

A Spatiotemporal Knowledge Graph-Based Approach for Low-Altitude Aircraft Path Planning

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Abstract

With the rapid development of low-altitude economy in China, path planning for low-altitude aircraft faces challenges such as strong environmental dynamics, complex constraints, and difficult real-time decision-making. To achieve efficient and universal path planning capabilities, this paper proposes a three-layer Spatiotemporal knowledge graph(3L-STKG) architecture comprising a conceptual layer, an instance layer, and a spatiotemporal layer. Guided by ontological spatiotemporal knowledge, this architecture enables efficient route planning in complex scenarios and addresses the challenges of path planning in low-altitude environments. The proposed method pre-matches the maneuverability constraints from the conceptual layer with the grid traversal attributes of the spatiotemporal layer through a cross-layer semantic association mechanism, dynamically constructing an accessible correlation network. On this basis, the path planning problem is transformed into a minimum weighted connected subgraph search problem in the ontology-constrained spatiotemporal network, and an improved A* algorithm is used to solve for the global optimal path. The experimental results show that the planning time in specific scenarios is reduced by 88.54% compared with traditional methods, while supporting rapid adaptation to multiple aircraft types. The research results provide a theoretical framework for intelligent decision-making of low-altitude aircraft in complex environments and have broad application prospects in fields such as emergency rescue and urban logistics.

1. Introduction

1.1 Research Background and Significance

With the continuous advancement of low-altitude reform policies and the vigorous development of the digital economy in China, the large-scale application of low-altitude vehicles represented by rotorcraft and unmanned aerial vehicles (UAVs) in scenarios such as emergency rescue, urban logistics, and intelligent inspection has become a reality (Zhang et al, 2022, Smith et al, 2021). How to achieve efficient path planning and intelligent decision-making for low-altitude vehicles in complex dynamic environments has become an interdisciplinary research hotspot in the aerospace and intelligent transportation fields, which is of great theoretical significance and engineering value for improving airspace resource utilization, ensuring mission execution efficiency, and flight safety.

The main objective of low-altitude vehicle path planning is to construct an optimal feasible path from the starting point to the endpoint based on cost functions (such as the shortest voyage, minimum energy consumption, and minimum risk), while satisfying the vehicle's dynamic constraints (such as maximum overload and minimum turning radius), task priority requirements, airspace control rules (such as no-fly zones and restricted flight altitudes), and passability conditions (such as obstacle distribution and meteorological impacts). Relevant studies have shown that efficient path planning can reduce flight energy consumption by 22%-35% and shorten mission time by 15%-28% (Chen et al, 2020), and its importance is particularly significant in complex dynamic environments.

1.2 Research Status and Challenges

Existing research achievements mainly focus on static or slowly varying environments such as indoor spaces and airport clear zones, predominantly employing geometric modeling combined with heuristic search algorithms like swarm and ant colony algorithms (Zhang et al, 2010, Pal et al, 2022, Wang et al, 2019). Experiments show that when wind speed fluctuations exceed 20%, traditional pre-planning methods based on static maps require an average of 4.2 replanning attempts to reach the target point, with the mission failure rate increasing to 18% (Brown et al, 2021). Literature indicates that when the number of constraint dimensions exceeds five, the probability of guaranteeing the global optimality of planning solutions drops below 65%, primarily due to the lack of joint modelling of maneuverability and airspace rules (Smith et al, 2020).

In typical complex scenarios such as urban low-altitude logistics, path planning technology faces three core challenges:

1. Strong environmental dynamics, such as real-time meteorological changes in flight zones, obstacle movements, or other aircraft activities, which can cause abrupt changes in path passability.
2. Complex constraint conditions, including aircraft maneuverability, no-fly zone restrictions, and other factors that influence path planning results.
3. High real-time decision-making requirements, as dynamic environmental impacts necessitate real-time updates during flight, with planning time controlled within the 100ms level.

