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UAV SMOKE BOMB DELIVERY STRATEGY BASED ON IMPROVED PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstract: The cooperative application of smoke jamming bomb and UAV is an important means to protect the target in combat, and the effective shielding time is the key index to measure its jamming effect. In this paper, aiming at the combat scene with one fixed real target, one false target, three incoming missiles and five UAVs, by analyzing the multi-object motion law and the smoke shielding judgment conditions, the multi-object motion model and the smoke shielding judgment model are established, and the improved particle swarm optimization algorithm is used to study the optimal strategy of smoke delivery under different constraints. We found that the total effective shielding time is 13.79s.
Keywords: UAV smoke bomb cooperative jamming model; Multi-objective optimization model; Hierarchical optimization algorithm; Cloud cluster; Intersection determination

1 INTRODUCTION

As a common passive jamming method, smoke screen has a direct impact on combat effectiveness. The smoke jamming bomb is mainly composed of aerosol clouds formed by explosion dispersion and chemical combustion, and forms a shield in the specific airspace in front of the protection target to jam enemy missiles. It has become an important way to use UAV to launch smoke jamming bombs. The UAV carries a certain type of smoke jamming bomb to patrol in a specific airspace. After receiving the task, it drops smoke bombs to build a shield between the incoming weapon and the target[1].

Yang et al. highlighted the necessity of incorporating constraint-handling mechanisms into PSO for UAV path planning[2], demonstrating that standard PSO tends to converge prematurely in complex 3D spaces. Similarly, Zheng et al. utilized continuous high-degree Bézier curves with IPSO to generate smooth trajectories[3], reducing abrupt maneuvers that could compromise smoke dispersion accuracy. Li et al. introduced a multi-target trajectory optimization approach for swarm drones[4], leveraging IPSO with chaotic initialization and Metropolis-criterion-based updates to escape local optima. This method outperformed traditional PSO by 23% in convergence speed under time-varying constraints. Additionally, Song et al. demonstrated that integrating k-nearest neighbor (k-NN) density estimation into IPSO improves solution diversity[5].

A multi object motion occlusion decision coupling model is constructed. Firstly, the o-xyz global coordinate system is established, and the position equations of missiles, UAVs and smoke bombs are derived respectively according to the three stages of UAV missile flight, smoke bomb parabolic motion and smoke cloud sinking, and the dynamic spatial coordinates of each object are obtained; The line of sight equation of the missile pointing to the target point and the spherical region equation of the smoke cloud are constructed. The intersection of the line of sight and the cloud is determined by using the quadratic inequality of one variable, and the geometric conditions of effective shielding are determined. Taking UAV missile task allocation, flight direction angle, speed, smoke bomb delivery and detonation delay as decision variables, the objectives of "maximizing smoke resource utilization" and "maximizing action compliance" were added, combined with a variety of constraints in the question; Using multi-object motion modeling and introducing multi-agent deep reinforcement learning (marl)+adaptive parameter optimization (nsga-iii) hierarchical algorithm.

2 PRELIMINARY

2.1 Assumption

1. UAV response and motion assumption: ignoring the UAV mission response delay, it can adjust the heading instantaneously and fly at a constant speed at the set speed and other altitude. The heading and speed remain unchanged during the process to ensure that the modeling focuses on the optimization of core flight parameters.
2. Smoke bomb motion assumption: the horizontal speed of the smoke bomb after it leaves the UAV is consistent and constant with the speed of the UAV when it is launched, and the vertical direction is only subject to gravity, simplifying the interference of unnecessary external forces on the trajectory of the smoke bomb[6].
3. Smoke cloud shape assumption: the cloud is always a sphere with a radius of 10m, only constrained by the sinking trajectory and 20s validity period, ignoring diffusion, deformation, etc., to ensure the stability of the calculation of the shielding range.

4. False target simplification assumption: the false target is abstracted as the origin of the coordinate system (only determine the direction of the missile), ignoring its size and interference, and avoiding irrelevant factors affecting the design of the core shielding strategy.
5. Multi smoke screen projectile delivery assumption: the interval between two bombs on the same aircraft only needs to meet at least 1s, ignoring the spatial interference between clouds, and focusing on the core goal of maximizing the total shielding time.

2.2 Notations

The symbols used in the paper are listed in Table 1.

