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RAILWAY MULTI UAV COLLABORATIVE ENCIRCLEMENT STRATEGY BASED ON GREY WOLF OPTIMIZATION DYNAMIC ENCIRCLEMENT POINTS

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Abstract. To address the threat of invading drones along railway lines, this paper proposes a multi-UAV cooperative capture strategy based on the Grey Wolf Optimizer (GWO) algorithm and dynamic capture points. Firstly, a motion model in three-dimensional space is established according to the movement characteristics of invading drones along railway lines. Secondly, three-dimensional capture points are dynamically generated based on the movement direction of invading drones, and a negotiation allocation mechanism is designed to achieve optimal matching between capture points and UAVs. Then, an objective function combining path consumption and encirclement effect is constructed, and the GWO algorithm is used to optimize the UAV heading angle increment in real-time. Finally, the effectiveness of the algorithm is verified through three-dimensional simulations. The simulations show that this strategy can achieve efficient capture in three-dimensional environments. Compared with strategies without GWO optimization, the average capture time is reduced by 55.5%, and the capture success rate is improved by 4.8%. Furthermore, in comparison with other mainstream optimization algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Differential Evolution (DE), our approach yields superior performance in both the average number of capture steps (55.7 steps) and success rate (100%), providing an efficient and reliable technical solution for railway airspace security protection.

Keywords: multi-UAV cooperation, railway safety, dynamic capture point, Grey Wolf optimization, three-dimensional capture.

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1. Introduction

With the popularization and cost reduction of drone technology, airspace security along railway lines is facing unprecedented challenges. Drones, characterized by high mobility, low detectability, and ease of operation, have emerged as significant threats to railway transportation safety (Askarzadeh et al., 2023; Unger et al., 2023) Meanwhile, with the advancement of low-altitude airspace opening policies, the number of low-altitude targets such as drones and light aircraft has increased dramatically. The frequent occurrence of illegal drone crossings along railway lines in countries worldwide has brought unprecedented threats to railway safety (as shown in Table 1).

These incidents have highlighted the urgency of railway airspace defense – traditional security systems are ill-equipped to handle the low, slow, and small characteristics of low-altitude, slow-moving, small unmanned aerial vehicles (UAVs), making the development of more intelligent and flexible active interception technologies imperative (Askarzadeh et al., 2024).

As a long-distance linear area with complex and variable terrain, railways are more vulnerable to illegal drone flights. Although existing drone countermeasure technologies can play a certain role in enclosed areas, their detection and countermeasure capabilities are still insufficient in dealing with the special scenario of railway lines (Conte et al., 2023; Rugo et al., 2022). Traditional air defense methods face notable limitations in railway scenarios: radio interference can cause spectrum conflicts with railway communication systems, disrupting dispatch instructions; laser interception equipment is costly and limited by lighting conditions and range in complex terrains (such as mountainous areas and tunnel groups); manual eviction takes 15 to 30 minutes to respond, far lagging behind the rapid maneuverability of drones. In contrast, multi-drone cooperative capture technology can achieve full process automation of detection-tracking-encirclement-eviction of intruding targets through distributed intelligent agent collaboration. Its core advantages are threefold: (1) Rapid response – the process from target recognition to formation deployment takes only 3 to 5 minutes, representing

Table 1. Global drone incursions along railway lines

Country	Incident Type	Immediate Consequences	Causes
China	2025 Jiangsu Gao You incident: Agricultural drone lost control and entered railway corridor.	High-speed train emergency braking, constituting an accident.	Insufficient electromagnetic interference protection design, lack of operational guidelines.
Russia	2024 Ukraine drone attack on freight railway.	Nine carriages derailed, fuel tank explosion.	Weak low-altitude defense system, lack of early warning mechanisms.
Germany	2024 Erfurt drone collision with high-speed rail.	Nine carriages derailed, fuel tank explosion.	Child operator error or intentional interference.
UK	2017 Essex unauthorized flight into railway corridor.	Administrative penalty, no direct disaster.	Operators lacked awareness of no-fly zones.

an 80% improvement over manual methods; (2) High adaptability – the system can dynamically adjust capture strategies in complex railway terrains such as bridges, culverts, and mountainous areas; and (3) Cost-effectiveness – the deployment cost of a single small-to-medium-sized capture drone is about 1/20th that of laser equipment, and the drones are reusable. This technology not only addresses the shortcomings of traditional defense methods but also, through flexible interception, minimizes collateral damage to railway facilities and the surrounding environment, establishing itself as a core research direction for ensuring railway airspace safety.

Research on multi-robot pursuit-evasion problems began in the 1990s, and with the penetration of UAV technology in security fields, it has gradually developed into a core direction of distributed intelligent agent cooperative interception of low-altitude slow-moving targets. Current research mainly advances along three dimensions: environment modeling (Yan et al., 2023; Zhao et al., 2024; Basit et al., 2015; Cao et al., 2023) decision-making mechanisms (Ziyi et al., 2025; Yang et al., 2025; Chen et al., 2025; Xu et al., 2023; Hu et al., 2025), and optimization algorithms (Hafez et al., 2015; Liu et al., 2024; Zhu et al., 2023; Muslimov, 2023; Shin & Bang, 2020; Yu et al., 2023). However, dynamic capture in complex three-dimensional railway scenarios still faces significant bottlenecks.

