

COMMUNICATION-CONSTRAINED COORDINATED PATH PLANNING FOR USV-UAV SYSTEMS IN MARITIME ENVIRONMENTS USING AN IMPROVED PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstract - This paper presents a communication-constrained coordinated path planning method for heterogeneous unmanned surface vehicle (USV)-unmanned aerial vehicle (UAV) systems operating in maritime environments. The path planning problem is formulated as a multi-objective optimization problem that simultaneously considers propulsion energy consumption, obstacle avoidance, communication maintenance, and trajectory smoothness. To enhance the search capability of the conventional Particle Swarm Optimization (PSO), an Improved PSO (IPSO) algorithm is developed by integrating four complementary mechanisms: guided particle initialization, adaptive inertia-weight strategy, Gaussian-based local refinement, and stagnation-triggered Lévy-flight exploration with particle redistribution. These mechanisms improve the balance between global exploration and local exploitation while alleviating premature convergence. Simulation results demonstrate that the proposed IPSO consistently achieves lower optimization cost, shorter coordinated trajectories, and improved solution stability than the conventional Genetic Algorithm (GA) and standard PSO.

Key words - USV-UAV system; coordinated path planning; improved particle swarm optimization; communication constraints; obstacle avoidance

1. Introduction

In recent years, heterogeneous unmanned systems, particularly the combination of USVs and UAVs, have attracted considerable research interest due to their applications in maritime surveillance, search and rescue, environmental monitoring, infrastructure inspection, and ocean observation [1]-[6]. By exploiting the complementary capabilities of both platforms, coordinated USV-UAV systems can accomplish maritime missions more efficiently than either vehicle operating independently. UAVs provide rapid aerial observation and high maneuverability, whereas USVs offer extended endurance, larger payload capacity, and a stable platform for UAV deployment and recovery.

Despite these advantages, coordinated path planning for heterogeneous USV-UAV systems remains a challenging optimization problem. The planned trajectories must simultaneously satisfy multiple operational constraints, including obstacle avoidance, communication connectivity, propulsion energy efficiency, and trajectory smoothness. Conventional optimization methods such as GA can generate feasible solutions but usually require considerable computational effort in large search spaces. Standard PSO provides faster convergence and simpler implementation; however, it is prone to premature convergence and local optima in complex multi-constrained path-planning

problems [7] - [9]. Although numerous PSO variants have been proposed, their application to communication-constrained coordinated path planning for heterogeneous USV-UAV systems remains relatively limited.

To address these challenges, this paper proposes an IPSO-based coordinated path-planning framework for heterogeneous USV-UAV systems operating in maritime environments. The coordinated path-planning problem is formulated as a multi-objective optimization model that considers propulsion energy consumption, obstacle avoidance, communication maintenance, and trajectory smoothness. To improve the search capability of conventional PSO, four complementary mechanisms are integrated into a unified IPSO framework: guided particle initialization, adaptive Gaussian-exponential inertia-weight strategy, Gaussian-based local refinement, and stagnation-triggered Lévy-flight exploration with particle redistribution. Together, these mechanisms improve the balance between global exploration and local exploitation while reducing premature convergence. The proposed approach is validated through comparative simulations against GA and standard PSO.

The main contributions of this work are summarized as follows:

- A communication-constrained coordinated path-planning model is established for heterogeneous USV-UAV systems operating in maritime environments.
- A multi-objective optimization framework is formulated to simultaneously minimize propulsion energy consumption while enforcing communication maintenance, obstacle avoidance, and trajectory smoothness, thereby generating collision-free and communication-aware coordinated trajectories.
- An IPSO framework integrating guided particle initialization, an adaptive Gaussian-exponential inertia-weight strategy, Gaussian-based local refinement, and stagnation-triggered Lévy-flight exploration with particle redistribution is developed to improve the balance between global exploration and local exploitation while mitigating premature convergence.
- Comparative simulations with GA and standard PSO, together with statistical significance tests, runtime analysis, and ablation studies, validate the effectiveness of the proposed IPSO framework and quantify the contribution of each improvement mechanism.

