

Article

Cooperative Coverage Scheme for CDUAV Acquisition with Mixed Field-of-View Constraints During Mid-Terminal Guidance Handover Process

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Highlights

What are the main findings?

- The development of an ellipsoidal probability model for the confidence region of CDUAV trajectory prediction errors.
- The proposal of a two-dimensional optimisation framework for intelligent cooperative coverage of the mixed field-of-view of the interceptor's seeker.

What are the implications of the main findings?

- Improvement in the accuracy of the description of the CDUAV probability region.
- Improvement in the success rate of CDUAV acquisition through multi-seeker mixed field-of-view detection during the mid-terminal guidance handover process.

Abstract

The high speed and manoeuvrability of cross-domain unmanned aerial vehicles (CDUAVs) significantly reduce the handover window between mid-terminal guidance stages, challenging reliable target acquisition. To address this, we propose an optimisation method for interceptor selection and field-of-view (FOV) cooperative coverage based on high-probability region (HPR) modelling. First, a predictive error covariance propagation model is constructed based on error propagation theory, and the HPR is established via eigenvalue decomposition. Second, the cooperative detection by heterogeneous interceptor seekers is formulated as a coverage optimisation problem with mixed FOV, and a cost minimisation model under complete coverage constraints is established. Finally, an improved genetic algorithm (IGA) is employed for solution, and a coverage area ratio screening mechanism based on two-dimensional close-packing theory is designed to enhance optimisation efficiency. Simulation results demonstrate that the probabilistic modelling approach for CDUAV HPR can accurately characterise the anisotropic distribution of target position uncertainty; the algorithmic mechanism reduces redundant computational load by 62.5% and shortens the optimisation time by 36.7%; the intelligent coverage optimisation framework provides a more generalisable solution for cooperative detection by heterogeneous interceptors' seekers under conditions of target localisation uncertainty.

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1. Introduction

Cross-domain unmanned aerial vehicles (CDUAVs) can fly at high speeds across atmospheric layers. Their high speed and high manoeuvrability make their trajectories difficult to predict accurately compared to conventional targets [1]. A composite guidance system based on the predicted point of attack is typically employed by interceptors to effectively defend against CDUAVs [2]. During the mid-course guidance phase, the interceptor adjusts its trajectory based on the predicted flight path of the target. During the transition from mid-terminal guidance to terminal guidance (i.e., the handover between mid-terminal guidance), the interceptor's seeker must rapidly and accurately acquire the target within its high-probability region (HPR) to ensure the reliable entry into terminal guidance [3]. Therefore, it is crucial to investigate the HPR distribution of the CDUAV during the mid-terminal guidance handover and the detection envelope capability of the interceptor's seeker, which is important for improving the handover success rate.

Specifically, during the re-entry glide phase, CDUAVs can sustain flight speeds above Mach 5 while executing combined longitudinal jump-glide and lateral turn manoeuvres, causing trajectory prediction errors to diverge rapidly as the prediction horizon extends. During the mid-terminal guidance handover, the onboard seeker must complete search, detection, and lock-on within the target's HPR within a narrow time window, typically 1–3 s, to ensure a smooth transition to terminal guidance; if acquisition fails, the interceptor loses continuous target tracking, resulting in mission failure. More critically, at prediction horizons of 100–150 s, the position prediction uncertainty of CDUAVs can reach several to tens of kilometres, far exceeding the instantaneous field-of-view of any single seeker, rendering the conventional 'one-to-one' detection mode insufficient for reliable acquisition.

Existing methods exhibit shortcomings at two levels: uncertainty modelling and coverage optimisation. At the uncertainty modelling level, Monte Carlo methods can produce statistically converged error envelopes through extensive trajectory sampling, but typically require a large number of high-quality trajectory samples with computation times exceeding 10 s per evaluation, making it difficult to meet the timing requirements of mission planning. Spherical assumption methods treat prediction errors as isotropically distributed, neglecting the anisotropic characteristics of CDUAV errors—our simulation results indicate that at prediction horizons of 100–150 s, the ratio of normal-to-radial error standard deviations can exceed 1.7:1, causing spherical models to overestimate coverage requirements along minor axes (wasting seeker resources) or underestimate them along major axes (creating detection blind spots). At the coverage optimisation level, analytical geometry methods achieve rapid solutions by simplifying the HPR and the FOV into matching geometric shapes; however, this shape-matching requirement fundamentally limits the cooperative use of heterogeneous seekers—when the FOV geometry of different seeker types does not match the HPR, such methods become inapplicable, whereas multi-platform heterogeneous seeker cooperation is a common requirement in practical engagement scenarios. These limitations collectively motivate the development of a modelling and optimisation framework that addresses anisotropic uncertainty characterisation and heterogeneous seeker cooperative coverage optimisation.

HPR modelling primarily employs trajectory prediction techniques, which can be categorised into two types based on their technical approach: state prediction and parameter estimation. State prediction methods rely on historical target trajectory data and

achieve prediction by directly extrapolating state variables through time series analysis. These primarily include Kalman filtering and its variants (EKF, UKF, PF, etc.) [4,5], neural network prediction (LSTM, Transformer) [6–9], and time series analysis methods such as ARIMA. This approach does not require a physical motion model and offers high short-term accuracy, but lacks model constraints for medium- to long-term (50–200 s) high-precision (≤ 10 km) prediction. Parameter estimation methods achieve trajectory prediction by establishing a physical model of the target's motion and combining tracking data with kinematic equations. This method estimates the target's aerodynamic [10], manoeuvring [11], and control parameters [12] as well as aerodynamic acceleration [13] via high-dimensional motion models and non-linear filtering, then integrates the reconstructed motion model to obtain the predicted trajectory. Unlike data-driven state prediction, model-driven parameter estimation is constrained by both historical data statistics and the motion model, effectively suppressing noise and anomalous observations. Given the requirements for medium- to long-term prediction accuracy for CDUAVs, this paper employs a parameter estimation method to construct a trajectory prediction model. However, due to the lack of prior information on non-cooperative targets, a mismatch between the prediction model and the actual motion trajectory is inevitable. This mismatch error propagates and accumulates over time during the trajectory integration of the dynamical equations, leading to the continuous propagation of prediction errors across the spatio-temporal dimensions. Furthermore, in terms of uncertainty treatment, robust nonlinear control methods have also provided valuable insights into handling modelling errors and external disturbances for highly manoeuvrable aerial vehicles. For example, backstepping sliding mode control methods based on super-twisting observers achieve stable control of quadrotor UAVs under disturbance conditions by designing disturbance observers for online estimation and compensation of modelling errors and external disturbances; robust backstepping sliding control methods with disturbance compensation ensure system robustness by incorporating disturbance bounds into the control law design. These methods address uncertainty from the perspective of control design, i.e., considering worst-case uncertainty during the design phase to guarantee system performance; in contrast, the present paper addresses uncertainty from the perspective of quantification, aiming to describe the statistical distribution characteristics of prediction errors to provide probabilistic inputs for subsequent coverage optimisation. The two approaches to uncertainty treatment are complementary: robust control methods focus on “resisting” uncertainty, while the proposed method focuses on “characterising” uncertainty. Existing research primarily employs two approaches to characterise target position uncertainty: first, through Monte Carlo simulation to determine the statistical error distribution, which involves significant computational effort and is difficult to express analytically [14]; Second, by simplifying the HPR to a spherical region, thereby neglecting the differences in the target's manoeuvrability across different directions.

The traditional ‘one-to-one’ detection mode is constrained by the physical limitations of a single seeker's detection range and field-of-view, making it difficult to achieve complete coverage of the target HPR and leading to detection blind spots. If the target is not acquired initially, the seeker must re-scan its FOV, and the resulting delay may reduce the acquisition success rate. Consequently, to address the challenge of collaborative detection of CDUAVs, a ‘many-to-one’ cooperative detection mode must be adopted [15,16]. By optimally configuring multiple seekers in concert, the mixed detection FOV can achieve complete coverage of CDUAV HPR. Common coverage optimisation methods include Voronoi diagram-based partitioning optimisation [17–19], analytical geometric methods, and coverage optimisation based on intelligent algorithms [20–22]. The Voronoi diagram-based partitioning optimisation method can generate theoretically optimal polygonal partitions in static scenarios; however, when faced with dynamic boundaries, it requires con-

tinuous structural reconstruction, and its computational complexity makes it difficult to meet real-time requirements. Analytical geometric methods achieve rapid solutions by simplifying the HPR and the FOV into matching geometric shapes. Zhou et al. [23] simplified the HPR into a rectangle and the FOV into a square, and computed the coverage function analytically under rectangle–square matching conditions. In contrast, Luo et al. [3] assumed the HPR as a sphere and the FOV as a spherical cone, establishing coverage models in a matching spherical coordinate system. They established geometric coverage models of multiple spherical-apical conical FOVs relative to the HPR sphere, and subsequently employed a solid geometry approach for the solution. However, the aforementioned analytical geometric methods all rely on the assumption of geometric compatibility; when the FOV geometric model and the HPR geometric model are incompatible, it is difficult to solve the problem analytically. Consequently, inspired by coverage optimisation techniques in wireless seeker networks (WSN) [24–28], the use of intelligent optimisation algorithms to solve coverage optimisation problems under conditions of geometric mismatch represents a new approach to addressing the coverage of the HPR by the FOV. This method can effectively adapt to dynamic changes in HPR parameters and issues of geometric mismatch between the FOV and the HPR, while simultaneously addressing the cooperative configuration of seekers with different field-of-view sizes, thereby demonstrating greater generalisation capability.

In summary, to address the challenge of target acquisition during the handover between mid-terminal guidance for CDUAVs, this paper proposes an intelligent coverage optimisation method for multi-seeker cooperative detection based on probabilistic modelling of CDUAV trajectory prediction errors. First, an ellipsoidal HPR probability model is established using error propagation theory; Second, multi-seeker cooperative detection is formulated as a two-dimensional geometric coverage optimisation problem for HPR within mixed FOV; finally, by employing an improved genetic algorithm and a coverage area ratio screening mechanism, the optimal interceptor's seeker configuration and coverage points are determined under conditions of complete coverage.

The main contributions of this article are summarized as follows:

1. An ellipsoidal HPR modelling method based on a complete covariance propagation chain. Existing parametric methods either assume isotropic errors (spherical [3]) or uniform error bounds (rectangular [23]), failing to capture anisotropy, while Monte Carlo methods are computationally prohibitive. The novelty of this work lies in establishing a complete covariance propagation chain from filtering estimation errors, parameter fitting residuals, to integration accumulation errors, deriving the closed-form covariance matrix of prediction errors through three sequential propagation steps, and constructing the ellipsoidal HPR model via eigenvalue decomposition. The key distinction from existing methods is that this propagation chain explicitly describes the anisotropic characteristics of CDUAV prediction errors within an analytical framework, and the computational efficiency is improved by approximately two orders of magnitude compared to Monte Carlo methods (0.0973 s vs. 16.1084 s).
2. A cooperative coverage optimisation framework with mixed geometric shapes. Existing analytical coverage methods require shape matching between HPR and FOV (e.g., rectangle–square [23], sphere–cone [3]), limiting heterogeneous seeker cooperation. The novelty of this work lies in proposing a generalised mixed-integer non-linear programming (MINLP) formulation that decouples the HPR geometry (ellipse after projection) from the FOV geometry (circle), enabling optimal cooperative coverage by arbitrary combinations of seeker types without requiring geometric shape matching. The key distinction from existing methods is that this approach removes the shape-matching constraint, achieving for the first time heterogeneous geometric

- coverage optimisation with elliptical HPR and circular FOV, and providing a general solution framework for multi-platform heterogeneous seeker cooperative detection.
3. An area ratio screening mechanism based on close-packing theory. Existing methods lack dedicated dimensionality reduction for coverage MINLP problems. The novelty of this work lies in deriving the theoretical lower bound of the coverage ratio from two-dimensional hexagonal close-packing theory $P_{\min} = 1/\eta_{\max} \approx 1.102$, determining the upper bound through engineering constraints, and identifying the optimal screening interval $[1.9, 2.9]$ based on multi-criteria evaluation. The key distinction from generic pruning strategies is that this mechanism possesses explicit theoretical foundations directly linked to the geometric characteristics of the coverage problem, reducing redundant computations by 62.5% while simultaneously improving solution quality from 33.70 to 31.80.

2. Materials and Methods

2.1. Probabilistic Modelling of CDUAV Prediction Errors

To provide an accurate probabilistic description of trajectory prediction errors for CDUAVs, this section first establishes a three-degree-of-freedom kinematic reference model based on the velocity–turn–climb (VTC) coordinate system. Taking into account the time-varying nature of the aerodynamic parameters of CDUAVs, as well as the lack of prior information, a global parameter estimation strategy is adopted. This strategy fuses unknowns, such as the CDUAV's area of action, mass, and angle of attack, into equivalent aerodynamic acceleration components [29]. This simplifies the dynamic equations and reduces model mismatch errors. Error propagation theory is then used to derive the covariance transfer relationships for the filtering estimation, parameter fitting and trajectory integration processes sequentially. The variance of the state variables at prediction time is then extracted and mixed with critical values of the statistical distribution to determine the boundaries of the statistical distribution of the trajectory prediction error. Finally, the HPR is constructed via eigenvalue decomposition.

2.1.1. Reconstruction of the Motion Model

The VTC coordinate system is selected as the modelling reference frame, and a three-degree-of-freedom point-mass model is employed to describe the motion of the centre of mass of the CDUAV. This coordinate system uses the direction of the point mass's instantaneous velocity as the reference axis, facilitating the separation of tangential and normal dynamics [30].

Assumption 1. *The CDUAV motion environment is based on the assumption of a stationary spherical Earth. The Earth is treated as a homogeneous sphere of radius R_e , whose gravitational field is centrally symmetric; the magnitude of the local gravitational acceleration g varies only with the distance from the centre r , following an inverse-square law $g(r) = g_0(R_e/r)^2$, and its direction is always radial towards the centre of the Earth. Here, g_0 is the standard value of gravitational acceleration at sea level.*

Assumption 2. *The CDUAV's flight phase is the mid-glide stage, during which it primarily executes a pre-set manoeuvre pattern (longitudinal jump-glide + lateral turn manoeuvre). Manoeuvring to evade threats is not taken into account; when extrapolating the trajectory for the prediction phase, it is assumed that the target continues to execute the same manoeuvre pattern.*

The rationality of this assumption is based on the following considerations: CDUAVs typically execute pre-programmed manoeuvre patterns during the re-entry glide phase,

with their manoeuvre modes determined by the flight control system, and they do not actively alter their manoeuvre strategies in the absence of external threat awareness; moreover, the high-speed flight characteristics of CDUAVs limit the response time for evasive manoeuvres, making it difficult to achieve substantial trajectory deviations within a short period. However, if the target executes an unforeseen evasive manoeuvre during the prediction interval, the fitting model will fail; this limitation is further discussed in Section 4.

Under the above assumptions, the six-dimensional state vector of the CDUAV's centre of mass in the VTC coordinate system is defined as:

$$\mathbf{x} = [r, \lambda, \phi, v, \gamma, \chi]^T \quad (1)$$

where r is the distance from the centre of the Earth to the CDUAV point; λ, ϕ are the longitude and latitude of the CDUAV (in radians); v is the magnitude of the CDUAV's velocity relative to the Earth; and γ, χ are the track angle and heading angle, respectively.

The equations of motion can be expressed as:

$$\begin{cases} \dot{r} = v \sin \gamma \\ \dot{\lambda} = \frac{v \cos \gamma \sin \chi}{r \cos \phi} \\ \dot{\phi} = \frac{v \cos \gamma \cos \chi}{r} \\ \dot{v} = -\frac{D}{m} - g \sin \gamma \\ \dot{\gamma} = \frac{L \cos \sigma}{mv} + \frac{\cos \gamma}{v} \left(\frac{v^2}{r} - g \right) \\ \dot{\chi} = \frac{L \sin \sigma}{mv \cos \gamma} + \frac{v \cos \gamma \sin \chi \tan \phi}{r} \end{cases} \quad (2)$$

where σ is the bank angle; L, D are the aerodynamic lift and drag, expressed as $L = qSC_L, D = qSC_D$. Here, $q = \rho v^2 / 2$ is the dynamic pressure, ρ is the atmospheric density, and this paper employs an exponential decay model for approximation, i.e., $\rho = \rho_0 \exp(-h/H)$, $h = r - R_e$ is the altitude, and H is the scale height; C_L, C_D are dimensionless lift-drag coefficients, approximated by fitting aerodynamic data that include the angle of attack α ; S is the target's characteristic reference area, and m is the CDUAV's mass.

