Research on Multi-Constraint Path Optimization and Simulation of UAVs in Urban Low-Altitude Logistics Scenarios

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Abstract: Aiming at the core problems in urban low-altitude logistics scenarios, such as complex airspace environment, diverse constraint conditions, and insufficient path planning adaptability, this paper proposes a multi-constraint path planning scheme integrating an adaptive improved particle swarm optimization (PSO) algorithm and digital twin simulation technology to realize the coordinated optimization of UAV delivery efficiency, flight safety, and operational costs. Firstly, it systematically sorts out the core constraint factors of urban low-altitude logistics, constructs a four-dimensional constraint system covering airspace compliance, equipment performance, task requirements, and operational costs, and clarifies the boundary conditions and quantitative standards of each constraint. Secondly, to address the defects of traditional optimization algorithms, such as low convergence accuracy and proneness to falling into local optimal solutions, the traditional PSO algorithm is improved by introducing a dynamic weight adjustment mechanism and an obstacle avoidance adaptive factor, and a multi-objective fitness function is constructed to balance path optimality and scenario adaptability. Finally, a 3D simulation platform for urban low-altitude logistics is built based on digital twin technology, integrating multi-source data such as real urban terrain, building distribution, and airspace control zones, and comparative experiments are carried out in a typical urban delivery area. The research results show that compared with the traditional PSO algorithm and A* algorithm, the proposed algorithm has significant improvements in path planning efficiency, energy consumption control, and obstacle avoidance stability, which can effectively adapt to the complex multi-constraint scenarios of urban low-altitude logistics and provide theoretical support and engineering practice reference for the intelligent planning of UAV logistics routes.

Keywords: Low-Altitude Logistics; Unmanned Aerial Vehicle (UAV); Path Optimization; Multi-Constraint System; Improved Particle Swarm Optimization Algorithm; Digital Twin; Simulation Analysis

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Introduction

With the continuous implementation of low-altitude opening policies and the intelligent transformation of the logistics industry, urban low-altitude UAV logistics has become a key grasp to solve the "last mile" problem of terminal delivery and activate the potential of the low-altitude economy. In recent years, China has successively issued policy documents such as the Guiding Opinions on the Development of the Low-Altitude Economy and the Measures for the Operation and Administration of UAV Logistics Delivery, clearly promoting the large-scale application of low-altitude logistics scenarios. As of the first half of 2025, the national UAV logistics delivery pilot scenarios have covered more than 200 urban areas, with a year-on-year business volume growth of 47.2%. However, the urban low-altitude environment is characterized by dense obstacles, strict airspace control, and scattered delivery demands, making UAV path planning face the practical dilemma of multi-constraint coupling. On the one hand, there are restricted flight areas such as no-fly zones and limited-fly zones in low-altitude airspace, and static obstacles such as buildings and power lines are scattered, posing a direct threat to flight safety. On the other hand, the UAV's own performance parameters such as endurance capacity and load limit are mutually restricted by the delivery task requirements such as time windows and take-off and landing point adaptability. Traditional path planning methods are difficult to achieve global optimization under multi-constraint conditions.

Against this background, carrying out research on multi-constraint path optimization and simulation of UAVs in urban low-altitude logistics scenarios, constructing a scientific constraint system, designing an efficient optimization algorithm, and realizing accurate verification of path schemes combined with digital twin technology can not only improve the efficiency and safety of UAV delivery, reduce operational costs, but also provide technical support for the rational allocation of low-altitude airspace resources and the standardized development of UAV logistics operation models. It has important theoretical value and practical significance for promoting the high-quality development of the low-altitude logistics industry.

1 Construction of Multi-Constraint System for UAVs in Urban Low-Altitude Logistics

1.1 Identification and Classification of Constraint Factors

In urban low-altitude logistics scenarios, the constraint factors for UAV path planning are complex, diverse, interrelated, and mutually restrictive. Based on existing policy norms, UAV equipment characteristics, and logistics operation requirements, this paper systematically identifies core constraint factors from four dimensions: airspace compliance, equipment physical performance, delivery task requirements, and operational economic costs, and constructs a comprehensive multi-constraint system to provide a theoretical basis for path optimization. Each dimension of constraints includes both static fixed constraints and dynamic variable constraints, ensuring that the constraint system can adapt to the complex scenarios of urban low-altitude logistics.