2. System Model and Problem Formulation

2.1. USV-UAV System Model

Consider a heterogeneous USV-UAV system composed of one USV and one UAV operating in a maritime environment with static obstacles. To reduce computational complexity while preserving the essential characteristics of coordinated path planning, the workspace is modeled using a semi-three-dimensional (2.5D) coordinate system, as illustrated in Figure 1 [3], [4]. In this formulation, the USV navigates on the two-dimensional sea surface, whereas the UAV flies at a constant altitude.

The position of the USV is defined as:

$$\mathbf{p}_s = [x_s, y_s]^T \quad (1)$$

whereas the position of the UAV is defined as:

$$\mathbf{p}_a = [x_a, y_a, h]^T \quad (2)$$

where $h = 100$ m denotes the constant flight altitude of the UAV.

Accordingly, the coordinated trajectories are represented by the waypoint sequences:

$$\mathbf{P} = (\mathbf{P}_s, \mathbf{P}_a) \quad (3)$$

where $\mathbf{P}_s = \{\mathbf{p}_{s,k}\}_{k=0}^{N+1}$ and $\mathbf{P}_a = \{\mathbf{p}_{a,k}\}_{k=0}^{N+1}$ denote the waypoint sequences of the USV and UAV, respectively, where N is the number of intermediate waypoints. The first and last waypoints correspond to the predefined start and goal positions, whereas the remaining intermediate waypoints are optimized by the coordinated path-planning algorithm.

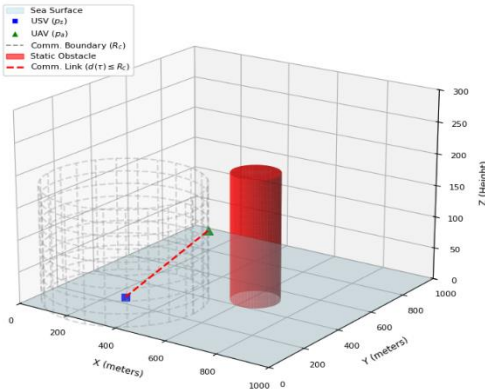


Figure 1. Semi-3D (2.5D) model of the heterogeneous USV-UAV system

2.2. System Constraints [3], [4]

2.2.1. Velocity Constraints of the USV and UAV

To ensure the kinematic feasibility of the generated trajectories, the velocities of both vehicles are constrained by their maximum operating speeds:

$$\|\dot{\mathbf{p}}_s(t)\| \leq v_s^{\max}, \|\dot{\mathbf{p}}_a(t)\| \leq v_a^{\max} \quad (4)$$

where $v_s^{\max}$ and $v_a^{\max}$ denote the maximum allowed speeds of the USV and UAV, respectively.

Since the proposed method performs waypoint-based trajectory optimization rather than continuous-time trajectory generation, these velocity constraints are enforced during the optimization process by limiting the maximum particle velocity in each search dimension. This prevents

excessively large waypoint updates between consecutive iterations and improves the stability of the optimization.

2.2.2. Communication Constraint

The communication distance between the USV and UAV at a sampled point along the coordinated trajectories is computed as:

$$d(\tau) = \sqrt{((x_a(\tau) - x_s(\tau))^2 + (y_a(\tau) - y_s(\tau))^2 + h^2)}, \quad (5)$$

where τ denotes a sampled point generated along the trajectory segments between two consecutive waypoints. To maintain reliable wireless communication throughout the mission, the following geometric constraint must be satisfied: $d(\tau) \leq R_c$, where R_c represents the maximum communication range.

For simplicity, wireless communication is modeled as a geometric distance constraint without considering channel fading, antenna characteristics, or sea-surface multipath propagation. During fitness evaluation, each trajectory segment is uniformly sampled to verify communication connectivity continuously, enabling the detection of communication violations that may occur between consecutive waypoints.

2.2.3. Obstacle Avoidance Constraint

Let the set of static obstacles be defined as:

$$\mathcal{O} = \{O_i\}_{i=1}^M, \text{ where } M \text{ is the total number of obstacles.}$$

To guarantee collision-free navigation, every point along the planned trajectories of both the USV and UAV must satisfy the minimum safety clearance:

$$\text{dist}(\mathbf{p}(\tau), O_i) \geq d_{\text{safe}},$$

where $\text{dist}(\mathbf{p}(\tau), O_i)$ denotes the Euclidean distance between the sampled trajectory point and obstacle O_i , and d_{safe} is the prescribed minimum safety clearance selected according to the vehicle safety margin.