In Equation (2), the term $\dot{v}, \dot{\gamma}, \dot{\chi}$ comprises the CDUAV's aerodynamic parameter C_L, C_D , structural and mass parameter S, m , and control parameter α, σ . Regarding CDUAV non-cooperative targets, these parameters are unobservable. Therefore, we perform a parametric reconstruction of the motion model in Equation (2), decomposing the lift-drag term in the $\dot{v}, \dot{\gamma}, \dot{\chi}$ equation in the VTC coordinate system. a_v, a_t, a_c are the overall estimated parameters representing the CDUAV's acceleration components along the three axes in the VTC coordinate system; these three parameters collectively characterise the CDUAV's manoeuvrability.

$$\begin{bmatrix} a_v \\ a_t \\ a_c \end{bmatrix} = \begin{bmatrix} -\frac{D}{m} \\ \frac{L \sin \sigma}{m} \\ \frac{L \cos \sigma}{m} \end{bmatrix} = \frac{\rho v^2}{2} \begin{bmatrix} -\frac{C_D S}{m} \\ \frac{C_L S}{m} \cdot \sin \sigma \\ \frac{C_L S}{m} \cdot \cos \sigma \end{bmatrix} \quad (3)$$

where a_v, a_t, a_c are the overall estimated parameters, and $L \cos \sigma, L \sin \sigma$ are the aerodynamic lift components.

The motion model can be reformulated as:

$$\begin{cases} \dot{r} = v \sin \gamma \\ \dot{\lambda} = \frac{v \cos \gamma \sin \chi}{r \cos \phi} \\ \dot{\phi} = \frac{v \cos \gamma \cos \chi}{r} \\ \dot{v} = a_v - g \sin \gamma \\ \dot{\gamma} = \frac{a_c}{v} + \frac{\cos \gamma}{v} \left(\frac{v^2}{r} - g \right) \\ \dot{\chi} = \frac{a_t}{v \cos \gamma} + \frac{v \cos \gamma \sin \chi \tan \phi}{r} \end{cases} \quad (4)$$

2.1.2. Modelling of Error Propagation

Trajectory prediction for CDUAVs is a non-linear dynamical integration process based on the current filtered state. In this process, uncertainty is not static but is progressively propagated and accumulated through coordinate transformations, manoeuvre parameter identification and numerical integration. According to first-order error propagation theory [31–34], the covariance matrix at the input can be linearly propagated to the prediction time via the system's Jacobian matrix.

1. Spatial coordinate transformation of the initial filtering error

Tracking errors primarily stem from radar measurement noise, motion model mismatch and process noise, and represent the estimation bias in the target state vector. The nine-dimensional augmented state vector constructed in this paper includes position and velocity in the ENU coordinate system, as well as the equivalent acceleration components in the VTC coordinate system; its expression is as follows:

$$\mathbf{x}_{k\text{ENU}} = [x_k, y_k, z_k, \dot{x}_k, \dot{y}_k, \dot{z}_k, a_{v,k}, a_{t,k}, a_{c,k}]^T \quad (5)$$

where x_k, y_k, z_k and $\dot{x}_k, \dot{y}_k, \dot{z}_k$ are the three-dimensional position vector and three-dimensional velocity vector in the ENU coordinate system, respectively; k is the tracking time; and a_v, a_t, a_c is the equivalent aerodynamic acceleration component of CDUAV in the VTC coordinate system. Online identification of the CDUAV's manoeuvring characteristics is achieved through extended state estimation.

Since the three-degree-of-freedom kinematic equations established in this paper are based on the VTC coordinate system, the errors must be transferred to the VTC coordinate system via a coordinate transformation. $\mathbf{P}_{k\text{ENU}}$ is the error covariance matrix of the target state vector in the ENU coordinate system, and $\mathbf{T}(\cdot)$ is the non-linear transformation function from ENU to VTC; therefore, the initial error covariance matrix $\mathbf{P}_{k\text{VTC}}$ in the VTC coordinate system can be expressed as:

$$\mathbf{P}_{k\text{VTC}} = \mathbf{J}_{\text{ENU}}^{\text{VTC}} \mathbf{P}_{k\text{ENU}} \left(\mathbf{J}_{\text{ENU}}^{\text{VTC}} \right)^T \quad (6)$$

The Jacobian matrix $\mathbf{J}_{\text{ENU}}^{\text{VTC}}$ of a coordinate transformation can be expressed as:

$$\mathbf{J}_{\text{ENU}}^{\text{VTC}} = \frac{\partial \mathbf{T}}{\partial \mathbf{x}_{k\text{ENU}}} \quad (7)$$

Specifically, $\mathbf{J}_{\text{ENU}}^{\text{VTC}}$ is a 9×9 block matrix whose structure depends on the geometric relationship of the ENU-to-VTC coordinate transformation. This matrix can be written in block form according to the grouping of the state vector in Equation (5):

$$\mathbf{J}_{\text{ENU}}^{\text{VTC}} = \begin{bmatrix} \mathbf{R}_{\text{ENU}}^{\text{VTC}} & \mathbf{0}_{3 \times 3} & \mathbf{0}_{3 \times 3} \\ \frac{\partial \mathbf{v}_{\text{VTC}}}{\partial \mathbf{r}_{\text{ENU}}} & \mathbf{R}_{\text{ENU}}^{\text{VTC}} & \mathbf{0}_{3 \times 3} \\ \mathbf{0}_{3 \times 3} & \mathbf{0}_{3 \times 3} & \mathbf{I}_{3 \times 3} \end{bmatrix} \quad (8)$$

where $\mathbf{R}_{\text{ENU}}^{\text{VTC}}$ is the rotation matrix from ENU to VTC, determined by the velocity direction (track angle γ and heading angle χ), which rotates position and velocity errors from the ENU frame to the VTC frame; $\partial \mathbf{v}_{\text{VTC}} / \partial \mathbf{r}_{\text{ENU}}$ reflects the coupling effect that position errors influence the VTC coordinate orientation through the velocity direction, whose elements are related to the expressions for $\dot{\gamma}$ and $\dot{\chi}$ in Equation (4), and are typically small in practice, allowing approximation as zero; $\mathbf{I}_{3 \times 3}$ is the identity matrix, since the equivalent acceleration components a_v, a_t, a_c are defined directly in the VTC coordinate system and do not require coordinate transformation. The diagonal elements of $\mathbf{P}_{k_{\text{VTC}}}$ represent the variances of the respective state variables, providing a description of the initial uncertainty for subsequent dynamical integration.

2. Quantification of uncertainty in the identification of dynamic parameters

The high manoeuvrability of CDUAVs during the re-entry glide phase results in significant non-linear fluctuations in its state parameters. If the state variable v, γ, χ is extrapolated by direct integration, even a small deviation in the slope will lead to significant cumulative error over time. Therefore, this paper selects the state differential term a_v, a_t, a_c which is directly driven by the equivalent acceleration $\dot{v}, \dot{\gamma}, \dot{\chi}$ as the object of fitting.

First, this paper derives the differential rate of change $\dot{\mathbf{y}} = [\dot{v}, \dot{\gamma}, \dot{\chi}]^T$ for velocity, track inclination and heading angle, and employs non-linear least squares online identification to estimate the equivalent aerodynamic parameter $\mathbf{a}$. Taking into account the periodic characteristics of the CDUAV's manoeuvres, a fitting function $f(a, k)$ is constructed that includes both a linear trend and harmonic terms.

$$f(a, k) = a(1) \sin(a(2)k + a(3)) + a(4)k + a(5) \quad (9)$$

where $a(1) \sim a(5)$ is the parameter to be fitted, and k is the tracking time.

To quantify the random error in the parameter identification process, let there be N observation points in the tracking segment, with the fitted residual vector denoted by $\mathbf{e}_{\text{nls}}$, the parameter error covariance matrix by $\mathbf{P}_a$, the corresponding Jacobian matrix by $\mathbf{J}_f = \partial f / \partial \mathbf{a}$, and the variance of the unbiased estimate of the residuals by σ_{nls}^2 . This yields.

By performing a first-order Taylor expansion of the fitting function $f(a, k)$ around the parameter estimate $\hat{\mathbf{a}}$, the relationship between the parameter deviation δ_a and the observation deviation $\delta_{\dot{\mathbf{y}}}$ is $\delta_{\dot{\mathbf{y}}} = \mathbf{J}_f \delta_a + \mathbf{e}_{\text{nls}}$. According to the properties of least squares estimation, the covariance of the parameter deviation is:

$$\mathbf{P}_a = (\mathbf{J}_f^T \mathbf{J}_f)^{-1} \mathbf{J}_f^T \cdot \text{Cov}(\mathbf{e}_{\text{nls}}) \cdot \mathbf{J}_f (\mathbf{J}_f^T \mathbf{J}_f)^{-T} \quad (10)$$

Assuming that the residual components are independent and identically distributed with variance σ_{nls}^2 , i.e., $\text{Cov}(\mathbf{e}_{\text{nls}}) = \sigma_{\text{nls}}^2 \cdot \mathbf{I}$, substituting this into the above expression allows σ_{nls}^2 to be factored out, the intermediate terms $\mathbf{J}_f^T \mathbf{J}_f$ and $(\mathbf{J}_f^T \mathbf{J}_f)^{-1}$ cancel, and since $\mathbf{J}_f^T \mathbf{J}_f$ is symmetric, $(\mathbf{J}_f^T \mathbf{J}_f)^{-T} = (\mathbf{J}_f^T \mathbf{J}_f)^{-1}$; therefore, the expression simplifies to Equation (11).

$$\mathbf{P}_a = \sigma_{\text{nls}}^2 (\mathbf{J}_f^T \mathbf{J}_f)^{-1} \quad (11)$$

where $\sigma_{\text{nls}}^2 = \mathbf{e}_{\text{nls}}^T \cdot \mathbf{e}_{\text{nls}} / (N - n_p)$ is the variance of the unbiased estimate of the fitting residuals (n_p is the number of parameters to be estimated), and $\mathbf{J}_f$ is the Jacobian matrix of the fitting function with respect to the parameter vector.

This matrix dynamically reflects the degree to which the fitted model approximates the CDUAV's actual manoeuvring characteristics; when the CDUAV performs a sharp manoeuvre, causing the residuals to increase, the diagonal elements of $\mathbf{P}_a$ also increase, thereby automatically widening the confidence boundaries during the prediction phase.

3. Propagation of dynamical integration errors

Once the initial state covariance matrix $\mathbf{P}_{k_{\text{VTC}}}$ and the fitted parameter covariance matrix $\mathbf{P}_a$ have been obtained, they are propagated to the prediction time step t_p via the dynamic equations. The prediction process is based on numerical integration; the covariance matrix at the current time step is used as the input for the next time step in an iterative manner, causing errors to accumulate and amplify non-linearly in the state space as the integration time increases.

Let the state-space equation be denoted by $\mathbf{x}_p = \Phi(\mathbf{x}_k, \mathbf{a})$. By applying a first-order Taylor expansion to localise the non-linear system, the total error covariance matrix $\mathbf{P}_p$ at the prediction time can be expressed as:

$$\mathbf{P}_p = \mathbf{J}_x \mathbf{P}_{k_{\text{VTC}}} \mathbf{J}_x^T + \mathbf{J}_a \mathbf{P}_a \mathbf{J}_a^T \quad (12)$$

where $\mathbf{J}_x = \partial\Phi / \partial\mathbf{x}_k$ and $\mathbf{J}_a = \partial\Phi / \partial\mathbf{a}$ are the Jacobian matrices of the state transition equation with respect to the initial state and the fitting parameters, respectively.

Here, $\mathbf{J}_x$ and $\mathbf{J}_a$ are computed through numerical differentiation. Since the state transition function $\Phi(\mathbf{x}_k, \mathbf{a})$ is implemented via numerical integration without an analytical expression, its partial derivatives cannot be computed analytically. Therefore, a forward difference approximation is employed: a small perturbation Δx_j is applied to the j -th state variable, and numerical integration is performed again; the partial derivative is then approximated by the ratio of the output change to the perturbation, i.e., $[\mathbf{J}_x]_{ij} \approx (\Phi_i(\mathbf{x}_k + \Delta x_j \mathbf{e}_j, \mathbf{a}) - \Phi_i(\mathbf{x}_k, \mathbf{a})) / \Delta x_j$, and similarly for $\mathbf{J}_a$, with $\Delta = 10^{-6}$.

To accurately describe the distribution of uncertainty in the CDUAV's position, an eigenvalue decomposition is performed on $\mathbf{P}_p$.

$$\mathbf{P}_p = \mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^T \quad (13)$$

where the eigenvector matrix $\mathbf{Q}$ determines the directions of the principal axes of the error ellipsoid, while the diagonal elements of the eigenvalue matrix $\mathbf{\Lambda} = \text{diag}(\lambda_1, \lambda_2, \lambda_3)$ determine the degree of dispersion along each principal axis.

It should be pointed out that the above covariance propagation model relies on first-order linearisation, i.e., the assumption that the system nonlinearity is sufficiently low within the uncertainty range for higher-order terms to be neglected. Whether this assumption holds depends on the length of the prediction horizon and the magnitude of the initial uncertainty. At shorter prediction horizons (e.g., 50–100 s), the trajectory sensitivity to initial states and parameters is relatively low, and the linearisation error is minor; as the prediction horizon extends, nonlinear effects become more pronounced, and the linearisation error increases accordingly. The comparison with the Monte Carlo method (Table

1) verifies that the first-order linearisation accuracy is acceptable within the prediction horizons considered in this paper.

Table 1. Statistical consistency between parametric and Monte Carlo methods.

Prediction Time	Direction	Envelope Matching Ratio	True Trajectory in Monte Carlo Envelope	True Trajectory in Parametric Envelope
50 s	X	1.13 ± 0.07	100.0%	100.0%
	Y	2.41 ± 0.07	100.0%	100.0%
	Z	1.23 ± 0.03	90.0%	92.0%
100 s	X	0.96 ± 0.10	100.0%	100.0%
	Y	2.24 ± 0.06	88.0%	100.0%
	Z	1.20 ± 0.04	94.0%	96.0%
150 s	X	0.95 ± 0.11	100.0%	100.0%
	Y	1.84 ± 0.05	56.0%	94.0%
	Z	1.12 ± 0.04	96.0%	96.0%

In summary, the probabilistic modelling of trajectory prediction errors for CDUAVs establishes a complete chain of uncertainty propagation from the tracking end to the prediction end by taking into account filtering errors, fitting residuals and the cumulative effects of integration. Figure 1 illustrates the logical flow of this modelling process, providing a visual representation of the coupling mechanisms between the various error sources and the dynamic update paths of the covariance matrix.