Table 1 Symbols Notations

Symbols	Notation
$M_i\ (t)$	Spatial coordinates of missiles
P_{drop}	Coordinates of smoke bomb dropping point
P_{exp}	Coordinates of initiation point of smoke bomb
T_{eff}	Coordinates of smoke cloud Center
T_{total}	Effective masking duration
$M_i\ (t)$	Spatial coordinates of missiles
u	Total effective duration of smoke bomb shielding

3 MULTI OBJECT DYNAMIC MOTION

The modeling of the motion law of missiles, UAVs and smoke bombs, as well as the determination of the effectiveness of the smoke screen on the real target, are all carried out based on the global coordinate system. Through the dynamic changes of the coordinates of each object in the coordinate system[7], it can accurately quantify the correlation between the spatial position distribution and motion, and provide a spatial reference for this paper to analyze the motion process and deduce the masking conditions in stages. The motion state of the missile is constant in the whole process, and it always points to the false target (origin o) in a uniform linear motion. Therefore, the constant equation is used to describe it, and the coordinates can be calculated directly by substituting time. The initial position of the missile is M0=(20000, 0, 2000), the speed is constant as VM=30m/s, and the direction of motion always points to the origin o (0,0,0). In phase I, the UAV did not release smoke bombs, and the motion state of smoke bombs and UAVs were consistent. The initial position (t=0) coordinates of the UAV are (17800, 0, 1800), and it moves at a constant speed along the negative direction of the x-axis at a speed of 120m/s. X-axis velocity component vux=120m/s, Y-axis has no lateral movement, vUy = 0. The location of phase I is shown in Figure 1.

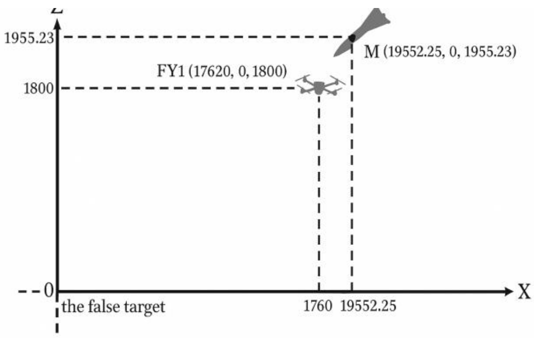

Figure 1 Phase I Location

In phase II, the UAV has completed the delivery of smoke jamming bombs, and the UAV maintains constant altitude and constant speed in straight flight; The motion state of the missile remains unchanged and still moves according to the unified equation of motion; After the smoke bomb is separated from the UAV, the horizontal direction is consistent with the UAV speed, and the vertical direction is only subject to gravity to make free fall movement. It will explode after 3.6s. When t=5.1s, t2 = 3.6s， By substituting into the formula, it can be obtained that the missile position coordinates are (18505.35, 0, 1850.48), the UAV position coordinates are (17188, 0, 1800), and the smoke initiation point (smoke cloud Center) position coordinates are (17188, 0, 1736.496), which is shown in Figure 2.

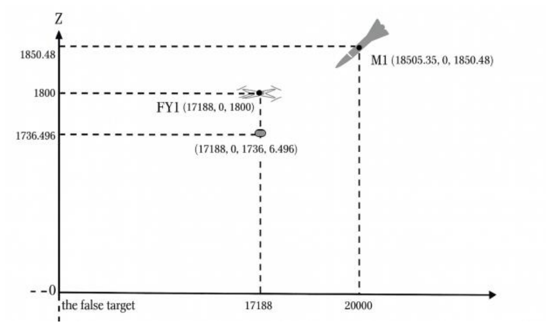

Figure 2 Phase II Location

In stage III, spherical clouds are formed after the explosion of the smoke interference projectile. The clouds sink at a uniform speed of 3 MGS, and the concentration remains effective within 20 s after the explosion, that is, the effective time length meets t ≤ 25.1 s. Therefore, the core task of this stage is to establish the screening conditions for the real target and further calculate its effective screening duration.