Similar to communication verification, obstacle collisions are detected by uniformly sampling intermediate points along each trajectory segment, providing continuous collision checking over the entire trajectory.

2.3. Multi-Objective Optimization Function

The coordinated path-planning problem is formulated as the following constrained multi-objective optimization problem [10], [11]:

$$J = J_{\text{energy}} + \eta_c J_{\text{comm}} + \eta_o J_{\text{obs}} + \eta_s J_{\text{smooth}}, \quad (6)$$

where η_c , η_o , and η_s denote the weighting coefficients associated with communication maintenance, obstacle avoidance, and trajectory smoothness, respectively. These coefficients were determined empirically through preliminary parameter tuning and kept identical for all algorithms to ensure fair comparison.

The total coordinated trajectory length is computed as:

$$L = L_s + L_a, \quad (7)$$

where, L_s and L_a denote the total trajectory length of the USV and UAV, respectively:

$$L_s = \sum_{k=1}^{N+1} \|\mathbf{p}_{s,k} - \mathbf{p}_{s,k-1}\|, \\ L_a = \sum_{k=1}^{N+1} \|\mathbf{p}_{a,k} - \mathbf{p}_{a,k-1}\|$$

The propulsion energy is approximated as a weighted linear function of the trajectory lengths:

$$J_{\text{energy}} = \alpha_s L_s + \alpha_a L_a, \quad (8)$$

where α_s and α_a denote the energy coefficients of the USV and UAV, respectively. This simplified model assumes that propulsion energy is proportional to the traveled distance. Vehicle-specific effects, such as UAV hovering, climbing, and turning energy, together with USV wave resistance and ocean-current disturbances, are not explicitly considered in the present work and are left for future investigation.

The communication penalty is accumulated over all sampled trajectory points:

$$J_{\text{comm}} = \sum_{\tau} \left(\frac{\max(0, d(\tau) - R_c)}{R_c} \right)^2 \quad (9)$$

Similarly, the obstacle penalty is accumulated over all sampled trajectory points:

$$J_{\text{obs}} = \sum_{\tau} \sum_{i=1}^M \Phi(p(\tau), O_i) \quad (10)$$

with the penalty function:

$$\Phi(p(\tau), O_i) = \left(\frac{\max(0, d_{\text{saf}} - \text{dist}(p(\tau), O_i))}{d_{\text{saf}}} \right)^2 \quad (11)$$

The smoothness cost of the coordinated USV-UAV system is defined as:

$$J_{\text{smooth}} = J_{\text{smooth}}^{\text{USV}} + J_{\text{smooth}}^{\text{UAV}}, \quad (12)$$

where the turning-angle cost for each vehicle is:

$$J_{\text{smooth}}^{\text{vehicle}} = \sum_{i=1}^N [\theta_i^2 + \max(0, \theta_i - \theta_{\max})^2], \quad (13)$$

where θ_i denotes the turning angle at the i -th waypoint and $\theta_{\max}$ is the maximum allowable turning angle.

2.4. IPSO Algorithm

The proposed IPSO is developed based on the standard PSO framework [7], [8]. Rather than introducing new PSO operators, it integrates four complementary search-enhancement mechanisms: guided particle initialization, adaptive Gaussian-exponential inertia weighting, Gaussian-based local refinement, and stagnation-triggered Lévy-flight exploration with particle redistribution. These mechanisms enhance the balance between global exploration and local exploitation while mitigating premature convergence without altering the standard PSO update equations.

2.4.1. Solution Representation

Each particle encodes the coordinates of the N intermediate waypoints for both the USV and UAV, while the start and goal waypoints remain fixed. Accordingly, the particle position is represented as:

$$x_i = [p_{s,1}, \dots, p_{s,N}, p_{a,1}, \dots, p_{a,N}].$$

During fitness evaluation, the complete coordinated trajectories are reconstructed from these waypoints, and intermediate points are uniformly sampled along each trajectory segment to evaluate the communication and obstacle constraints. The fitness of each particle is then computed using the constrained multi-objective cost function defined in (6).