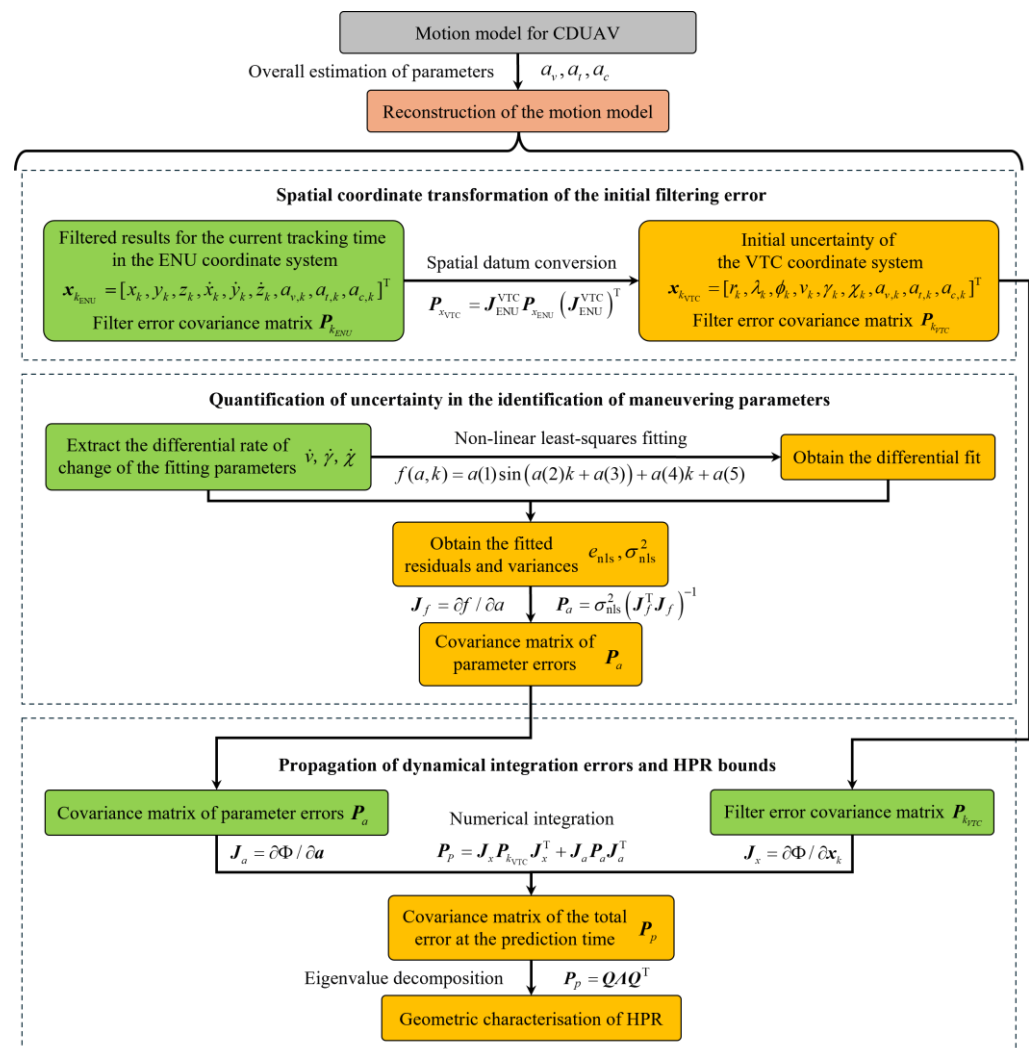


Figure 1. Logical flowchart for error probability modelling.

2.2. Modelling of the Target HPR

On the basis of the error covariance matrix $\mathbf{P}_p$ derived from the above calculations, this section proceeds to construct a geometric model of the CDUAV's position using the HPR. Compared with the simplified spherical assumptions or scalar error pipelines employed in conventional research, the error probability model provides a more accurate characterisation of the anisotropic distribution of errors across the various degrees of freedom of the CDUAV.

Let $\mathbf{P}_{\text{pos}}$ denote the three-dimensional sub-covariance matrix of the CDUAV's position at the prediction time (extracted from the first three rows and first three columns of $\mathbf{P}_p$). Perform an eigenvalue decomposition on $\mathbf{P}_{\text{pos}}$ to obtain the eigenvalues $\lambda_1, \lambda_2, \lambda_3$ and the corresponding unit eigenvectors $\mathbf{q}_1, \mathbf{q}_2, \mathbf{q}_3$.

At a confidence level $1-\alpha$ (typically taken as 99.7%, corresponding to $k_\sigma = 3$), the HPR can be defined as an ellipsoid centred at the predicted location $\hat{\mathbf{r}}_p$, with its principal axes determined by $\mathbf{Q} = [\mathbf{q}_1, \mathbf{q}_2, \mathbf{q}_3]$.

$$\mathcal{E} = \left\{ \mathbf{r} \in \mathbb{R}^3 \mid (\mathbf{r} - \hat{\mathbf{r}}_p)^T \mathbf{P}_{\text{pos}}^{-1} (\mathbf{r} - \hat{\mathbf{r}}_p) \leq k_\sigma^2 \right\} \quad (14)$$

In accordance with the 3σ confidence principle, the semi-axis length L_i of HPR can be expressed as:

$$L_i = k_\sigma \sqrt{\lambda_i}, \quad i = 1, 2, 3 \quad (15)$$

Considering that multi-seeker detection typically takes place on a specific two-dimensional projection plane (the focal plane of the interceptor seeker), the three-dimensional ellipsoidal HPR must be projected onto this plane. The complete derivation of this projection is presented below.

Step 1: Determine the projection plane. In the VTC coordinate system, according to Assumption 3 regarding the zero-effort miss (ZEM) condition, the line of sight is aligned with the velocity direction (v -axis). Therefore, the projection plane is the two-dimensional plane perpendicular to the v -axis, i.e., the $t-c$ plane in the VTC coordinate system.

Step 2: Extract the position covariance sub-matrix. The three-dimensional sub-matrix $\mathbf{P}_{\text{pos}}$ of the position component is extracted from the prediction error covariance matrix $\mathbf{P}_p$. Since $\mathbf{P}_{\text{pos}}$ is already expressed in the VTC coordinate system, $\mathbf{P}_{\text{pos}}$ is likewise in the VTC coordinate system.

Step 3: Construct the projection operator. The projection matrix $\mathbf{S}$ is defined to extract the lateral t and normal c components from the three-dimensional VTC coordinates:

$$\mathbf{S} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (16)$$

The first row of this matrix extracts the t -direction component, and the second row extracts the c -direction component, discarding the v -direction (radial) component.

Step 4: Compute the projected two-dimensional covariance matrix. The three-dimensional position covariance $\mathbf{P}_{\text{pos}}$ is projected onto the two-dimensional plane:

$$\mathbf{P}_{2D} = \mathbf{S} \cdot \mathbf{P}_{\text{pos}} \cdot \mathbf{S}^T \quad (17)$$

where $\mathbf{P}_{2D}$ is a 2×2 positive definite matrix whose elements reflect the error variances in the lateral and normal directions and the coupling between them.

Step 5: Eigenvalue decomposition to determine ellipse parameters. Eigenvalue decomposition is performed on $\mathbf{P}_{2D}$:

$$\mathbf{P}_{2D} = \mathbf{Q}_{2D} \mathbf{\Lambda}_{2D} \mathbf{Q}_{2D}^T \quad (18)$$

where $\mathbf{\Lambda}_{2D} = \text{diag}(\lambda_{2D,1}, \lambda_{2D,2})$, $\lambda_{2D,1} \geq \lambda_{2D,2} > 0$. The semi-axis lengths of the two-dimensional HPR ellipse are:

$$a = k_\sigma \sqrt{\lambda_{2D,1}}, \quad b = k_\sigma \sqrt{\lambda_{2D,2}} \quad (19)$$

The orientation of the ellipse is determined by the eigenvectors of $\mathbf{Q}_{2D}$. In the VTC coordinate system, since the errors generated by the CDUAV's longitudinal jump-glide and lateral turn manoeuvres in the lateral and normal directions are weakly coupled, $\mathbf{P}_{2D}$ is typically approximately diagonal, and thus the major and minor axes of the ellipse are approximately aligned with the $t-c$ coordinate axes. Figure 2 illustrates the cumulative expansion of trajectory prediction errors and a schematic representation of the spatial distribution of the HPR at a given prediction time.

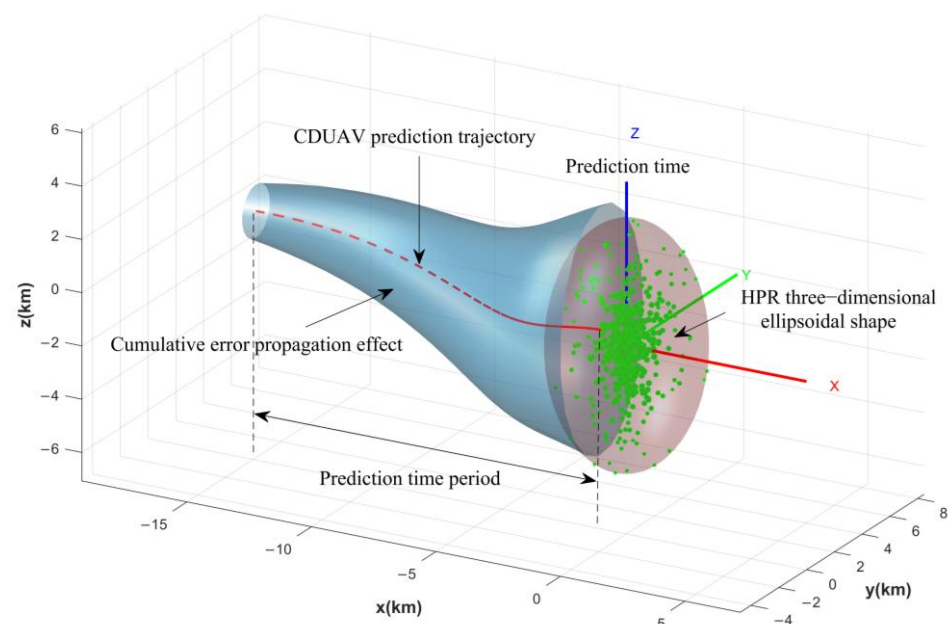


Figure 2. Cumulative diffusion of prediction errors and a schematic diagram of the target HPR.

2.3. Universal FOV Geometric Model for the Interceptor Seeker

Once the ellipsoidal geometric characterisation of the HPR has been established, the core task of seeker detection becomes to achieve effective coverage of the HPR using the FOV of the multi-seeker, subject to limited resource constraints. Taking into account the differences in detection performance and cost between different interceptor's seeker, this paper constructs a parametric, general-purpose geometric model for the FOV.

Seekers designed to defend against CDUAVs typically employ an infrared planar imaging mode [35–37], with their effective detection area in three-dimensional space represented by a spherical cone with the seeker centre as its apex, a generatrix length of $R_{\max}$ (the maximum detection range), and a half-apex angle of θ_{fov} . Given that during the re-entry glide phase of a CDUAV, the detection range is considerable and the FOV is narrow (typically $4^\circ \sim 10^\circ$), the influence of the curvature of the distant spherical cap can be neglected; consequently, this cone can be approximated as a circular area in the detection cross-section.

To reduce the dimensionality from three-dimensional space to a two-dimensional optimisation problem, it is necessary to determine the projection reference for the detection cross-section. Based on an analysis of the HPR's anisotropy, and given that the target employs longitudinal jump-gliding and lateral turning manoeuvres, its primary manoeuvring directions are concentrated in the longitudinal and lateral axes, while the line-of-sight direction (radial) corresponds to the seeker's illumination direction. Consequently, this paper projects the seeker's FOV onto a two-dimensional orthogonal plane perpendicular to the line-of-sight direction (i.e., the plane perpendicular to the v axis in the VTC coordinate system).

Assumption 3. Under the zero-effort miss (ZEM) condition, the interceptor approaches the target along the velocity direction, and the seeker's line of sight is aligned with the velocity vector. The seeker's focal plane is therefore perpendicular to the velocity direction, which coincides with the $t-c$ plane of the VTC coordinate system at the prediction time. It should be noted that this assumption only determines the LOS-velocity alignment at the handover instant; the velocity direction may evolve over the prediction horizon, and such evolution is captured by the rotation of the VTC coordinate system and reflected in the error covariance propagated within this coordinate system.

The seeker type is denoted by i ; the radius of the FOV formed by $R_{fov,i}$ on this projection plane can be expressed as:

$$R_{fov,i} = R_{max,i} \cdot \sin \theta_{fov,i} \quad (20)$$

Assumption 4. Under ideal conditions, where atmospheric disturbances and edge effects are disregarded, the process by which a seeker detects and tracks a target can be simplified to a Boolean logic judgement based on geometric inclusion.

The coordinates of the centre of the j seeker's FOV on the projection plane are denoted by c_j , and the coordinates of any point within the HPR are denoted by p . An indicator function $\mathbb{I}(\cdot)$ is defined to determine whether point p is covered by that FOV.

$$\mathbb{I}(c_j, p) = \begin{cases} 1, & \|p - c_j\|_2 \leq R_{fov,j} \\ 0, & \|p - c_j\|_2 > R_{fov,j} \end{cases} \quad (21)$$

where $\|\cdot\|_2$ is the Euclidean norm. If a target is covered by multiple FOVs simultaneously, its mixed coverage status is determined by the logical operations applied to the individual FOVs, as shown in Equation (24). Although this deterministic modelling method does not explicitly incorporate a detection probability distribution, it indirectly ensures the reliability of target detection within the confidence interval by requiring 100% geometric coverage of the HPR boundary.

The performance differences between various types of interceptors are primarily reflected in the combination of R_{max} and θ_{fov} , which in turn manifest as differences in the FOV radius $R_{fov,i}$ and the cost C_i . As shown in Figure 3, by adjusting these parameters, the general model is capable of characterising the properties of a wide range of seekers with different FOV capabilities.

During the detection and engagement of a CDUAV, the seeker on a single interceptor often struggles to provide complete coverage of a high-performance target (HPR) exhibiting complex manoeuvring characteristics. To address this, this paper proposes a multi-interceptor cooperative coverage strategy: by optimising the spatial configuration of the FOVs of seekers from different interceptor models on a projection plane, the mixed cov-

erage area is designed to fully enclose the ellipsoidal cross-section of the HPR. This strategy transforms the complex three-dimensional dynamic tracking problem into a two-dimensional static geometric coverage optimisation problem, thereby laying the geometric foundation for the subsequent development of a mixed-integer programming model aimed at minimising costs.

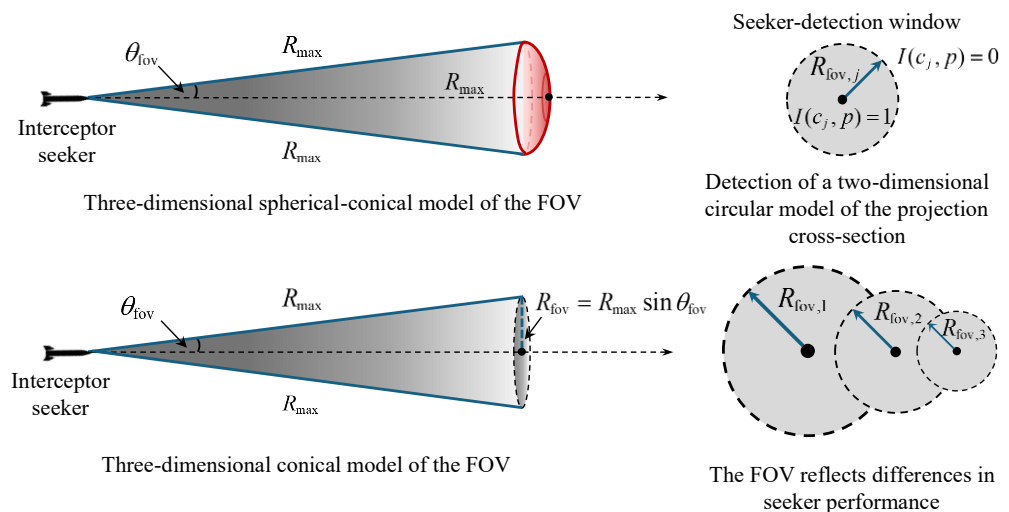


Figure 3. Schematic diagram of a general geometric model for an FOV.

2.4. Coverage Optimisation Modelling of a Mixed FOV for an HPR

The key to a successful handover between mid-terminal guidance systems is that, once the interceptor's seeker is activated, its FOV must immediately detect the target's position and lock onto it. To improve the success rate of the handover, this paper employs a multi-interceptor seeker FOV coverage technique, ensuring that the mixed FOVs of multiple seeker types provide complete coverage of the target's HPR, thereby guaranteeing that the actual target remains within the mixed coverage area.