Early research focused on two-dimensional (2D) planar environments. For example, Yan et al. (2023) studied a multi-agent pursuit-evasion game between two adversarial teams in 2D space, establishing a planar motion differential game model. They combined qualitative and quantitative analysis methods of small-scale games and optimal task allocation to achieve multi-agent pursuit in 2D planes. Furthermore, Zhao et al. (2024) constructed a non-cooperative differential game model, transforming terminal performance indicators into integral indicators and using iterative methods to determine covariates, from which optimal pursuit strategies were derived. Although these methods achieve static target encirclement in simulations, they do not consider real-world challenges such as three-dimensional (3D) terrain constraints (e.g., bridges, tunnels, and mountainous terrain along railways), electromagnetic interference from catenary wires, and blind spots in multi-target cooperative vision. In recent years, research on 3D environments has gradually increased: Basit et al. (2015) used a monocular camera and a quadrotor tracker for any target in a 3D coordinate system for joint localization, building a spatial kinematics model including pitch and heading angle control. A series of experiments using real quadrotors to track evaders were conducted, verifying the dynamic feasibility of multi-UAV 3D pursuit-evasion. Cao et al. (2023) studied multi-UAV formation capture in 3D environments, proposing an omnidirectional minimum volume 3D Voronoi diagram algorithm. By constraining capture angles, effective target capture was achieved, while introducing a wolf pack algorithm with variable step sizes to enable multi-UAV formations to capture dynamic targets in obstacle-filled environments. However, existing models have not effectively incorporated the complex electromagnetic environment along railway lines or the altitude and distance constraints of no-fly zones, resulting in the poor adaptability of 3D encirclement strategies in real-world railway scenarios.

At the level of encirclement decision-making, existing methods face dual challenges of balancing path efficiency and encirclement quality, as well as computational delays that constrain response speed. Ziyi et al. (2025) proposed a countermeasure method of using multiple drones to track and capture invading drones. The trajectory of the target drone was predicted using Bezier curves, and the shortest path from each drone to the target point and the required angle coverage to form a closed encirclement were quantified. However, traditional gradient optimization methods are prone to getting stuck in local optima when solving such non convex, multi constrained objectives, and require multiple iterations to balance energy consumption and interception success rate, which cannot meet the rapid replanning needs of invading drones during sudden maneuvers. Although reinforcement learning algorithms (Yang et al., 2025; Chen et al., 2025) partially alleviate real-time performance issues through real-time optimization, their high computational complexity leads to the problem of dimensionality explosion. When the railway scene targets rapidly change direction, communication interruption, or electromagnetic interference causes state estimation errors, decision stability significantly decreases. Although distributed auction mechanisms or hierarchical negotiation algorithms can improve local collaboration efficiency, the cost of maintaining global consistency is high, making it difficult to adapt to dynamic task priority switching in scenarios with multiple threats and concurrent threats in narrow railway lines and airspace (Xu et al., 2023; Hu et al., 2025).

Path planning and control parameter optimization are the core of achieving efficient collaboration (Hafez et al., 2015), but traditional numerical methods have fundamental limitations: gradient based SQP (Liu et al., 2024) and interior point method (Zhu et al., 2023) are prone to converge to local minimum traps when dealing with nonlinear constraints on the three-dimensional attitude angle (heading angle, pitch angle, roll angle) of unmanned aerial vehicles, and the computational complexity increases exponentially with the number of robots, making it difficult to meet the real-time online optimization requirements of multi machine clusters. Heuristic algorithms originate from their ability to guide search direction through heuristic functions, which can significantly improve search efficiency and balance optimality and computational cost, and are widely used in path planning (Kiani et al., 2021, 2022; Anka, 2025a). Intelligent biomimetic algorithms (such as PSO (Muslimov, 2023; Shin & Bang, 2020), GWO (Yu et al., 2023; Dewangan et al., 2019), sand cat swarm optimization (Anka & Aghayev, 2025; Kiani et al., 2023), artificial rabbits optimization (Anka et al., 2024), chimp optimization (Anka, 2025b)) have gradually become mainstream alternatives due to their advantages in global exploration and parallel search. The Grey Wolf Optimization Algorithm (GWO) demonstrates better ability to escape local optima and adapt to dynamic environments in continuous space optimization by simulating the cooperative mechanism of wolf pack social hierarchy (Kiani et al., 2021). Further research has shown that GWO can adaptively adjust the balance path length, obstacle avoidance penalty, and enclosure accuracy through weight in multi-objective fusion optimization. For example, improving GWO combined with chaotic mapping or adaptive inertia weight strategy can enhance the robustness of complex mountain 3D path planning (Yu et al., 2023). However, the current dynamic encirclement in railway scenarios still lacks a systematic solution that couples the efficient convergence characteristics of GWO with the deep constraints of railway airspace.

The special characteristics of intrusion prevention for railway drones (narrow linear areas, complex electromagnetic interference, dynamic avoidance of multiple obstacles, and sudden target movements) pose higher requirements for the capture strategy: 1. Environmental adaptability: real-time generation of three-dimensional dynamic capture points that meet railway height limits, electromagnetic compatibility, and obstacle avoidance requirements. Traditional two-dimensional or unconstrained three-dimensional models are difficult to directly migrate; 2. Real time decision-making power: The target may quickly dive along the railway line, maneuver in a snake shape, or use tunnels to cover and escape; Multi machine collaboration needs to ensure the effectiveness of encirclement even in scenarios where communication is unstable and local states are inaccurate. Traditional gradient methods are prone to falling into suboptimal positions due to initial solution deviations (Yu et al., 2021; Zhang et al., 2023; Adhikari et al., 2024). The dynamic capture point strategy can dynamically generate a three-dimensional network of surrounding nodes based on the target location, effectively addressing the limitations of environmental modeling (Joe & Oh, 2018; Kim et al., 2019). GWO algorithm, with its biomimetic leadership mechanism, quickly converges to a global near optimal solution, nonlinear spatial adaptability, and potential for distributed parallel computing, significantly improves real-time optimization efficiency under multi-objective trade-offs. The fusion of the two can effectively break through the existing bottleneck of railway 3D encirclement: railway scene customization: embedding constraints such as contact network safety distance, tunnel group height limit, and avoidance into dynamic encirclement point generation rules, The adaptive parameters of GWO (convergence factor non-linear decreasing, $\alpha/\beta/\delta$ guided update) support rapid reconstruction of encirclement stations when invading targets are maneuvering, significantly reducing interception delay and improving capture success rate. Therefore, constructing a dynamic encirclement point collaborative strategy based on GWO in the three-dimensional environment of railways is not only a cutting-edge extension of multi drone collaborative interception theory, but also a key technical path to solve the problem of low speed and small target protection in railway low altitude security. Subsequent research will elaborate on the system modeling, optimization mechanism design, and simulation verification of this method, providing intelligent solutions for railway airspace safety protection. The contribution of this article is as follows:

1. Unlike conventional scenarios, this work proposes a dynamic capture point generation mechanism tailored for railway 3D environments. By integrating linear features (e.g., track direction) and elevation constraints (e.g., safe clearance from overhead catenary systems) into the capture point update logic, the method generates 3D capture points with altitude parameters via functional modeling. Combined with railway route mapping, this approach enables targeted coverage of narrow airspace, addressing the limitations of traditional 3D models in adapting to railway settings and achieving real-time dynamic alignment between capture points and the railway environment.
2. Breaking through the limitations of single-objective path loss formulations that often fail to meet real-time requirements, this study establishes a multi-objective cooperative optimization framework based on the GWO, effectively overcoming the local optimum limitations inherent in traditional gradient-based methods. The GWO is implemented through an objective function that treats the increments in the heading and pitch angles as optimization variables. This function comprehensively incorporates both path loss defined as the distance to the capture point and real-time operational demands. Through carefully tuned parameter settings, it achieves an

effective balance between computational efficiency and rapid replanning capability, thereby addressing the need for timely response to target maneuvers in railway environments.

3. A distributed anti-interference cooperation strategy based on a matching mechanism is designed to enhance the robustness of multi-UAV coordination. A distance-based matching function dynamically assigns UAVs to capture points, while a local distance minimization principle maintains capture formation. By incorporating the hierarchical leadership structure of the GWO, the proposed method achieves a balance between global optimization and local adjustment within the GWO function. This resolves the cooperative failure issues of traditional negotiation-based methods in the complex electromagnetic environment of railway applications, thereby improving the success rate of target containment.

2. Problem statement

In the three-dimensional airspace environment of the railway, it is assumed that there are four unmanned aerial vehicles (UAVs) surrounding and jointly capturing one UAV invading the railway. Use set $U=\{u_1,u_2,u_3,u_4\}$ to represent the swarm of encircling drones, and E to represent invading drones. The three-dimensional detection range (spherical area) of the encircling drone is larger than that of the invading drone, with a detection angle of 2π. Each encircling drone can obtain the three-dimensional line of sight angle (θ_i, φ_i) (horizontal and elevation angles) and relative distance R_i of the invading drone in real time, and share position and target information through a railway dedicated communication link. The detection range of invading drones is smaller than that of surrounding drones, and their activity range is mainly concentrated in low altitude areas along the railway (0 to 50 m above the plane of the railway track). They may use railway facilities such as contact networks, tunnels, bridges, etc. for concealment or escape. Figure 1 shows a simulation of a three-dimensional encirclement environment, where red represents invading drones, asterisks represent encirclement points, triangles represent four encirclement drones, and green spheres represent encirclement ranges.

The three-dimensional position of an intruder UAV at time t is defined as P_t = (x_t, y_t, z_t), and its serpentine maneuver is governed by the following equations:

$$\begin{cases} x_t = x_0 + v_x t \\ y_t = y_0 + A\sin(\frac{2\pi}{T_s}), \\ z_t = z_0 \end{cases} \quad (1)$$

where (x_0, y_0, z_0) denotes the initial position of the intruder UAV, v_x represents its constant forward velocity along the railway axis (x-axis, aligned with the railway extension direction), is the lateral oscillation amplitude of the serpentine maneuver (along the y-axis, perpendicular to

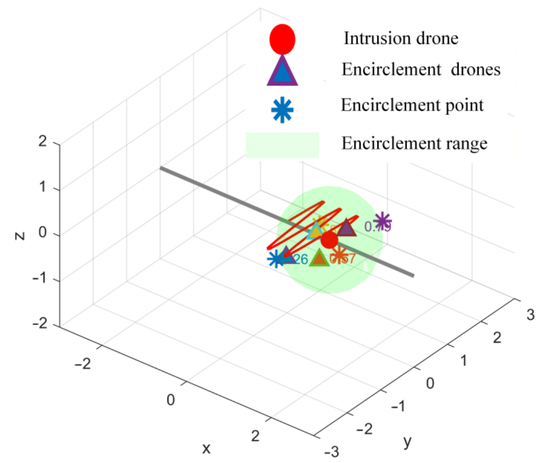

Figure 1. Three dimensional environment simulation for encirclement and capture

the railway), set to 1 m to constrain lateral deviation within the narrow airspace corridor along the railway and prevent excessive diversion beyond practical surveillance boundaries, and T_s denotes the oscillation period (unit: simulation time steps), assigned a value of 10, indicating that one complete lateral oscillation cycle is executed every 10 simulation steps, simulating the characteristic frequency of an evasive UAV actively avoiding interception.

The capture process is defined as: a swarm of unmanned aerial vehicles continuously tracks invading drones through a three-dimensional detection system, and dynamically generates capture points based on their real-time positions;

After allocating capture points through a negotiation mechanism, the GWO algorithm is used to optimize the motion trajectory, ultimately forming a closed three-dimensional encirclement outside the detection range of the invading drone, with a distance of less than 1.2 R (R = 1) from the capture point, and the encirclement must avoid key railway facilities (such as contact network safety distance not less than 2 m, no fly zones in tunnels, etc.), to determine the success of the capture.

