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Optimization of UAV Smoke Screen Cooperative Masking Using Improved PSO

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Abstract: Aiming at the scheduling problem of UAV smoke screen cooperative masking of incoming missiles, this paper proposes a hierarchical solution framework that combines geometric analysis and intelligent optimization. Firstly, based on kinematics and line of sight occlusion geometric analysis, the three-dimensional occlusion judgment is simplified to discrete point judgment, and the effective occlusion time of the benchmark strategy is calculated to be 1.3920 seconds. Then, an optimization model with the maximum occlusion time is established, and the particle swarm algorithm with dynamically adjusted inertial weight is used to solve the problem, and the optimal occlusion duration of 4.5900 seconds and the corresponding strategy are obtained. It is further extended to the scene of three smoke bombs being dropped consecutively on a single machine, and the effective occlusion time is increased to 6.4000 seconds by integrating Latin hypercube initialization, dynamic adjustment of learning factors and chaos perturbation strategies. The results show that the proposed improved particle swarm algorithm can effectively solve such high-dimensional nonlinear constraint optimization problems, and provide a theoretical basis and feasible scheme for the real-time planning of UAV active defense.

Keywords: Smoke screen jamming, Particle swarm optimization, Geometric occlusion model, Cooperative defense.

1. Introduction

With the rapid development of precision-guided weapons and optoelectronic reconnaissance technology, the threat to important ground targets is becoming increasingly serious. As a passive jamming method with high cost-effectiveness ratio and rapid response, smoke jamming bombs play a key role in battlefield protection by forming aerosol clouds to obscure targets and interfere with missile seekers or reconnaissance equipment [1]. With its flexible maneuverability, drones are ideal platforms for spreading smoke screens at the forefront. How to scientifically plan the flight trajectory of UAVs and the timing and location of smoke bombs to maximize the coverage time of incoming missiles is a complex problem involving dynamics, geometry and optimization theory, which is of great significance for improving the air defense survivability of key areas [2].

Existing studies are mostly based on empirical or simplified models in the evaluation of masking effectiveness. Early research focused on the physical modeling of smoke screen materials and diffusion properties [3]. With the improvement of computing power, the analysis of occlusion effects based on ray tracing or numerical simulations has gradually increased [4, 5]. However, the research on combining these models with UAV-missile dynamic game processes and using them for online strategy optimization is still limited [6, 7]. In terms of optimization algorithms, genetic algorithms and simulated annealing algorithms have been used to solve similar path planning or resource scheduling problems [8]. Particle swarm optimization algorithms show advantages in continuous space optimization problems due to their simple principles, few parameters, and fast convergence speed [9]. However, its traditional form is prone to local optimization, and its performance degrades when dealing with multi-peak and high-dimensional problems [10].

In view of the above challenges, this paper focuses on the optimization of UAV collaborative smoke screen masking strategy [11]. The core work of this paper is divided into three steps: the first step is to solve the problem of accurate calculation of masking efficiency under fixed strategy, and to provide a reliable performance evaluation basis for optimization by establishing an accurate geometric masking judgment model [12]. In the second step, the optimization model of the delivery strategy is constructed in the scenario of a single smoke screen, and the improved particle swarm algorithm is applied to solve it to verify the effectiveness of the optimization framework. In the third step, the collaborative optimization problem of continuous delivery of multiple bombs on a single platform is further studied, and the global exploration and local development capabilities of particle swarm algorithms are enhanced by introducing a variety of strategies to cope with more complex decision-making space [13, 14]. In recent years, many scholars have explored the improvement of particle swarm algorithms, such as the introduction of dynamic inertia weights [15, 16], adaptive learning factors, hybrid initialization strategies, and fusion chaos theory, which provide important references for the algorithm design in this paper [17, 18]. At the same time, research in related fields such as multi-agent collaborative decision-making and robust optimization in dynamic environments also provide theoretical support for this question [19, 20].

The main contributions of this paper are: 1) proposing a system solution framework from accurate evaluation to single-objective, multivariate co-optimization; 2) For problem scenarios of different complexity, a step-by-step improved particle swarm algorithm is designed, which effectively balances the search efficiency and the quality of the solution. 3) The optimal masking strategy and upper limit of performance under each step are obtained through numerical experiments, which provides a quantitative reference for practical engineering applications.