In this section, we reformulate the seeker-based cooperative coverage problem as a geometric inclusion problem involving the FOV and a discrete set of points on a two-dimensional HPR detection plane [11], and construct a mixed-integer non-linear programming (MINLP) model optimised for the system's cost-effectiveness ratio.

This paper employs an orthogonal projection method to map the three-dimensional uncertainty ellipsoid $\mathcal{E}_{3D}$ onto a two-dimensional observation plane Π_{obs} perpendicular to the line of sight.

$$\mathcal{E}_{2D} = \mathcal{P}(\mathcal{E}_{3D}) \subset \Pi_{obs} \quad (22)$$

Within this projection plane, $\mathcal{E}_{2D}$ is represented as an elliptical region centred at the predicted centre of mass, with major and minor axes determined by the eigenvalues of the covariance matrix. At the same time, the FOV of the k -th seeker is modelled as a closed circular region $\mathcal{C}_k$ with radius $R_{fov,k}$. Consequently, the problem of dynamic capture in three-dimensional space is transformed into a static geometric coverage problem on a two-dimensional plane, as shown in Figure 4.

To quantify the coverage performance of a combination of $\mathcal{U} = \bigcup_{k=1}^N \mathcal{C}_k$ heterogeneous seekers with mixed FOVs over a target area $\mathcal{E}_{2D}$, a discrete sampling method is intro-

duced. Let $\Omega = \{\mathbf{p}_j \in \mathbb{R}^2 \mid j = 1, \dots, N_s\}$ be a finite set of points uniformly distributed within $\mathcal{E}_{2D}$.

Define an indicator function $\mathbb{I}: \mathbb{R}^2 \times \mathbb{R}^2 \rightarrow \{0, 1\}$ to determine whether a point $\mathbf{p}_j$ lies within the FOV of the k -th seeker.

$$\mathbb{I}(\mathbf{p}_j, \mathbf{c}_k) = \begin{cases} 1, & \|\mathbf{p}_j - \mathbf{c}_k\|_2 \leq R_{\text{fov},k} \\ 0, & \|\mathbf{p}_j - \mathbf{c}_k\|_2 > R_{\text{fov},k} \end{cases} \quad (23)$$

where $\mathbf{c}_k$ is the coordinate of the centre of the FOV.

According to set theory, the coverage η is defined as the proportion of sampling points that are effectively covered.

$$\eta(\mathcal{U}, \Omega) = \frac{1}{|\Omega|} \sum_{j=1}^{N_s} \left[1 - \prod_{k=1}^M (1 - \mathbb{I}(\mathbf{p}_j, \mathbf{c}_k)) \right] \quad (24)$$

When $\eta = 1$, this indicates that the seeker's mixed FOV achieves complete topological coverage of the target's HPR projection area.

Taking into account both the cost-effectiveness of seeker resources and mission reliability, the following optimisation model has been established.

$$\begin{aligned} \min_{\mathbf{n}, \mathbf{c}_k} \quad & J = \sum_{m=1}^M n_m C_m \\ \text{s.t.} \quad & \eta(\mathcal{U}, \Omega) = 1 \\ & \sum_{m=1}^M n_m \leq N_{\max} \\ & \mathbf{c}_k \in \Pi_{\text{obs}}, \quad k = 1, \dots, M \end{aligned} \quad (25)$$

where $\mathbf{n} = [n_1, \dots, n_M]^T$ represents the number of seekers of each type, and C_m is the corresponding unit cost coefficient. This model is a typical NP-hard combinatorial optimisation problem, the difficulty of which lies in the strong coupling between the discrete selection of quantities and the continuous configuration of FOV positions.

The discrete sampling strategy is described as follows. The sampling point set Ω within the target HPR elliptical region consists of two parts: boundary points and interior points. The boundary points (200 in total) are uniformly distributed along the ellipse boundary to ensure coverage accuracy at the edge region; the interior points (500 in total) are uniformly and randomly sampled within the ellipse to verify the coverage completeness of the interior region. To verify the influence of discretisation precision on coverage determination, a sensitivity analysis of the number of sampling points was conducted: when the number of sampling points increases from 200 to 2000, the variation in the computed coverage rate is less than 0.5%, indicating that the current sampling strategy can adequately approximate the continuous coverage condition. Therefore, the discrete constraint $\eta = 1$ in Equation (25) can reliably approximate the theoretical full-coverage requirement.

It is important to clarify the physical meaning of the optimised FOV centre coordinates. Each centre coordinate specifies the interceptor's deployment position on the detection plane: the interceptor should be guided to a position such that, when the seeker is activated at the handover instant, its boresight (with the gimbal angle at zero) naturally covers the assigned region of the HPR. The optimised centre coordinates therefore serve as mid-course guidance references that determine where the interceptor should fly to, rather than seeker pointing commands after arrival. Under the ZEM condition, the interceptor's velocity direction is aligned with the line of sight, and the seeker boresight coincides with this direction upon activation, requiring no gimbal deflection to cover the assigned region.

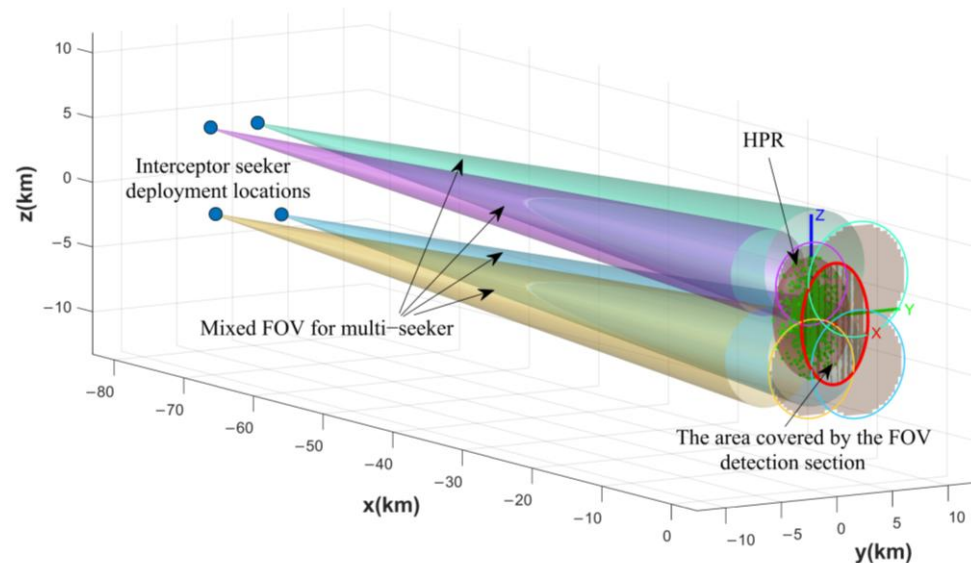


Figure 4. Schematic diagram of the mixed FOV of seekers covering the HPR.

2.5. Coverage Area Ratio Screening Mechanism

For MINLP problems, the solution space comprises discrete combinations of quantities and continuous spatial configurations. As the number of seeker types increases, the number of candidate combinations grows exponentially. To improve the efficiency of solutions, this paper introduces the coverage ratio P as a prior screening metric. By applying geometric pruning to the solution space, combinations that clearly fail to satisfy the coverage constraints are eliminated.

2.5.1. The Theoretical Lower Limit Based on Two-Dimensional Close-Packing Theory

Close-packing theory is a classical mathematical model that studies the arrangements of geometric bodies with the highest possible density within a given dimension [38,39]. In the two-dimensional Euclidean plane, when unit circles are arranged in a hexagonal close-packing configuration, a theoretical maximum packing fraction of approximately 90.69% is achieved; this is the configuration with the highest density of all planar arrangements.

In a hexagonal close-packing structure, circles are arranged closely together on a plane, each unit circle is tangential to six adjacent circles, forming a regular hexagonal lattice structure. The smallest repeating unit (unit cell) of this structure is a rhombus with side length $2r_c$ and angles of 60° and 120° , as shown in Figure 5.

Let the radius of the circle in the close-packing unit be r_c . Then the area of a single circle is expressed as:

$$A_{\text{circle}} = \pi r_c^2 \quad (26)$$

The area of this rhombic unit cell is expressed as:

$$A_{\text{unit}} = (2r_c)^2 \sin 60^\circ = 2\sqrt{3}r_c^2 \quad (27)$$

Since the sum of the areas of the sectors contained within the unit cell is equivalent to the area of a complete circle, the packing fraction η_{max} in a two-dimensional hexagonal close-packing structure is expressed as:

$$\eta_{\text{max}} = \frac{A_{\text{circle}}}{A_{\text{unit}}} = \frac{\pi}{2\sqrt{3}} \approx 0.9069 \quad (28)$$

The above derivation establishes the geometric limits of circular arrays when arranged without overlap. In relation to the problem of optimising the coverage of a target

HPR within a seeker's FOV, if multiple sets of circular FOVs are treated as close-packing units, then under theoretical limit conditions, the minimum total FOV area A_{fov} required to achieve complete coverage of the target area must satisfy the following conditions:

$$A_{\text{fov}} \geq \frac{A_{\text{HPR}}}{\eta_{\text{max}}} \quad (29)$$

The theoretical lower limit of the coverage ratio P_{min} is expressed as:

$$P_{\text{min}} = \frac{A_{\text{fov}}}{A_{\text{HPR}}} = \frac{1}{\eta_{\text{max}}} \approx 1.102 \quad (30)$$

This indicates that, in an ideal scenario with no edge effects, the total FOV area must be at least 1.102 times the target HPR area. Given that, in practical engineering applications, the FOV must overlap to some extent to compensate for boundary losses, this paper rounds up the theoretical lower limit and adds a safety margin, setting the lower bound of the screening range as $P_{\text{low}} = 1.2$.

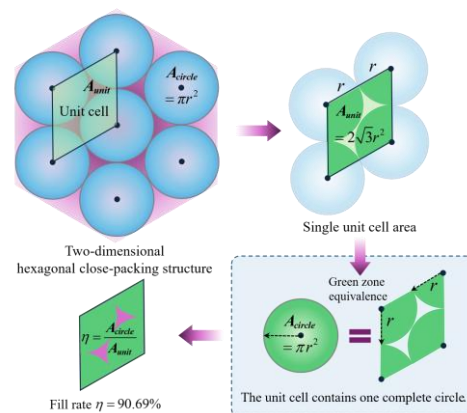


Figure 5. Schematic diagram of a two-dimensional hexagonal close-packing structure.

2.5.2. Configuration Upper Limit Based on Engineering Constraints

In engineering applications, given constraints on the number of seekers and associated costs, let the maximum number of seekers permitted for a single task be N_{max} (typically taken as 5), and the maximum FOV radius be $R_{\text{fov,max}}$. The upper limit P_{high} for the coverage ratio in an engineering configuration can then be expressed as:

$$P_{\text{high}} = \frac{N_{\text{max}} \cdot \pi R_{\text{fov,max}}^2}{\pi ab} \quad (31)$$

where a and b are the major and minor semi-axes of the target HPR projection ellipse, respectively.

2.6. Improvements to Genetic Algorithms

In the case of MINLP problems, the solution space is characterised by a strong coupling between discrete combinatorial and continuous locational components. Standard genetic algorithms are prone to getting stuck in local optima and exhibit limited convergence accuracy [40,41]. To address this, this paper proposes an improved genetic algorithm (IGA) that integrates adaptive parameter tuning, cooperative population evolution and bidirectional local search.

2.6.1. Adaptive Parameter Adjustment Mechanism

In the optimisation of seeker FOV coverage, the early stages of the evolutionary process require extensive exploration to identify viable combinations of parameters, while the later stages require fine-tuning of the centre coordinates to eliminate coverage blind

spots. Genetic algorithms with fixed parameters are unable to accommodate these phased requirements. To address this, a non-linear adaptive adjustment mechanism based on generation number has been introduced.

Let the total number of generations be G , the current generation be g , and the adjustment factor β be expressed as:

$$\beta = \frac{g-1}{G-1} \quad (32)$$

Let the crossover rate be p_c and the mutation rate be p_m ; the dynamic adjustment strategy is as follows:

Exploration Phase ($g \leq G/3$)

$$p_c = p_{c_0}, p_m = p_{m_0} \quad (33)$$

Balance Phase ($G/3 < g \leq 2G/3$)

$$p_c = p_{c_0} + 0.15\beta, p_m = p_{m_0} \cdot (1 - 0.4\alpha) \quad (34)$$

Exploitation Phase ($g > 2G/3$)

$$p_c = p_{c_0} + 0.3\beta, p_m = p_{m_0} \cdot (1 - 0.7\alpha) \quad (35)$$

where p_{c_0}, p_{m_0} are the base crossover rate and mutation rate, respectively.

The mechanism effectively mitigates the risk of overlooking low-cost seeker combinations due to premature convergence by maintaining a high variation rate during the exploration phase; during the exploitation phase, it ensures that the centre of the FOV can be fine-tuned by reducing the variation rate, thereby improving the fit to the complex boundaries of the target HPR.

2.6.2. Multi-Population Evolutionary Mechanisms

Due to significant variations in the FOV radius across different seeker models, the solution space contains multiple local optima comprising different combinations. A single population is highly susceptible to being dominated by a sub-optimal combination (such as over-reliance on seekers with large FOVs). To address this, a multi-group cooperative mechanism based on the principle of division of labour and collaboration has been designed.

This mechanism maintains three independent sub-populations $pop_i (i = 1, 2, 3)$, each configured with different search preferences: pop_1 focuses on global diversity, pop_2 focuses on balanced search, and pop_3 focuses on local refinement.

$$\begin{cases} pop_1 : CR_1 = 0.5, MR_1 = 0.4 \\ pop_2 : CR_2 = 0.7, MR_2 = 0.2 \\ pop_3 : CR_3 = 0.9, MR_3 = 0.1 \end{cases} \quad (36)$$

where pop_i denotes the subpopulation, CR denotes the crossover rate, and MR denotes the mutation rate.

To prevent homogenisation among subpopulations, a ring topology is employed for periodic information exchange. The migration time T_{mig} is defined as:

$$T_{mig} = \{gen | gen \bmod 5 = 0 \wedge gen < G\} \quad (37)$$

where $\bmod$ denotes the modulo operation.

Individual selection for migration is based not only on fitness rankings but also incorporates diversity constraints based on Euclidean distance, ensuring that incoming in-

dividuals introduce new genetic patterns to the target population, thereby maintaining the evolutionary vitality of the population as a whole.

2.6.3. Bidirectional Local Search Based on FOV Coordinates

This paper proposes a local search operator based on directional exploration along the two-dimensional coordinate axes of the target HPR. Let $\mathbf{c}_k = [y_k, z_k]^T$ denote the coordinates of the centre of the FOV of the k -th seeker in the elite population, and perform bidirectional fine-tuning as follows: explore with small steps along the y -axis to eliminate residual errors caused by lateral oscillations; explore with large steps along the z -axis to account for the significant uncertainty arising from longitudinal jumps and glides.

$$\begin{cases} y'_k = y_k + \xi_y \cdot a \cdot (2r - 1), & r \sim U(0,1) \\ z'_k = z_k + \xi_z \cdot b \cdot (2r - 1), & r \sim U(0,1) \end{cases} \quad (38)$$

where a, b represent the semi-axis of the target HPR projection ellipse, ξ_y, ξ_z is the step size coefficient, and r is a random number following a uniform distribution.

The acceptance criteria for the new location $\mathbf{c}'_k$ are defined as:

$$\mathbf{c}_k \leftarrow \begin{cases} \mathbf{c}'_k, & \text{if } \eta(\mathbf{c}'_k) > \eta(\mathbf{c}_k) \vee J(\mathbf{c}'_k) < J(\mathbf{c}_k) \\ \mathbf{c}_k, & \text{otherwise} \end{cases} \quad (39)$$

where $\eta(\cdot)$ is the coverage rate and $J(\cdot)$ is the total cost of the seeker array.