To address the above challenges, this paper proposes a three-layer spatiotemporal knowledge graph-based path planning(3L-STKG-PP) framework. The 3L-STKG comprises a concept layer, instance layer, and spatiotemporal layer, which achieves rapid path reasoning, planning, and dynamic optimization in complex environments. The research results will provide a new technical pathway for the autonomous navigation of low-altitude vehicles in complex scenarios and facilitate the deep integration of low-altitude economy and smart cities.

2. A Three-Layer Spatiotemporal Knowledge Graph-Based Path Planning (3L-STKG-PP) Method

2.1 Three-Layer Spatiotemporal Knowledge Graph Architecture

Traditional knowledge graphs are predominantly attribute graphs, focusing on expressing "entity-relationship-entity" triple relationships. To transform complex and dynamic path planning problems into spatiotemporal network minimum connected subgraph path search problems based on ontology constraints, this paper proposes a three-layer knowledge graph architecture comprising a concept layer, instance layer, and spatiotemporal layer. It innovates a cross-layer spatiotemporal knowledge fusion analysis mechanism of "ontological knowledge-spatiotemporal knowledge" to achieve efficient path matching and dynamic optimization planning based on graph computation.

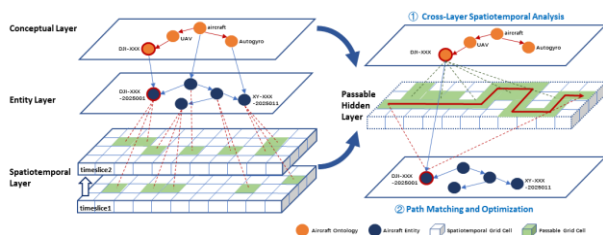


Figure 1. Three-Layer Spatiotemporal Knowledge Graph Architecture.

2.1.1 Concept Layer: The concept layer primarily represents ontological concepts related to low-altitude vehicles and flight missions. Among them, the ontological concepts of low-altitude vehicles mainly include data attributes such as basic information, physical structure, and maneuverability performance; ontological concepts of flight missions mainly include data attributes such as basic information, mission resources, mission time, mission area, mission route, and constraint conditions. Detailed Low-Altitude Vehicle and Flight Mission Ontology are shown in Figure 2.

