Forest fire emergency rescue and evacuation path planning based on improved APF

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ABSTRACT

Forest fire is a natural disaster that causes huge damage to human life and property. Emergency rescue and evacuation actions are crucial in such situations, and path planning is an important part of such actions. Artificial Potential Field (APF) method is a popular path planning method, but it has limitations in complex dynamic environments such as forest fires. In this paper, we propose an improved APF method for forest fire emergency rescue and evacuation path planning. This method uses a dynamic repulsive field to avoid obstacles in the fire scene and an improved attractive field to guide people towards the target. We also combine the classic Rothermel model in forest fire spread to further improve the realism of dynamic spread path planning in forest fires. Computational simulation results show that compared with the original APF method, this method still maintains an acceptable level of computational efficiency as the number of fire scene obstacles increases and is superior to traditional APF method in terms of path planning safety.

CCS CONCEPTS

• Computing methodologies → Modeling and simulation → Model development and analysis → Modeling methodologies

KEYWORDS

Emergency rescue and evacuation, Path planning, Artificial Potential Field, Optimization

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1 INTRODUCTION

Forest fires are one of the most devastating natural disasters that can cause significant damage to human life and property. The impact of forest fires on the environment and society can be severe, and the importance of mitigating their effects cannot be overstated.

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In such scenarios, emergency rescue and evacuation operations play a critical role in saving lives and reducing the damage caused by fires. Zhang et al. proposed a rescue integration approach to simulate the dynamic rescue process between forest fire spread and forest fire rescue, focusing on dynamic optimization between rescue forces and disaster relief forces [1]. However, in addition to rescue force scheduling, path planning is also an important component of emergency rescue and evacuation operations, as it enables people to navigate through hazardous environments and reach affected areas effectively. Wang et al. proposed a forest fire rescue drone optimal path planning based on Vortex Search (VS) algorithm, which mainly optimized spatial terrain and drone energy [2]. Intelligent algorithms that consider using the forest fire spread area as a dynamic obstacle for path planning and search and rescue in forest fire rescue processes have been rarely studied. In the field of obstacle avoidance algorithms for robot control, such as ant colony algorithm (ACO) [3], particle swarm algorithm (PSO) [4], artificial potential field method (APF) [5], Dijkstra algorithm [6], etc., they can be effectively used as methods in forest fire scenarios.

APF method is a concept derived from physics. This method was first applied to prevent a robotic arm from colliding with a workbench while grabbing objects. The method assumes that there are virtual attractive and repulsive obstacles around the target point in the virtual field, and the combined force of the two serves as the driving force for the robotic arm's motion. However, the traditional APF method has limitations in complex and dynamic environments like forest fires, where obstacles can be irregularly shaped and constantly changing. Subsequently, scholars have made a series of improvements to its attractive and repulsive fields. Liu et al. proposed a new dynamic collision avoidance process that focuses on the safety requirements of dynamic obstacles, and designed new attraction and repulsion functions [7]. Kei Kondo et al. proposed a method named P-APF (Predictive Artificial Potential Field), which generates potential field and repulsive vectors based on current information, predicted future trajectory of unmanned aerial vehicles, and observed obstacles [8]. Zhao et al. introduced the artificial potential field method into the A* algorithm, and dynamically weighted it through the heuristic function to eliminate redundant nodes in the path [9].

However, these path planning algorithms are still inadequate for complex and dynamic environments such as forest fire spreading. Therefore, in this paper, we propose an improved artificial potential field method that addresses the inability to adapt to dynamic environments by incorporating the characteristics of forest fire spreading. We introduce a spreading factor into the repulsive field of the artificial potential field method and decompose the attractive and repulsive fields to effectively prevent the fields from getting stuck in local optima. The proposed path planning algorithm is applicable to dynamic environments with forest fire spreading.

The remainder of this paper is organized as follows. In section 1, we review the literature on path planning methods for forest fire search and rescue operations. Section 2 describes the proposed improved APF method in detail. In section 3, we present the simulation results and compare our method with original APF method. Finally, section 4 concludes the paper and provides some future research directions.