This criterion ensures that the algorithm updates positions only when coverage is improved or costs are reduced, thereby optimising cost-effectiveness while ensuring mission reliability. Figure 6 illustrates the logical flow of the coverage optimisation algorithm, which employs a preliminary area ratio screening mechanism to perform geometric pruning of the solution space. Furthermore, by incorporating cooperative population co-evolution, adaptive parameter tuning and axis-oriented local search into the evolutionary cycle, the algorithm enhances the diversity of the solution space and improves optimisation accuracy.

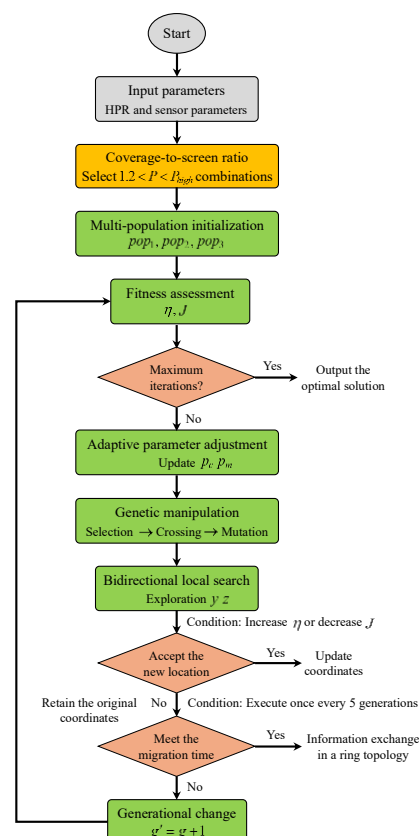


Figure 6. Algorithm flowchart.

3. Results

The simulation experiments in this paper were conducted on a PC running MATLAB R2024a with an Intel Core i7 CPU at 2.6 GHz and 16 GB of internal memory.

3.1. Simulation of Probabilistic Model for Trajectory Prediction Error

This section simulates probabilistic modelling methods, analyses the anisotropic distribution characteristics of the HPR at different prediction times, and validates these findings through comparison with Monte Carlo statistical methods. The simulation takes a typical CDUAV as its subject, conducting experiments on both the re-entry glide tracking phase and the prediction phase. The experiments are configured such that the target performs a composite manoeuvre involving longitudinal jump gliding and lateral oscillating gliding to simulate its penetration strategy. The initial state $(r_0, \lambda_0, \phi_0, v_0, \gamma_0, \chi_0)$ is set to $(35\text{km}, 0^\circ, 0^\circ, 2000\text{m/s}, -0.1^\circ, 65^\circ)$, the detection and tracking accuracy is set to $[10\text{m}, 0.01^\circ, 0.01^\circ]^T$, the tracking start point is set at 1000 s, the tracking duration is 200 s, the prediction duration is 150 s, and the confidence interval is 0.99. The simulation results are as follows:

Figure 7 illustrates the variation in the target position variable across the tracking and prediction segments. In the prediction segment, the red shaded area represents the range of the trajectory error distribution obtained from the probabilistic modelling method, while the purple shaded area represents the trajectory cluster envelope derived from the Monte Carlo simulation.

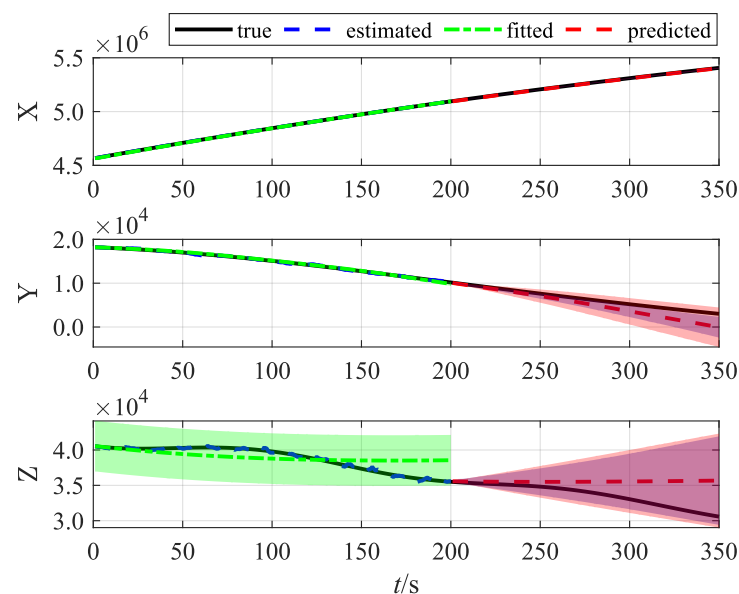
**Figure 7.** Directional distribution of trajectory prediction position errors.

Figure 7 shows that, as the prediction horizon increases, the trajectory error distribution broadens gradually; the parametric error envelope encompasses the true trajectory fluctuations, validating the method's effectiveness in a non-linear dynamical environment. It is worth noting that in the Y -direction (i.e., the lateral direction in the VTC coordinate system), the trajectory envelope obtained from the Monte Carlo simulation failed to fully cover the true trajectory in the latter half of the forecast period; however, the probabilistic modelling method continued to demonstrate good envelope performance. This indicates

that the parametric method is more robust than MC methods for long-term forecasts, where limited sample statistics lead to underestimation.

To evaluate the statistical consistency between the parametric method and the Monte Carlo method, two metrics are introduced: the envelope matching ratio and the true trajectory coverage ratio. The envelope matching ratio is defined as the ratio of the parametric envelope width to the Monte Carlo envelope width at a given prediction time. A ratio close to 1 indicates comparable envelope widths; a ratio greater than 1 indicates a wider parametric envelope; a ratio less than 1 indicates a narrower parametric envelope. The true trajectory coverage ratio is defined as the proportion of simulation rounds in which the true trajectory falls within the envelope, reflecting the bounding capability of each method against the actual trajectory error.

A total of 50 rounds of Monte Carlo simulations (500 runs per round) were conducted for the jump-glide oscillatory manoeuvre mode. In each round, both the Monte Carlo and parametric envelopes were computed, and the true trajectory was checked against both envelopes at prediction times of 50 s, 100 s, and 150 s. The results are shown in Table 1.

As shown in Table 1, the two methods exhibit the best agreement in the X (radial) direction, with matching ratios of 0.95–1.13 and both envelopes achieving 100% coverage of the true trajectory across all prediction times. In the Z (normal) direction, the matching ratios range from 1.12 to 1.23, indicating that the parametric envelope is slightly wider than the MC envelope, and both methods maintain coverage ratios above 90%. The most notable difference appears in the Y (lateral) direction: the parametric envelope is 1.84–2.41 times wider than the MC envelope, and the MC envelope's coverage of the true trajectory drops from 100% at 50 s to 56% at 150 s, whereas the parametric envelope retains 94% coverage even at 150 s. This indicates that the MC method, which characterises uncertainty through the dispersion of repeated predictions, tends to underestimate the lateral uncertainty at longer prediction horizons, while the parametric method, which propagates covariance through the dynamic model, provides a more conservative and stable envelope. Since the HPR used for coverage optimisation is determined primarily by the lateral and normal errors in the two-dimensional projection plane, the parametric method's broader and more reliable envelopes in these directions are advantageous for ensuring that the constructed HPR has a higher confidence level for target containment.

Table 2 further quantifies the performance differences between the two methods when predicting the endpoint at 150 s. The data show that, while maintaining comparable error margins, the probabilistic modelling method demonstrates significantly superior convergence performance to the Monte Carlo method, providing strong support for its application in seeker-based cooperative detection and capture tasks.

Table 2. Comparison of prediction errors for the 150 s.

Position Variable	Error Comparison	Time Comparison
radial error X	3.8845 km/5.4417 km	
lateral error Y	4.1693 km/2.4125 km	0.0973 s/16.1084 s
normal error Z	6.6074 km/6.1391 km	

The above comparison also helps clarify the effect of truncating higher-order terms in the first-order covariance propagation, Equation (12). In the lateral and normal directions, the parametric envelopes are consistently wider than the MC envelopes, indicating that the first-order model provides a sufficient uncertainty characterisation for coverage optimisation in these directions. The radial direction yields a narrower envelope at shorter prediction horizons, but this direction does not affect the HPR ellipse in the coverage plane. Notably the first-order propagation completes in 0.097 s, compared with 16.1 s for 500-run MC simulation; this two-order-of-magnitude speed advantage is essential for

meeting the sub-second timing constraint of the mid-terminal handover window. Higher-order propagation methods could improve the radial accuracy but would substantially increase the computational cost per step and will be considered in future work.

To further investigate the spatial distribution of HPR, Table 3 presents the distribution of positional error metrics for different prediction horizons; these error metrics directly define the spatial range within which the target HPR is likely to be located within a specific confidence interval.

Table 3. Distribution of location errors for different prediction durations.

Predicted Durations	Radial Error X	Lateral Error Y	Normal Error Z
50 s	1.3841 km	1.4983 km	2.3386 km
75 s	2.1382 km	2.2497 km	3.5343 km
100 s	2.8637 km	2.9908 km	4.6913 km
125 s	3.5889 km	3.7341 km	5.8459 km
150 s	3.8845 km	4.1693 km	6.6074 km

Table 3 reveals significant anisotropic characteristics: radial errors are relatively minimal, while normal errors diverge most significantly as the prediction duration increases; this distribution pattern exhibits a strong coupling effect with the target's predefined manoeuvre patterns. Given that the seeker's FOV is arranged radially, its detection range within the two-dimensional projection plane depends primarily on the error spans in the lateral and normal directions. Therefore, in subsequent research on cooperative seeker tracking, this paper will focus on the error distribution patterns of the target HPR in the lateral and normal directions, using these as the core geometric constraints for optimising the FOV configuration.

3.2. Simulation of the Coverage-to-Selection Mechanism

To evaluate the effectiveness of the coverage ratio screening mechanism and determine the optimal search range, simulation verification was conducted for the target HPR parameter $(a = 2.99\text{km}, b = 4.69\text{km})$ under a prediction duration of 100 s, as shown in Table 3 of this section. The experiment was configured with three types of interceptor seekers, with three units of each type. Let $R_{\text{fov},1} = 3.0\text{km}, R_{\text{fov},2} = 2.7\text{km}, R_{\text{fov},3} = 2.2\text{km}$ denote the FOV radius for each seeker type, and $C_1 = 9.5, C_2 = 8.3, C_3 = 6.4$ represent the cost coefficient. The upper limit of the coverage ratio for the engineering configuration is denoted as $P_{\text{high}} = 5 \times \pi \cdot 3.0^2 / \pi \cdot 2.99 \cdot 4.69 \approx 3.2$, and the evaluation range for the coverage ratio P is set to $[1.2, 3.5]$. Specifically, 1.2 is derived from two-dimensional close-packing theory, while 3.5 is determined by combining the upper limit of the engineering configuration with practical experience. Through exhaustive search and Monte Carlo optimisation of candidate combinations across different coverage ratio intervals, key performance metrics—including coverage probability, overlap, average cost and computation time—were statistically analysed. Their variation patterns are illustrated in Figure 8.

From the pattern of changes in the coverage metric, it can be seen that it rises gradually as the coverage area ratio increases and then levels off. Within the low area ratio range of $[1.2, 1.8]$, the coverage is 0. Although the theoretical lower limit derived from geometric limits is 1.2, due to the mixed constraints of discretisation sampling errors and the target HPR edge effect, the corresponding seeker FOV combination cannot provide sufficient geometric redundancy to compensate for coverage blind spots caused by irregular boundaries, resulting in the absence of feasible solutions within the solution space that satisfy the full coverage constraint. When $P \geq 1.9$, the coverage rate rises rapidly, climbing

swiftly from 0.02 to 0.92, indicating that the seeker FOV combination has now acquired the capability to provide effective coverage. When $P \geq 3.2$, the coverage rate curve tends towards saturation, and the marginal benefit of further increasing the FOV area ratio diminishes significantly.

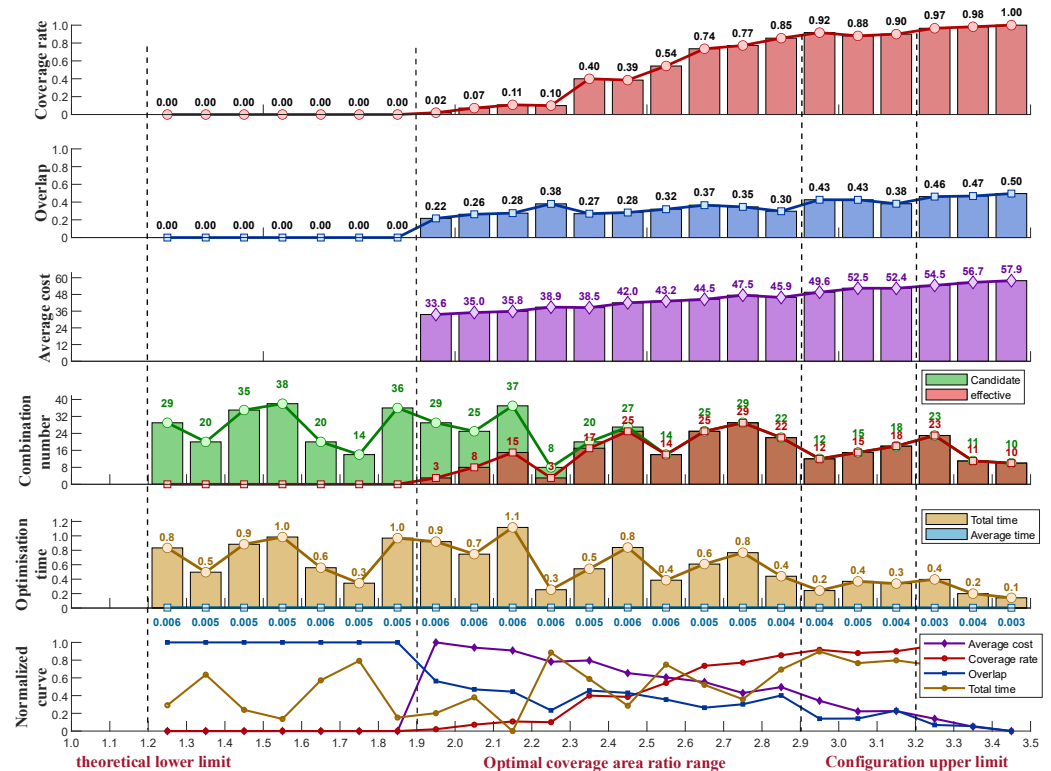


Figure 8. The effect of the coverage area ratio on optimisation metrics.

In terms of resource utilisation efficiency, the overlap metric exhibits a gradual upward trend as the coverage ratio increases. When $P = 3.5$, the overlap has risen to 0.50, implying that nearly half of the detection resources are consumed by redundant coverage. To ensure the system's cost-effectiveness, this metric provides an upper bound constraint for the coverage ratio selection range. The average cost serves as the core objective function in the coverage optimisation model presented in this paper. Simulation results indicate that the average cost curve exhibits an approximately linear upward trend. Consequently, during the optimisation process, exploration should be conducted as far as possible within the range below the configuration upper limit $P = 3.2$ to avoid the excessive introduction of high-cost seekers. Ideally, the global optimal solutions tend to be distributed within the low area ratio range of $[1.9, 2.1]$.

In terms of computational efficiency, the total optimisation time is positively correlated with the number of candidate combinations, while the average time per optimisation cycle remains stable at around 5 ms, demonstrating the algorithm's excellent computational efficiency. Within the range of area ratios $[1.9, 3.5]$, the solution space contains a large number of invalid solutions in the early stages; however, beyond $P = 2.5$, the solution space consists almost entirely of valid solutions.