3. Mathematical model of the encirclement problem

3.1. The motion equation of encircling unmanned aerial vehicles

Assuming the three-dimensional position of the i th unmanned aerial vehicle u_i is (x_i, y_i, z_i), the flight speed is V, the heading angle is ϕ_i (horizontal deflection angle), and the pitch angle is γ_i (vertical inclination angle), then its three-dimensional motion equation is:

$$\begin{cases} \dot{x}_i = V\cos\gamma_i\cos\phi_i \\ \dot{y}_i = V\cos\gamma_i\sin\phi_i \\ \dot{z}_i = V\sin\gamma_i \\ \dot{\phi}_i = u_{i1} \\ \dot{\gamma}_i = u_{i2} \end{cases}, \quad (2)$$

where u_{i1} and u_{i2} are the control inputs for heading angle and pitch angle, respectively, reflecting the rate of drone attitude adjustment. This equation considers the vertical motion of the railway in three-dimensional airspace and adapts to terrain constraints such as height differences in contact networks and tunnel height limits.

3.2. Target safe area

The security zone for invading drones is defined as a three-dimensional spherical area, with its real-time position as the center of the sphere and its own detection distance as the radius, to avoid surrounding drones entering the area and triggering target escape. Assuming the horizontal line of sight angle, elevation angle, and distance of the invading drone detected by the first encircling drone are θ_i, φ_i, and R_i, then the three-dimensional coordinates of the invading drone (x_m, y_m, z_m) are as follows:

$$\begin{cases} x_m = x_i + R_i \cos\varphi_i \cos\theta_i \\ y_m = y_i + R_i \cos\varphi_i \sin\theta_i \\ z_m = z_i + R_i \sin\varphi_i \end{cases}. \quad (3)$$

The target security domain expression is:

$$DM_{safe}(E) = \left\{ (x, y, z) \mid \sqrt{(x_m - x)^2 + (y_m - y)^2 + (z_m - z)^2} < f \right\}, \quad (4)$$

where f is the detection distance of the invading drone, and the surrounding drone needs to move outside of $DM_{safe}(E)$ and additionally meet the safety constraints of railway facilities (such as the contact network area $z \geq 5m$).

3.3. Set up capture points

The encirclement points are set up on the spherical surface (three-dimensional encirclement circle) of the target safety zone, with the same number as the encirclement drones (Equation (4)), and dynamically updated with the movement of the invading drones. Based on the motion direction vector $v_m = (\dot{x}_m, \dot{y}_m, \dot{z}_m)$ of the invading drone, the intersection point of its opposite direction with the encirclement circle is the first encirclement point m_1, and the remaining points are generated using the spherical uniform distribution algorithm:

$$\begin{cases} x_{mi} = x_m + f \cos\beta_i \cos\alpha_i \\ y_{mi} = y_m + f \cos\beta_i \sin\alpha_i \\ z_{mi} = z_m + f \sin\beta_i \end{cases}, \quad (5)$$

where $\alpha_i = \frac{2\pi(i-1)}{n}$ is the horizontal angle and β_i is the pitch angle (generated by the golden spiral algorithm to ensure uniform distribution on the sphere); f is the detection distance of the invading drone, which is the radius of the encirclement circle. At the same time, the capture points should avoid the no fly zone on the railway (such as when the tunnel range $x \in [a, b]$, the point $z \leq 3m$ is filtered).

The core of capturing point generation is layout in the opposite direction of target motion, intercepting in advance rather than chasing, first calculating the target motion direction vector. If the position of the invading drone at time t is $aim_p(t)$ and the position at time $t-1$ is $aim_p(t-1)$, then its motion direction vector is as follows:

$$\overrightarrow{dv} = aim_p(t) - aim_p(t-1) = [x(t) - x(t-1),\ y(t) - y(t-1),\ z(t) - z(t-1)]^T. \quad (6)$$

The reference direction of the capture point is taken in the opposite direction of the motion of target, ensuring that the encirclement point is laid out in advance on the forward path of target, rather than lagging behind and chasing.

4. Collaborative capture method based on GWO dynamic capture points

Negotiation method is used to allocate the best encirclement points, and an improved distance balanced negotiation method is adopted to allocate encirclement points, avoiding the deadlock problem of traditional greedy algorithms. The steps are as follows:

1) Initialize the location of the unmanned aerial vehicle (x_i, y_i, z_i) and the location of the capture point (x_{mi}, y_{mi}, z_{mi});
2) Calculate the three-dimensional Euclidean distance between the i-th drone and the j-th encirclement point: $D_{ij} = \sqrt{(x_i - x_{mj})^2 + (y_i - y_{mj})^2 + (z_i - z_{mj})^2}$;
3) Pre allocation based on the principle of minimum distance: Assign the nearest capture point to each drone and record the allocation quantity M_j for each capture point;
4) Conflict handling: If $M_j = 0$, mark the capture point as unallocated; If $M_j = 1$, the matching is successful, remove the corresponding drone and capture point; If $M_j > 1$, allocate the capture point to the farthest drone (balanced load) and remove the corresponding element.
5) Repeat the above steps until all encirclement points are allocated, ensuring that the drone swarm is dispersed in the railway scene and avoiding simultaneous entry into the contact network interference zone.

In order to achieve a better capture effect, a three-dimensional objective function is constructed that integrates path loss, encirclement effect, and railway constraints. The expression is:

$$J = \omega_1 J_1 + \omega_2 J_2 + \omega_3 J_3, \quad (7)$$

where $J_1 = \sum_{i=1}^{n} \sqrt{(x_i^{k+1} - x_{mi}^k)^2 + (y_i^{k+1} - y_{mi}^k)^2 + (z_i^{k+1} - z_{mi}^k)^2}$ is the total path loss from the unmanned aerial vehicle to the target capture point; $J_2 = \sum_{j=1}^{n} \left| \Omega_j - 4\pi/n \right|$ is the total deviation between the center angle Ω_j of the line connecting adjacent capture points and the target and the ideal uniform angle $4\pi/n$, reflecting the uniformity of the encirclement; Punish railway constraints (such as $pen(u_i) = 100$ when entering the contact network safety zone, otherwise it is 0); The weight satisfies $\omega_1+\omega_2+\omega_3=1$ and $\omega_3 \ge 0.2$ (prioritizing the safety of railway facilities).

