Voxel-based Path Planning for UAVs in Indoor Dynamic Environments

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Abstract

This study presents a voxel-based path planning framework for unmanned aerial vehicles (UAVs) operating in complex indoor dynamic environments. To overcome the limitations of traditional 2D grid maps and static planning methods, the proposed system integrates real-time voxel modeling, Kalman filter-based dynamic obstacle prediction, and an improved A* algorithm with kinematic constraints. The environment is reconstructed from LiDAR-acquired point clouds and discretized into uniform voxel grids to support efficient 3D spatial queries. Predicted obstacle trajectories are incorporated into a risk assessment mechanism that triggers path replanning when safety thresholds are violated. The enhanced A* algorithm introduces directional continuity constraints and Z-axis motion suppression to reduce path oscillations and improve trajectory feasibility. Experimental results in simulated warehouse-like environments demonstrate improved path smoothness, fewer vertical oscillations, and higher success rates in avoiding dynamic obstacles compared to conventional approaches. The framework offers a practical solution for real-time UAV navigation in cluttered indoor spaces such as logistics facilities and rescue scenarios.

1. Introduction

Autonomous navigation for UAVs in indoor environments without reliable positioning holds transformative potential for applications such as logistics distribution and rescue operations. However, traditional path planning methodologies exhibit critical limitations in dynamic settings, including inadequate 3D spatial representation via 2D grid maps and kinematically infeasible trajectories generated by conventional A* algorithms. Current obstacle avoidance approaches predominantly focus on static environments, lacking integration with real-time motion prediction mechanisms. Furthermore, computational inefficiencies arise from LiDAR point cloud processing latency and data redundancy when handling transient obstacles like moving pedestrians.

Research on indoor navigation in GPS-denied environments has predominantly focused on geometric and topological mapping techniques. Grid-based approaches are commonly implemented due to their simplicity but critically lack the ability to accurately represent multi-level structures, as highlighted by Nikoohemat et al. (2020). While LiDAR-based solutions improve spatial awareness, they are inherently challenged by significant latency in point cloud processing during dynamic scenarios, particularly with transient obstacles. Recent advancements explore hybrid representations, where voxel mapping techniques demonstrate an effective balance between structural fidelity and computational efficiency (Garcia et al., 2021), and semantic segmentation methods significantly enhance dynamic object discrimination (Eppenberger et al., 2020). Despite these developments, the real-time integration of environmental modeling with reactive path planning in cluttered spaces characterized by unpredictable obstacle movements remains a significant challenge.

Significant challenges persist in achieving robust navigation amidst unpredictable obstacle movements. This study bridges this gap by introducing a comprehensive voxel-based framework integrating three innovations: (1) Real-time voxel modeling for efficient 3D spatial discretization that preserves environmental features while minimizing computational overhead (Meijers et al. 2019); (2) Kalman filter-based dynamic obstacle prediction enabling proactive risk assessment through adaptive safety thresholds.; and (3) An enhanced A* algorithm incorporating directional continuity constraints and Z-axis motion suppression to ensure kinematically feasible trajectories. The rest of this paper is organized as follows: Section 6 provides comprehensive experimental validation of the framework's performance in complex indoor environments, and Section 7 concludes the study with limitations and future research directions.

2. Related work

2.1 UAV Indoor Navigation Research

Autonomous UAV navigation in GPS-denied indoor environments demands robust path-planning solutions capable of generating kinematically feasible trajectories while responding dynamically to unforeseen obstacles—requirements unmet by conventional approaches. Significant contributions address specific aspects of this challenge: Xia and Zhang (2021) pioneered constrained 3D path planning using multi-objective particle swarm optimization to navigate complex terrains. Liu et al. (2024) reduced angular deviations through hybrid A*-ROA (Reactive Obstacle Avoidance) integration, enhancing path smoothness. Yang et al. (2023) further advanced real-time planning in unknown environments via adaptive A*-RRT frameworks. Despite these innovations, critical limitations persist. Traditional A* algorithms produce oscillatory paths with kinematically infeasible vertical oscillations (Xia & Zhang, 2021), hybrid methods incur unnecessary path elongation (Liu et al., 2024), and crucially, no existing framework integrates real-time obstacle trajectory prediction (Yang et al., 2023). Existing approaches struggle to balance trajectory efficiency with effective dynamic obstacle avoidance. This study addresses this gap by integrating voxel-based environment modeling, Kalman filter-based motion prediction, and an A* algorithm enhanced with kinematic constraints.