To comprehensively balance the various metrics, this paper standardises each metric to eliminate differences in units and harmonise trends. The analysis indicates that within $[2.4, 2.7]$, multiple metric curves intersect at equilibrium points, and this region typically contains local optima, whereas within $[1.9, 2.1]$, the average cost advantage is greatest,

making it most likely to contain the global optimum; beyond $P \geq 2.9$, although coverage continues to rise and optimisation time is reduced, and the disadvantages in terms of average cost and overlap increase at a faster rate, leading to a significant reduction in overall benefits. Therefore, taking into account coverage reliability, economic efficiency and computational efficiency. Based on the above analysis, the optimal coverage ratio interval [1.9, 2.9] is determined as follows. The theoretical lower limit from close-packing theory is 1.2, but due to discretisation sampling errors and boundary effects, feasible solutions have near-zero probability for $P < 1.9$, making them impractical to search; therefore, the transition point $P = 1.9$, where the coverage rate first rises from zero to non-zero, is adopted as the practical lower bound. The engineering configuration upper limit is 3.2 (the area ratio of five largest FOVs), but the standardised multi-metric analysis shows that beyond $P = 2.9$ the coverage growth flattens while cost and overlap accelerate, with composite metric curves exhibiting clear divergence; therefore, the economic turning point $P = 2.9$ is adopted as the upper bound.

3.3. Simulation of Coverage Optimisation

Simulation experiments were conducted to optimise the HPR of targets with mixed FOVs, using a coverage ratio screening mechanism and an improved genetic algorithm (IGA). The experimental parameters were set as follows: the lateral and normal errors ($a = 2.99\text{km}, b = 4.69\text{km}$) for a 100 s prediction duration, as shown in Table 3, were selected as the parameters for the target HPR elliptical region; there were three types of interceptor seekers, with three interceptors of each type; the detection range is denoted as $R_{\max,1} = 58\text{km}, R_{\max,2} = 38\text{km}, R_{\max,3} = 32\text{km}$, the half-FOV angle as $\phi_1 = 3^\circ, \phi_2 = 4^\circ, \phi_3 = 4^\circ$, the seeker FOV radius as $R_{\text{fov},1} = 3.0\text{km}, R_{\text{fov},2} = 2.7\text{km}, R_{\text{fov},3} = 2.2\text{km}$, the corresponding cost coefficient as $C_1 = 9.5, C_2 = 8.3, C_3 = 6.4$, the coverage ratio screening interval as [1.9, 2.9], and the coverage constraint as $\eta = 1$. The target HPR elliptical region was discretised using 200 boundary points and 500 internal points for coverage verification; the maximum number of algorithm iterations was set to 20, and the population size was 15. The simulation results are as follows.

Figure 9 provides a visual representation of the optimised layout for mixed FOV coverage. Through a combination of filtering and cooperative optimisation, the algorithm ultimately determined the optimal configuration to be two M_1 -type FOVs and two M_3 -type FOVs, along with their corresponding deployment positions on the detection plane. This layout achieves 100% coverage of the target HPR elliptical region, with an optimal total cost of 31.80 (dimensionless units), a computation time of 0.62 s, and an FOV resource redundancy (overlap rate) of 18.86%.

Further analysis reveals that the optimised configuration combinations identify the optimal ratios for different types of seekers, thereby validating the effectiveness of the coverage optimisation method. The spatial distribution of the centres of the respective FOVs provides a precise positional reference for the deployment of seekers, enabling accurate terminal guidance during the interceptor's guided flight and further improving the success rate of target detection and acquisition. Furthermore, the 18.86% overlap rate indicates that the algorithm effectively controls resource redundancy between FOVs while pursuing low cost, thereby avoiding over-configuration.

Figure 10 presents statistical data on the multi-dimensional metrics of the IGA during the optimisation process. The cost convergence curve in Figure 10a shows that the global optimal cost rapidly decreased from an initial value of 248.94 to a final value of 31.80, while the average population cost also fell from 438.76 to 68.65. This significant reduction is attributable to the bidirectional local search strategy, which enables the algorithm to

perform fine-tuning of the centre coordinates during the later stages of evolution. The coverage variation curve in Figure 10b indicates that the algorithm first achieved 100% coverage of the constraints at the 19th generation, validating the efficiency of the IGA in handling full-coverage hard constraints. To verify the algorithm's stability, this study conducted 50 independent replicates to obtain the final cost set. The box-and-whisker plot in Figure 10c shows that the minimum final cost is 31.80, the median is 46.80, and the mean is 48.69. A comparison with Figure 8 reveals that a large number of final cost data points are concentrated in regions with a high density of feasible combinations, making it easy to get trapped in local optima. The outliers, on the one hand, illustrate the exploratory nature of the heuristic algorithm within a complex solution space; on the other hand, they highlight the difficulty of finding the global optimum. The average minimum cost in Figure 7 is 33.6, whereas the minimum final cost in this experiment is 31.80, indicating that this cost is very close to the theoretical global optimum. Taking into account various factors such as computational resources and time consumption, the fact that this experiment achieved a final cost of 31.80 serves as proof of the algorithm's optimisation capability. Furthermore, the population distance curve in Figure 10d further reveals the algorithm's search mechanism: the average Euclidean distance between population individuals gradually converged from an initial value of 86.22 to 6.01 (mean 30.58). This trend indicates that the algorithm maintained extensive search activity in the early stages to escape local minima, while in the later stages it gradually focused on the neighbourhood of the optimal solution through various population migration mechanisms, achieving a smooth transition from 'global exploration' to 'local exploitation'.

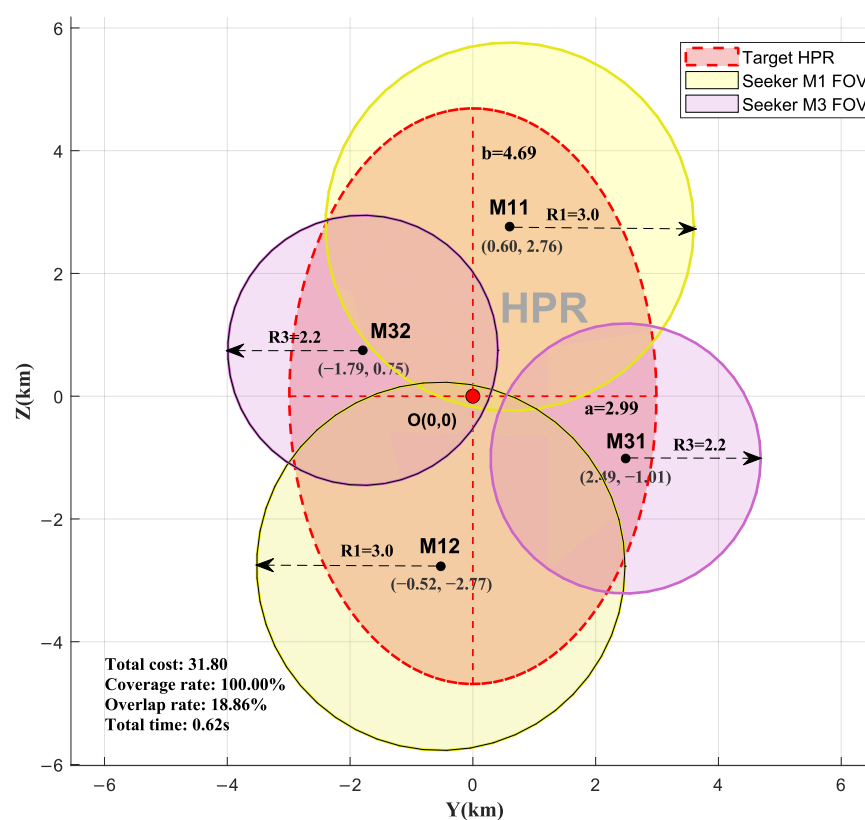


Figure 9. Coverage optimization layout diagram.

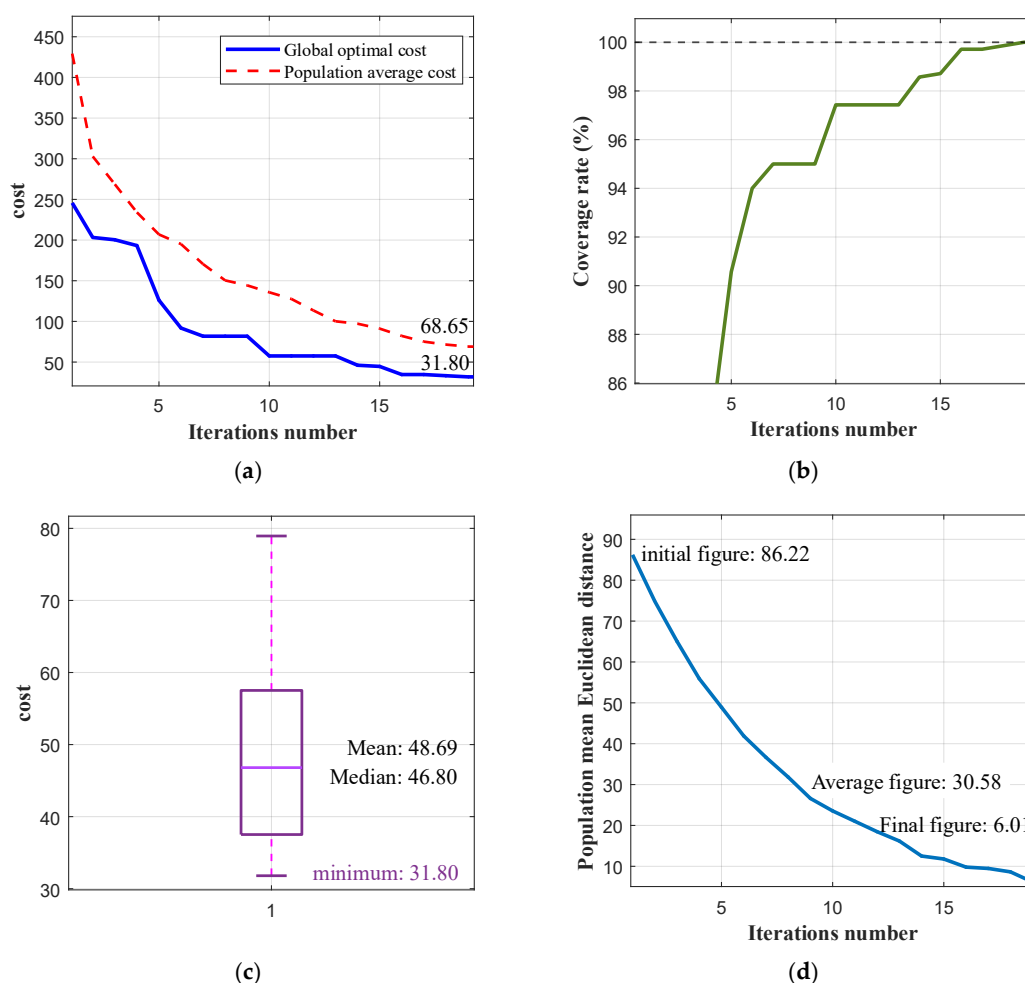


Figure 10. Data statistics for coverage optimisation. (a) Cost convergence curve. (b) Coverage rate trend curve. (c) Cost allocation. (d) Curve of changes in population distance.

To quantify the extent to which the coverage ratio filtering mechanism improves the algorithm's efficiency, a comparative experiment was designed to test the mechanism with and without the filtering mechanism, as shown below.

Figure 11 shows the simulation results comparing the scenarios with and without the coverage area ratio filtering mechanism: without the filtering mechanism, the algorithm must perform exhaustive optimisation on all 64 possible seeker combinations; however, after applying the coverage area ratio filtering mechanism, only 24 valid combinations proceed to the position optimisation stage, reducing the computational load by 62.5%. Following the introduction of the screening mechanism, the optimisation time was reduced from 0.98 s to 0.62 s, representing a 36.7% improvement in time efficiency. More importantly, the screening mechanism not only did not reduce the quality of the solution but actually further optimised the optimal cost from 33.70 to 31.80. This is because, after eliminating a large number of invalid and inefficient combinations, the computational resources saved were reallocated to the in-depth iteration of high-quality combinations, enabling the algorithm to more fully utilise the bidirectional local search strategy to exploit the potential of the solution space.

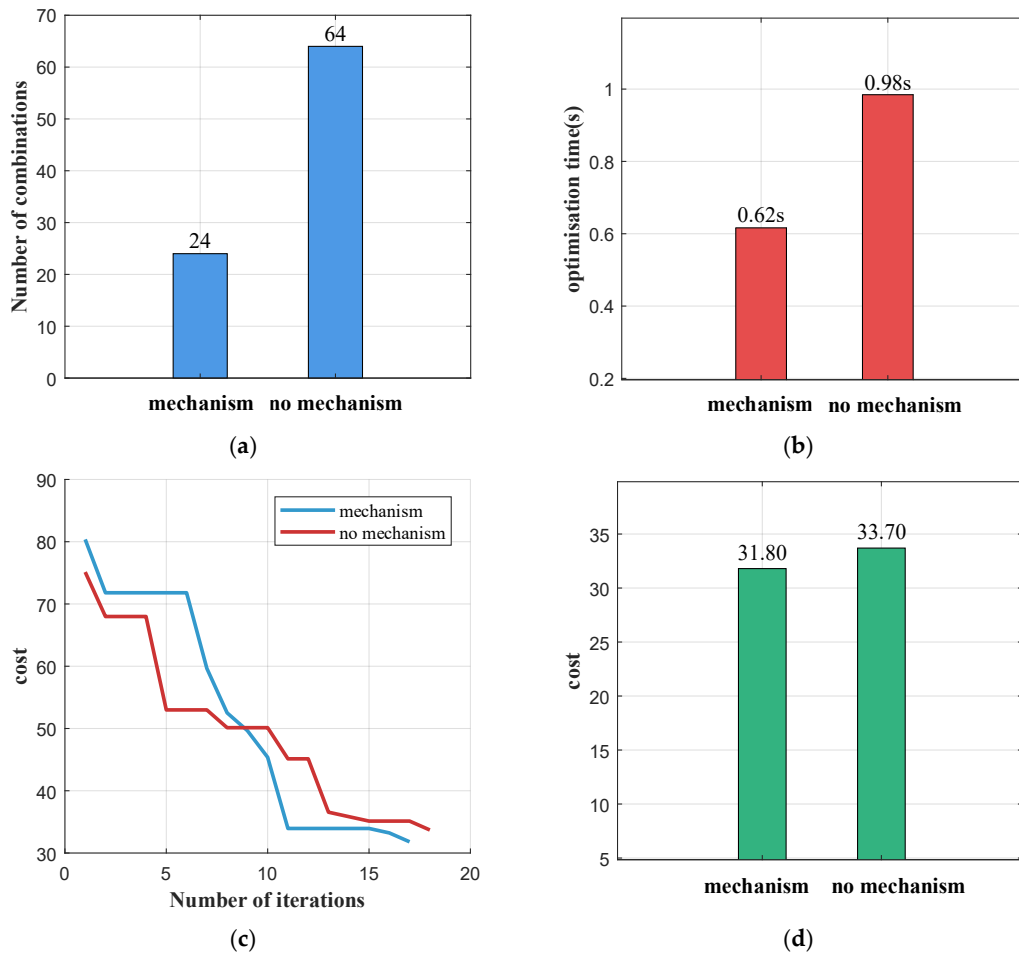


Figure 11. Comparison results. (a) Comparison of the number of filter combinations. (b) Comparison of optimisation times. (c) Comparison of convergence curves. (d) Comparison of optimal costs.

In summary, the improved genetic algorithm based on the coverage ratio screening mechanism is capable of effectively addressing the problem of optimising mixed-FOV coverage. By precisely identifying the optimal search region, this mechanism avoids the waste of computational resources associated with blind traversal, thereby achieving dual optimisation of both the cost of interceptor seeker configuration and solution efficiency, while ensuring 100% coverage.