2 METHOD

In this section, we describe the proposed improved artificial potential field (APF) method for forest fire search and rescue path planning. The method consists of three main components: a dynamic repulsive field, a modified attractive field, and modeling of obstacle extension in APF.

2.1 Modified Attractive Field

The potential function in traditional artificial potential fields is a function of distance. Assuming that the attractive potential function is:

$$U_{att} = \frac{1}{2} k_{att} \left(x_{pos} - x_{goal} \right)^n \tag{1}$$

where k_{att} is the attractive gain coefficient， x_{pos} is the position of the person, x_{goal} is the position of the target point. n is an arbitrary constant greater than zero, which is set to 2 in this method.

The attractive force can be expressed as the negative gradient of the attractive field:

$$F_{att} = -\nabla U_{att} = -k_{att} \left(x_{pos} - x_{goal} \right) \tag{2}$$

However, in traditional APF method, a simple attractive force is used, which can result in the person getting stuck in local minima. Therefore, we modify the attractive field model by incorporating a goal proximity factor and a goal direction factor. The modified attractive field is used to guide the person towards the target. The modified attractive field is defined as:

$$\begin{cases} F_{goal} = -k_{att1} \left(x_{pos} - x_{goal} \right) \\ F_{dir} = -k_{att2} \left(x_{pos} - x_{goal} \right) \left(x_{pos} - x_{lastpos} \right) tan \left(x_{pos} - x_{goal} \right) \\ F_{att} = (1 - \omega) F_{goal} + \omega F_{dir} \end{cases} \tag{3}$$

where F_{att} is the attractive force, F_{goal} is the goal proximity factor, $F_{dir}$is the goal direction factor, and ω is a weight parameter that determines the relative importance of the attractive forces.

2.2 Dynamic Repulsive Field

The traditional APF dynamic repulsive field potential function is modeled as:

$$U_{rep} = \begin{cases} \frac{1}{2} \eta \left(\frac{1}{d_i} - \frac{1}{r_0} \right)^2, & d_i \le r_0 \\ 0, & d_i > r_0 \end{cases} \tag{4}$$

where d_i is the distance between the person and the ith obstacle, r_0 indicates the impact range of the obstacle, η is the repulsive force gain factor; Further, similar to the definition of attractive force, the repulsive force is defined as the negative gradient of the repulsive field:

$$F_{rep} = -\nabla U_{rep} = \begin{cases} \eta \frac{1}{d_i^2} \left(\frac{1}{d_i} - \frac{1}{r_0} \right) \left| x_{pos} - x_i \right|, & d_i \le r_0 \\ 0, & d_i > r_0 \end{cases} \tag{5}$$

where x_i is the position of the ith obstacle.

In the traditional APF method described above, only a static repulsive field is used, that is, r_0 does not dynamically change over time, which is difficult to apply in dynamic environments such as forest fires. In addition, the distance from the target point is not considered in the repulsive force field, which is likely to result in the gravitational force being much greater than the repulsive force when the target point is too far away, resulting in the repulsive force becoming ineffective. Therefore, we use a dynamic repulsive field that constantly updates the repulsive force based on the spread of obstacles and the location of target points to adapt to changing environments. The dynamic repulsive field is defined as:

$$\begin{cases} F_{rep1} = \sum_{i}^{n} \frac{k_{rep1}}{d_i^2}\left(\frac{1}{d_i} - \frac{1}{r_0}\right)(x_{goal} - x_{pos}) \\ F_{rep2} = k_{rad} \sum_{i}^{n} k_{rep2}\left(\frac{1}{d_i} - \frac{1}{r_0(t)}\right)^2 (x_{pos} - x_i) \\ F_{rep} = (1-\eta)F_{rep1} + \eta F_{rep2} \end{cases} \tag{6}$$

where F_{rep} is the total repulsive force generated by obstacles, F_{rep1} is the repulsive force generated by surrounding obstacles, taking into account the distance between the current position and the target point, in order to prevent the target location from being too far away and the gravitational force becoming too strong, which would render the repulsive field ineffective. k_{rep1} is the repulsive force gain factor for F_{rep1}, k_{rad} is the influence range factor of the obstacles; k_{rep2} is the repulsive force gain factor for F_{rep2}. η is a weight parameter that determines the relative importance of the two f repulsive forces. In addition, the modeling of the impact range of the dynamic spread of fire point obstacles $r_0(t)$ is described in detail in Section 2.3.