If the position of the i-th UAV is $P_i=[x_i, y_i, z_i]^T$, the constraint function is as follows:

$$g_1(P_i)=\begin{cases}1 & \left|y_1-y_{cat}\right|<d_{cat} \\ 0 & \text{otherwise}\end{cases}, \tag{8}$$

where $\left|y_1-y_{cat}\right|$ represents the distance between the UAV and the contact network, and d_{cat} represents the specified standard distance. If it is less than this distance, it violates the contact network constraint.

Using the GWO algorithm to find the minimum value of the objective function, obtain the optimal heading angle ϕ_i and pitch angle γ_i for surrounding unmanned aerial vehicles. The steps are as follows: initialize the wolf pack: take the attitude angle (ϕ_i, γ_i) of n unmanned aerial vehicles as the individual wolf pack, with dimension $2n$, search range $\phi_i \in[-\pi/6, \pi/6]$, and $\gamma_i \in[-\pi/12, \pi/12]$ (adapted to railway low altitude maneuvering restrictions); Calculate fitness: Using the objective function J as the fitness value, select α (optimal), β (suboptimal), δ (third optimal) wolves; Update position: Other wolves (ω) adjust their posture angle based on α, β, δ's position:

$$\begin{cases}D_\alpha=\left|C_1X_\alpha-X\right|, X_1=X_\alpha-A_1D_\alpha \\ D_\beta=\left|C_2X_\beta-X\right|, X_2=X_\beta-A_2D_\beta \\ D_\delta=\left|C_3X_\delta-X\right|, X_3=X_\delta-A_3D_\delta \\ X(t+1)=\dfrac{X_1+X_2+X_3}{3}\end{cases}, \tag{9}$$

where $A=2ar_1-a, C=2r_2$ decreases linearly from 0 with iteration, and r_1, r_2 is a [0,1] random vector; Termination condition: When the maximum number of iterations is reached (set to 50) or the fitness value is less than the threshold (0.1), output the optimal attitude angle.

The process of the capture strategy is as follows:

1. Real time detection of the location of the invading drone, combined with railway facility data (contact network coordinates, tunnel range), generate a dynamic capture point through Equation (5);
2. Using negotiation method to allocate capture points for unmanned aerial vehicles;
3. Using the current attitude angle as the initial value, optimize the objective function J through GWO to obtain the optimal heading angle ϕ_i^* and pitch angle γ_i^*; update the drone attitude using proportional control: $u_{i1}=k_1(\phi_i-\phi_i^*)$, $u_{i2}=k_2(\gamma_i-\gamma_i^*)$ (k_1, k_2 are proportional coefficients); Determine if the conditions for successful capture (all drones reaching the capture point and forming a closed encirclement) are met: If yes, end; otherwise, return to step.

5. Simulation result analysis

To verify the effectiveness of the railway multi drone collaborative encirclement strategy based on GWO dynamic encirclement points in three-dimensional scenes, a simulation system based on code implementation was designed to capture the invading drone moving along the railway line. The encirclement process, algorithm convergence, and effectiveness were analyzed. The experimental scenario simulates the intrusion of unmanned aerial vehicles flying at low altitude along the main railway line. Four encirclement unmanned aerial vehicles depart from random initial positions and achieve collaborative encirclement through the following process:

1. Target motion update: Calculate the new position of the invading drone at each step, and move at a constant speed along the x-axis.
2. Dynamic capture point generation: Based on the current and previous positions of the target, four capture points are generated, distributed on a sphere with a radius of 1.2 meters around the target. Two of the points have a height difference of +0.3 meters, and the other two have a height difference of –0.3 meters, forming a three-dimensional encirclement situation.
3. Encirclement point matching: The three-dimensional Euclidean distance between the drone and the encirclement point is calculated through a distance function, and then the matching function uses the Hungarian algorithm to achieve optimal matching, ensuring that each drone is assigned a unique encirclement point.
4. GWO optimization: For each drone, with J as the objective function (minimizing the distance to the matching capture point), the GWO algorithm is used to optimize the heading angle increment and pitch angle increment, and update the drone attitude.
5. Position update and encirclement determination: The drone moves in a new posture and calculates the distance to the matching encirclement point at each step. When the distance between all four drones is less than 1.2, the encirclement is determined to be successful and the simulation is terminated.

5.1. Simulation environment design

The simulation environment is a three-dimensional airspace along the railway line, and the core parameters strictly follow the code initialization configuration: the initial position of the invading drone (target) is (0, 0, 0), and it moves uniformly in a straight line along the railway line (y = 0 plane) without any maneuvering disturbance. The initial positions of four unmanned aerial vehicles (UAVs) were randomly distributed in $x, y \in[-3,3]$, with a range of $z \in[-1,1]$ and a speed of v = 0.3 units per step; Initial heading angle $\phi \in[-\pi, \pi]$, pitch angle $\theta \in[-\pi/4, \pi/4]$. Encirclement parameters: Encirclement radius R = 1, success threshold $\text{capture}=R*1.2=1.2$; The capture points are generated by a function and distributed radially along the direction of target movement.