3.4. Simulation of Coverage-Optimised Scalability

To further verify the robustness of the proposed improved genetic algorithm (IGA) and the coverage ratio screening mechanism when addressing multi-scale problems in the target HPR, four sets of scale-up simulations were designed. The error data corresponding to the four prediction durations of 75 s, 100 s, 125 s and 150 s in Table 3 were selected as parameters for the target HPR, with the major and minor semi-axes denoted as $(a_1 = 2.25\text{km}, b_1 = 3.53\text{km})$, $(a_2 = 2.99\text{km}, b_2 = 4.69\text{km})$, $(a_3 = 3.73\text{km}, b_3 = 5.85\text{km})$ and $(a_4 = 4.17\text{km}, b_4 = 6.61\text{km})$ respectively, and the area of HPR ranging from 24.95km^2 to 98.44km^2 . The seeker types were expanded to 5, with 3 seekers of each type; the detection range was set to $R_{\max,1} = 58\text{km}, R_{\max,2} = 67\text{km}, R_{\max,3} = 38\text{km}, R_{\max,4} = 32\text{km}, R_{\max,5} = 26\text{km}$, the seeker half-FOV angle to $\phi_1 = 3^\circ, \phi_2 = 3^\circ, \phi_3 = 4^\circ, \phi_4 = 4^\circ, \phi_5 = 4^\circ$, the FOV radius for each seeker type to $R_{\text{fov},1} = 3.5\text{km}, R_{\text{fov},2} = 3.0\text{km}, R_{\text{fov},3} = 2.7\text{km}, R_{\text{fov},4} = 2.2\text{km}, R_{\text{fov},5} = 1.8\text{km}$, and the corresponding cost to $C_1 = 11.4, C_2 = 9.5, C_3 = 8.3, C_4 = 6.4, C_5 = 5.9$ (dimensionless).

units). The coverage ratio screening interval was set to $[1.9, 2.9]$, the coverage constraint to $\eta = 1$, and the upper limit on the number of seekers to 5. The simulation results are as follows.

Figure 12 illustrates the optimal coverage layouts for the four specifications. The experimental results show that all four sets of experiments successfully achieved the requirement of 100% coverage. As the prediction duration increases, the cumulative uncertainty of the target's motion causes the HPR spatial range to expand gradually, and the corresponding interceptor configuration becomes more complex: when the HPR1 range is reached, the optimal cost is 15.90, and full coverage can be achieved with just two seekers; when the HPR2 range is reached, the optimal cost increases to 22.80, and the number of seekers rises to three; upon reaching the HPR3 range, the optimal cost is 35.60, requiring the deployment of four seekers; upon reaching the HPR4 range, the optimal cost reaches 48.90, utilising the maximum limit of five seekers. This trend demonstrates that the algorithm is capable of automatically adjusting the combination of interceptor types and their spatial distribution in response to dynamic changes in target uncertainty, reflecting its ability to search for the global optimal solution within a complex solution space.

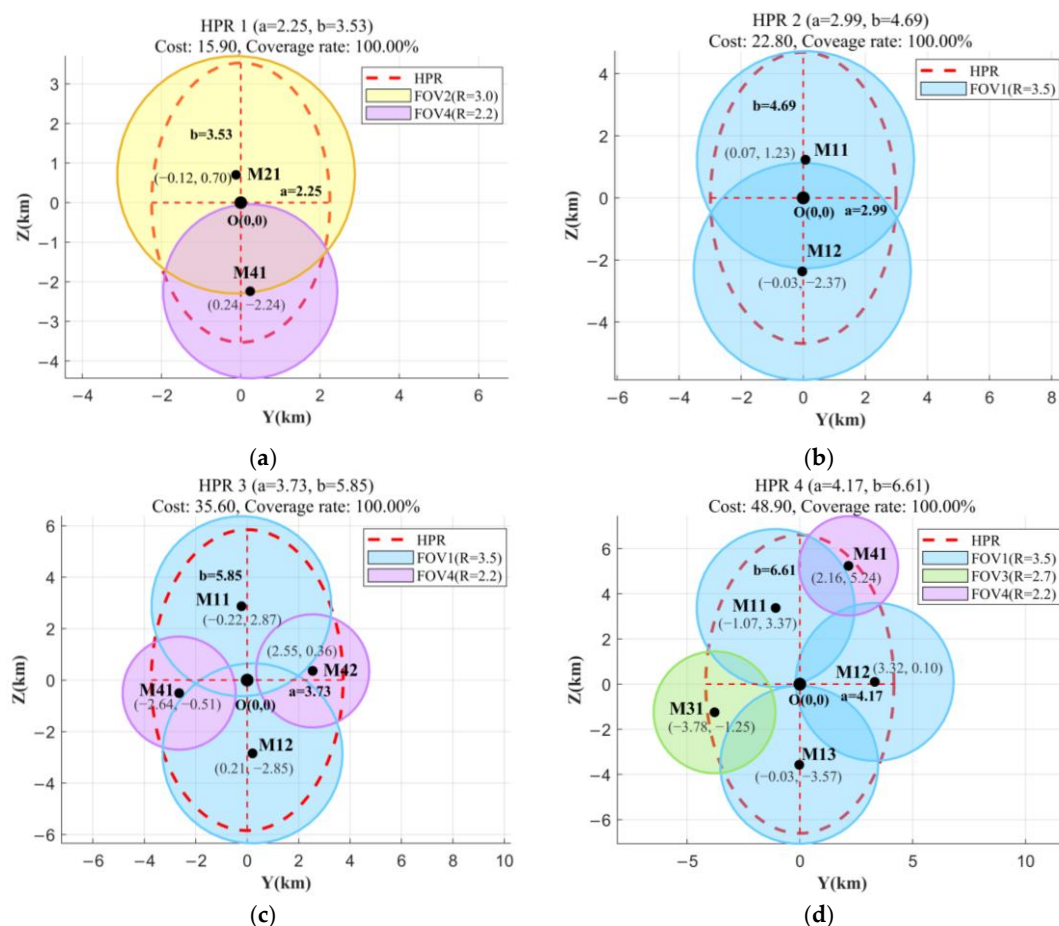


Figure 12. Comparison results. (a) FOV coverage layout of HPR1. (b) FOV coverage layout of HPR2. (c) FOV coverage layout of HPR3. (d) FOV coverage layout of HPR4.

Figure 13 illustrates the performance characteristics of the algorithm from a statistical perspective. First, the optimisation time is closely related to computational complexity. The number of candidate combinations for HPR1 to HPR4 was 54, 155, 105 and 44 respectively, with corresponding optimisation times of 3.30 s, 9.44 s, 4.58 s and 1.59 s. Notably the number of candidate combinations does not increase monotonically with HPR area,

but rather begins to decline after peaking at HPR2. This is because, under the constraint that ‘the total number of seekers is less than or equal to 5’, when the HPR scale exceeds a certain threshold (such as HPR3 and HPR4), a large number of combinations involving small-radius seekers are eliminated early on because their total area cannot meet the lower limit of the area ratio (1.9 times). Although this screening mechanism limits the richness of the solution space for large-scale targets, it effectively prevents the proliferation of invalid computations. Second, the variation in the number of feasible solutions reflects the difficulty of the location optimisation. For the smaller HPR1 and HPR2, the number of candidate combinations closely matches the number of feasible solutions (e.g., 54 vs. 47 for HPR1), demonstrating that the area ratio screening mechanism possesses good generalisation. However, for the large-scale HPR4, although there were 44 candidate combinations, only 10 ultimately yielded feasible solutions that met the 100% coverage requirement. This is primarily because edge coverage of the large elliptical region demands extremely high precision in the seeker centre position; within a limited number of iterations, the algorithm struggles to perform fine-grained positional optimisation for all theoretically feasible combinations. Finally, the fitted curve showing how cost varies with the target HPR area reveals a good linear relationship between the two. This indicates that, under constant seeker parameter conditions, the algorithm maintains a high degree of stability and consistency across different scales, and its output cost metrics provide important reference value for selecting prediction durations in practical engineering applications. The convergence curves further confirm that, despite the influence of variations in target scale, all key metrics converge rapidly within the set limit of 20 iterations, validating the algorithm’s rapid response capability under conditions of scale expansion.

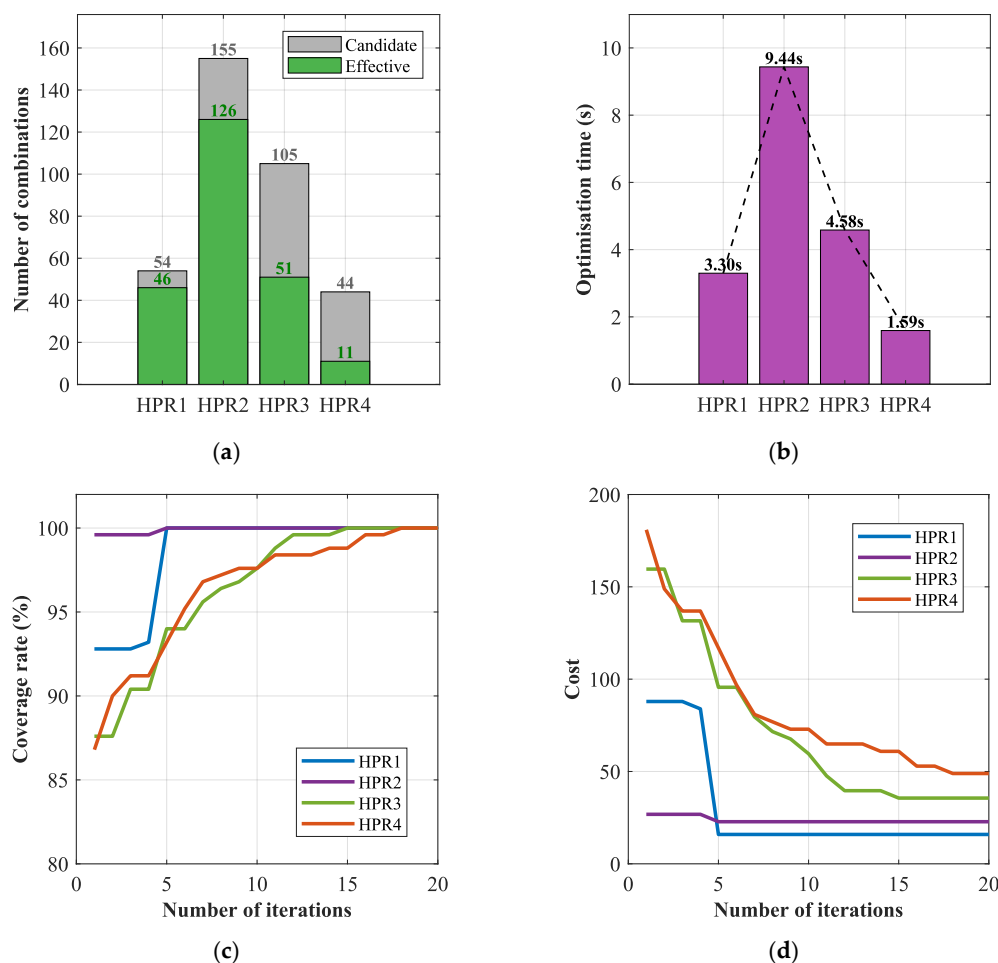


Figure 13. Comparison results. (a) Comparison of the number of candidates and effective solutions. (b) Comparison of optimisation times. (c) Coverage rate convergence curve. (d) Optimal cost convergence curve.

Notably the optimisation time is closely related to the number of seeker types. When the number of seeker types is no more than 3, the optimisation can be completed within 0.62 s, which meets the sub-second requirement. In practice, the prediction end typically sends target tracking and prediction results to the interceptors with a 2 s period, so the optimisation time for computing coverage points and handover guidance positions should be less than 2 s. The scale-up experiment reveals that when the number of seeker types exceeds 3, the retained candidate combinations increase substantially and the computation time grows beyond the available prediction time window. Under such conditions, the mid-course guidance would be unable to update the guidance positions in time, preventing the interceptors from reaching the handover positions and significantly reducing the target detection and acquisition success rate. This finding suggests that, for the proposed cooperative coverage framework, the number of interceptor types should be limited to no more than 3 to ensure timely computation within the handover timing constraint.

In summary, the scale-up simulation not only validates the effectiveness of the IGA and the coverage ratio screening mechanism in addressing the multi-scale HPR coverage optimisation problem, but also demonstrates that, under resource-constrained conditions, the algorithm strikes a balance between solution quality and computational efficiency through intelligent screening and local search.

3.5. Simulation of Optimised Algorithm Comparisons

To evaluate the performance of the improved genetic algorithm (IGA) proposed in this paper for the seeker coverage optimisation problem, this section selects the standard genetic algorithm (SGA), adaptive particle swarm optimisation (APSO), grey wolf optimisation (GWO) and adaptive differential evolution (JADE) as comparison methods. The experiments were conducted on four mixed-FOV detection areas (HPR1–HPR4) of varying scales in a scale-up simulation. Each algorithm was run independently 100 times for each specification, with other parameters remaining the same as in the previous section. The simulation results are shown below:

Figure 14 shows the box-and-whisker plots of cost distributions for the five algorithms across 100 independent runs. The figure illustrates that the stability of the algorithms exhibits a certain correlation with the target scale. In the HPR1 scenario, which has the smallest scale, the solution space is relatively simple, and all five algorithms were able to explore the theoretical minimum cost; at this point, the box span of the IGA was slightly larger, and its advantage was not particularly evident. However, as the problem size increases, the box ranges of the IGA and SGA algorithms gradually narrow, and their median costs outperform those of the other comparison algorithms, indicating that GA-based algorithms possess certain advantages when handling mixed discrete-continuous variables. Notably in the HPR4 scenario, APSO failed to produce a valid box plot, indicating that it was unable to find a feasible solution satisfying the full coverage constraint within a finite number of iterations. In contrast, the IGA maintained stable output quality across all four scale scenarios, demonstrating strong robustness.

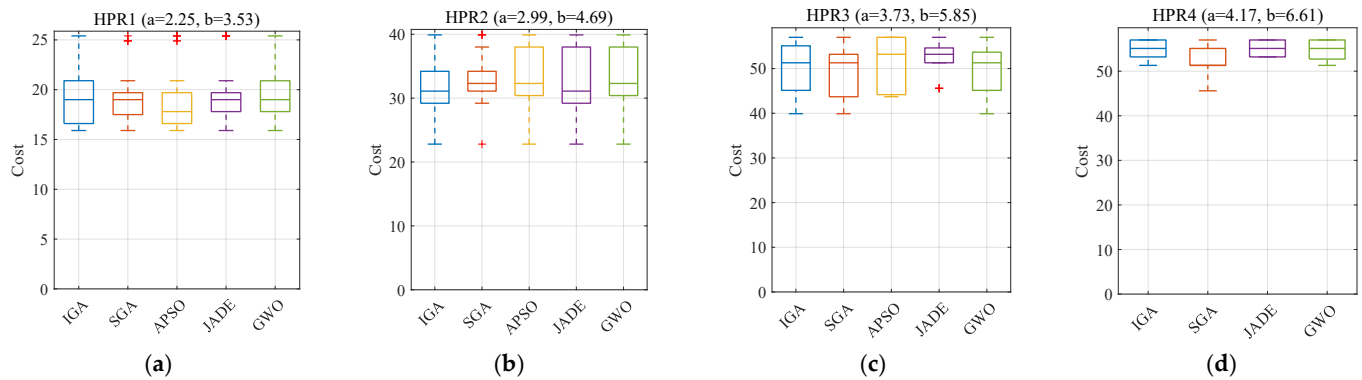


Figure 14. Cost distribution in algorithm comparison. (a) Cost distribution of algorithms for HPR1. (b) Cost distribution of algorithms for HPR2. (c) Cost distribution of algorithms for HPR3. (d) Cost distribution of algorithms for HPR4.

Figure 15a compares the convergence processes of the various algorithms using HPR2 as an example. The IGA exhibited a strong downward trend from the early stages of evolution, rapidly entering a stable phase around the third generation, and ultimately converging to a global optimal cost of 22.8; the advantages of the IGA are evident. This difference is primarily attributed to the ‘area ratio pre-screening mechanism’ and the ‘bi-directional local search strategy’ introduced by the IGA. The former effectively eliminates a large number of invalid spatial layouts, while the latter performs fine-tuning of the seeker centre coordinates in the later stages of evolution, thereby achieving stronger global exploration capabilities than other algorithms. The comparison of optimisation success rates in Figure 15b further reveals the engineering applicability limits of the IGA. In the HPR1 task, the success rate of the IGA was lower than that of other algorithms, which may be partly related to the random nature of the algorithm’s solution process. However, in the HPR2 to HPR4 scenarios, the success rate of the IGA consistently ranked among the highest. Notably in the HPR4 scenario, where the APSO algorithm failed completely, the IGA still maintained a high success rate in optimisation, validating the effectiveness of cooperative mechanisms in maintaining population diversity and preventing premature convergence. In terms of computational efficiency, as shown in Figure 15c, the average execution time for the IGA is relatively long; this increase in time is primarily due to the frequent re-evaluation of individual fitness by the local search module. However, given the significant benefits of the IGA in ensuring 100% coverage and reducing the system’s total cost, this strategy of trading computational time for solution quality holds greater value in practical target detection and capture mission planning within offline planning and interceptor guidance flight scenarios.