2.3 Modeling of Fire Obstacle Extension and Path Solution in APF

r_0 is the propagation speed calculated by the Rothermel model for forest fire spread. It varies according to different combustible parameters. In the artificial potential field, obstacles are treated as fire points, and the extension speed of obstacles r_0 is generated based on the fuel information at the obstacle's location. The obstacle radius is updated at each step of the path planning based on R. The formula for calculating $r_0(t)$ is as follows:

$$r_0 = \frac{I_R \times \xi \times (1 + \Phi_w + \Phi_s)}{\rho_b \times \varepsilon \times Q} t \tag{7}$$

where I_R is reaction intensity; ξ is propagating flux ratio; Φ_w is wind factor; Φ_s is slope factor; ρ_b is bulk density; ε is the effective heating number; Q is heat of preignition; t is the spread time. The formulas for calculating the parameters mentioned above are given in the table1.

Table 1. Formulas for Calculating Rothermel Model Parameters.

Parameter Symbols.	Description	Formulas	Units
I_R	Reaction intensity	$I_R = \Gamma' W_n \hbar \eta_M \eta_s$	kJ/(m·min)
Γ'	Optimum reaction velocity	$\Gamma' = \Gamma'_{max}(\beta/\beta_{op})^A \exp[A(1 - \beta/\beta_{op})]$ $A = 8.9033\sigma^{-0.7913}$	min^{-1}
Γ'_{max}	Maximum reaction velocity	$\Gamma'_{max} = (0.0591 + 2.926\sigma^{-1.5})^{-1}$	min^{-1}
β_{op}	Optimum packing ratio	$\beta_{op} = 0.20395\sigma^{-0.8189}$	-
η_M	Moisture damping coefficient	$\eta_M = 1 - 2.59\frac{M_f}{M_s} + 5.11\left(\frac{M_f}{M_s}\right)^2 - 3.52\left(\frac{M_f}{M_s}\right)^3$	-
η_s	Mineral damping coefficient	$\eta_s = 0.174{S_E}^{-0.19}$	-
ξ	Propagating flux ratio	$\xi = (192 + 7.9095\sigma)^{-1}$	-
Φ_w	Wind factor	$\Phi_w = C(3.128U)^B(\beta/\beta_{op})^{-E}$ $C = 7.47\exp(-0.8711\sigma^{0.55})$ $B = 0.15988\sigma^{0.54}$ $E = 0.715\exp(-0.01094\sigma)$	- - -
W_n	Net fuel load	$W_n = W_0(1 - S_T)$	lb/ft^2
Φ_s	Slope factor	$\Phi_s = 5.275\beta^{-0.3}(tan\phi)^2$	-
ρ_p	Oven-dry bulk density	$\rho_p = W_0/\delta$	lb/ft^3
ε	Effective heating number	$\varepsilon = \exp(-4.528/\sigma)$	-
Q	Heat of preignition	$Q = 581 + 2594M_f$	Btu/lb
β	Packing ratio	$\beta = \rho_b/\rho_p$	-

In addition, since the focus of this article is to discuss the computational effectiveness and performance of the improved APF method in dynamic forest fire propagation modeling, and path planning in highly complex forest fire propagation scenarios is not realistic, in order to facilitate discussion, this article has made a corresponding simplification of the forest fire propagation model, using only the propagation speed in the Rothermel model as the expansion speed of fire point obstacles, Without considering the combustible changes and fire dynamics during the spread of forest fires. Further settings for Rothermel model parameters are based on reference [9].