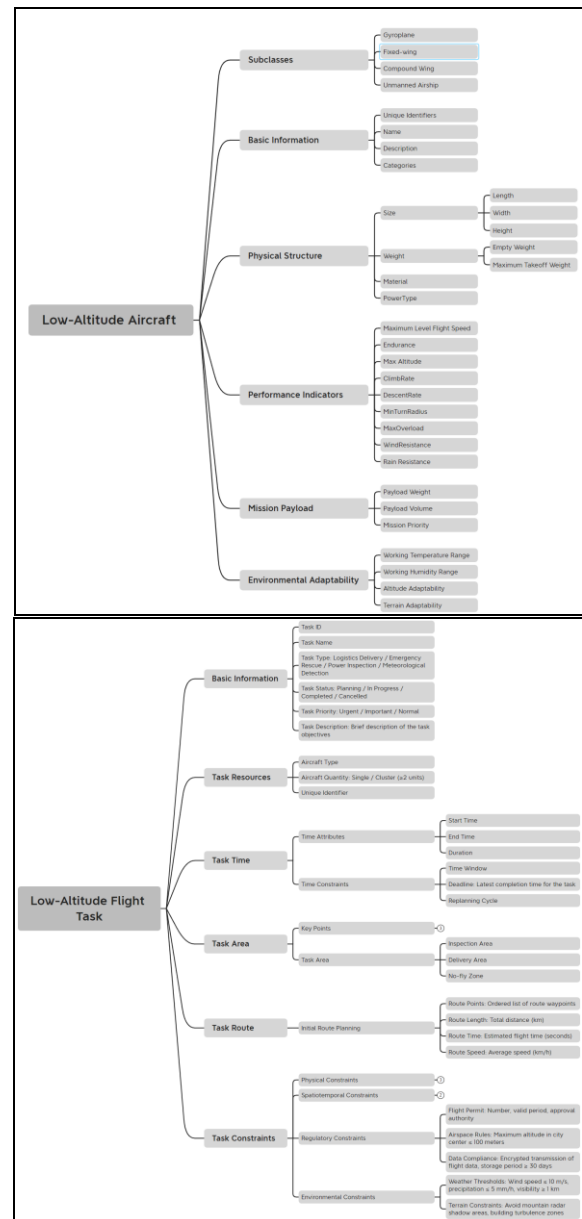


Figure 2. Ontological Information of Low-Altitude Vehicles and Flight Missions

2.1.2 Instance Layer: The instance layer primarily consists of entity sets of low-altitude vehicles and flight missions, along with their corresponding associative relationships. The characters includes not only the attribute elements defined in the ontology (e.g., basic information, physical structure) but also real-time state data such as current position, remaining fuel, remaining battery, and associated flight mission information. Flight missions emphasize details such as mission time, operation area, flight route, and constraint conditions, which are critical for dynamic path adjustment.

This layer bridges abstract ontological definitions with real-world operational data, enabling the knowledge graph to support time-sensitive reasoning (e.g., calculating remaining flight range based on battery level) and constraint enforcement (e.g., verifying mission routes against no-fly zone boundaries in real time). By integrating both static ontology attributes and dynamic sensor data, the Instance Layer ensures the path planning framework remains grounded in empirical reality

while maintaining semantic consistency with higher-level conceptual models.

2.1.3 Spatiotemporal Layer: The spatiotemporal layer constructs a hierarchical spatiotemporal knowledge graph based on spatiotemporal grid encoding. First, a 4D spatiotemporal grid model $G(S, T, V, E)$ is established, defined as:

$$G(S, T, V, E) = \begin{cases} S = \{s_i \mid s_i \in \text{GEOSOT 3D grid codes}, i = 1, 2, \dots, N\} \\ T = \{t_j \mid t_j \in \square^+, j = 1, 2, \dots, M\} \\ V = \{v_{i,j} \mid \text{attributes of grid } s_i \text{ at time } t_j\} \\ E = \{(s_i, s_k, t_j) \mid \text{spatial adjacency or temporal between } s_i, s_k \text{ at } t_j\} \end{cases} \quad (1)$$

where:

1. The spatial dimension S adopts hierarchical grid encoding by GEOSOT. The low-altitude area (0–1000 m above sea level) is divided into cubic grid cells (e.g., Level 10 grid encoding: G3D1039.9N116.3E0050, with a cell size of 10m × 10 m × 10 m).
2. The temporal dimension T is discretized into equal-interval time slices, each associated with a unique temporal code (e.g., hourly slots from 09:00–10:00 UTC).
3. The attribute set V of each grid cell includes:
 - a) Static Terrain: Roads, water systems, vegetation, pipelines, buildings, obstacles, etc.
 - b) Dynamic Constraints: Rainfall intensity, wind speed, temporary restricted zones, etc.
 - c) Passability Metrics: Passable, Non-passable, Conditionally passable (e.g., passable only below 50 m altitude).

Finally, spatiotemporally adjacent grid cells are connected via adjacency relationships E , completing the construction of spatiotemporal knowledge graph triples: $\langle G_1, E_1, G_2 \rangle$. This encoding scheme enables efficient querying of spatial-temporal correlations (e.g., "find all passable grids within 500 m of [116.49°E, 39.91°N] between 10:00–10:30 UTC") and dynamic constraint propagation across adjacent cells.

2.2 Cross-Layer Knowledge Fusion Framework

This paper proposes a novel cross-layer knowledge Fusion Framework that addresses the coupling problem between ontological constraints and spatiotemporal environments in vehicle path planning. By fusing the low-altitude vehicle ontological knowledge from the concept layer with spatiotemporal environmental knowledge from the spatiotemporal layer, a multi-dimensional constraint passability model is constructed to generate a passable spatiotemporal hidden layer, enabling efficient path planning.