2.4.2. Velocity and Position Update

The particle velocity and position are updated according to:

$$v_i^{t+1} = \omega(t)v_i^t + c_1 r_1 (p_i^{\text{best}} - x_i^t) + c_2 r_2 (g^{\text{best}} - x_i^t) \quad (14)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (15)$$

where c_1 and c_2 are the cognitive and social learning coefficients, respectively, while r_1 and r_2 are uniformly distributed random numbers in the interval $[0, 1]$.

2.4.3. Adaptive Gaussian-Exponential Inertia-Weight Strategy

$$\omega(k) = \omega_{\min} + (\omega_{\max} - \omega_{\min}) \exp \left[- \left(\frac{\lambda k}{K_{\max}} \right)^2 \right], \quad (16)$$

where, $K_{\max}$ is the maximum number of iterations, $\omega_{\max}$ and $\omega_{\min}$ denote the initial and final inertia weights, respectively, and λ controls the decay rate of the Gaussian-exponential function. Larger values of λ result in a faster transition from exploration to exploitation.

The Gaussian-exponential function provides a smoother decrease in the inertia weight than the conventional linear strategy, thereby maintaining stronger global exploration during the early search stage while enhancing local exploitation in the later stage. Similar nonlinear inertia-weight strategies have been shown to improve the balance between exploration and exploitation, leading to faster convergence and reduced susceptibility to premature convergence [9], [12].

2.4.4. Search Enhancement Strategies

To improve the search capability of the standard PSO [9], four complementary enhancement mechanisms are incorporated: guided particle initialization, Gaussian local refinement, stagnation-triggered Lévy-flight exploration, and particle redistribution.

Instead of purely random initialization, particles are generated around a smooth reference trajectory connecting the start and goal positions. The reference trajectory is randomly curved using a sinusoidal offset, while Gaussian perturbations are added to produce a diverse initial population and accelerate the early search stage.

During optimization, Gaussian local refinement is performed around the current global best solution:

$$\epsilon_k \sim \mathcal{N}(0, \sigma_k), \quad (17)$$

where the standard deviation decreases linearly with the iteration number,

$$\sigma_k = \sigma_0 \left(1 - \frac{k}{K_{\max}} \right), \quad (18)$$

where σ_0 denotes the initial perturbation scale. This adaptive perturbation improves local exploitation around promising solutions while gradually reducing search fluctuations as the optimization converges.

To alleviate premature convergence, Lévy-flight exploration is activated when the global best solution stagnates for several consecutive iterations. Owing to its heavy-tailed distribution, Lévy flight enables occasional long-distance exploration around the current global best and improves the ability to escape local optima. If the generated candidate improves the current global best, the global best solution is updated accordingly.

After a successful Lévy-flight update, a small proportion of the worst-performing particles are

redistributed within a neighborhood of the updated global best to restore population diversity. The corresponding particle velocities are reset to zero to maintain consistency between the updated positions and velocity states.

2.5. Proposed IPSO Algorithm

The overall procedure of the proposed IPSO algorithm is summarized in *Algorithm 1*.

Algorithm 1. Proposed IPSO algorithm for coordinated USV-UAV path planning

Input: System parameters, obstacle map, start and goal positions, swarm size N_p , maximum number of iterations K_{max} .

Output: Optimal coordinated trajectories of the USV and UAV.

- 1: Generate the initial swarm using guided particle initialization.
- 2: Initialize particle velocities
- 3: Evaluate the fitness of all particles using Eq. (6).
- 4: Initialize pbest and gbest.
- 5: for $k = 1$ to K_{max} do
- 6: Compute the adaptive inertia weight using Eq. (16).
- 7: Update particle velocities using Eq. (14).
- 8: Update particle positions using Eq. (15).
- 9: Evaluate particle fitness.
- 10: Update pbest and gbest.
- 11: Generate a Gaussian-refined candidate solution around gbest.
- 12: If the candidate provides a lower objective value than gbest then
- 13: Update gbest.
- 14: End if
- 15: If stagnation is detected or periodic exploration is triggered then
- 16: Generate a Lévy-flight candidate around gbest.
- 17: If the candidate provides a lower objective value than gbest then
- 18: Update gbest.
- 19: Redistribute the worst-performing particles.
- 20: End if
- 21: End if
- 22: end for
- 23: Return the best coordinated trajectories.

