Autonomous Collision-Free Navigation of UAV in Unknown Tunnel-Like Environments

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I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have emerged as essential tools for performing inspections and explorations in challenging underground environments, including mines, drainage systems, and subterranean infrastructures. These complex tunnel-like settings introduce significant operational challenges such as GNSS-denied localization, limited visibility, sparse visual features, electromagnetic interference (EMI), and dynamic obstacles. Consequently, there is a critical need for sophisticated autonomous navigation solutions combining advanced Simultaneous Localization and Mapping (SLAM), multi-modal sensor fusion, and AI-based path planning strategies to ensure safe and efficient UAV operations.

II. RELATED WORK

Reviews of state-of-the-art SLAM techniques [1,2] consistently highlight ORB-SLAM2 and ORB-SLAM3 for their high positional and pose accuracy. These visual-inertial SLAM systems effectively address localization and mapping challenges in diverse environments. LiDAR-based approaches such as LOAM and LIO-SAM have also demonstrated excellent accuracy, particularly in GNSS-denied and low-light conditions. Additionally, recent studies emphasize hybrid SLAM frameworks combining visual, inertial, and LiDAR data, significantly enhancing robustness and precision in complex underground scenarios [3]. Multi-sensor fusion approaches integrating visual-inertial and LiDAR data provide a promising solution, offering substantial improvements in accuracy and reliability for UAV navigation in tunnel-like environments [4,5]. Based on this extensive review, sensor-fused SLAM is identified as the optimal choice for underground UAV applications.

Recent advancements in Deep Reinforcement Learning (DRL) are significantly enhancing SLAM capabilities, particularly in adaptive trajectory planning and real-time obstacle avoidance. DRL-based SLAM systems learn optimal navigation strategies through environmental interaction, providing crucial adaptability in unpredictable and complex scenarios where traditional algorithms falter.

III. METHODOLOGY

A comprehensive comparative analysis of state-of-the-art visual and LiDAR SLAM approaches under challenging low-light and GNSS-denied scenarios were done to determine the methods suitable for implementation as a proof of concept. The results of the analysis are presented in Table 1.

TABLE I. COMPARATIVE ANALYSIS OF LATEST SLAM VARIANTS UNDER LOW-LIGHT AND GNSS-DENIED CONDITIONS

SLAM Variant	**Low-light Performance**	**GNSS-Denied Robustness**	**EMI Resilience**	**Computational Demand**
Visual SLAM				
ORB-SLAM3	Moderate	Moderate	Moderate	Medium
DSM	Poor	Good	Moderate	Medium
VINS-Fusion	Good	Moderate	Moderate	High
Kimera	Moderate	Moderate	Moderate	High
LiDAR SLAM				
LOAM	Good	Good	High	High
LIO-SAM	Good	Excellent	High	High
FAST-LIO	Excellent	Excellent	High	High
Visual-LiDAR Fusion	Excellent	Excellent	High	High

Based on the analysis, the Visual-LiDAR Fusion scheme, which belongs to the category of Multi-Modal Sensor Fusion and Advanced SLAM, was selected for prototype implementation. This navigation system incorporates a robust multi-modal sensor fusion strategy, employing LiDAR, stereo vision cameras, infrared imaging, and inertial measurement units (IMUs). This comprehensive sensor suite significantly improves localization accuracy and environmental awareness, particularly under conditions of poor visibility and EMI disturbances. Hybrid SLAM methods, integrating Visual-Inertial SLAM and LiDAR-based mapping techniques, deliver reliable, precise and real-time map generation and localization.

Additionally, the combination of sensor fusion and AI-driven path planning enhances the system's ability to adapt to varying environmental conditions, ensuring reliable navigation performance in unstructured and dynamic underground spaces.

A selection of most widely cited path planning algorithms was used for a comparative analysis to determine their suitability for the constrained operating environment of the UAV. The results of the analysis are presented in Table 2.

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TABLE II. COMPARATIVE ANALYSIS OF PATH PLANNING ALGORITHMS

Algorithm	Real-Time Adaptability	Dynamic Obstacle Handling	Optimality of Paths	Computational Efficiency
RRT*	Moderate	Good	Moderate	Medium
A*	Low	Good	Good	Medium
D* Lite	High	Moderate	Excellent	Medium
DRL	Excellent	Excellent	Excellent	High

Based on the analysis, the Deep Reinforcement Learning (DRL) path planning algorithm, which belongs to the category of Intelligent Path Planning with DRL, demonstrated superior adaptability, efficiently managing dynamic obstacles and environmental variability. This framework leverages DRL algorithms to dynamically determine optimal flight paths. This AI-driven approach enables adaptive real-time obstacle avoidance, responsive trajectory management, and stable UAV operation, crucial for navigating complex and unpredictable tunnel-like environments.