5.2. Result analysis

In order to verify the effectiveness of the proposed algorithm, 500 encirclement experiments were designed, and a comparison was made between the encirclement

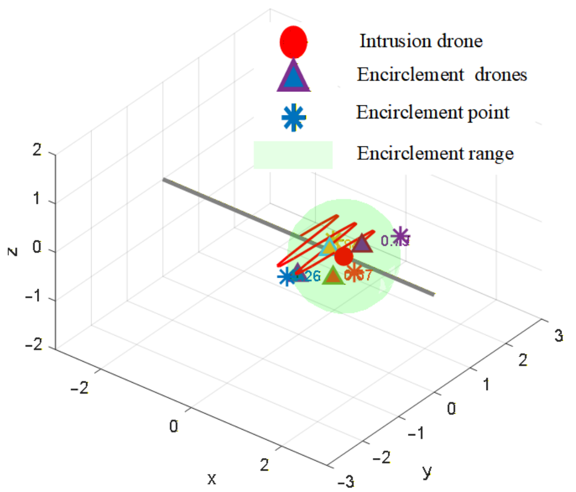

Figure 2. Four unmanned aerial vehicle (UAV) encirclement scenes under the proposed algorithm

algorithm without GWO optimization and the proposed algorithm, mainly comparing the success rate and average encirclement time.

Figure 2 provides a three-dimensional scene to visually verify the form of four unmanned aerial vehicles (UAVs) surrounding the invading UAVs in a three-dimensional manner. The red circle represents the invading UAV, the colored triangle represents the encirclement of the UAV and the matching encirclement point (asterisk) from multiple directions in space, and the green semi transparent sphere (encirclement range) is defined by the encirclement threshold. The capture point constructs a vertical dimension difference through height parameters, forming a three-dimensional enclosure structure of circumferential distribution+height difference, which is suitable for the high and low staggered environment along the railway line (such as overhead contact lines and tunnels); The Euclidean distance calculated by the distance function between the unmanned aerial vehicle and the capture point is displayed in real-time in the 3D scene, effectively supporting the determination of capture standards and ensuring the integrity and accuracy of spatial encirclement.

Figure 3 dynamically displays the distances between four unmanned aerial vehicles (UAVs) and their respective capture points. It can be seen from the figure that all four distance curves quickly converge to the capture threshold (within 1.2), and the final capture states of the four UAVs are all within 1, reflecting the optimization efficiency of the GWO algorithm. With the wolf pack cooperation mechanism of the GWO algorithm, even if the initial distance difference is significant (such as UAVs 2, 3, and 4 being relatively far from UAV 1), they can still quickly approach the capture point within ten steps; The objective function takes minimizing the distance between the drone and the capture point as the optimization core, driving continuous adjustment of heading and pitch angles; The logic of multi machine synchronous compliance set simultaneously ensures that all drones meet the threshold at the same time, avoiding capture loopholes caused by local compliance.

From Figure 4, it can be seen that the success rate of encirclement reached 100% in 500 simulation experiments, and the highest frequency of successful encirclement was around 10 steps. The core comes from the triple collaborative mechanism of algorithms: real-time tracking of dynamic capture points, dynamic generation of capture

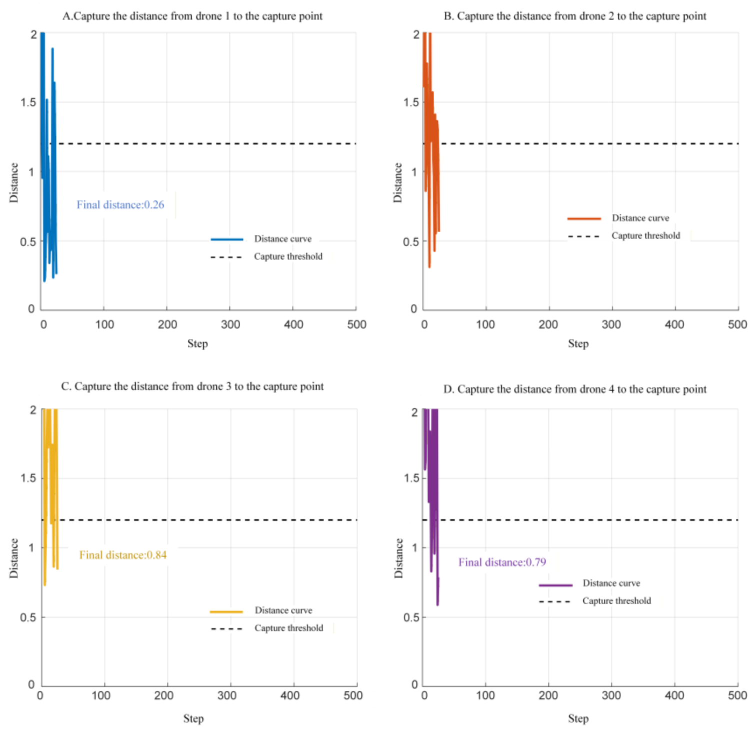

Figure 3. Distance curves of four unmanned aerial vehicles from their respective capture points

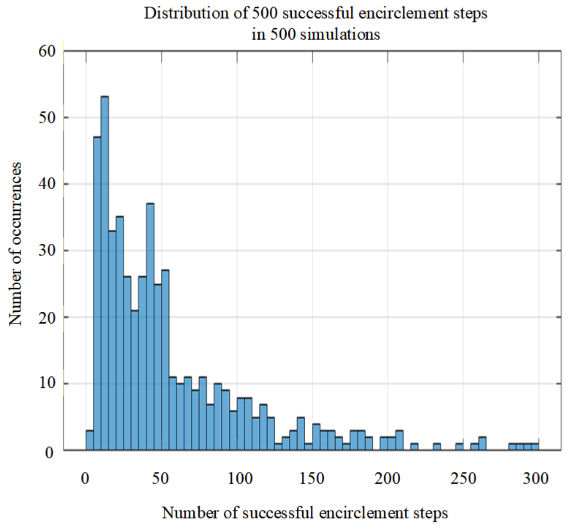

Figure 4. Distribution of 500 successful encirclement steps in 500 simulations

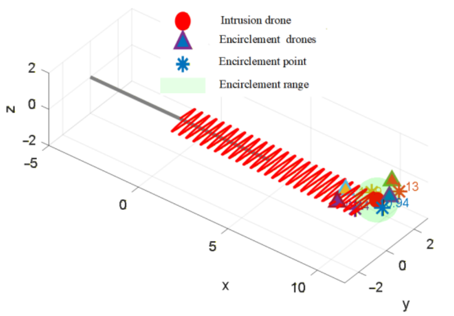

Figure 5. Four drone encirclement scenarios without GWO optimization algorithm

points with height differences based on the target position, adaptation to the linear motion characteristics of railways, conflict free optimal matching (the matching function allocates capture points through the Hungarian algorithm to avoid drone capture point pairing deadlocks), and efficient GWO optimization (multiple iterations to quickly solve attitude angle increments and drive drones to accurately approach capture points). The combination of the three makes the system highly robust in scenarios where the target is moving at a constant speed in a straight line, completely eliminating the risk of capture failure.