2.2.1 Spatiotemporal Grid Level Adaptation: The spatiotemporal grid coding divides the Earth's space into different sizes of spatiotemporal grids based on the size of different levels. Firstly, based on the ontological attribute parameter set of the vehicle $P = \{l, r, d\}$ (representing fuselage length, minimum turning radius, and safety buffer distance, respectively), a grid level adaptation criterion is defined as: $\delta = \max\{l + 2d, 2r\}$, where δ denotes the side length of a single grid cell, ensuring it satisfies the minimum spatial constraints for vehicle passage. The spatio-temporal grid division hierarchy is established based on the cell size required for the movement of unmanned aerial vehicles. Further, according to the vehicle's flight parameters (e.g., flight altitude, operational range), the flight area $G = \{g_i, level\}_{i=1}^N$, is delimited to form the basic spatiotemporal search space.

2.2.2 Multi-Constraint Passability Modeling and Hidden Layer Representation: Secondly, a set of spatiotemporal grid cells $G_s = \{g_i, level\}_{i=1}^M$, satisfying static passage conditions

within the flight area is filtered, where static constraints include hard constraints such as obstacle avoidance and no-fly/control zone. Further, vehicle maneuverability parameters (e.g., wind resistance, rain resistance) and dynamic environmental factors (wind speed, rainfall intensity, conflict index, etc.) are introduced to construct a fuzzy comprehensive evaluation

model: $\rho(s, t) = \frac{\sum_{k=1}^K w_k \mu_k(s, t)}{\sum_{k=1}^K w_k}$, where w_k are factor weights,

μ_k is the passability evaluation function for the k -th factor. The resulting passability value $\rho \in (0, 1]$ serves as a soft constraint, generating the actual passable spatiotemporal grid cell set $G_p = \{g_i, level\}_{i=1}^K$ and constructing the passable spatiotemporal hidden layer H .

Additionally, to achieve numerical representation of this hidden layer, graph neural networks (GNNs) are used for vectorization. Treating G_p as a node set, each node is endowed with a feature vector containing its passability value ρ . Neighborhood information is aggregated layer-by-layer via graph convolutional networks (GCNs):

$$h_i^{(l)} = \sigma \left(\sum_{u \in N(i)} \frac{h_u^{(l-1)} \cdot \rho(u)}{|N(i)|} \cdot W^{(l)} \right) \quad (2)$$

where:

1. $h_i^{(l)}$ is the feature vector of node i at the l -th GCN layer,
2. $N(i)$ denotes the set of neighboring nodes of i ,
3. $W^{(l)}$ is the learnable weight matrix and bias vector at layer l ,
4. $\sigma(\cdot)$ is the activation function (e.g., ReLU).

This hierarchical aggregation enables the hidden layer to capture spatiotemporal correlations between grid cells, such as the impact of wind speed gradients on adjacent cells' passability. The vectorized hidden layer H is then integrated into path planning algorithms (e.g., A^*) as a dynamic cost map, allowing real-time adaptation to multi-constraint environments.

2.3 Path Search Based On Improved A* Algorithm:

Lastly, In the passable spatiotemporal hidden layer H , a heuristic search algorithm weighted by passability values is designed. The search cost function is defined as:

$$f(n) = g(n) + \lambda \frac{h(n)}{e^{\rho(n)}} \quad (3)$$

$g(n)$ is the cumulative cost from the starting point to node n (including time cost and energy consumption), $h(n)$ is a heuristic cost function using Manhattan distance, which represents the distance from the current node to the destination. λ is a weight coefficient greater than 1, and $\rho(n)$ is the passability value of the node. By reducing the cost of high-passability areas, the path search is guided to converge toward the optimal path with high passability values.

After path generation, a caching mechanism $M = \{(V, P_i)\}$ is established to associatively store the optimal path P with its corresponding passable hidden layer feature vector. When processing similar tasks, similarity matching is performed based on conditions such as regional passability features, start and end points, to support rapid retrieval of historical path planning results. Additionally, local conflict areas can be fine-tuned to form a closed-loop optimization mechanism of "planning-caching-reusing-fine-tuning", ensuring the validity of planning results while improving planning efficiency.