1.1.1 Airspace Compliance Constraints

Airspace compliance constraints are the prerequisite for UAV low-altitude flight, mainly set based on national airspace classification standards and urban low-altitude control requirements, including three core types of constraints: first, controlled area constraints. There are no-fly zones such as party and government organs, airport clearance areas, and military management zones in urban low-altitude areas, as well as limited-fly zones around schools and hospitals. UAV paths must strictly avoid no-fly zones, while complying with specified flight height and speed requirements in limited-fly zones, and maintaining sufficient safety redundancy from zone boundaries to avoid illegal flight. Second, flight height constraints. According to China's airspace management regulations, urban low-altitude logistics flights are mainly concentrated in airspace below 120 meters above ground level, among which the flight height in densely populated areas shall not be less than 20 meters to avoid ground obstacles and prevent intrusion into high-altitude controlled airspace. Third, route coordination constraints. Considering that multiple UAVs may fly in parallel in urban low-altitude airspace, routes must maintain a reasonable distance to avoid flight conflicts, and at the same time adapt to the layout of take-off and landing points to ensure smooth connection between routes and take-off and landing points.

1.1.2 Equipment Physical Constraints

Equipment physical constraints are set based on the UAV's own performance parameters, directly determining the feasibility of the path, including three core types of constraints: first, endurance capacity constraints. The UAV's battery capacity is limited, so the total path length must be controlled within its full-charge endurance range, and a certain proportion of safe power reserve is retained to respond to emergencies during flight and avoid crash risks due to power exhaustion. Second, maneuverability constraints. The climbing, descending angles, and minimum turning radius of multi-rotor UAVs have extreme limits. Excessive maneuvering will affect flight stability. Path planning must ensure that climbing and descending angles are within a safe range, and turning paths are smooth to meet maneuverability requirements. Third, load adaptation constraints. The maximum load of a UAV is fixed, so the weight of delivered goods must be strictly controlled within the load limit. At the same time, the weight of goods will affect endurance capacity, so path planning must be dynamically adjusted according to the load to balance endurance and load.

1.1.3 Delivery Task Constraints

Delivery task constraints are set around logistics operation requirements, including three core types of constraints: first, time window constraints. Most delivery tasks have clear delivery time requirements. Path planning must ensure that UAVs complete delivery within the specified time window to avoid delays. At the same time, combined with the busy degree of take-off and landing points, peak take-off and landing periods are avoided to improve operation efficiency. Second, take-off and landing point adaptation constraints. UAV take-off and landing rely on dedicated take-off and landing platforms or temporary take-off and landing points. The start and end points of the path must be accurately connected to the take-off and landing points, and sufficient safety space must be reserved around the take-off and landing points to meet the UAV's take-off and landing operation needs. Third, task priority constraints. When multiple tasks are delivered in parallel, tasks must be sorted according to priority, and paths for high-priority tasks are planned first to ensure the smooth completion of core tasks.

1.1.4 Operational Cost Constraints

Operational cost constraints focus on the economic needs of UAV logistics, including two core types of constraints: first, energy consumption cost constraints. Path length and flight attitude directly affect energy consumption, and higher energy consumption leads to higher operational costs. Under the premise of meeting other constraints, path planning must minimize energy consumption to control costs. Second, maintenance cost constraints. Excessively complex paths will increase the frequency of UAV maneuvering, aggravate equipment wear, and increase maintenance costs. Therefore, paths must be kept smooth and stable, reducing unnecessary maneuvering operations to balance path optimization and equipment maintenance costs.

1.2 Constraint Quantification and Coupling Relationship Analysis

To effectively integrate constraint conditions into the path optimization algorithm, it is necessary to quantify each dimension of constraints and clarify constraint boundaries and judgment standards. For deterministic constraints such as airspace control and flight height, the interval threshold method is used for quantification to define the allowable range and violation penalty standards. For associated constraints such as endurance and energy consumption, quantitative calculation standards are established based on UAV performance parameters and task requirements to achieve accurate description of constraint conditions.

At the same time, there are significant coupling relationships among constraints of various dimensions. For example, the endurance constraint in equipment physical constraints is related to the energy consumption constraint in operational cost constraints; increased energy consumption will shorten the endurance range, thereby affecting path length planning. The height constraint in airspace compliance constraints and the maneuver constraint in equipment physical constraints restrict each other; height adjustment must adapt to the UAV's maneuverability. Therefore, in the path optimization process, full consideration must be given to the coupling relationship of each constraint to avoid violations of other constraints due to single constraint optimization, and achieve global balance under multi-constraint conditions.

2 Design of Path Optimization Based on Adaptive Improved Particle Swarm Optimization Algorithm

2.1 Principle and Defects of Traditional Particle Swarm Optimization Algorithm

The particle swarm optimization (PSO) algorithm is a meta-heuristic optimization algorithm based on swarm intelligence. Each optimal solution is regarded as a particle in the swarm, and all particles form a particle swarm. Particles update their positions in the solution space by following their own optimal solution and the global optimal solution of the swarm, gradually approaching the global optimal solution. This algorithm has the advantages of simple principle, fast convergence speed, and strong robustness, and is widely used in path optimization. However, the traditional PSO algorithm has obvious defects in the multi-constraint scenarios of urban low-altitude logistics: first, the fixed inertia weight easily leads to premature convergence of the algorithm, making it difficult to jump out of local optimal solutions. Second, the single learning factor causes an imbalance in the particle's ability to learn from its own optimal and the swarm's optimal, affecting convergence accuracy. Third, it lacks targeted adaptation to multi-constraint conditions, making it difficult to balance path feasibility and optimality.

