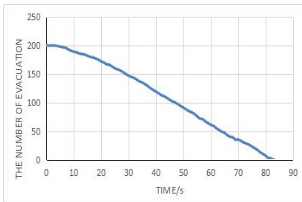

Figure 9: Evacuation of an exit.

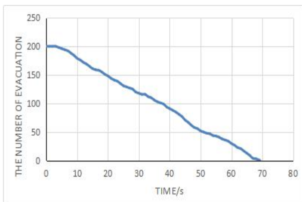

Figure 10: Evacuation of two exits.

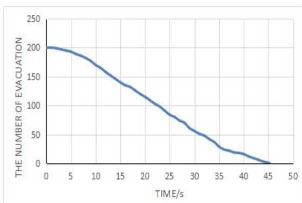

Figure 11: Evacuation of three exits.

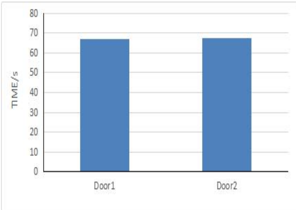

Figure 12: Evacuation number of exits at two exits.

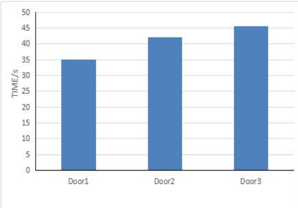

Figure 13: Evacuation number of exits at three exits.

Therefore, the number of people at each exit has changed, and the number of people at exit 3, which is opposite to exits 1 and 2, will also gather more people, leading to congestion, and the evacuation speed will slow down, making the evacuation time longer.However, some of the evacuation time is reduced after adding obstacles. It can be speculated that the congestion around the exit slows down because the path becomes longer after adding obstacles. As a result, the speed of individual evacuations slows down.However, this simulation is more in line with the actual evacuation situation, but it needs to strengthen the external command and guidance, so as to achieve the goal of balanced allocation of evacuation resources in practice.

4.3. Width of Exit

In order to study the influence of evacuation exit size on evacuation efficiency, the maximum gate width can be set to 2.2 meters without reducing the number of seats, considering the location of seats in the venue.In the experiment, the gate width was analyzed as 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2.0, 2.1, 2.2 m, 19 m long and 16 m wide, with 361 people evacuated.In this paper, different exit widths are simulated and analyzed. There are currently 16 projects in which the building space has the same layout, but different exit widths are taken into account. Different pedestrian characteristics lead to the difference of individual evacuation path choice. Therefore, reasonable optimization of exit width can effectively improve the evacuation efficiency and reduce the construction cost.

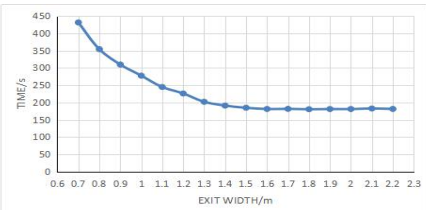

Figure 14: Different exit widths and evacuation times.

The comparison results of different exit widths are shown in figure 14.In the initial stage of simulation, the overall evacuation time decreases with the increase of the exit width. When the door width exceeds 1.6m, the evacuation time fluctuates slightly with the increase of the exit width and remains stable. When the exit width is 1.6m, the evacuation efficiency and resource utilization reach a good balance in the limited space. From the point of view of evacuation density, when the exit width is different, the different positions appear obviously different degree of crowding. According to the analysis, when the exit width is 0.7 m to 1.4 m, the exit position appears obvious crowding and the maximum density reaches 1.74 people /m.2In the scheme with an exit width greater than 1.4m, there is no serious crowding at the exit location. The maximum export density is about 1.57 persons /m. 2Different from the general conclusion that wide exit can reduce crowding, when the exit width is 1.3, 1.4, 1.9, 2.0, 2.1, 2.2 m, the maximum density of the exit population is low and the evacuation efficiency is high.

The relevant building design codes have been constantly improved, and the number of personnel and entrances of individual buildings have been clearly specified. However, there is no clear conclusion about the exit width to improve the efficiency of crowd evacuation. In this study, the best exit size under the most effective evacuation condition is explored on the basis of the existing building mode by using the exit setting of the existing small venue.

4.4. The Results of the Analysis

It can be seen that the path planning method for evacuating people based on the improved algorithm is successful. Considering the behavior tendency and path choice of evacuating people, some very simple no-obstacle plans have been successfully evaluated. When the behavior choice of the improved fish swarm algorithm is effectively selected, a better path can be chosen and the evacuation time can be reduced. We optimize the results of the swarm algorithm model and show that the factors we choose are effective. In the evacuation scenario, it can be concluded that even in the simple scenario, the visibility of the door plays a great role in the convenience of evacuation and increases the evacuation time.