3. Simulations and Results

3.1 Simulation Environment

Simulation Platform: Python

Hardware Configuration: Intel(R) Core(TM) Ultra 7 265KF 3.90 GHz, 32GB RAM, NVIDIA RTX 5080

Test Scenario: The test scenario simulates the low-altitude airspace over urban blocks, generating corresponding spatiotemporal knowledge graph data. The spatial dimension employs GeoSOT global subdivision encoding, while the temporal dimension uses a 1-hour interval, comprehensively considering the regular monitoring cycles of meteorological elements (e.g., wind speed, precipitation) and the average execution duration of low-altitude missions. Each spatiotemporal node is associated with simulated attributes such as obstacles, restricted zones, and meteorological conditions. Specifically, considering the differentiated distribution characteristics of urban functions:

1. 20% of nodes are randomly designated as impassable regions, simulating hard constraints like high-rise buildings and restricted airspace.
2. 60% of nodes are designated as conditionally flyable regions, simulating soft constraints such as pipelines, wind speeds, and rainfall.
3. The remaining nodes are classified as passable regions.

This configuration ensures a realistic representation of urban low-altitude environments, enabling comprehensive testing of path planning algorithms under complex constraints.

3.2 Evaluation Metrics

To comprehensively assess the performance of the proposed algorithm in complex low-altitude environments, three evaluation metrics are defined from three perspectives: planning efficiency, spatial optimization, and environmental adaptability.

Planning Time(s): The time consumed from initiating path computation at the start node to obtaining the optimal path at the end node. A shorter duration indicates higher computational efficiency.

Path Efficiency Ratio: The ratio of the total length of the planned path to the Manhattan distance between the start-node and end-node. A lower ratio signifies better spatial utilization efficiency.

$$\text{Efficiency Ratio} = \frac{\text{Total Length of Planned Path}}{\text{Manhattan Distance between Start Node and End Node}} \quad (4)$$

Avg Traversal Cost: Calculated by dividing the total length of the planned path by the sum of their passability values. A lower value indicates better overall passability:

$$\text{Avg Traversal Cost} = \frac{\text{Total Length of Planned Path}}{\sum \rho(n)} \quad (5)$$

These metrics collectively evaluate the algorithm's efficiency, spatial optimality, and adaptability to dynamic environmental constraints in urban low-altitude scenarios.

3.3 Experiment Results

Randomly generated simulation datasets containing 10^4 , 10^6 , 4×10^6 , 25×10^6 , 10^8 spatiotemporal grid cells were tested. For each dataset size, 100 random <start point, end point> pairs were generated. The performance of the traditional A* algorithm was compared against the proposed 3L-STKG-PP path planning method. Evaluation metrics including planning duration, path efficiency ratio, and passage cost were computed and analyzed as mentioned in Section 3.2. N in figure 3 is the unilateral length in the square map.

Planning Efficiency: The 3L-STKG-PP approach demonstrated significant improvements, especially with increasing grid cell counts. The average planning time can be reduced to 0.033s, at 10^6 nodes, which can meet the needs of dynamic planning for unmanned aerial vehicles. At 10^8 nodes, the time could even be reduced by 88.54% compared to the traditional A* algorithm, achieving sub-1 second response times suitable for real-time decision-making.

Path Quality: The 3L-STKG-PP approach marginally outperformed the traditional approach in both path efficiency ratio (optimized spatial utilization) and passage cost (smoother traversal through high-passability regions).

These results show that the 3L-STKG-PP approach has two advantages:

1. **Scalability:** The STKG method's efficiency advantage grows exponentially with dataset size, maintaining real-time performance even at 10^8 nodes.
2. **Adaptability:** By leveraging spatiotemporal knowledge graphs, the algorithm effectively balances path optimality and computational speed under dynamic constraints..