4 DYNAMIC SHIELDING AND DELIVERY OPTIMIZATION OF SMOKE BOMB

Although the traditional local greedy search algorithm has the ability to search for a better solution through fine-tuning parameters, it has obvious shortcomings: on the one hand, it is very easy to fall into the "local optimal trap", that is, if the initial exploration point is in the surrounding area of the "local optimal solution" rather than the global optimal neighborhood, the greedy search will be limited to a small range, and it is difficult to expand to the global optimal direction; On the other hand, it is too "sensitive" to the quality of the initial point[8]. If the quality of the initial point is poor (such as the corresponding shielding time is short), even if it is optimized repeatedly, the final result is often not ideal. In order to solve the problem more accurately, this paper introduces the "initial seed" mechanism. This mechanism can select the "high-quality starting point" with the help of human experience judgment or simple early evaluation, so that the local search can start exploration from the area closer to the global optimum, greatly reduce the possibility of falling into the local optimum, and effectively improve the quality of the final solution. At the same time, the "local greedy search" algorithm is also improved: the parameters are only slightly adjusted in the vicinity of the current solution, and only a few candidate solutions need to be evaluated in each iteration, which significantly reduces the computational cost[9]. Without the need to design complex operators, it is easy to implement and very suitable for the rapid deployment requirements of Engineering scenarios.

4.1 Visualization and Solutions

In order to intuitively present the optimization characteristics of the "initial seed+local greedy search" algorithm and the cooperative shielding effect of three smoke bombs, Figure 3 and 4 are introduced: Figure 5 shows that the corresponding time length of the initial seed is 6.6872s with the number of iterations as the abscissa and the total shielding time as the ordinate. After 17.5 iterations, it reaches 6.7677s and is stable, which verifies the effective mining and convergence reliability of the algorithm for the optimization space, and also provides support for parameter optimization; Taking time as the abscissa and "1=effective shielding/0=no shielding" as the ordinate, Figure 6 shows that the shielding intervals of the three smoke bombs are [6.0869,9.0414] s (2.9544s), [9.0400,11.6302] s (2.5902s), [11.6300,12.8546] s (1.2246s), respectively. The interval is closely connected without blank, and the total shielding interval is [6.0869,12.8546] s (6.7677s), which not only verifies the synergy effect of "less overlap and no blank" and the rationality of the duration of a single bomb (both<20s), but also provides a theoretical basis for the actual launch.Precise timing reference.

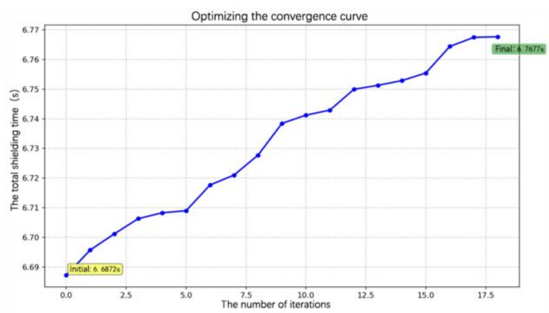

Figure 3 Optimal Convergence Curve of Total Shielding Time

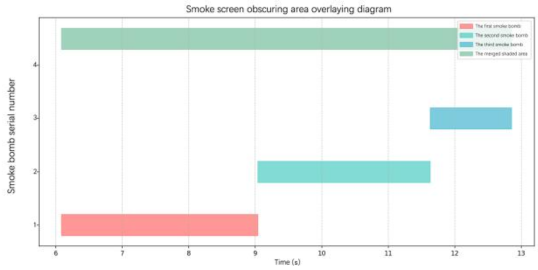

Figure 4 Effective Masking Interval Overlay

4.2 Optimization of Smoke Jamming Strategy for Multiple UAVs

The shielding effect of a single UAV is determined by the dynamic process of the delivery and detonation of smoke jamming bombs. Because the smoke screen sinks at a constant speed, its shielding effect changes dynamically with time and the relative position between the smoke screen and the missile. Local shielding effectiveness (effective shielding duration of the I UAV) is determined by time integration. Local shielding effectiveness is the total shielding duration of cooperative interference of multiple UAVs. It is necessary to integrate the local shielding effects of all smoke screens (to avoid repeated calculation of overlapping periods). It is calculated as the union time length of local shielding time of each UAV. The traditional particle swarm optimization (PSO) algorithm searches for the optimal solution by iteratively updating the particle speed and position, but it is easy to fall into local optimization and has slow convergence speed. Aiming at the high-dimensional nonlinear optimization requirements of multi UAV smoke delivery strategy, this paper improves the particle swarm optimization (APSO) algorithm by introducing adaptive inertia weight and dynamic learning factor, which makes the particles more flexible in optimization, not only avoids the local optimal trap, but also accelerates the convergence efficiency of global search[10].