The computational complexity is dominated by the repeated fitness evaluation of all particles throughout the optimization process. For a solution of dimension D in an environment containing M obstacles, the overall computational complexity is $O(N_p K_{max} (D + M))$, where N_p is the swarm size. The proposed search-enhancement mechanisms require only a small number of additional candidate evaluations and simple vector operations in each iteration. Consequently, they introduce only a constant computational overhead and do not alter the overall asymptotic computational complexity of the proposed IPSO algorithm.

3. Simulation Results and Discussion

3.1. Simulation Scenario Setup

The proposed method was evaluated in a simulated maritime environment covering a $1000 \text{ m} \times 1000 \text{ m}$ workspace. Static obstacles representing islands and anchored vessels were modeled as circular regions. All simulations

were implemented in Python using the *NumPy*, *SciPy*, and *Matplotlib* libraries on a personal computer equipped with an AMD Ryzen 7 PRO 2700U processor, 8 GB RAM, and Windows 10 Pro. The algorithm parameters were determined through preliminary parameter-tuning experiments to balance solution quality and computational efficiency.

Vehicle parameters: The maximum velocities of the USV and UAV were set to $v_s^{max} = 20 \text{ m/s}$ and $v_a^{max} = 40 \text{ m/s}$, respectively, to satisfy the kinematic constraints during optimization. The propulsion energy coefficients in (8) were set to $\alpha_s = 1$ and $\alpha_a = 1.8$.

Algorithm parameters: The swarm size N_p was fixed at 60 for GA, PSO, and IPSO to ensure a fair comparison, while each particle encoded five intermediate waypoints for both the USV and UAV. The maximum number of iterations was set to $K_{max} = 400$. For IPSO, the adaptive Gaussian-exponential inertia weight varied smoothly from 0.9 to 0.4, with $c_1 = 2.2$, $c_2 = 1.8$, $\lambda = 4$, and the Lévy-flight parameter $\beta = 1.5$. For the conventional PSO, the parameters were $\omega = 0.7$ and $c_1 = c_2 = 2$. The penalty coefficients were selected as $\eta_c = \eta_o = 500$, $\eta_s = 20$, and $\sigma_o = 10$.

System constraints: The communication range was set to $R_c = 300 \text{ m}$, the minimum obstacle clearance was set to $d_{safe} = 10 \text{ m}$, and the maximum allowable turning angle was set to $\theta_{max} = 60^\circ$.

These parameter values were kept identical for all comparative algorithms to ensure a fair performance evaluation. Each algorithm was independently executed 20 times under identical simulation conditions to evaluate optimization performance, robustness, statistical significance, and computational efficiency.

3.2. Trajectory Planning Results

Figure 2 illustrates the coordinated trajectories generated by the proposed IPSO algorithm in two representative maritime environments with different obstacle densities. The blue solid and green dashed lines denote the optimized trajectories of the USV and UAV, respectively, while the red circles represent obstacle regions together with their safety margins.

As shown in Figure 2(a), the dispersed-obstacle environment provides several feasible navigation corridors between obstacles. Consequently, both vehicles follow similar trajectories that remain close to the direct route between the start and goal positions, deviating only where necessary to satisfy the required obstacle clearance. The resulting trajectories are smooth and compact while preserving communication connectivity throughout the mission.

Figure 2(b) presents a more challenging multi-layer obstacle environment, where feasible passages are narrower and distributed across several obstacle clusters. In this case, the proposed IPSO algorithm generates coordinated trajectories according to the available free space. During the early stage of the mission, the USV and UAV temporarily adopt different routes to avoid nearby obstacles while maintaining communication connectivity. After passing the congested region, their trajectories gradually converge, allowing both vehicles to safely reach the destination. All trajectory segments remain outside the

obstacle safety margins, demonstrating the capability of the proposed method to generate feasible coordinated trajectories under complex environmental conditions.

In both scenarios, the optimized trajectories exhibit smooth directional transitions without unnecessary zigzag motions. This behavior results from the turning-angle penalty incorporated into the objective function, which encourages gradual heading changes while preserving sufficient maneuverability for obstacle avoidance. Furthermore, because communication connectivity is continuously verified during fitness evaluation along each trajectory segment rather than only at discrete waypoints, the optimized trajectories satisfy the prescribed communication constraint.