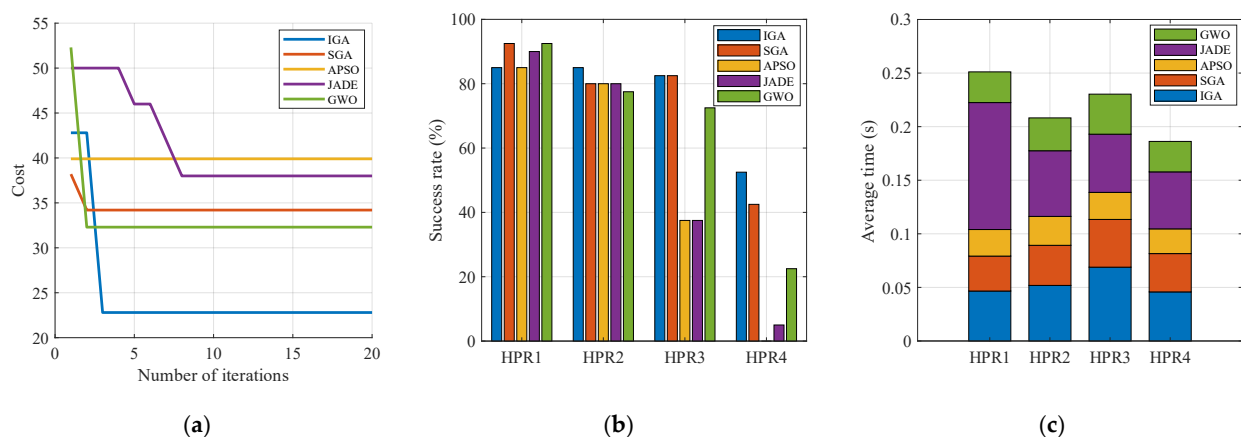


Figure 15. Comparison of other indicators. (a) Comparison of convergence curves. (b) Comparison of success rates in optimisation. (c) Comparison of solution efficiency.

4. Discussion

This paper extends previous work on HPRs for homogeneous seekers. CDUAV detection and acquisition is increasingly challenging: tracking accuracy drops significantly compared to conventional targets, often yielding only a probability region, making it difficult for interceptors to reliably acquire such targets. Previous HPR modelling largely relies on Monte Carlo simulations for statistical error analysis. Although this method offers high versatility, its high computational demands and time-consuming nature severely hinder rapid target localisation and identification. To address this, this paper employs a parametric modelling approach to enhance efficiency. However, this parametric description primarily reflects the propagation and amplification effects of inherent errors under predefined manoeuvre patterns. If the target executes an unforeseen evasive manoeuvre within the predicted interval, the original kinematic fitting model will fail, resulting in the HPR being unable to accurately envelop the target's actual position. In such cases, it is necessary to re-execute target motion tracking and recognition and establish a new fitting model; this constitutes the primary limitation of current HPR construction methods.

Regarding seeker configuration, the traditional approach tends to focus on enhancing the performance of individual seekers so that their FOV is sufficient to cover the entire target HPR. Although this method simplifies coverage logic, given the declining cost of CDUAVs, using expensive, high-performance interceptors to detect and engage low-cost targets is not consistent with a defence strategy that optimises cost-effectiveness. To this end, this paper focuses on achieving equivalent coverage through mixed configurations utilising low-performance seekers. In particular, given the trend towards deploying multi-interceptor systems, balancing the differences in detection capabilities between heterogeneous seekers against the total system cost represents a core challenge in achieving large-scale deployment.

The coverage optimisation model in this paper adopts a deterministic detection assumption, i.e., a target within a seeker's FOV can be successfully detected, without considering factors such as detection probability, false alarms, and sensor performance limitations. On the one hand, for infrared seekers, during the mid-terminal guidance handover, the distance between the target and the interceptor is typically on the order of tens of kilometres, at which point the target signal-to-noise ratio on the infrared focal plane is relatively high, and the detection probability can generally exceed 0.9; meanwhile, the requirement for 100% geometric coverage of the HPR boundary is itself a conservative hard constraint, and even with some detection probability loss, full geometric coverage still provides a fundamental guarantee for reliable detection. Moreover, the optimised FOV positions determined through coverage optimisation can be further used to derive the interceptor positions during the handover; under cooperative conditions, as long as the target appears within any seeker's FOV, target information can be shared to guide other interceptors for swarm acquisition, and therefore the deterministic coverage constraint provides a geometric foundation for this cooperative mechanism. On the other hand, false alarms and sensor limitations do affect actual detection performance. False alarms may cause the seeker to incorrectly lock onto non-target signals, increasing the time cost of target identification; the minimum detectable power and response time of the sensor limit detection capability under low signal-to-noise ratio conditions. A possible approach to incorporating these factors is to replace the deterministic coverage constraint with a probabilistic one, requiring the cumulative detection probability at each point within the HPR to exceed a given threshold, which involves quantitative modelling of seeker detection probability with respect to distance, signal-to-noise ratio, and other pa-

rameters. This aspect has not been addressed in this paper and will be progressively refined in future work.

The seeker FOV coverage in this paper involves a Boolean binary model, which is a simplification of the actual detection process. A probabilistic detection model accounting for spatially varying SNR and non-uniform detection probability would be more physically rigorous. The geometric model, however, provides a sufficient condition for detection: if the HPR at the 99.7% confidence level is fully covered by the mixed FOV, and the detection probability within the FOV interior is close to unity, then the overall target acquisition probability is at least 0.997. The binary constraint thus gives a lower-bound guarantee on detection probability rather than replacing the probabilistic detection model. Moreover, this paper focuses on exploring the cooperative coverage optimisation framework for mid-terminal handover, and the seeker detection model is simplified to keep the coverage optimisation tractable. It should be noted that coverage optimisation takes place at a planning stage before the interceptors reach the handover positions; introducing a detection probability model at this stage adds complexity without a corresponding gain in decision reliability. The binary model provides a tractable alternative with a clear probabilistic interpretation, and the probabilistic detection model will be pursued in future work.

To further illustrate the advantages of the proposed method relative to existing approaches, a comparative analysis is conducted at two levels: HPR modelling and coverage optimisation.

Existing HPR modelling methods primarily include spherical assumption methods and rectangular parametric methods. Spherical assumption methods treat prediction errors as isotropically distributed, unable to describe the directional differences in target errors, and if the sphere radius is determined by the maximum error standard deviation, the HPR volume will be severely overestimated. Taking the results at the 150 s prediction horizon in Table 2 as an example, the position error standard deviations in the three directions are 3.8845 km (radial), 4.1732 km (lateral), and 6.6074 km (normal), respectively; if the spherical assumption is adopted with the maximum value of 6.6074 km as the radius, the spherical HPR volume is approximately 1208.7 km³, while the ellipsoidal HPR volume is approximately 449.1 km³, representing an overestimation of approximately 169%, requiring additional seeker resources to cover a non-existent uncertainty region. Although rectangular parametric methods can distinguish error magnitudes in different directions, their main drawback is the lack of consideration for the target's probability distribution—a rectangle cannot describe the probability distribution and range within the target's 3 σ confidence region, and the rectangular boundary does not match the iso-probability contour of the actual error distribution, making it prone to coverage gaps at the boundaries and leading to target acquisition failure.

Existing geometric coverage methods mainly rely on the geometric shapes of HPRs and FOVs for analytical solutions; however, this approach has significant limitations: in the two-dimensional coverage space, when the geometric shapes of HPRs and FOVs do not match (e.g., a circular FOV covering an elliptical HPR), traditional geometric analytical methods cannot solve the problem; in particular, when FOV sizes differ, i.e., in heterogeneous seeker cooperative coverage scenarios, traditional methods are even less capable of handling the situation. The proposed method employs an optimisation approach with maximum coverage rate as the objective for rapid solution, offering stronger generalisation capability that can accommodate both homogeneous and heterogeneous seeker FOVs in covering HPRs under geometric mismatch conditions. Section 3.5 has already provided a comprehensive comparison between the IGA and four optimisation algorithms (SGA, APSO, JADE, GWO); across 100 independent runs, the IGA achieved the lowest average

cost and highest success rate for all HPR specifications, verifying the superior performance of the IGA in solving this MINLP problem.

It should be noted that in the quantification of target trajectory prediction uncertainty, Monte Carlo simulation is the most widely used method in current engineering practice, obtaining statistically convergent error distributions through large-scale trajectory sampling with high accuracy but significant computational cost. The proposed parametric method addresses the excessive computational time of Monte Carlo methods, achieving rapid uncertainty propagation while maintaining comparable accuracy. Moreover, the probabilistic modelling in this paper serves as a prerequisite for coverage optimisation rather than an independent research topic; therefore, the comparison is primarily conducted against the Monte Carlo method for validation. In future work, the prediction-segment probabilistic modelling problem will be compared with other uncertainty propagation methods in a dedicated and comprehensive study.

Although this paper has made some progress, the following areas require further refinement due to limitations in modelling assumptions and experimental conditions: First, the current model does not yet fully account for interference from complex electromagnetic environments or the non-uniform distribution of seeker detection probabilities, and the impact of FOV geometric distortion on coverage performance requires further quantification. Second, the relative motion between seekers and targets during the detection and capture phase is relatively complex, and the parallel approach assumption adopted in this paper has certain limitations. Finally, although the improved algorithm performs well in terms of stability and global optimisation, there is still considerable room for improvement in computational efficiency. Furthermore, as CDUAVs are non-cooperative targets, the availability of measured trajectory samples is extremely limited due to data security constraints. To address the challenges of trajectory prediction and HPR probability modelling under small-sample conditions, this paper conducts a systematic study based on a numerical simulation platform. The key parameters in the simulation environment are primarily derived from the data framework of CAV-H class re-entry gliders to ensure the physical consistency of the dynamic model. Although the simulation results cannot fully replicate the complex and variable nature of the actual flight environment, the simulated scenarios constructed in this paper have been designed to approximate real-world constraints as closely as possible. We are fully aware of the limitations arising from the lack of measured data and will endeavour, in future research, to incorporate more diverse data sources to facilitate continuous iteration and empirical validation of the existing model.

Furthermore, the dynamic model in this paper is based on the stationary spherical Earth assumption, without considering the effects of environmental disturbances. In actual flight environments, wind field disturbances and atmospheric density deviations are two primary environmental factors affecting trajectory prediction accuracy. Wind field disturbances mainly affect the horizontal motion components of CDUAVs, while atmospheric density deviations influence the rates of change of velocity and track angle by altering the aerodynamic forces. For the hypersonic flight state of CDUAVs, the impact of atmospheric density deviations is relatively minor, but wind field disturbances may have non-negligible effects at lower altitudes. A feasible approach to incorporating environmental disturbances into the uncertainty propagation framework is to model wind fields and atmospheric density as additional stochastic processes and superimpose their covariance onto the parameter fitting covariance P_a , thereby reflecting environmental uncertainty in HPR construction. This will be pursued in future work.

The current trajectory prediction model assumes that the target maintains its established manoeuvre pattern over the prediction horizon. In practical combat scenarios, however, the target may execute evasive manoeuvres in response to interceptor approach,

which the current model cannot anticipate. If such a manoeuvre change occurs, the fitted model will fail, and it will be necessary to re-execute target motion tracking and model identification. These problems will be pursued in future work.

Looking ahead, this research will extend from the optimisation of seeker coverage layouts to the control of dynamic interceptor formations, with a focus on investigating the integrated detection and capture of interceptors within formations under coverage conditions.

5. Conclusions

This paper addresses the challenge of target acquisition for CDUAVs caused by prediction uncertainty by proposing an optimisation method for cooperative coverage using a combination of multi-seeker mixed FOVs based on probabilistic target modelling. By constructing a geometric model of the target state confidence region, the complex spatial target acquisition problem is transformed into a two-dimensional coverage optimisation problem for the target cross-section using a combination of multi-type seeker mixed FOVs. An improved genetic algorithm is then employed to determine the optimal seeker configuration and coverage points. Simulation experiments have validated the effectiveness and robustness of the proposed method. The main conclusions are as follows.

First, a probabilistic model for target prediction uncertainty based on ellipsoidal distribution was established, enabling an accurate description of the target's spatial state. Addressing the conservativeness and asymmetry issues of traditional spherical models when describing long-term prediction errors, this paper constructs an ellipsoidal confidence region model that is dependent on the prediction duration. This model is capable of more accurately quantifying the spatial distribution characteristics of high-speed manoeuvring targets across different time scales, providing a more physically meaningful mathematical foundation for target detection and tracking.

Then, a two-dimensional optimisation framework for mixed FOV cooperative coverage is proposed. Based on the radial geometric characteristics of the seeker FOV, this paper simplifies the three-dimensional spatial coverage problem into a geometric coverage optimisation problem on the two-dimensional detection cross-section of the seeker FOV. On this basis, taking into account the coverage conditions and cost constraints of multiple seeker types, a mixed-integer nonlinear programming model is established with the objective of minimising total cost. This method effectively addresses the limitations of traditional single-FOV models when dealing with heterogeneous seeker cooperation, and provides a new solution pathway for coverage optimisation involving mixed discrete-continuous variables.

Finally, an improved genetic algorithm based on an area ratio screening mechanism was designed, achieving dual improvements in computational efficiency and optimisation accuracy. By introducing two-dimensional close-packing theory and combining it with multi-criteria evaluation, the optimal screening range for the coverage area ratio was determined to be 1.9–2.9. Experiments demonstrate that this mechanism effectively eliminates invalid solution spaces, reducing redundant computations by 62.5% and shortening the optimisation time by 36.7%. In comparisons with various mainstream swarm intelligence algorithms, the algorithm proposed in this paper exhibits outstanding success rates and stability in finding optimal solutions, proving its excellent performance in addressing complex constraint coverage problems.

Although the proposed method has demonstrated satisfactory performance under the conditions considered, several limitations remain. First, the parametric probabilistic modelling relies on prior assumptions about the target's manoeuvre pattern, and the fitting model will fail if the target executes an unforeseen evasive manoeuvre. Second, the coverage optimisation adopts a deterministic detection assumption without considering

detection probability, false alarms, and sensor performance limitations. Third, the dynamic model is based on the stationary spherical Earth assumption without incorporating environmental disturbances. Fourth, when the number of heterogeneous seekers becomes excessive, the combination scale grows rapidly and the optimisation time may exceed the time constraint of the guidance handover. To address these limitations, future work will focus on incorporating environmental disturbances and detection uncertainty into the probabilistic modelling framework; developing probabilistic coverage constraints to replace the deterministic ones; and investigating online coverage optimisation methods for dynamic scenarios to improve computational efficiency.

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Abbreviations

The following abbreviations are used in this manuscript:

CDUAV	Cross-domain unmanned aerial vehicles
HPR	High-probability region
FOV	Field of view
IGA	Improved genetic algorithm
EKF	Extended Kalman filter
UKF	Unscented Kalman filter
PK	Particle filter
LSTM	Long short-term memory
ARIMA	Autoregressive integrated moving average model
WSN	Wireless seeker networks
VTC	Velocity–turn–climb
ENU	East–north–up
ZEM	Zero-effort miss
MINLP	Mixed-integer non-linear program
SGA	Standard genetic algorithm
APSO	Adaptive particle swarm optimisation
GWO	Grey wolf optimisation
JADE	Adaptive differential evolution

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