2. Methods

2.1. Calculation Model of Occlusion Duration Under Fixed Strategy

This step aims to evaluate the effective occlusion duration for a given UAV flight and smoke screen drop parameters. First, establish a kinematic model.

The missile M1 was initially located at (20000, 0, 2000) meters and flew in a straight line at a speed $V_{M_1} = 300m/s$ towards the origin (false target). Its position varies over time as follows:

$$\begin{cases} x_{M1} = 20000 - V_{M1} \cos\theta_1 \cdot t \\ z_{M1} = 2000 - V_{M1} \sin\theta_1 \cdot t \\ \theta_1 = \arctan\left(\frac{z_{M10}}{x_{M10}}\right) \end{cases} \tag{1}$$

The UAV F_{Y1} was initially located at (17800, 0, 1800) meters and flew towards the false target at a speed $V_{FY1} = 120m/s$. After receiving the task, drop a smoke screen at $t_1 = 1.5s$, and detonate at an interval of $3.6s$ at $t_2 = 5.1s$. The smoke screen movement is divided into three stages: the horizontal displacement of the UAV, the flat throwing of the smoke screen, and the cloud descending at a uniform speed of $3m/s$ after detonation.

For the true target, an upright cylinder with a base center of (0,200,0), a height of 10 meters, and a radius of 7 meters is the core of its occlusion judgment to determine whether the line of sight from the missile's viewpoint to any point on the cylinder is intercepted by a smoke screen with a radius of 10 meters. To improve the computational efficiency, it is necessary to locate the most exposed (least obscured) key points on the cylinder. To this end, a datum plane containing the missile's viewpoint and cylindrical axis is introduced, and a set of planes parallel to this datum are used to analyze the field of view cone and cylinder at the same time. In any two-dimensional section, the cone section forms an ellipse, and the cylindrical section is a rectangle. Based on the characteristics that the ellipse correspondence function is a convex function and the rectangle is a convex set, it can be proved that the rectangle is fully included by the ellipse that its four vertices are located inside the ellipse. Generalizing this two-dimensional conclusion system to all parallel sections, the set of rectangular vertices of all sections exactly constitutes the circumference of the upper and lower bases of the original cylinder. Therefore, the most exposed key points on the cylinder are distributed on the circumference of the upper and lower bases, and the three-dimensional occlusion judgment problem is simplified to only determine whether the points on these two circles are effectively occluded by the smoke screen.

The upper and lower circumference are discretized into several points, and the occlusion judgment is transformed into a judgment of whether these discrete points are occluded. For any point $P_{i(x_i,y_i,z_i)}$, determine whether the line segment connecting the current position of the missile $P_{M(x_M,y_M,z_M)}$ and the point intersects the sphere with the center of the smoke cloud $P_{D(x_D,y_D,z_D)}$ as the center of the sphere and the radius r=10m.

Simultaneous Column Parameter Equations vs. Spherical Equations:

$$\begin{cases} \text{Spherical Equations:} (x - x_D)^2 + (y - y_D)^2 + (z - z_D)^2 = r^2 \\ x = x_{M1} + c(x_i - x_{M1}) \\ y = y_{M1} + c(y_i - y_{M1}) \\ displaystylez = z_{M1} + c(z_i - z_{M1}) \\ c \in [0,1] \end{cases} \tag{2}$$

To solve quadratic equations about the parameter c. If there is a solution $c \in [0,1]$, the line segment intersects the sphere and the point is obscured. If all discrete points are occluded at a certain moment, the target at that moment is considered to be effectively occluded. The total effective occlusion time is obtained by accumulating all effective occlusion moments.

2.2. Optimization Model of Single Smoke Screen Delivery Strategy

On the basis of the first step, the fixed constraints on the flight and delivery parameters of the UAV are lifted, and the goal is to maximize the masking time.

The objective function is to maximize the effective masking duration T. The decision variables include: UAV flight direction angle β (angle to the X-axis), flight speed V_{FY1}, smoke screen drop time t_1, explosion time t_2 (or interval between drop and explosion $\Delta t = t_2 - t_1$.