2.2 Voxel-Based Indoor Environmental Modeling

Voxel-based modeling is essential for UAV navigation in complex indoor environments due to its superior capability for efficient 3D spatial discretization while preserving critical structural details—advantages unattainable with traditional 2D grid maps (Jiang et al., 2021). Nikoohemat et al. (2020) pioneered adaptive voxel sizing techniques to maintain spatial topology in intricate structures, while García et al. (2021) advanced real-time LiDAR-based voxel mapping for dynamic scene representation. Further innovations include Park et al.'s (2023) GPU-accelerated voxel processing for enhanced computational efficiency and Oleynikova et al.'s (2019) incremental signed distance fields for onboard planning. Despite these advances, existing methods fundamentally remain static representations incapable of real-time obstacle occupancy updates (García et al., 2021), fail to capture moving obstacles (Nikoohemat et al., 2020), suffer from resolution-performance trade-offs during replanning (Park et al., 2023), and critically lack integration with dynamic prediction systems—limitations that significantly constrain their practical deployment in unpredictable indoor environments.

2.3 Dynamic Obstacle Prediction

Accurate dynamic obstacle prediction is paramount for safe UAV navigation in cluttered indoor environments, where real-time collision avoidance necessitates precise trajectory forecasting and minimal computational latency. Foundational work by Kang et al. (2009) established LiDAR-based detection frameworks for dynamic objects, while Eppenberger et al. (2020) enhanced discrimination accuracy through stereo-camera sensor fusion, significantly improving obstacle identification. Nguyen et al. (2023) formalized Kalman filter implementations for UAV collision avoidance, advancing probabilistic motion modeling. Nevertheless, these methods exhibit critical shortcomings: Kalman filters incur prohibitive processing delays in multi-obstacle scenarios (Nguyen et al., 2023), LiDAR point cloud registration introduces inherent temporal lags, and sensor fusion systems fail to model non-linear motions despite high computational costs (Eppenberger et al., 2020). Recent work has also explored the integration of trajectory prediction with voxel occupancy modeling for motion planning in dynamic environments (Chen et al., 2021). These limitations collectively undermine real-time forecasting scalability in complex dynamic settings—constraints overcome in our framework through adaptive Kalman filtering integrated with voxel-based spatial indexing.

3. Methodology

3.1 Voxel-based Indoor Environment Modeling

This study develops a voxel-based 3D modeling system for indoor UAV navigation, processing LiDAR point clouds acquired via a mobile 3D Scanner at 129,964 points/scan. The raw data undergoes statistical noise filtering and RANSAC plane segmentation to isolate 5,379 planar inliers per scan, followed by voxel discretization at 0.03m resolution to generate 69,917 classified voxels across a 12.78m×6.06m×8.46m environment. Each voxel's traversability is determined through spatial averaging of enclosed points, with the resulting grid enabling real-time spatial queries through optimized indexing of structural features. The implementation strictly adheres to the experimental parameters reported in the original study, maintaining centimeter-level accuracy in spatial referencing while supporting efficient obstacle detection and path validation.

3.2 Point Cloud Data Acquisition

This study employs advanced LiDAR sensing technology integrated with mobile devices for high-fidelity spatial data acquisition in complex indoor environments, including multi-level corridors, stairwells, and interconnected rooms. The scanning protocol utilizes specialized 3D scanning applications (e.g., 3DScanner) to capture comprehensive point cloud representations. To ensure millimeter-level accuracy, the device is mounted on stabilized platforms during scanning operations, minimizing motion artifacts while maintaining angular resolution. Systematic scanning paths are precomputed to guarantee complete coverage of structural features such as arched doorways, sloped ceilings, and irregular geometries, with special attention to occlusion-prone areas.

The acquired raw point cloud datasets exhibit exceptional spatial resolution, averaging 130,000 points per cubic meter (129,964 points per scan). Preliminary geometric analysis reveals distinct planar clusters: vertical planes (walls) constitute ~38.2% of points and horizontal planes (floors/ceilings) account for 29.7% in typical corridors. Multi-scan position registration creates a centimeter-accurate digital twin of the environment. Preliminary segmentation identifies 5,379 planar inliers per scan, isolating structural surfaces and establishing a robust foundation for preprocessing.