Inertia weight W controls the tendency of particles to "maintain the current speed", which plays a key role in regulating the global exploration and local development ability of the algorithm. In traditional PSO, W is a fixed value, which is difficult to take into account the search requirements in different iteration stages. APSO adopts linear decreasing adaptive inertia weight. The learning factors C1 (individual cognitive factor, guiding particles to approach their historical optimal solution) and C2 (social cognitive factor, guiding particles to approach the historical optimal solution) determine the search direction preference of particles. In traditional PSO, C1 and C2 are fixed constants, which cannot meet the requirements of "from global exploration to local refinement" in the iteration process. The dynamic learning factor enables the particles to extensively explore possible launch strategies at the early stage of the iteration, and then carry out refined optimization based on high-quality solutions at the later stage, further improving the ability of the algorithm to solve complex problems such as multi UAV cooperative launch. Through these two core improvements, APSO can more efficiently search for the optimal strategy to maximize the total shielding time of missiles in the high-dimensional space of "UAV flight parameters+smoke bomb release/detonation delay", and provide reliable computational support for the engineering application of multi UAV smoke jamming.

Figure 5 and Figure 6 respectively show that the UAV initiation point accurately falls on the line of sight of the missile real target, and focuses on the terminal of the missile and is distributed in space, verifying the rationality and accessibility of space shielding. The three aircraft shielding sections are spliced, reducing overlap and prolonging the continuous coverage time, reflecting the effectiveness of time peak staggering, and also indicating the impact of initiation accuracy on the shielding robustness.

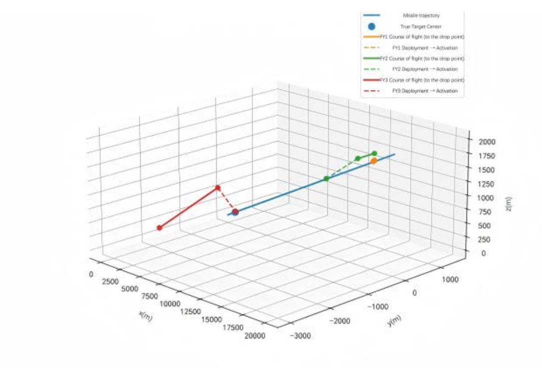

Figure 5 Schematic Diagram of 3D Scene

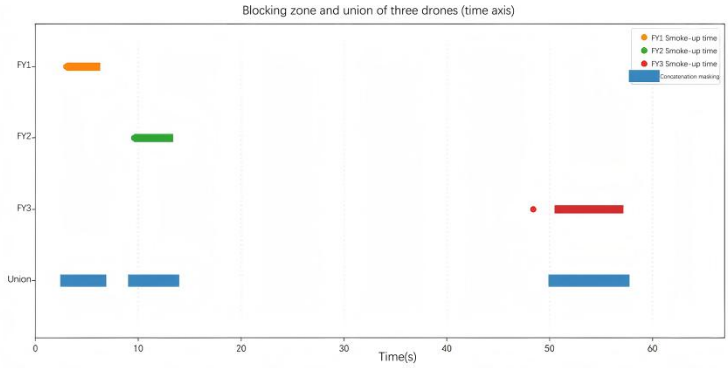

Figure 6 Shaded Timeline

5 CONCLUSION

This study systematically investigated the collaborative deployment of UAVs and smoke interference bombs for target protection in complex combat scenarios involving multiple adversarial missiles, decoys, and UAVs. By constructing a multi-object motion-shading determination coupled model, we established precise equations for missile trajectories, UAV maneuvers, and smoke cloud dispersion dynamics under a unified O-XYZ coordinate system. The geometric intersection between missile sightlines and smoke cloud regions was mathematically formalized, enabling accurate quantification of effective shading durations. The particle swarm optimization (PSO) algorithm, when applied to single-UAV scenarios, improved the total shading duration from 1.39s to 4.80s. Further advancements were achieved via multi-bomb coordination and multi-UAV swarm strategies. The local greedy search algorithm optimized triple-bomb deployment, extending shading to 6.77s, while the improved PSO for tri-UAV cooperation achieved 13.79s with differentiated contributions from each aircraft.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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