Constraints include:

$$\begin{cases} 70 \le V_{FY1} \le 140m/s \\ 0 \le \beta \le 2\pi rad \\ t_1 \ge 0 \\ t_2 - t_1 \ge 0 \\ 0 < t < \frac{\sqrt{x_{M10}^2 + y_{M10}^2 + z_{M10}^2}}{V_{M1}} \text{ (total missile flight time)} \\ z_{D11} \ge 0 \text{ (non-negative smoke µ¯ explosion height)} \end{cases} \tag{3}$$

The optimization problem is a single-objective continuous optimization problem with complex nonlinear constraints.

The particle swarm algorithm is used to solve the problem. In order to improve performance, a linear decreasing inertia weight strategy is introduced:

$$w = w_{start} - (w_{start} - w_{end}) \times (iter / iter_{max}) \tag{4}$$

Where iter is the current number of iterations, and $iter_{max}$ is the maximum number of iterations. Set the initial inertia weight $w_{start} = 1.2$ and end inertia weight $w_{end} = 0.6$. The larger w value in the early stage of the algorithm is conducive to global exploration, and the smaller w value in the later stage is conducive to local fine search, so as to balance the global and local optimization capabilities.

2.3. Optimization Model of Multi-Smoke Screen Cooperative Delivery Strategy

Consider a drone dropping three smoke screens in a row to further extend the masking time. The delivery time of the three smoke bombs (D_1, D_2, D_3) is (t_1, t_3, t_5), and the explosion time is (t_2, t_4, t_6). The objective function is still to maximize the total effective occlusion duration T. The decision variable is expanded to: $(\beta, V_{FY1}, t_1, t_2, t_3, t_4, t_5, t_6)$.

On the basis of the original constraints, new constraints are added. Chronological constraints: $(t_3 - t_1 \geq 1, t_5 - t_3 \geq 1)$ (at least 1 second between bombs); The drop-explosion timing constraints of each smoke screen are: $(t_2 > t_1, t_4 > t_3, t_6 > t_5)$; The explosion height of each smoke screen is not negatively constrained.

In order to solve the challenges posed by higher-dimensional decision spaces and more complex solution forms, three improvements are made to the PSO algorithm:

Population initialization based on very small Latin hypercube sampling: First, a large number of ordinary Latin hypercube samples are generated, and then the group of samples with the smallest distance between any two sample points is selected as the initial population. This ensures the uniformity and diversity of the initial particles in the search space, and the formula is expressed as:

$$\max\{\min_{i\neq j} d(A_k(i,:), A_k(j,:))\}, \quad k = 1,2,\ldots,N_{LHS} \quad (5)$$

Dynamic adjustment of learning factors: The social learning factor c_2 increases linearly with the number of iterations, focusing on individual experience in the early stage and strengthening the trend of learning to the group optimal in the later stage, which is conducive to convergence to the overall optimum.

$$c_2 = c_{2,start} + (c_{2,end} - c_{2,start}) \times (iter / iter_{max}) \quad (6)$$

Chaotic perturbation of particle position: Regularly use Logistic chaos mapping to apply small disturbances to the position of particles to help the algorithm jump out of the local optimum. The logistic mapping is:

$$x_{n+1} = \mu \cdot x_n \cdot (1 - x_n),\ \mu = 3.9 \quad (7)$$

The perturbation formula is:

$$x_{new} = x_{old} + rate \cdot (x_{chaos} - 0.5) \quad (8)$$

3. Results and Discussion

3.1. Step 1 Results

According to the given fixed strategy (UAV speeds 120m/s towards the false target, drops the bomb after receiving the task for 1.5s, and explodes after 3.6s), the established geometric occlusion model is applied to perform the time step traversal calculation. The circumference of the upper and lower surfaces of the target cylinder is discrete into 1000 points each, and the time frame before the missile hits the false target is judged in steps of 0.001s. It was finally calculated that the effective masking time of the smoke jamming bomb against the missile M1 was 1.3920 seconds. The results provide a baseline for subsequent optimization.