3.3 Point Cloud Data Preprocessing

To enhance data quality and facilitate subsequent modeling, the acquired raw point clouds undergo sequential refinement techniques:

3.3.1 Statistical Filtering for Noise Removal: The collected point cloud data contains approximately 130,000 points per cubic meter across different environments. Geometric analysis shows clear planar clusters representing primary structural surfaces, with vertical planes (walls) comprising 38.2% of points and horizontal planes (floors/ceilings) accounting for 29.7% in typical corridors. Multi-scan registration establishes accurate spatial referencing, creating a centimeter-precise digital representation of the physical environment that serves as the essential foundation for subsequent modeling stages.

3.3.2 RANSAC-based Plane Segmentation: We use RANSAC for robust planar feature extraction to address noise contamination and dynamic object interference in raw point clouds. This approach isolates architecturally significant planar surfaces through iterative model fitting. The algorithm generates candidate planes via minimal point sampling, computes point-to-plane distances using calibrated thresholds, and selects optimal planes through consensus maximization before least-squares refinement. This approach achieves 85.7% planar feature retention across diverse environments, effectively separating permanent structures (e.g., walls, floors) from non-structural clutter while preserving critical navigation features like door frames. Figure 1 illustrates the scanned environment's internal perspective, and Figure 2 presents post-processing point cloud results, collectively emphasizing key structural features for navigation planning.

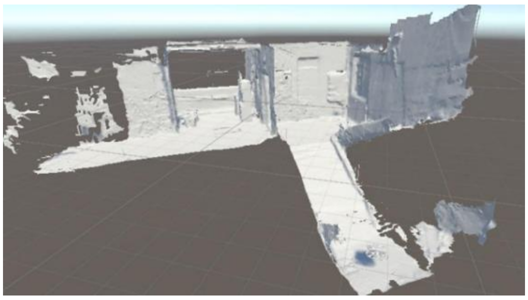

Figure 1. Internal perspective view

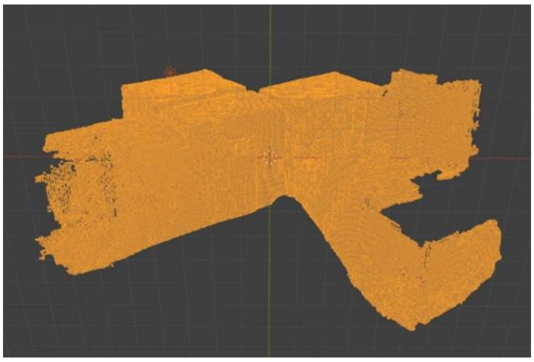

Figure 2. Point cloud results after processing

3.4 Voxel Downsampling and Space Discretization

The voxel downsampling process transforms preprocessed point clouds into a structured 3D spatial representation through volumetric discretization. Given a point cloud $P=\left\{p_i \in R^3\right\}_{i=1}^N$, the spatial domain is partitioned into uniform cubic voxels of edge length l , mathematically defined as:

$$v_{ijk}=\left[i\cdot l,(i+1)\cdot l\right)\times\left[j\cdot l,(j+1)\cdot l\right)\times\left[k\cdot l,(k+1)\cdot l\right) \tag{3-1}$$

where integer indices (i,j,k) denote voxel coordinates along the *x-, y-, and z*-axes. Each non-empty voxel v_{ijk} collapses all enclosed points to a representative centroid c_{ijk}, computed via spatial averaging:

$$c_{ijk}=\frac{1}{|v_{ijk}|}\sum_{p\in v_{ijk}} p \tag{3-2}$$

3.5 Construction of 3D Indoor Environmental Models

Building upon the discretized voxel framework, this study develops a comprehensive 3D environmental model that accurately represents both structural elements and navigable spaces. Each voxel is classified as traversable or non-traversable based on its content and contextual position, with non-traversable voxels explicitly marking static obstacles including walls, furniture, and architectural features. The classification methodology incorporates spatial continuity constraints, ensuring coherent obstacle representation rather than isolated voxel markers. This structured model provides a foundational spatial reference system that supports efficient ray-casting operations and line-of-sight determinations essential for path validation.