Similar to Figure 2, Figure 5 visually verifies the form of the three-dimensional encirclement of the four unmanned aerial vehicles around the invading unmanned aerial vehicle. Although the invading unmanned aerial vehicles are surrounded by the surrounding unmanned aerial vehicles (triangles) and the surrounding points (blue stars) from the spatial dimension, the distance annotation between the unmanned aerial vehicles and the surrounding points is significantly discrete, and the wrapping tightness of the surrounding range (green sphere) is far inferior to the GWO optimization scheme. The core reason is the swarm intelligence guidance without GWO. The drone only adjusts its heading and pitch angle through a local strategy of distance feedback → attitude fine-tuning, which makes it difficult to accurately and synchronously approach the encirclement point, resulting in insufficient spatial layout uniformity. However, the continuous updating of dynamic encirclement points still supports the completion of the final encirclement.

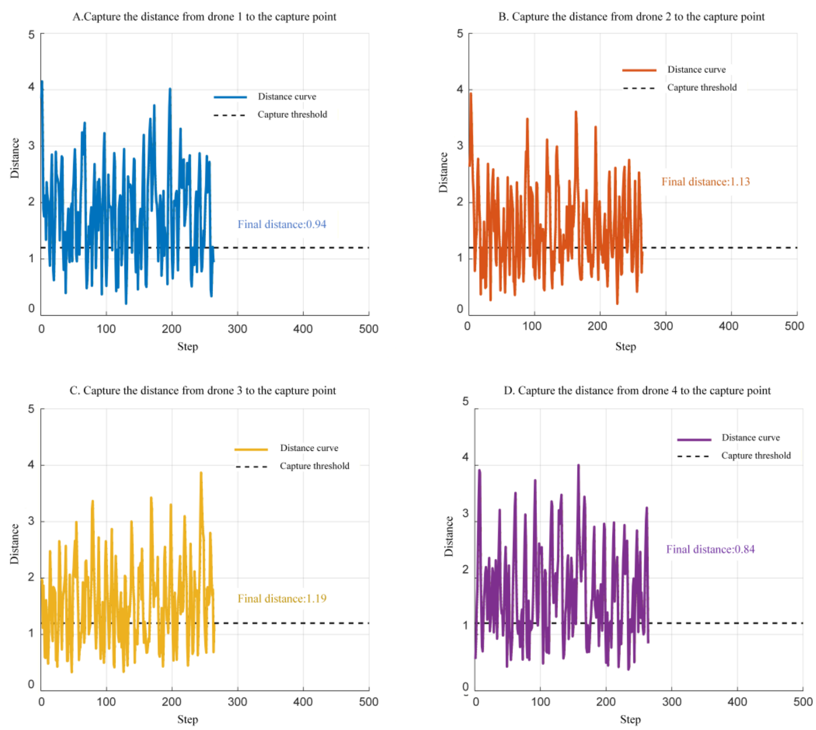

Figure 6. Curve of distance encirclement points for 4 drones without GWO optimization

Figure 6 shows the distance from the capture drone to the capture point, and all four distance curves exhibit an oscillatory convergence characteristic: the distance rapidly decreases in the initial stage, but frequently breaks through the capture threshold (dashed line) midway, and only stabilizes after multiple rounds of adjustment (such as the curve of drone 4 fluctuating violently in the 0 to 3 range). The final capture state of drone 2 and drone 3 is above 1. This is because in the absence of GWO algorithm, attitude adjustment relies on simple proportional control, lacking the hierarchical collaborative optimization of alpha/beta/delta wolves, resulting in the drone easily falling into a cycle of over adjustment → reverse correction → over again, and the stability of the distance curve is extremely poor, directly prolonging the capture time.

Figure 7 shows the histogram of the distribution of successful capture steps. From Figure 6, it can be seen that compared with the proposed algorithm, the capture success rate decreased to 95.2% in 500 simulation experiments, and the frequency of successful capture mostly appeared around 100 steps, significantly more than the number of steps in the proposed algorithm, and there were cases where around 500 steps appeared. The low step count corresponds to the optimal initial position scenario (where the drone naturally approaches the capture point), and local adjustments can quickly meet the standard, reflecting the initial advantage adaptability of the dynamic capture point strategy; High step count: Originating from initial position differences or attitude oscillations, without the global optimization capability of GWO, local adjustments require repeated corrections, resulting in exponential growth in capture time and exposing the strong sensitivity to initial conditions. Reducing the robustness of the system in scenarios where the target is moving uniformly in a straight line poses a risk of capture failure.