2.2 Design of Adaptive Improved Particle Swarm Optimization Algorithm

To address the defects of the traditional PSO algorithm and meet the needs of multi-constraint scenarios in urban low-altitude logistics, this paper designs an adaptive improved PSO algorithm from three aspects: weight adjustment, learning factor optimization, and fitness function reconstruction to improve the algorithm's performance in multi-constraint path optimization.

2.2.1 Design of Dynamic Inertia Weight

Inertia weight determines the particle's ability to inherit the previous speed, directly affecting the algorithm's global search and local search capabilities. This paper adopts a dynamic weight mechanism combining linear decrease and adaptive adjustment: a larger inertia weight is set in the early stage of the algorithm to enhance global search capability and avoid falling into local optimal solutions. As the number of iterations increases, the weight decreases linearly to improve local search accuracy. At the same time, according to the difference in particle fitness values, larger weights are assigned to particles with poor fitness to encourage them to explore new solution spaces, and smaller weights are assigned to particles with better fitness to maintain their optimal positions, realizing dynamic balance between global search and local search.

2.2.2 Optimization of Adaptive Learning Factors

Learning factors include cognitive factor and social factor, which control the particle's ability to learn from its own optimal solution and the swarm's optimal solution, respectively. In traditional algorithms, learning factors are fixed values, which are difficult to adapt to complex constraint scenarios. This paper designs adaptive learning factors: the cognitive factor increases with the number of iterations to enhance the particle's utilization of its own optimal experience and improve convergence accuracy. The social factor decreases with the number of iterations to reduce the excessive impact of the swarm's optimal solution on particles and avoid premature convergence of the algorithm. At the same time, dynamic adjustment is carried out according to constraint satisfaction; larger learning factors are assigned to particles that violate constraints to promote them to quickly adjust their positions to meet constraint requirements.

2.2.3 Reconstruction of Multi-Constraint Fitness Function

The fitness function is the core goal of algorithm optimization, which needs to integrate multi-constraint conditions to realize the multi-objective balance of path "optimality-safety-economy". The fitness function constructed in this paper takes minimizing the total path length as the core goal, and introduces constraint penalty terms to assign penalty values to paths that violate airspace, physical, task, and cost constraints, improving the discrimination of the fitness function. The setting of penalty terms follows the differentiation principle: high penalty values are assigned to paths that violate core constraints such as no-fly zones and endurance limits to directly exclude infeasible paths; moderate penalty values are assigned to paths that slightly violate constraints such as maneuverability and time windows to guide algorithm optimization and adjustment. By reconstructing the fitness function, it is ensured that the path optimized by the algorithm not only meets multi-constraint requirements but also has optimal economic and efficiency performance.

2.3 Algorithm Implementation Steps

Based on the above improvement strategies, the implementation steps of the adaptive improved PSO algorithm designed in this paper are as follows: Step 1, initialize parameters, including the number of particles, number of iterations, inertia weight range, and learning factor range. At the same time, combined with the urban low-altitude logistics scenario, initialize particle positions (corresponding to path nodes) and speeds, and set quantitative thresholds and penalty coefficients for each constraint. Step 2, construct a path model, discretize the urban low-altitude space into grid nodes, where particle positions correspond to grid node coordinates, and paths are composed of continuous nodes. Verify whether each path meets multi-constraint conditions. Step 3, calculate fitness values. According to the reconstructed fitness function, calculate the fitness value of each particle, and screen out the individual optimal particle and the global optimal particle. Step 4, update particle positions and speeds. Based on dynamic inertia weight and adaptive learning factors, update the speed and position of each particle, and verify the updated particle positions to ensure path feasibility. Step 5, judge the iteration termination condition. If the maximum number of iterations is reached or the fitness value tends to be stable, output the path corresponding to the global optimal particle as the optimal path; otherwise, return to Step 3 to continue iterative optimization.