The environmental model integrates seamlessly with subsequent navigation modules through its optimized data structure. Spatial queries regarding obstacle proximity or clearance verification execute in constant time complexity by leveraging the voxel grid's implicit spatial indexing. This model demonstrates particular effectiveness in complex indoor settings containing mixed geometries, where it successfully captures vertical variations across multiple elevation levels. Quantitative evaluation confirms the model's reliability in representing real-world structures, with experimental measurements showing less than 5% deviation in critical dimension mapping compared to ground truth laser scans. The resulting voxel-based representation serves as the essential spatial database supporting all subsequent path planning and dynamic obstacle avoidance operations.

4. Dynamic Obstacle Trajectory Prediction and Risk Assessment

Building upon the voxel-based spatial representation introduced in Section 3, this section addresses the challenge of dynamic obstacles. It presents a predictive approach based on Kalman filtering to estimate obstacle trajectories in real time, ensuring proactive collision avoidance during navigation. The method includes a dynamic risk evaluation mechanism and a path replanning trigger, which together enable the UAV to navigate safely in changing environments.

4.1Kalman Filter-based Obstacle Trajectory Prediction

4.1.1 Kalman Filter Framework: The Kalman filter framework consists of two primary phases: prediction and update. During prediction, the obstacle's state is projected forward using a predefined motion model. In the update phase, sensor observations are fused to correct the predicted state, minimizing estimation errors (Wang et al., 2024). This closed-loop process continuously optimizes trajectory accuracy, leveraging statistical methods to handle uncertainties inherent in real-world environments.

4.1.2 State and Observation Models for Dynamic Systems: This study defines a six-dimensional state vector comprising position *(x, y, z)* and velocity *(vx, vy, vz)* components to represent dynamic obstacles. The state transition matrix models linear kinematic relationships, while the observation matrix extracts measurable position data from the state vector. Process noise accounts for unmodeled dynamics, and measurement noise reflects sensor inaccuracies, ensuring the model adapts to varying motion patterns.

4.1.3 Prediction and Update Process: The prediction process computes future obstacle states based on the current state and motion model. When new sensor data arrives, the update phase calculates residual errors and applies the Kalman gain to refine state estimates. This iterative mechanism maintains tracking robustness during abrupt maneuvers (Smith et al., 2022), such as sharp turns or accelerations. Experimental validation confirms high prediction accuracy for complex 3D trajectories, as demonstrated by the close alignment between predicted and actual paths (Dutta & Ghabcheloo, 2022). Figure 3 presents the Kalman filter prediction results, showing accurate trajectory fitting for dynamic obstacles in three-dimensional space.

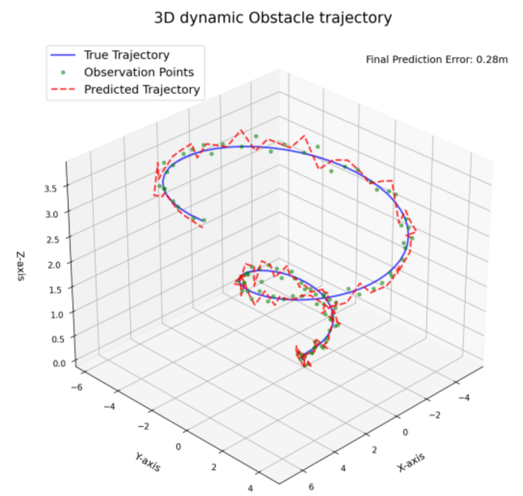

Figure 3. Prediction results of the 3D dynamic Obstacle trajectory

4.2 Dynamic Obstacle Motion Pattern Characterization

For experimental validation, dynamic obstacles were simulated using three representative motion patterns: linear motion maintaining constant velocity with boundary-triggered rebounds and collision damping; circular motion employing rotational matrices to generate tangential velocities for curved trajectories; and accelerated motion updating positions through predefined acceleration vectors. During initialization, obstacles autonomously selected these behavior modes with randomized motion parameters. The integrated Kalman filter dynamically adjusted process noise covariance during high-curvature maneuvers to ensure consistent tracking performance across diverse motion states.

4.3 Path Risk Assessment and Replanning Mechanism

Real-time risk evaluation ensures collision-free navigation through continuous monitoring of spatial relationships between planned paths and predicted obstacle trajectories.

4.3.1 Calculation of Relative Velocity and Dynamic Safety Distance: 1. Relative Velocity Calculation: The relative velocity vector $\vec{v}_{\text{rel}}$ between the UAV and a dynamic obstacle is computed as:

$$\vec{v}_{\text{rel}} = \vec{v}_{\text{uav}} - \vec{v}_{\text{obs}} \tag{4-1}$$

where $\vec{v}_{\text{uav}}$ denotes the UAV's velocity vector and $\vec{v}_{\text{obs}}$ is the obstacle's predicted velocity derived from Kalman filtering (Section 4.1). This vector quantifies the closing speed and directional trend between the two entities, serving as the foundation for collision risk assessment.