Based on the artificial potential field established above that varies dynamically with time, we calculate the coordinate position from the starting point to the next point by the combined force generated by the gravitational and repulsive fields, given the starting point and the target point, with the following expressions:

$$\Delta x_{pos} = p * \frac{F_{att} + F_{rep}}{|F_{att} + F_{rep}|} \tag{8}$$

where Δx_{pos} denotes the distance of motion from the starting point to the next point, p denotes the unit search step, and $\frac{F_{att}+F_{rep}}{|F_{att}+F_{rep}|}$ denotes the direction of motion indicated by the combined force generated through the attractive and repulsive fields.

3 RESULT AND DISCUSSION

According to the above model, this paper carried out simulation and modeling of path planning in the scenario of forest fire spread. The simulation environment was set as a 100×100 grids, where each grid represents a type of fuel land in Rothermel model. Based on the Rothermel model, a certain propagation speed is possessed after ignition. To simplify the calculation, all grids in this paper were set as the same type of fuel land, and different numbers of obstacles (fire points) were generated in the grids.

Figure 1 illustrates the path planning process of traditional APF and improved APF at different times within a 100*100 grid. The same search step and obstacle quantity were set in both methods. It is found that under the same obstacle quantity and search step conditions, compared to traditional APF, the improved APF spends more time reaching the target point. However, it exhibits a better "detour" effect when facing obstacles that spread and expand over time, ensuring the safety of the person in the forest fire rescue scenario.

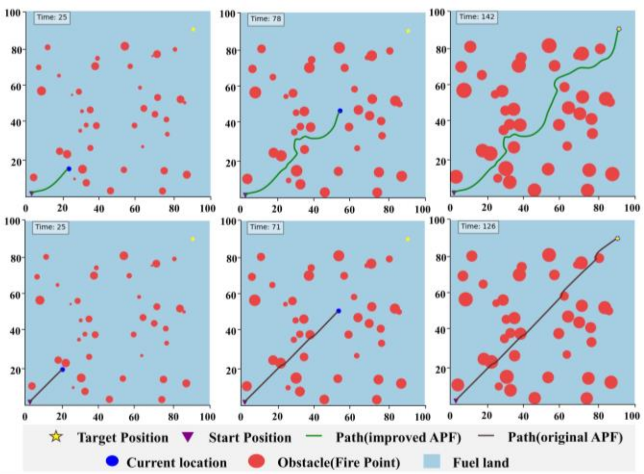

Figure 1 Comparison of path planning results between the original artificial potential field method and the improved artificial potential field method.

In order to effectively evaluate the efficiency and feasibility of the APF method, this paper compares it with the original APF in terms of operation time, path length, and path planning effects under different obstacles. In addition, the effects of different model parameters (including attractive gain factor, repulsive gain factor, radiation range of fire point obstacles, and unit search step) on path planning effectiveness and length are also discussed.

3.1 Comparison between the Original APF and Improved APF

In this section, simulations were conducted to investigate the impact of increasing obstacle density on the efficiency of both methods with the same step size. Figure 2 shows the changes in the running time of the two algorithms with different numbers of obstacles. The results indicate that the computation time of the original APF is slightly lower than that of the improved APF before the number of obstacles in the fire scene reaches 40. However, after the number of obstacles exceeds 40, the running time of the improved APF algorithm is slightly higher than that of the original APF algorithm, which is due to the fact that the improved APF algorithm requires more "detour" movements during path planning to ensure that the planned route does not collide with the diffusing obstacles. In general, the running time of both does not exceed 0.1s, and the impact of this degree of runtime increment on the efficiency of the algorithm is acceptable.