3.2. Step 2 Results

The particle swarm algorithm with dynamic inertia weight is used to optimize the single smoke screen bomb delivery strategy. The algorithm parameters are set as follows: the number of particles is 150, the maximum number of iterations is 200, the individual learning factor $c_1 = 2.5$, and the social learning factor $c_2 = 1.0$. After optimization, the results were significantly better than the fixed strategy.

Table 1. Optimal delivery strategy for single smoke screens

Parameters	7.14°
Flight direction (angle to X-axis)	120.97 m/s
Flight speed	(17800.00, 0.00, 1800.00)
Smoke Screen Drop Point Coordinates (m)	(17891.35, 11.45, 1797.16)
Smoke Screen Explosion Point Coordinates (m)	4.5900 s
Effective masking duration	7.14°

As shown in Table 1, the optimized policy increases the occlusion duration from 1.3920 seconds to 4.5900 seconds, an increase of more than 230%. The optimal flight direction slightly deviates from the route of flying directly to the false target, indicating that the smoke ball can be better deployed on the missile's line of sight path by adjusting the course. The flight speed is close to the upper limit of the allowance, which helps the drone reach a more favorable drop position as soon as possible.

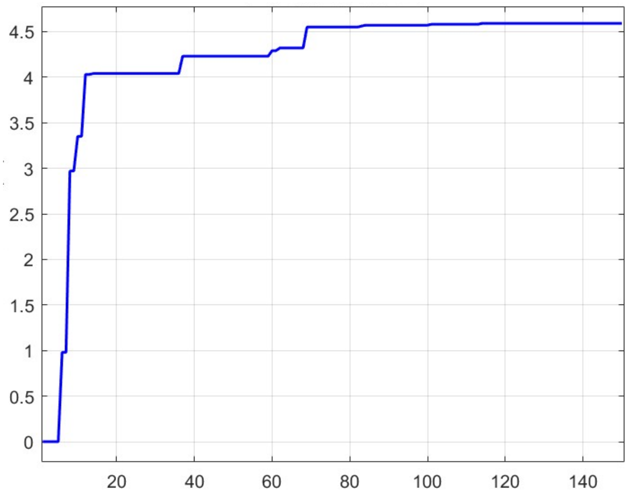

Figure 1. Particle Swarm Optimization convergence curve

From the convergence curve in Fig. 1, it can be seen that the algorithm is close to the optimal value after about 50 generations, and then performs a local fine search, and finally stabilizes at 4.5900 seconds, indicating the effectiveness of the dynamic inertia weight strategy.

3.3. Step 3 Results

After including age, height, weight, and more sequencing technical variables, the multiple linear regression model had limited explanatory power (adjusted R^2=0.265). By introducing the combined effect of age and height on Y concentration by introducing the thin plate spline interpolation model, the goodness of fit of the model was significantly improved to R^2=0.6851, and the sum of squares of residuals (SSE) was 2.985×10^4.

Table 2. Three smoke screen optimal delivery parameters and masking time

Smokescreen number	Drop point coordinates (m)			Detonation point coordinates (m)			Independent effective occlusion duration (s)
	x	y	z	x	y	z	
1	17800.00	0.00	1800.00	17800.00	0.00	1800.00	2.556
2	17920.49	13.90	1800.00	17920.49	13.90	1800.00	4.272
3	20361.64	295.49	1800.00	22671.45	561.92	0.00	0.000

From Table 2, it can be seen that the maximum total effective occlusion time under the synergy of the three smoke bombs is 6.4000 seconds. Although the independent shielding time of the third bullet is 0, the existence of the three achieves continuous occlusion longer than single or double shells through time relay or space combination. The total duration is not a simple addition of the independent duration of each projectile, indicating that there is overlap or synergistic masking effect in time.