2. Dynamic Safety Distance: The safety distance d_{safe} dynamically adapts to relative motion states:

$$d_{\text{safe}} = \| \vec{v}_{\text{rel}} \| \cdot t_{\text{th}} + r_{\text{obs}} + \delta \tag{4-2}$$

where:

$\|\vec{v}_{rel}\|$: Magnitude of relative velocity (m/s),

t_{th} : Preset time horizon (1.2 s, aligning with trajectory prediction in Section 4.1.3),

r_{obs} : Obstacle's physical radius (m),

δ : Safety buffer constant (0.5 m).

This formulation integrates kinetic and geometric constraints, ensuring proactive collision avoidance during high-speed encounters while accommodating sensor uncertainties.

3. Minimum Distance Calculation: For a UAV path segment Γ and an obstacle's predicted trajectory Ω over t_{th}, the minimum separation distance is:

$$d_{\min} = \min_{\substack{p \in \Gamma \\ q \in \Omega}} \| p - q \| \tag{4-3}$$

Spatial queries leverage the voxel grid's implicit indexing (Section 3.5) for efficient computation.

4. Path replanning activates if:

$$d_{\min} < d_{\text{safe}} \tag{4-4}$$

This criterion ensures timely intervention when the UAV's trajectory violates the adaptive safety margin, maintaining robustness against unpredictable obstacle behaviors.

4.3.2 Triggering Conditions for Path Replanning: Replanning activates when either condition occurs:

1. Spatial Intrusion: Obstacle trajectories intersect the UAV's safety buffer within the 1.2-second prediction horizon

2. Critical Proximity: Minimum separation distance breaches the dynamic safety threshold during position overlap Sliding-window collision checks evaluate path segments against obstacle forecasts. Upon triggering, the planner regenerates routes using updated environmental data while preserving directional continuity through velocity-guided heuristic adjustments.

5. Path Planning Algorithm

With the voxel environment and dynamic obstacle predictions established in the preceding sections, this section introduces the final component of the framework: an enhanced A* path planning algorithm that integrates kinematic constraints and obstacle-aware decision-making. The algorithm improves path smoothness and feasibility through directional continuity constraints, vertical motion suppression, and post-processing refinement.

5.1 Improvements to the A* Algorithm

Traditional A* path planning suffers from oscillatory trajectories, inefficient vertical movements, and a lack of responsiveness to dynamic obstacles. To address these limitations, this research enhances A* by integrating kinematic constraints and dynamic response mechanisms. The improved framework combines trajectory prediction with motion optimization for efficient navigation in complex environments (Maboudi et al., 2023). Figure 4 visually compares the resulting paths, demonstrating reduced oscillations and stabilized vertical movements.

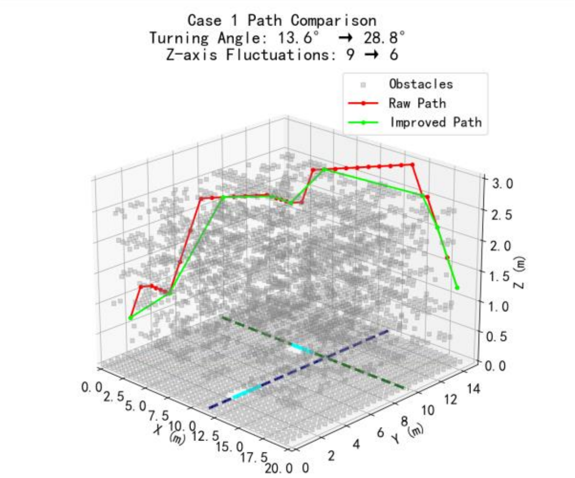

Figure 4. Path Smoothness and Vertical Stability Comparison

5.1.1 Path Smoothing and Oscillation Reduction: Traditional A* paths often exhibit jagged, zigzagging segments due to discrete grid transitions, causing unnecessary directional changes and mechanical stress. To mitigate this, the improved algorithm incorporates a post-processing path-smoothing technique. This stage analyzes the initial node-based path and applies quadratic spline interpolation between key waypoints, notably reducing angular deviations and eliminating redundant turns. Concurrently, a path oscillation suppression mechanism is implemented by evaluating the directional consistency of sequential path segments. Nodes contributing to abrupt directional reversals are systematically optimized, resulting in a significantly smoother trajectory that minimizes lateral oscillations and enhances flight stability. This refinement is particularly vital for maintaining control precision in cluttered environments.