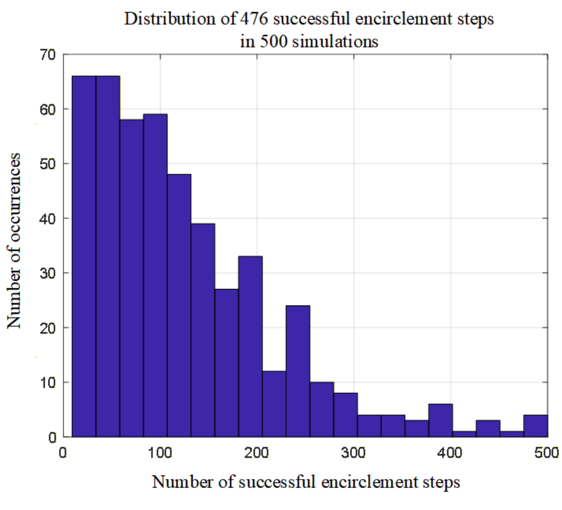

Figure 7. Distribution of 476 successful encirclement steps in 500 simulations

Table 2 shows that under the proposed algorithm, the success rate increased from 95.2% without GWO algorithm to 100%, and the average number of capture steps is 55.7, which is lower than the 125.3 steps without GWO algorithm. This is due to the collective intelligence characteristics of GWO algorithm through the hierarchical cooperation of alpha wolf (global optimum) and beta wolf (local guidance), the iteration redundancy is reduced, and the efficient optimization of attitude parameters is achieved; The fastest 9 steps come from the initial position of the drone being extremely close to the capture point. The GWO algorithm can converge within 1 iteration (with attitude angle increment approaching 0), verifying the ability of the strategy to respond immediately to the initial advantageous scenario; The slowest 299 steps are due to the fact that when the initial position is remote, the dynamic capture point continuously updates with the target, combined with the gradual attitude adjustment of the GWO algorithm, and ultimately the encirclement can still be completed, reflecting the robust adaptability of the strategy to the initial disadvantage scenario. The combination of the three comprehensively demonstrates the efficiency and stability balance of the algorithm under different initial conditions. However, without GWO algorithm, due to the lack of global optimization capability, local adjustments may not converge within 500 steps, indicating a deficiency in the robustness of the strategy; The reason for the average 125.3 steps is that the oscillation correction effect of local adjustments continues to consume steps, highlighting the efficiency bottleneck when optimizing without swarm intelligence; The minimum number of steps depends on the initial position dividend, while the maximum number of steps is trapped in perpetual adjustment due to attitude oscillations. When verifying the absence of GWO, the algorithm performance is dominated by initial conditions and lacks global convergence stability.

To better evaluate the performance of the algorithm in railway scenarios, this study employed Particle Swarm

Table 2. Comparison of two algorithm simulations

Parameter indicators	Methods without GWO optimization	Proposed method
Total number of simulations	500	500
Number of successful encirclement attempts	476	500
Number of failed attempts to capture	26	0
Average Steps	125.3	55.7
Minimum number of steps	9	2
Maximum number of steps	500	299

Optimization (PSO), Genetic Algorithm (GA), and Differential Evolution (DE) as alternatives to GWO for adjusting the UAV attitude angles, while keeping other parameters (such as the number of UAVs, initial positions, and constraints) unchanged. Each simulation was repeated 500 times, and the detailed results are presented in Table 3.

The Table 3 shows that the average capture time of GWO algorithm in this article (55.7 steps) is significantly better than PSO (120.5steps), GA (98.8 steps), and DE (80.4steps), and the capture success rate (100%) is higher than PSO (97.6%), GA (94.3%), and DE (96.1%). The primary reasons for these results can be summarized as follows: PSO updates particle positions through information sharing among individuals. In railway scenarios, this mechanism is prone to local optima. When an intruder UAV suddenly performs serpentine maneuvers (lateral deviation along the y-axis), the global best solution in PSO may remain trapped near the interception point corresponding to the original trajectory of target. This causes all UAVs to converge toward this local region, creating a coverage gap. GA mimics biological evolution through selection–crossover–mutation. Its iterative process relies on maintaining population diversity, which leads to slower convergence. As a result, the interception point updates lag behind the actual position of target, keeping the UAVs in a pursuit rather than interception state. DE suffers from a lack of hierarchical guidance in its selection operation, which tends to generate invalid solutions under railway constraints. In contrast, the $\alpha/\beta/\delta$ hierarchy in the GWO algorithm employs a three-level guidance strategy. This ensures that even when the target suddenly changes direction, the UAVs can rapidly adjust their positions based on guidance from the β and δ wolves, thereby avoiding localized clustering caused by misjudgment of a single optimal direction.

In summary, the dynamic capture point strategy without GWO optimization has achieved a high success rate through dynamic updates of capture points. However, due to the oscillation of local attitude adjustment and strong dependence on initial conditions, it is inferior to the GWO collaborative scheme in terms of capture efficiency and stability, which verifies the necessity of swarm intelligence optimization in complex scenarios.

6. Conclusions

This paper proposes a multi drone collaborative capture strategy that integrates Grey Wolf Optimization (GWO) algorithm and dynamic capture points to address the threat of invading drones in railway safety protection. The research is completed through system design and simulation verification. The main achievements are as follows: in terms of model construction, the three-dimensional motion model established by analyzing the motion characteristics of invading drones along the railway line can accurately reflect the actual threat scenario, laying a theoretical foundation for the design of subsequent encirclement strategies. In terms of algorithm design, the proposed dynamic capture point generation mechanism and negotiation allocation method have achieved the optimal allocation of capture resources. By combining the GWO algorithm to optimize the heading angle increment in real-time, the capture efficiency in three-dimensional environments has been significantly improved (reducing time costs by 55.5%) and success rate (increasing by 4.8%). Further comparison with various mainstream optimization algorithms such as particle swarm optimization, genetic algorithm, and differential evolution shows that the GWO algorithm used in this paper has significant advantages in convergence speed and solution quality, achieving the shortest average capture time (55.7 steps) and the highest capture success rate (100%). The engineering application value has been verified through simulation, and the feasibility of the strategy has been validated. Its dynamic response capability provides a scalable technical framework for airspace protection in complex railway environments. In the future, algorithm robustness can be further optimized through actual sensor data fusion.

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Disclosure statement

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