

Spatiotemporal Dynamic Geometric Occlusion Model and Optimal Strategy Optimization for Single-Shot Smoke Jammer Interference by UAVs

Yiqing You, Dongxu Zhang*, Changxi Cheng

School of Intelligent Engineering, Hubei Enshi College, Enshi Tujia and Miao Autonomous Prefecture 13250, China

* Corresponding author: Dongxu Zhang (Email: woqushi7@gmail.com)

Abstract: This paper first constructs a spatiotemporal dynamic geometric occlusion model for evaluating the interference effectiveness of a single smoke grenade deployed by the FY1 UAV against the high-speed M1 missile in a complex scenario. This model rigorously formalizes the ambiguous concept of “effective concealment” mathematically, defining it as the complete obstruction of the missile's line-of-sight to the entire visible contour of the actual target by the smoke sphere. By establishing dynamic trajectory equations for the missile, UAV, and smoke grenade, combined with high-precision time-sliced numerical simulations, the model successfully quantifies the effective concealment duration under a given strategy, yielding a result of 1.39 seconds. Building upon this foundation, to address the challenge of finding the optimal deployment strategy, this paper embeds the simulation model into a nonlinear programming framework with boundary constraints, aiming to maximize effective concealment duration. Given the lack of an analytical expression for the objective function and its nonlinear nature, a two-stage grid search algorithm—coarse-to-fine—is designed and implemented, effectively balancing the need for global exploration and local precision. Through this optimization framework, the maximum effective obscuration duration ultimately achieved reached 4.5850 seconds. The research significance of this work is threefold: Firstly, it provides a theoretically innovative framework for quantitatively assessing dynamic countermeasures, moving beyond qualitative descriptions. Secondly, it offers a practical methodological contribution through the robust optimization algorithm, which is applicable to complex, simulation-based problems lacking gradient information. Finally, the findings have direct practical implications for enhancing the survivability of UAVs in asymmetric warfare, demonstrating a substantial improvement in defensive capabilities through optimal tactical planning.

Keywords: UAV, Effective Shielding, Smoke Screen Interference.

1. Introduction

In the context of modern asymmetric warfare, deploying low-cost, high-efficiency unmanned aerial vehicle (UAV) swarms for tactical missions—particularly employing smoke countermeasures as passive defense—has become a critical technology for countering high-velocity missile threats[1-2]. This study focuses on the scenario where the UAV FY1 deploys a single smoke decoy to counter the incoming missile M1. The primary challenge in evaluating single-deploy effectiveness lies in precisely quantifying the total effective obscuration time the smoke cloud provides to the target under given flight and deployment parameters. Previous research addressing such problems often required complex physical motion models and precise geometric detection logic[3]. The innovation of this work lies in successfully formalizing the tactical concept of “effective obscuration” into a rigorous mathematical definition: the condition where both the missile's line of sight and the line connecting the target sampling point intersect the smoke sphere. Through a technical approach involving trajectory establishment, target discretization, geometric determination, and integral solution, this paper constructed a high-fidelity three-dimensional dynamic geometric obscuration model. Building upon this foundation, we further formulated an optimization problem for determining the optimal deployment strategy. This aims to identify the optimal four-dimensional decision parameters—UAV flight speed, direction, smoke grenade deployment timing, and detonation delay—to maximize obscuration

effectiveness. To tackle this nonlinear optimization challenge involving a black-box simulation model as the objective function, this paper innovatively designed a two-stage grid search algorithm progressing from coarse to fine. This approach rapidly locates the optimal region through sparse grid global exploration in the first stage, then ensures solution accuracy via dense grid local refinement in the second stage. This hierarchical search strategy represents another major innovation in this section, offering a robust and efficient solution for tackling high-dimensional optimization problems lacking analytical expressions[4-5].

2. Basic Occlusion Efficiency Modeling and Validation Under Fixed Parameters for Single Projectiles

2.1. Model Establishment

What constitutes “effective shielding” in the geometric shielding model? The concept of “effective shielding” is strictly mathematized. It is defined as a moment when all lines of sight from the missile to the entire visible contour of the real target are blocked by the smoke sphere. This is achieved by sampling the surface of the target cylinder and conducting point-by-point verification. At any given moment, a line of sight is a line segment connecting the missile's current position to one of the sampling points on the surface of the real target[6].