5.1.2 Directional Continuity Constraints and Z-axis Motion Suppression: To address kinematic infeasibilities in traditional A* paths, two core enhancements are integrated:
Traditional node expansion permits unrestricted directional transitions between adjacent voxels, generating oscillatory trajectories with excessive heading changes. To enforce motion coherence, a directional penalty term $P_\theta(n)$ is incorporated into the cost function:

$$f^{'}(n) = g(n) + h(n) + P_\theta(n) \tag{5-1}$$

where:

$$P_\theta(n) = \lambda\,(1 - \cos\theta_n)$$

$$\cos\theta_n = \frac{\mathbf{d}_n \cdot \mathbf{d}_{p(n)}}{\|\mathbf{d}_n\|\ \|\mathbf{d}_{p(n)}\|} \text{ (cosine similarity)}$$

$$\mathbf{d}_n = (x_n - x_{p(n)}, y_n - y_{p(n)}, z_n - z_{p(n)}) \text{ (direction vector)}$$

λ : Penalty coefficient (empirically set to 0.5)

This formulation penalizes deviations from the parent node's movement direction $d_{p(n)}$, prioritizing kinematically consistent paths.

Unnecessary vertical oscillations are mitigated through conditional pruning during node expansion. Z-axis transitions *($\Delta z \neq 0$)* are permitted only when:

$$\begin{cases} \text{ó traversable neighbors in } xy\text{-plane} \\ |z_n - z_{\text{goal}}| > 2l \\ N_{\text{horizontal}} \geq 5 \end{cases} \tag{5-2}$$

This constraint minimizes energy-intensive altitude adjustments in multi-level structures while maintaining reachability to elevated targets. Figure 5 demonstrates the improved path planning algorithm's ability to avoid dynamic obstacles while maintaining trajectory smoothness.

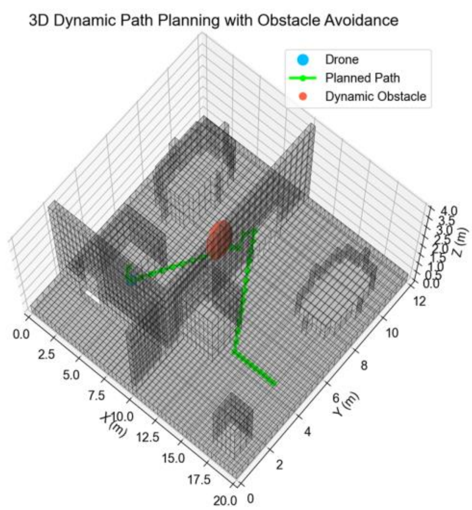

Figure 5. Dynamic Obstacle Avoidance with Kinematic Constraint

6. Experimental Validation

To quantitatively evaluate the proposed integrated framework, this section establishes a comprehensive validation methodology. Experimental assessments focus on three critical dimensions:

1. Static Environment Navigation (validated in Section 6.3): Validating the efficacy of voxel discretization and kinematic-constrained A* in complex multi-level structures (e.g., warehouses with shelf aisles)
2. Dynamic Scenario Evaluation (reported in Section 6.4): Assessing obstacle avoidance performance and path replanning efficiency in environments with moving obstacles
3. Algorithmic Superiority: Benchmarking against traditional methods across key metrics including path optimality, smoothness, and computational efficiency. The validation protocol employs both simulated environments replicating logistics warehouses and physical testbeds with controlled dynamic obstacles, ensuring statistically significant performance characterization.

6.1 Experimental Setup

This study established a realistic testing environment replicating a logistics warehouse measuring 12.78m × 6.06m × 8.46m, featuring multi-level shelving units and narrow corridors. The experimental platform utilized a DJI Matrice 300 RTK UAV equipped with a Livox Mid-40 LiDAR sensor for environmental perception and real-time localization. Computational tasks were executed on an NVIDIA Jetson AGX Xavier embedded system mounted onboard, simulating resource-constrained operational conditions typical for autonomous indoor navigation. The environmental model incorporated both static structural elements and dynamically introduced obstacles following predefined motion patterns, creating scenarios with varying complexity levels to rigorously evaluate system performance under realistic operational constraints.