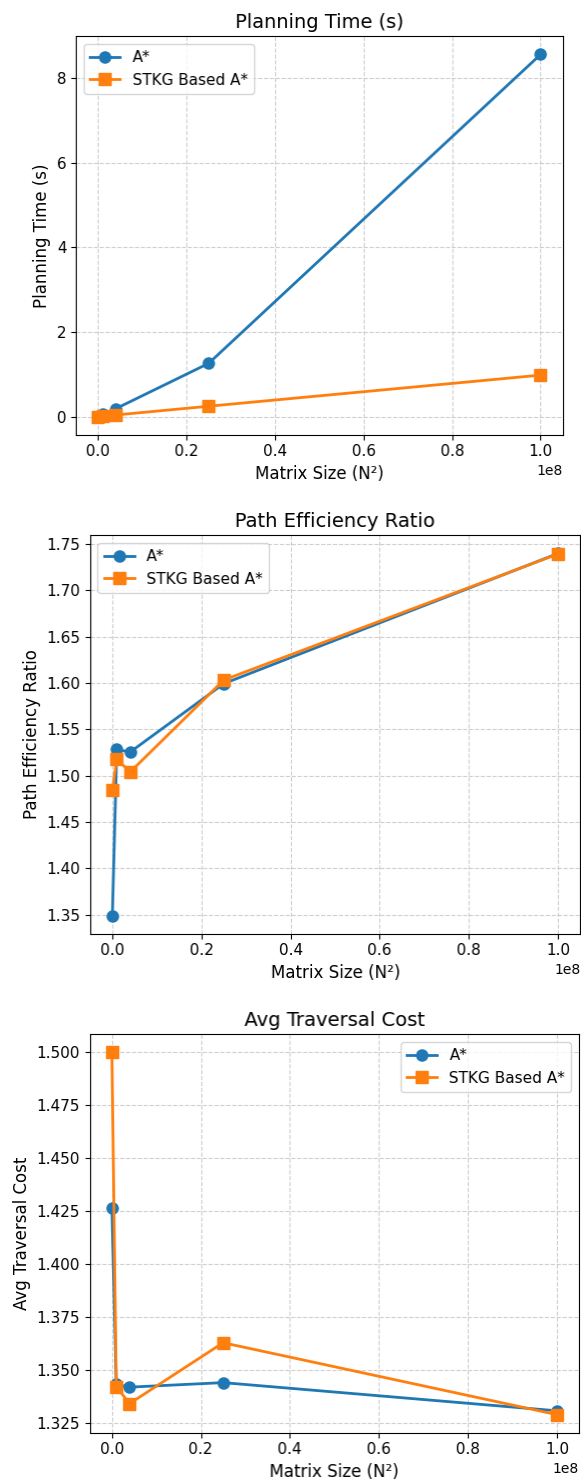


Figure 3. Comparison of Test Results between 3L-STKG-PP and Traditional A*.

In addition, this study compares three heuristic cost functions—Euclidean distance, Manhattan distance, and passability-weighted Manhattan distance using identical start and end points within the same regional scope. The evaluation focuses on pre-planning time, path efficiency ratio, and passage cost. Results indicate that while the Euclidean distance heuristic yields marginally better path efficiency and passage cost metrics, its pre-planning time grows exponentially with node count, rendering it unsuitable for rapid iteration. In contrast, the proposed passability-weighted Manhattan distance heuristic demonstrates optimal performance across all metrics,

particularly in large-scale scenarios, making it better suited for practical applications requiring real-time adaptability.