2.1.1. Model Preparation

The core objective of this problem is to quantitatively

$$c = \|C - M\|^2 - R^2 \quad (7)$$

If the discriminant of the equation $\Delta = b^2 - 4ac < 0$, the line does not intersect the sphere. If $\Delta \geq 0$, solve for the two roots s_1 and s_2 . The line segment MP intersects the sphere

$$\forall p_i \in S_{\text{target}}, \text{LineSegment}(P_{M1}(t), p_i) \cap \text{Sphere}(C_{\text{smoke}}(t), R_{\text{smoke}}) \neq \emptyset \quad (8)$$

2.2. Model Solution

Determine key time points and coordinates:

UAV flight: At the start of the mission ($t = 0$), UAV FY1 is located at (17800, 0, 1800) and flies at a constant speed of 120 m/s towards the decoy target (origin) at an altitude of 1800 meters.

Deployment point: The smoke bomb is deployed after flying for 1.5 seconds. The precise 3D coordinates of the UAV at this moment need to be calculated as the deployment point.

Detonation point: After deployment, the smoke bomb moves under the action of gravity and detonates after 3.6 seconds. Its precise 3D coordinates at detonation need to be calculated through the projectile motion model. The simulation starts at this moment ($t_{\text{detonation}} = 1.5 \text{ s} +$

if and only if the interval $[s_1, s_2]$ intersects with $[0, 1]$.

Finally, the mathematical expression for the "complete shielding" condition at time t is:

3.6 s = 5.1 s).

Establish dynamic position models:

Missile M1: Its position is a function of time. It flies from the initial point (20000, 0, 2000) to the origin at a speed of 300 m/s.

Smoke cloud center: Starting from the detonation point, its position is a function of time and sinks vertically at a constant speed of 3 m/s.

In this problem, we consider the scenario where UAV FY1 deploys a smoke interference bomb. By accurately calculating the smoke expansion, the missile's flight trajectory, and their interaction, we obtain that the effective shielding time of the smoke interference bomb on missile M1 is 1.39 seconds[7-8]. Simulation results are shown in table 1.

Table 1 Simulation results

Indicator type	Specific content
Simulation start time	5.10 s
Simulation end time	25.10 s
Deployment point coordinates	[17620.00, 0.00, 1800.00]
Detonation point coordinates	[17188.00, 0.00, 1736.50]
Effective shielding duration of the smoke interference bomb on M1	1.39 seconds

3. Global Optimization of Single Projectile Dynamic Strategies Using a Two-Stage Grid Search Algorithm

3.1. Model Establishment

To address the challenge of finding the optimal deployment strategy, we embed the simulation model into a more advanced optimization framework. The core of this problem is to determine a set of decision parameters to maximize a performance indicator (effective shielding duration) that can only be evaluated through complex simulation. Since the objective function $f(X)$ lacks an analytical expression and its response surface may be highly nonlinear and multi-modal, traditional optimization algorithms such as gradient descent are difficult to apply. The two-stage grid search adopted in the code is a robust global optimization method. Its core idea is to balance the capabilities of global exploration and local exploitation under the premise of controllable computing resources through a hierarchical refinement strategy. This problem can be formulated as a nonlinear programming problem with boundary constraints[9-10].

Decision variables: Let v be the UAV flight speed, θ be the flight direction angle, t_{launch} be the deployment time, and $\Delta t_{\text{explode}}$ be the fuze delay. The deployment strategy of the UAV is defined as a four-dimensional decision vector X :

$$X = (v, \theta, t_{\text{launch}}, \Delta t_{\text{explode}}) \quad (9)$$

Objective function: The optimization goal is to maximize the total effective shielding duration $T_{\text{occlusion}}$. This duration

is an implicit function of the decision vector X , and its value is calculated by the spatiotemporal dynamic shielding simulation model.