Overall, the trajectory planning results confirm that the proposed IPSO algorithm successfully generates collision-free and communication-aware coordinated trajectories for heterogeneous USV-UAV systems operating in maritime environments with different obstacle distributions.

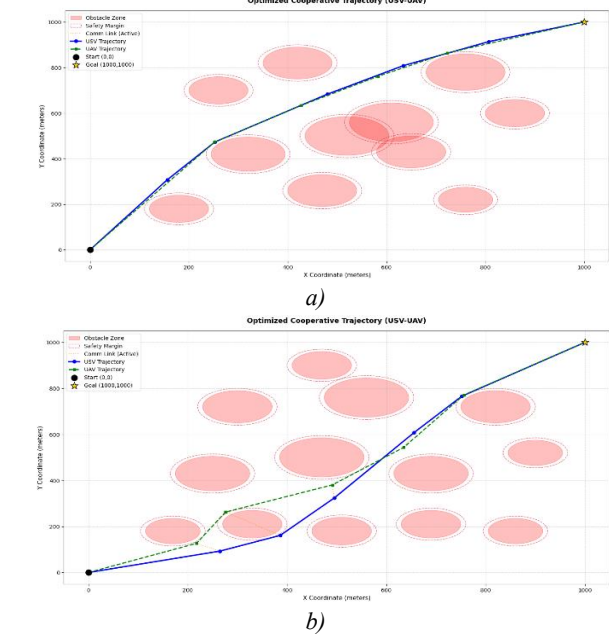


Figure 2. Coordinated 2D trajectories of the USV-UAV system planned by the proposed IPSO algorithm: (a) Dispersed-obstacle environment; (b) Multi-layer obstacle environment

3.3. Performance Evaluation

The performance of the IPSO was evaluated over 20 independent optimization runs and compared with the standard GA and PSO. The quantitative results are summarized in Table 1, while the corresponding convergence curves are shown in Figure 3.

As shown in Table 1, IPSO consistently outperformed both benchmark algorithms in terms of solution quality, convergence stability, and computational efficiency. Compared with GA and standard PSO, IPSO achieved the lowest objective cost together with the smallest standard deviation, indicating strong robustness against random initialization. In addition, IPSO generated the shortest coordinated trajectories while satisfying all communication, obstacle-avoidance, and smoothness constraints. The substantially larger mean cost and standard deviation observed for the standard PSO can mainly be attributed to

occasional runs in which the swarm converges to solutions with significant communication or obstacle-avoidance violations. Because these violations are heavily penalized in the objective function, with penalty coefficients of $\eta_c = \eta_o = 500$, a small number of poorly converged runs can produce very large objective values, resulting in a large gap between the best and mean costs. Despite incorporating several search-enhancement mechanisms, the proposed algorithm also required the shortest average execution time, demonstrating that these mechanisms introduce only negligible computational overhead.

Table 1. Performance comparison of GA, PSO, and the proposed IPSO over 20 independent runs

Algorithm	GA	PSO	Proposed IPSO
Best Cost	4378.20	4564.88	4102.51
Mean Cost	11404.08	77903.80	4141.77
Std. Dev.	9340.79	56678.46	37.20
Best Length (m)	3064.35	2979.85	2901.31
Mean Length (m)	3906.33	3819.24	2928.67
Avg. Time (s)	98.164	51.066	45.397

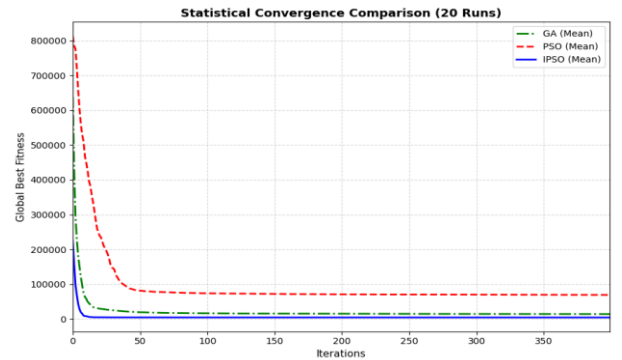


Figure 3. Convergence curves of GA, conventional PSO, and the proposed IPSO algorithm

The convergence curves in Figure 3 further illustrate the effectiveness of the proposed method. IPSO rapidly decreases the objective value during the early search stage and converges smoothly toward a stable solution, whereas GA and standard PSO converge more slowly and stabilize at considerably higher objective values. These observations are consistent with the quantitative results reported in Table 1 and demonstrate that the proposed improvement mechanisms effectively enhance both convergence speed and optimization stability.