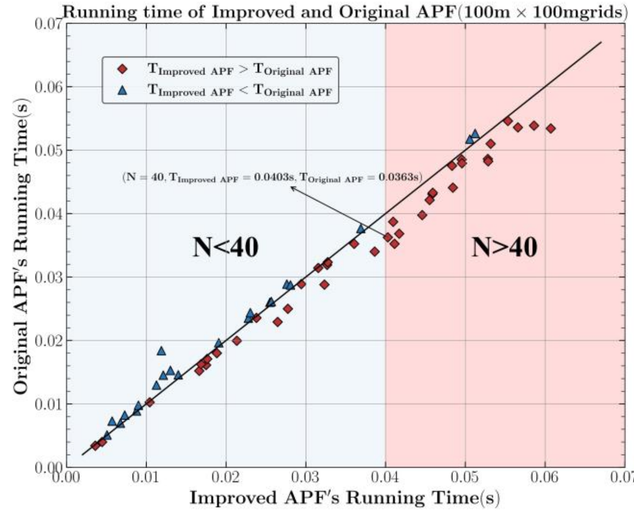

Figure 2 Comparison of running time between the original APF and the improved APF

In addition, Figure 3 illustrates the trend of the planned path length for both methods as the number of obstacles varies. Compared to the original APF algorithm, the improved APF algorithm produces longer path lengths and exhibits a non-linear growth rate, while the original APF model's path length increases linearly with the number of obstacles.

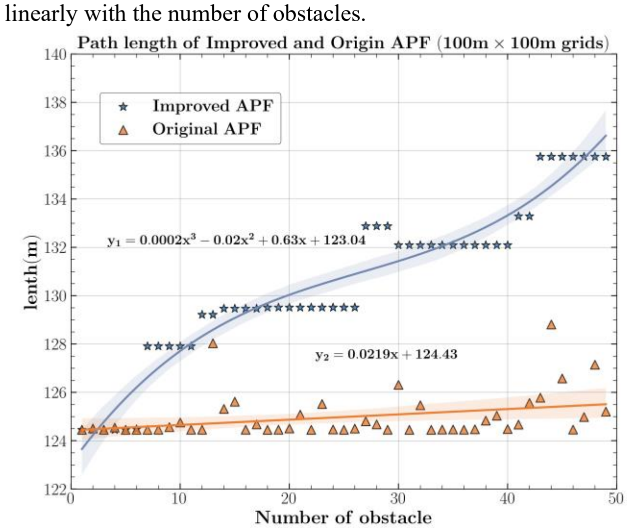

Figure 3 Comparison of planned path lengths between the original APF and the improved APF

However, the length of the path alone cannot fully indicate its superiority or inferiority in the scene. To further illustrate the quality of the planned path, we introduce a safety index for the planning path, defined as follows:

$$P_{value} = \frac{1}{T}\sum_{t=0}^{T} \min\left(\left|x_{pos} - x_i\right| - k_{rad} r_0 t\right), i = 1,2,\ldots,N \quad (9)$$

where N denotes the total number of obstacles in the scene; the constant of the radiation range of obstacles k_{rad} is set to 3 in Figure 4; t denotes the propagation time of the fire; and T denotes the total time step. This index is used to calculate the relative distance between the radiation range of the obstacles in the fire field and the current position of the person throughout the path planning process. A higher value indicates a greater distance from the nearest obstacle in the path planning process, indicating higher safety. As shown in Figure 4, in most cases, the path planned by the improved APF algorithm has a higher P_{value} than the original APF algorithm, indicating that the path planned by the improved APF algorithm has higher safety.

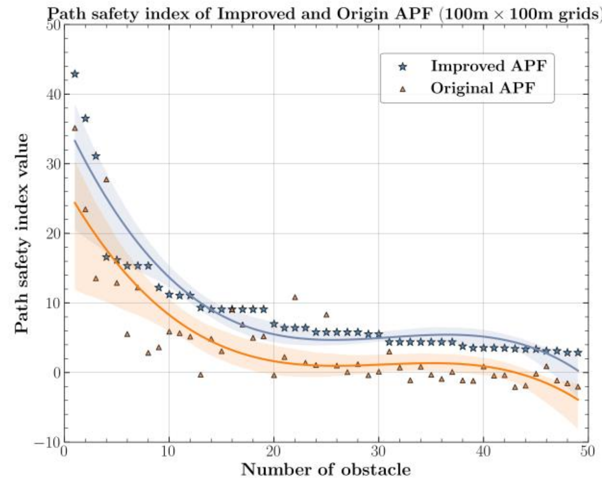

Figure 4 Comparison of Path Safety Indexes between Original APF and Improved APF

3.2 Sensitive Analysis of Attractive and Repulsive Field Model Parameters

In this section, to evaluate the impact of attractive and repulsive field model parameters in the improved APF, the effects of changes in attractive gain coefficient, repulsive gain coefficient, and search step size on the running time and planning efficiency of the improved APF method were compared. The simulation conditions are shown in Table 2.