Constraint conditions: The decision variables are subject to boundary constraints set by physical and mission requirements:

$$\begin{cases} 70 \leq v \leq 140 & (\text{m/s}) \\ 0 \leq \theta < 360 & (\text{degrees}) \\ t_{\text{launch}} \geq 0 & (\text{s}) \\ \Delta t_{\text{explode}} \geq 0 & (\text{s}) \end{cases} \quad (10)$$

3.2. Model Solution

This paper adopts a hierarchical grid search algorithm from coarse to fine to solve this optimization model.

Solution platform: Python 3.x, combined with NumPy for high-performance numerical computing.

Core algorithm steps:

Stage 1: Global exploration and candidate region localization

Purpose: Quickly identify promising regions that may contain the global optimal solution in the vast four-dimensional parameter space.

Method: Construct a sparse grid covering the entire parameter space. This stage sets a total of $8 \times 18 \times 10 \times 8 = 11520$ grid points.

Iterative solution: Traverse all sparse grid points and evaluate each parameter combination X_i by calling the spatiotemporal dynamic shielding simulation model. To accelerate computation, the simulation uses low fidelity (time

step $DT_COARSE = 0.08$ s).

Convergence: Record the grid point X_{coarse}^* with the optimal evaluation result as the center for the fine search in the second stage.

Stage 2: Local exploitation and precise refinement

Purpose: Refine the final optimal solution through high-precision search in the "promising" region located in the first stage.

Method: Construct a denser encrypted grid (Fine Grid) with a reduced range centered at X_{coarse}^* , containing $7 \times 9 \times 7 = 3087$ nodes.

Iterative solution: Traverse all encrypted grid points and evaluate by calling the simulation model. To ensure accuracy, the simulation uses the highest fidelity (time step $DT_FINE =$

0.005 s).

Convergence: The algorithm terminates after traversing all encrypted grid points, and the grid point X_{fine}^* with the optimal evaluation result is the final optimal deployment strategy.

By implementing the two-stage grid search algorithm from coarse to fine constructed by us, we successfully solved the optimal strategy for the UAV to deploy smoke interference bombs to maximize the effective shielding duration. The calculation results show that among all possible strategy combinations, there is a clear optimal solution, and the maximum achievable effective shielding duration is 4.5850 seconds. Optimization results are shown in table 2.

Table 2 Optimization results

Indicator type	Specific content
Maximum effective shielding duration	4.5850 seconds
UAV flight speed	103.3333 m/s
UAV flight direction	5.2273 degrees
Smoke bomb deployment time	0.7667 s
Detonation delay after deployment	0.3667 s (detonates at $t = 1.1333$ s)
Smoke bomb deployment point	(17878.89, 7.22, 1800.00)
Smoke bomb detonation point	(17916.62, 10.67, 1799.34)

4. Conclusions

This study successfully constructed and solved two core tasks for a single smoke grenade deployed by a UAV to jam missiles: evaluating the interference effectiveness of a single grenade and optimizing the deployment strategy. For single-smoke-grenade interference effectiveness evaluation, we established dynamic trajectory equations encompassing missiles, UAVs, smoke grenades, and smoke clouds. We rigorously defined three-dimensional geometric occlusion criteria based on target surface sampling and calculated effective occlusion duration under given strategies via high-precision numerical simulations. For optimal deployment strategy optimization, we employed the aforementioned simulation model as the objective function, constructing an optimization model with UAV flight parameters and smoke grenade timing parameters as decision variables. To address this optimization problem, we employed a two-stage hierarchical grid search algorithm, progressing from coarse to fine grids. This approach effectively balanced computational resources and solution accuracy, successfully increasing the effective concealment duration from 1.39 seconds under the baseline strategy to 4.5850 seconds under the optimal strategy.

However, the solution process relies on discretizing continuous-time problems, meaning computational accuracy is inherently constrained by simulation time steps—creating an inherent trade-off between precision and computational resources. Furthermore, while the grid search algorithm employed here is robust, its computational complexity increases dramatically for higher-dimensional optimization problems. Future research should focus on enhancing computational efficiency in simulation evaluation. Potential avenues include exploring machine learning agent models to

approximate high-cost evaluation functions or replacing existing grid search optimizers with more efficient heuristic global optimization algorithms such as genetic algorithms or particle swarm optimization (PSO). These approaches would accelerate convergence and lay the groundwork for implementing more complex real-time tactical decision-making.

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