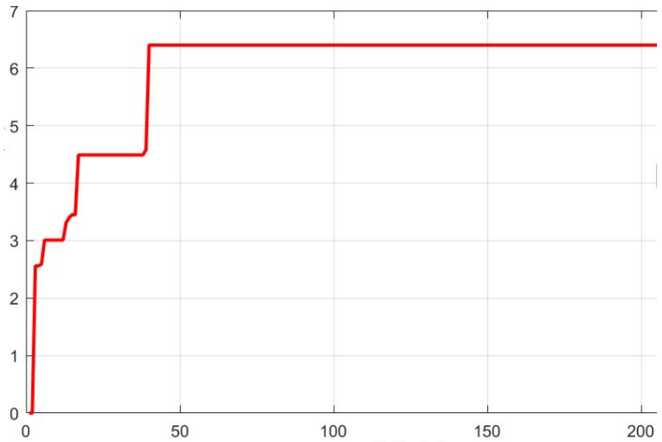

Figure 2. Particle Swarm Optimization convergence curve

From the convergence curve in Fig. 2, it can be seen that the improved particle swarm algorithm can find the optimal solution in the early stage of iteration, and continue to explore through chaos perturbation and other mechanisms in the middle and late stages, and finally converge to 6.4000 seconds. Compared with the single-bomb optimization result (4.5900 seconds) in the second step, the multi-bomb coordination strategy further increases the masking time by about 39.4%, which verifies the value of the multi-bomb delivery strategy and improves the algorithm's ability to deal with complex problems.

4. Conclusion

In view of the tactical background of UAV dropping smoke bombs to interfere with incoming missiles, this paper establishes a complete mathematical model and algorithm framework from accurate evaluation of masking efficiency to step-by-step optimization of delivery strategy. Firstly, through rigorous geometric analysis, the occlusion determination problem of the three-dimensional cylindrical target is simplified to the judgment of the discrete points on its key contour lines (upper and lower bottom circumference), and a single-point occlusion model based on line segment-sphere intersection detection is established, so that the effective occlusion time under any given strategy can be efficiently and accurately calculated, which lays a reliable performance evaluation foundation for subsequent optimization.

Secondly, based on the evaluation model, this paper constructs the strategy optimization problem in different complexity scenarios step by step. In the first step, an optimization model was established for the delivery of a single smoke screen, with the flight direction, speed, bomb delivery and detonation timing of the UAV as the decision variables. In order to solve this model, a particle swarm algorithm based on linear decreasing inertia weights is introduced, and the global optimal solution is successfully searched by dynamically balancing the global exploration and local development capabilities, and the effective masking time is significantly increased from 1.3920 seconds to 4.5900 seconds of the initial fixation strategy, and the specific optimization strategy parameters are given, which verifies the effectiveness of the model and optimization algorithm.

Further, this paper expands the problem to the collaborative optimization scenario of multiple smoke screens continuously placed on a single platform. In the face of the challenges of increasing decision-making variables, complex spatial morphology, and possible multiple peaks, three key improvements have been made to the particle swarm algorithm: using very small Latin hypercube sampling to ensure initial population diversity; The dynamic adjustment strategy of social learning factors is implemented to guide the algorithm to converge to the global optimal in the later stage. A position perturbation mechanism based on Logistic chaos mapping is introduced to enhance the algorithm's ability to jump out of the local optimum. The multi-strategy improved particle swarm algorithm solves the multi-smoke screen cooperative optimization model, and finally obtains the optimal occlusion time of up to 6.4000 seconds, which is 39.4% higher than that of the single bomb strategy. The results show that multiple smoke bombs can effectively connect and superimpose the occlusion time through the collaborative arrangement of time series and space, rather than simply adding them, highlighting the importance of collaborative planning.

The research work in this paper shows that the combination of accurate physical geometry model and advanced intelligent optimization algorithm can effectively solve the dynamic, nonlinear and high-dimensional tactical decision optimization problems such as UAV smoke screen occlusion. The proposed improved particle swarm algorithm performs well in solving quality and stability by integrating multiple enhancement strategies. The model and algorithm framework established in this paper not only provide scientific tools and quantitative basis for the optimization of smoke screen delivery strategy, but also can be generalized to other similar dynamic resource scheduling and collaborative jamming problems, such as multi-UAV collaborative reconnaissance and electronic warfare resource allocation, which has good theoretical value and application prospects. Future work can consider introducing more complex battlefield environmental factors (such as wind and terrain), missile maneuver modes, and multiple targets (such as considering both masking duration and resource consumption) for more comprehensive optimization.

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