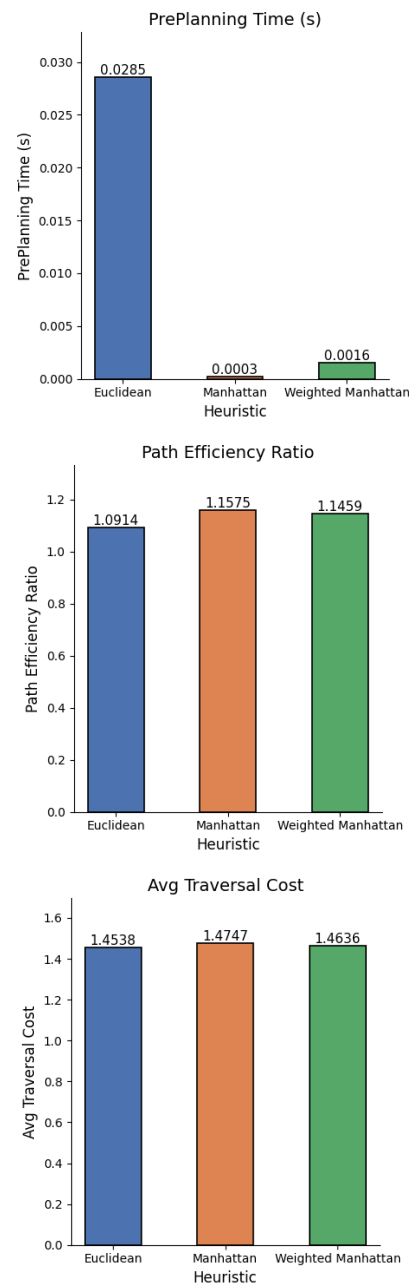


Figure 4 Comparison of Test Results for Different Heuristic Cost Functions

4. Conclusions and Future Work

4.1 Research Findings

The three-layer knowledge graph architecture proposed in this study, consisting of a conceptual layer, instance layer, and spatiotemporal layer, effectively integrates ontological knowledge of low-altitude aircraft with spatiotemporal constraints through cross-layer associations, thereby enhancing the efficiency of path planning. The conceptual layer rigorously formalizes ontological concepts of aircraft and flight missions; the instance layer delineates entity sets and their relationships; and the spatiotemporal layer constructs a graph using spatiotemporal grid encoding and correlates environmental attributes, providing comprehensive knowledge support for path

planning. The cross-layer association mechanism elegantly transforms the complex path planning problem into a shortest path search problem in graph theory. By pre-matching the maneuverability constraints from the conceptual layer with the grid passability attributes from the spatiotemporal layer through a cross-layer spatiotemporal analysis mechanism, a dynamic reachability network is constructed, significantly improving the algorithm's adaptability to dynamic environments and enabling rapid, rational path planning decisions in response to environmental changes. The 3L-STKG-PP algorithm effectively leverages fuzzy representations of spatiotemporal passability, ensuring global optimality while enhancing computational efficiency.

Experiments demonstrate substantial reductions in planning time across both static and dynamic scenarios, with planning durations within seconds for large-scale spatiotemporal node datasets, thus providing robust support for rapid decision-making of low-altitude aircraft in complex environments.

4.2 Future Directions

The heuristic function adopted in this study is currently simplistic and struggles to meet the demands of large-scale, high-speed, dynamic low-altitude planning scenarios. To address this, the next step will involve introducing reinforcement learning (RL) to optimize heuristic function parameters. By leveraging RL's adaptive capabilities, the parameters will be dynamically adjusted according to varying environmental states and mission requirements, further enhancing the improved A* algorithm's search efficiency and path quality in complex, changing environments. This will enable the algorithm to more rapidly find global or near-global optimal paths.

Additionally, the methodology will be extended to multi-agent collaborative path planning scenarios, focusing on researching coordination mechanisms among multiple low-altitude vehicles. Key challenges to address include conflict avoidance, task allocation, and collaborative flight in shared airspace, with the goal of achieving efficient multi-vehicle coordination to meet the needs of simultaneous operations in urban logistics distribution, emergency rescue, and similar applications. To validate the algorithm's robustness, real-world flight testing will be conducted. This involves building a physical flight testbed to evaluate the algorithm in authentic low-altitude environments, including tests under diverse meteorological conditions, complex terrains, and various interference factors. By collecting actual flight data, the algorithm can be further optimized and refined to ensure reliability and stability in practical applications.

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