To further verify the observed performance improvement, the Wilcoxon signed-rank test was performed using the objective values obtained from the 20 independent runs. As summarized in Table 2, IPSO significantly outperformed both GA and standard PSO, with p-values well below the 0.05 significance level. These results confirm that the observed improvements are statistically significant and are unlikely to be caused by random variations across repeated optimization runs.

Table 2. Wilcoxon signed-rank test results

Comparison	W-statistic	p-value	Result
IPSO vs. PSO	0.00	1.9073×10^{-6}	Significant
IPSO vs. GA	0.00	1.9073×10^{-6}	Significant

3.4. Ablation Study

A progressive ablation study was conducted to quantify the contribution of each proposed enhancement mechanism. Five algorithm variants were independently executed over 20 runs under identical simulation settings, and the results are summarized in Table 3.

Table 3. *Progressive ablation study of the proposed IPSO algorithm*

Algorithm Variant	Best Cost	Mean Cost	Std. Dev.	Avg. Time (s)
Variant A (Standard PSO)	4564.88	77903.80	56678.46	51.200
Variant B (A + Guided Initialization)	4107.36	4170.79	50.90	43.724
Variant C (B + Adaptive Inertia Weight)	4099.38	4140.85	37.79	44.012
Variant D (C + Gaussian Local Refinement)	4098.89	4149.61	46.68	45.221
Variant E (Full IPSO: D + Lévy Flight & Redistribution)	4102.51	4141.77	37.20	44.756

The results show that guided particle initialization provides the largest improvement over the standard PSO. By generating a more informative initial swarm instead of purely random particles, the optimization process starts from more promising regions of the search space, leading to substantially better convergence quality and robustness. Building upon this initialization, the adaptive inertia-weight strategy further improves the balance between global exploration and local exploitation, resulting in a more stable optimization process.

The improvements introduced by Gaussian local refinement and the stagnation-triggered Lévy-flight exploration with particle redistribution are comparatively smaller. This behavior is expected because, after guided initialization and adaptive inertia weighting, the swarm has already converged close to high-quality solutions, leaving limited room for further improvement. Consequently, these mechanisms mainly provide incremental refinements during the later stage of the search process, and their influence on the final objective value is naturally less pronounced.

Nevertheless, both mechanisms remain important for improving search robustness. Gaussian refinement enhances local exploitation around promising solutions, whereas Lévy-flight exploration together with particle redistribution helps the swarm escape occasional local optima and restores population diversity without restarting the optimization process. As a result, the complete IPSO achieves the best overall optimization performance while maintaining nearly the same execution time as the simpler variants.

4. Conclusion

This paper presented an IPSO algorithm for communication-constrained coordinated path planning of a heterogeneous USV-UAV system operating in maritime environments with static obstacles. The coordinated path-planning problem was formulated as a multi-objective optimization problem that simultaneously considers propulsion energy consumption, obstacle avoidance, communication maintenance, and trajectory smoothness.

To improve the search performance of the conventional PSO, the proposed IPSO integrates guided particle

initialization, a Gaussian-exponential adaptive inertia-weight strategy, Gaussian local refinement, and stagnation-triggered Lévy-flight exploration with particle redistribution. These complementary mechanisms improve the balance between global exploration and local exploitation, enhance search robustness, and mitigate premature convergence. The ablation study further showed that guided particle initialization provides the largest performance improvement, while the remaining enhancement mechanisms mainly improve convergence stability and search robustness.

Simulation results, together with statistical significance tests and ablation studies, demonstrated that IPSO consistently achieved lower objective values, shorter coordinated trajectories, faster convergence, and higher solution stability than the conventional GA and standard PSO.

Future work will extend the proposed framework to more realistic maritime environments by considering moving obstacles, ocean currents, wind disturbances, and time-varying communication channels. The proposed method will also be extended to multi-USV/multi-UAV cooperative missions and validated through experiments on real autonomous platforms.

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