Through the crowd path planning, the evacuation model based on fish swarm algorithm was analyzed, and the improved swarm algorithm was used for crowd evacuation.For the optimization of artificial fish swarm algorithm, the optimal information strategy and cluster analysis are proposed to optimize artificial fish swarm algorithm.In this algorithm, the distance factor is used to set the initial state of the artificial fish, and the optimal information strategy is used to encode the artificial fish, so as to dynamically change the visual field of the artificial fish.Evacuated improved algorithm of path planning method can be seen that is successful and evacuation tendency and route choice behavior of the crowd, have been successfully assessed the accessibility of some very simple and the plan of the disabled, valid at the time of the new algorithm's behavior choice fish choice more optimal path and reduce the evacuation time through the research results of swarm optimization model is optimized, and suggests that the choice of factors related to personnel that differences in behaviour is effective.

When setting the exit width of the building, consider the normal evacuation population. When the exit width reaches 1.5 m, the evacuation time will not decrease with the increase of the exit width. However, a small fluctuation was observed. Therefore, the exit width is set to 1.5 m, which is the best advantage of evacuation time and construction cost.As the width of the exit increases, the population density of the exit position decreases. It is different from the conclusion that the exit crowd density and average density are the lowest and evacuation efficiency is the highest when the exit width is 1.3, 1.4, 1.9, 2.0, 2.1, 2.2 m under normal circumstances.

5. Conclusions

When the path optimization problem of artificial fish swarm algorithm is studied, the optimal information strategy and cluster analysis are used to optimize artificial fish swarm algorithm.In this algorithm, the distance factor is used to set the initial state, and the optimal information strategy is used to encode the artificial fish, so as to dynamically change the visual field of the artificial fish, thus completing the crowd path planning.Based on the improved fish swarm algorithm model, the evacuation time is taken as the evaluation standard of the fitness function, and the fitness function is expressed as the time to reach the exit.Through the analysis, it can be concluded that the behavior selected by the improved algorithm is effective as a relevant factor of path planning.Then, on the basis of the improved model, it is simulated and analyzed. Through the analysis of barrier-free and obstruction-free conditions, the evacuation situation of different exits is simulated and the number of people at each exit is analyzed, so as to provide reference for the study of evacuation plan.

Acknowledgments

Ths work is supported by National Natural Science Foundation of China under Grant Nos.71961016.

References

[1] Li Xiaolei, Shao Zhijiang, Qian Jixin. An optimization model based on animal autonomous system: fish swarm algorithm [J]. Systems engineering theory and practice, 2002 (11) : 32-38.

[2] Neshat, M., Sepidnam, G., Sargolzaei, M., et al. Artificial fish swarm algorithm: a survey of the state-of-the art, hybridization, combinato Rial and indicative applications [J]. Journal of Artificial Intelligence Review, 2014, (4).

[3] Zhang yingjie, li zhiwu, feng zhonghua. An improved artificial fish swarm algorithm based on dynamic parameter adjustment [J]. Journal of hunan university (natural science edition), 2012,39 (05) : 77-82.

[4] Zhu xuhui, ni zhiwei, cheng meiying. Adaptive improved artificial fish swarm algorithm with variable step size [J]. Computer science, 2015,42(2) : 210-216.

[5] Xiansidong, zhang jianfeng. Fuzzy time series model based on improved artificial fish swarm algorithm [J]. Statistics and decision, 2008,34 (08) : 68-72.

[6] Wu changyou. An improved artificial fish swarm optimization algorithm [J]. Journal of intelligent systems, 2015,10 (03) : 465-469.

[7] Liu donglin, li lele. A novel improved artificial fish swarm algorithm [J]. Computer science, 2017,44 (04) : 281-287.

[8] Zhang xiaobo, peng jin-ye, liu tian. Adaptive field and step size chaotic artificial fish swarm algorithm [J]. Microelectronics and computers, 209,36 (06) : 5-9 + 14.

[9] Liu yunyuan. Research and application of chaotic swarm intelligence and its optimization algorithm [D]. Wuhan university of science and technology, 2008.

[10] Dai yuntao, zhao xiren, liu liqiang. Longitudinal motion parameter identification based on improved particle swarm optimization algorithm [J]. Ship mechanics, 2010,14 (Z1) : 44-50.

[11] Peng kai, huang yiqing, shao shouchen. TSP solution model based on hybrid algorithm of particle swarm optimization and artificial fish swarm [J]. Journal of sichuan university of science and technology (natural science edition), 2017,30 (01) : 27-31 + 37.

[12] Li Xue-mei, zhang su-qin. Review of several optimization algorithms based on bionics theory [J]. Computer application research, 2009,26 (06) : 2032-2034.

[13] Zhang yan, chu xiaoli. An improved artificial fish swarm algorithm [J]. Computer system application, 2011, 20 (5) : 199-201.

[14] Zhang Anshu, Shi Wenzhong. Mining significant fuzzy association rules with differential evolution algorithm[J]. Applied Soft Computing Journal, 2019(30), 928－963.