Table 2 Parameter settings for different simulation cases of attractive and repulsive field models

Case	Attractive and repulsive field model parameters in improve APF			
	$k_{att1,2}$	$k_{rep1,2}$	k_{rad}	p
1	0~300, step=1	300	4	1
2	2	0~300, step=1	4	1
3	300	300	1~4, step=0.1	1
4	300	300	4	0.1~2, step=0.05

In the table, there are four simulation cases that discuss the impact of changes in one parameter of the improved artificial potential field (APF) algorithm on the final planned path result in obstacle scenes. Figure 5 shows the changes in path safety index and path length under different parameters. From Figure 5(a), it can be seen that as the gravity gain coefficient increases, both the safety index and path length show a downward trend. This is because the attraction generated by the target point is too strong, which reduces the influence of repulsion generated by the fire scene. In Figure 5(b), as the repulsive factor increases, the safety index of the path also increases, and the corresponding path length also increases. This indicates that more "detour" behavior is exhibited during the process of increasing repulsive factor. In Figure 5(c), as the radiation factor of fire point obstacles increases, the safety index of path shows a linear downward trend, while the change in path length is not significant. From Figure 5(d), it can be found that when the search step length is relatively low, the safety index of path shows a negative value. According to formula (6), when the safety index of path shows a negative value, it means that the route enters into radiation range of fire point obstacles.

From a practical point of view, the search step length in improved APF method can be regarded as the speed at which personnel move from the fire scene. When the speed is low, the movement range of personnel is small, and they cannot escape from the radiation range of the spreading fire scene in time. When the speed is high, the movement range of personnel is large, and they can escape from the radiation range of the fire scene in a limited time. However, there is also an upper limit to the impact of their movement speed on path safety index. If the movement step length is too large ($p > 1$ in this case), the gain in path safety index is not significant.

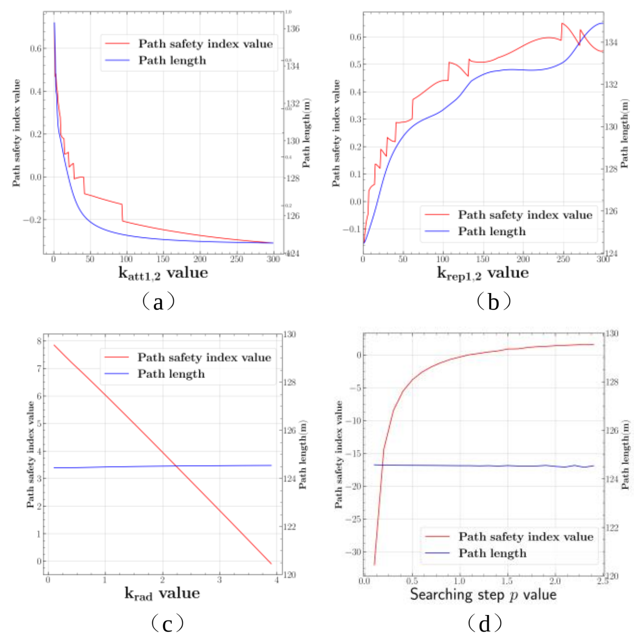

Figure 5 Changes in path safety indicators and path length with improved APF model parameters; a) $k_{att1,2}$ parameter changes; b) $k_{rep1,2}$ parameter changes; c) k_{rad} parameter changes; d) p parameter changes;