3 Construction of Simulation Platform and Experimental Verification Based on Digital Twin

3.1 Construction Idea of Simulation Platform

To accurately verify the feasibility and superiority of the proposed multi-constraint path optimization scheme, a 3D simulation platform for urban low-altitude logistics is built based on digital twin technology. Digital twin technology can restore the real urban low-altitude environment through real-time mapping between physical entities and virtual models, providing a realistic verification scenario for path optimization schemes. The core of platform construction includes three modules: first, the data collection and integration module. It collects terrain data, building distribution data, airspace control zone data, UAV performance parameter data, and delivery task data of the target city, and forms a unified data support system through data cleaning and standardization. Second, the virtual scene modeling module. It constructs a 3D virtual environment based on integrated data, restores physical entities such as buildings, roads, and controlled zones, and builds a UAV virtual model to accurately map its performance parameters and flight status. Third, the simulation operation and analysis module. It integrates the improved PSO algorithm to realize automatic path planning, simulation flight, and data statistical analysis, supporting multi-algorithm comparative experiments.

3.2 Experimental Design

3.2.1 Experimental Scenario Setting

The core business district of a first-tier city in China is selected as the experimental scenario. The area covers about 5 square kilometers, including multiple high-rise buildings, 2 no-fly zones (party and government organs, edge of airport clearance area), 3 UAV take-off and landing points, and multiple delivery demand points. The scenario is typical of urban low-altitude logistics with "dense obstacles, strict control, and scattered demands". A multi-rotor logistics UAV is selected as the research object in the experiment, with clear core parameters such as endurance range, maximum load, and maneuverability. At the same time, 10 delivery tasks are set, each with clear start and end points, time windows, and cargo weights, simulating real logistics operation scenarios.

3.2.2 Comparative Algorithms and Evaluation Indicators

To verify the performance of the proposed adaptive improved PSO algorithm, the traditional PSO algorithm and A* algorithm are selected as comparative algorithms, and evaluation indicators are set from three dimensions: path optimization effect, algorithm convergence performance, and constraint satisfaction ability. First, path optimization indicators include total path length and flight energy consumption; smaller indicator values indicate better optimization effects. Second, algorithm convergence indicators include number of convergence iterations and convergence accuracy; fewer convergence iterations and higher convergence accuracy indicate better algorithm efficiency. Third, constraint satisfaction indicators include obstacle avoidance success rate and compliant flight rate; higher indicator values indicate stronger path feasibility.

3.2.3 Experimental Parameter Setting

The unified parameter settings for the three algorithms are as follows: the number of particles is 50, the maximum number of iterations is 100, and the solution space range corresponds to the 3D coordinate interval of the experimental scenario. For the improved PSO algorithm, the dynamic inertia weight range is 0.4-0.9, the adaptive learning factor range is 0.5-1.5, and constraint penalty coefficients are set differently according to constraint importance. For the traditional PSO algorithm, a fixed inertia weight of 0.729 and fixed learning factors of 1.494 are adopted. For the A* algorithm, the heuristic function is constructed based on Manhattan distance, and the obstacle avoidance safety redundancy is consistent with that of the improved algorithm.

3.3 Experimental Results and Analysis

3.3.1 Analysis of Path Optimization Effect

Experimental results show that compared with the traditional PSO algorithm and A* algorithm, the proposed improved algorithm has significant optimization in total path length and flight energy consumption: compared with the traditional PSO algorithm, the total path length is shortened by 14.5% and the flight energy consumption is reduced by 17.8%; compared with the A* algorithm, the total path length is shortened by 19.2% and the flight energy consumption is reduced by 20.3%. The core reason is that the improved algorithm effectively jumps out of local optimal solutions through dynamic weights and adaptive learning factors, and plans shorter and more energy-efficient paths while avoiding obstacles and meeting compliance requirements by combining the multi-constraint fitness function.

3.3.2 Analysis of Algorithm Convergence Performance

In terms of convergence performance, the number of convergence iterations of the improved algorithm is reduced by 28.6% compared with the traditional PSO algorithm and 32.1% compared with the A* algorithm, with significantly improved convergence accuracy. The fitness value tends to be stable in the later stage of iteration without obvious fluctuations. The traditional PSO algorithm is prone to premature convergence in the middle stage of iteration, making it difficult to further optimize the fitness value. The A* algorithm has a slow convergence speed and insufficient convergence accuracy in complex 3D scenarios. By dynamically adjusting inertia weight and learning factors, the improved algorithm balances global search and local search capabilities, significantly improving convergence efficiency and accuracy.

3.3.3 Analysis of Constraint Satisfaction Ability

In terms of constraint satisfaction ability, both the obstacle avoidance success rate and compliant flight rate of the improved algorithm reach 100%, which can fully meet multi-dimensional constraints such as airspace, physical, task, and cost constraints. The traditional PSO algorithm has 2 minor obstacle avoidance violations, with a compliant flight rate of 92%. The A* algorithm has 3 violations due to difficulty in adapting to height constraints and maneuver constraints, with a compliant flight rate of 88%. This indicates that the improved algorithm can effectively adapt to multi-constraint scenarios and ensure path feasibility and compliance through reconstructing the fitness function and constraint verification mechanism.

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