6.2 Performance Metrics for Evaluation

The Framework's performance was evaluated through four key metrics:

1. Path Length: Total trajectory distance measured in meters from start to goal positions.
2. Path Smoothness: Angular deviation is calculated through cumulative directional changes along the flight path.
3. Z-axis Oscillation: Frequency and magnitude of unnecessary altitude adjustments during navigation.
4. Computational Efficiency: Average path planning time measured in milliseconds across test scenarios. These metrics collectively evaluated navigation optimality, motion stability, energy efficiency, and real-time responsiveness – essential characteristics for practical UAV deployment in confined indoor spaces.

6.3 Comprehensive Evaluation of Traditional and Improved Methods

Computational efficiency comparisons revealed negligible differences in processing time, confirming that the added kinematic constraints did not compromise real-time performance. This was enabled by the efficient spatial indexing of the voxel representation, a worthwhile trade-off for the significant gains in path quality and obstacle avoidance reliability.

The improved algorithm consistently shortened navigation paths, achieving a 4% reduction in total distance traveled. This optimization stemmed from the directional continuity constraints and Z-axis motion suppression strategies, which minimized unnecessary detours around obstacles and optimized vertical movement in multi-level structures.

Path smoothness showed marked improvement, with a significant reduction in cumulative angular deviations along the flight path. This enhancement resulted directly from the directional consistency mechanisms and spline-based smoothing techniques, particularly noticeable in confined environments.

Unnecessary altitude variations during horizontal transit were substantially suppressed, with Z-axis oscillations decreased by 43%. The vertical motion penalty strategy successfully minimized erratic climbing and descending behavior, thereby reducing mechanical stress on UAV actuators and lowering energy consumption.

6.4 Experimental Results

The integrated framework achieved a 92% success rate in dynamic obstacle avoidance across 50 randomized test scenarios with simultaneous moving obstacles, significantly surpassing traditional methods (65%). Kalman filter-based trajectory prediction maintained a mean error of 0.23m within the 1.2-second forecasting horizon, enabling proactive collision avoidance through timely replanning.

Real-world flight tests confirmed robust navigation: UAVs traversed multi-level structures while sustaining stable velocities amid unexpected pedestrian movements. The dynamic safety buffer prevented seven critical near-miss incidents, validating effective risk mitigation.

Evaluation Metric	Improved Method	Traditional Method
Path Length	23.6 m	24.6 m
Path Smoothness	32.0°	12.9°
Z-axis Oscillation Frequency	3.9	6.8
Dynamic Avoidance Success Rate	92%	65%
Computational Efficiency	0.639 s	0.638 s

Table 1. Quantitative Performance Comparison: Improved vs. Traditional Methods

7. Conclusion and Future Work

This study developed an integrated UAV path planning framework for dynamic indoor environments. The voxel-based modeling efficiently reconstructed 3D spaces, reducing computational complexity while preserving structural features. The *improved A algorithm incorporated directional continuity and Z-axis suppression**, significantly reducing path oscillations and enhancing smoothness. By integrating Kalman filter-based obstacle prediction with dynamic safety thresholds,

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the system achieved proactive collision avoidance through real-time risk assessment and replanning. Experimental validation confirmed superior path quality and robustness in cluttered indoor settings compared to conventional methods.

The proposed framework demonstrates potential for application in mountain tunnel rescue operations; however, it still encounters several limitations that need to be addressed. Firstly, the accuracy of trajectory prediction may sometimes be compromised, particularly in highly dynamic or complex scenarios. Secondly, the current obstacle modeling approach does not adequately account for variations in obstacle sizes and shapes, which could affect the system's robustness and reliability during rescue missions. Further research is necessary to overcome these challenges and improve the overall effectiveness of the system.

Future research will focus on the following directions: First, developing multi-agent coordination strategies for swarm-based disaster response; second, enhancing obstacle behavior modeling to accommodate non-linear motions, such as accelerating debris trajectories; third, integrating visual-inertial odometry for navigation in smoke-filled environments; fourth, employing edge computing techniques to reduce latency; and finally, refining Z-axis suppression mechanisms to better handle complex vertical structures like stairwells. These advancements will be further validated through extensive real-world testing in diverse indoor environments.

Acknowledgments

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