4 CONCLUSION

Based on the modeling process and simulation results described above, we have developed an improved APF method. Compared with the original APF method, the main changes of this method are as follows:

1) The calculation formula of the attraction field has been improved by adding a directional factor, ensuring reasonable direction during the path planning process;

2) The repulsive field model has been improved by introducing the distance cost between the current point and the target point, effectively solving the problem of the loss of repulsive effectiveness when the target point is too far away;

3) For the obstacles that generate the repulsive field, we have introduced the Rothermel model to calculate the diffusion process of the obstacles (fire points), successfully achieving path planning in a dynamic environment;

4）We have introduced the concept of path safety index and conducted sensitivity analysis on the four parameters in the model to explore the impact of attraction gain coefficient, repulsive gain coefficient, fire point obstacle radiation factor and search step length on path safety index. We found that in the fire scene, path safety index will decrease with the increase of attraction gain coefficient and fire point obstacle radiation factor, and will increase with the increase of repulsive gain coefficient. In addition, path safety index shows negative values at smaller search step lengths, indicating that there is a certain degree of danger in the path and it is necessary to increase the search step length to ensure path safety.

In conclusion, this method aims to provide reference and calculation ideas for path planning in forest fire search and rescue. Due to limited computing resources, we have simplified the simulation of the forest fire spread model to a certain extent. In future algorithm improvements, we will consider introducing more complex repulsive fields, such as considering the repulsive gain factor as a function that changes with the fire field and the gravity weight as a function that changes with the target point, in order to provide theoretical references for search and rescue and path planning in forest fire scenarios.

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REFERENCES

[1] Zhang, HongGuang, ZiHan Liang, HuaJian Liu, Rui Wang, and YuanAn Liu. "Ensemble framework by using nature inspired algorithms for the early-stage forest fire rescue—A case study of dynamic optimization problems." Engineering Applications of Artificial Intelligence 90 (2020): 103517.

[2] Wang, Chunying, Ping Liu, Tongxun Zhang, and Jinju Sun. "The adaptive vortex search algorithm of optimal path planning for forest fire rescue UAV." In 2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), pp. 400-403. IEEE, 2018.

[3] Colorni, Alberto, Marco Dorigo, and Vittorio Maniezzo. "An Investigation of some Properties of an" Ant Algorithm"." In Ppsn, vol. 92, no. 1992. 1992.

[4] Kennedy, James, and Russell Eberhart. "Particle swarm optimization." Proceedings of ICNN'95-international conference on neural networks. Vol. 4. IEEE, 1995

[5] Wang, Huijuan, Yuan Yu, and Quanbo Yuan. "Application of Dijkstra algorithm in robot path-planning." 2011 second international conference on mechanic automation and control engineering. IEEE, 2011.

[6] Wang, Huijuan, Yuan Yu, and Quanbo Yuan. "Application of Dijkstra algorithm in robot path-planning." 2011 second international conference on mechanic automation and control engineering. IEEE, 2011.

[7] Liu, Wei, Kun Qiu, Xiaofei Yang, Ronghao Wang, Zhengrong Xiang, Yue Wang, and Weixiang Xu. "COLREGS-based collision avoidance algorithm for unmanned surface vehicles using modified artificial potential fields." Physical Communication 57 (2023): 101980.

[8] Kondo, Kei, and Takeshi Tsuchiya. "Predictive Artificial Potential Field for UAV Obstacle Avoidance." In Asia-Pacific International Symposium on Aerospace Technology, pp. 493-506. Singapore: Springer Nature Singapore, 2021.

[9] Zhao, Hongqiang, and Zhanshun Cheng. "Path Planning of Six-wheel-drive Rescue Robot Based on A* Algorithm and Artificial Potential Field Method." In 2022 37th Youth Academic Annual Conference of Chinese Association of Automation (YAC), pp. 308-313. IEEE, 2022.

[10] Rothermel, Richard C. A mathematical model for predicting fire spread in wildland fuels. Vol. 115. Intermountain Forest & Range Experiment Station, Forest Service, US Department of Agriculture, 1972.