IV. EXPERIMENTAL SETUP

The proof-of-concept system constructed for testing and evaluation has two major areas of design decisions: (1) hardware and (2) software. The selection of hardware considered the requirement of the Visual LiDAR Fusion SLAM technique while the selection of software considered the availability of open-source code repositories and comprehensive device support for drone applications.

The hardware setup consisted of a DJI f450 quadcopter frame equipped with a CUAV V5 Plus flight controller. The flight controller integrates a 32-bit ARM Cortex M7 core processor (216 MHz, 512 KB RAM, 2 MB Flash), sensors including InvenSense ICM20689 and ICM20602 (accelerometer/ gyroscope), Bosch BMI055 (accelerometer/ gyroscope), MS5611 barometer, and IST8310 magnetometer. Additional sensors included an RPLiDAR A2 (2D LiDAR) for initial testing, followed by Livox Mid-360 (3D LiDAR) for enhanced three-dimensional perception. A high-performance onboard computer facilitated real-time data processing and navigation algorithm execution. An ORBBEC Astra stereo camera with depth estimation capability through an IR sensor was used for Visual SLAM testing.

The software setup involved ROS (Robot Operating System) for middleware, ORB-SLAM3 for visual-inertial SLAM, LIO-SAM for LiDAR-inertial SLAM, and TensorFlow for implementing Deep Reinforcement Learning-based path planning algorithms.

The test system was used to perform four categories of experiments for environments with static and dynamic obstacles under moderate and low lighting conditions.

V. RESULTS AND DISCUSSION

The experimental results demonstrate the performance of 2D LiDAR SLAM and Stereo Vision SLAM in a structured indoor environment. The 2D LiDAR-based SLAM, using RPLiDAR A2, effectively mapped the environment, capturing structural details but facing challenges in feature-sparse areas. Stereo Vision SLAM, utilizing ORB-SLAM3, provided detailed visual localization but was sensitive to lighting variations. The integration of these techniques improved mapping consistency and robustness in GNSS-denied conditions.

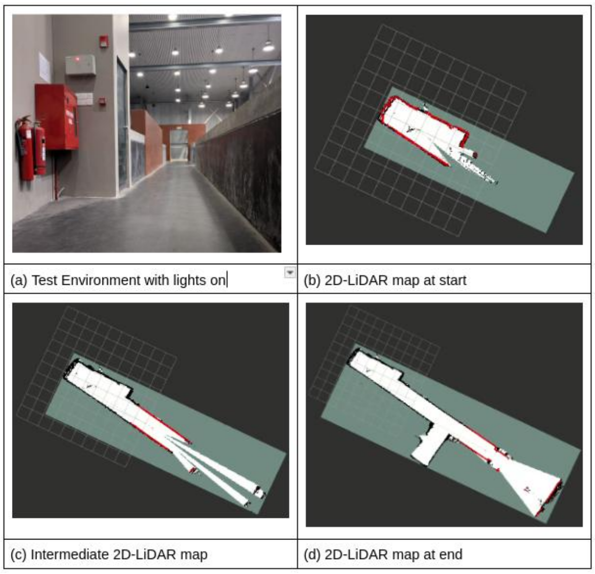

Fig. 1. 2D-LiDAR map building experiment under low lighting conditions.

Fig. 2. Depth-Map + RGBD Image for experiment under low lighting conditions.

VI. CONCLUSION

The results of the experiments show that the proposed Visual-LiDAR Fusion-based SLAM system improves localization accuracy and environmental awareness in GNSS-denied and low-light conditions. Additionally, DRL-based path planning enhanced the UAV's ability to navigate complex tunnel-like environments by dynamically optimizing its trajectory and improving obstacle avoidance. These findings confirm the effectiveness of sensor-fused SLAM techniques and AI-driven path planning in enhancing UAV autonomy for underground applications. Future work will focus on optimizing computational efficiency and real-world testing, especially for environments with rough surfaces that leads to greater scattering of light beams.

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