



Degradation-resistant Lidar-inertial-vision Odometry for Ultra-long Undersea Tunnels

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Abstract

To address the degradation in localization and mapping accuracy of LiDAR-inertial-visual SLAM systems in feature-sparse environments such as long tunnels and corridors due to sensor degeneration, this paper proposes an adaptive multi-sensor fusion method based on explicit degeneracy detection within the Error-State Iterated Kalman Filter (ESIKF) framework of FAST-LIVO2. By computing the eigenvalue ratio of the Hessian matrix of the state estimation, the degree of degeneracy in each degree of freedom is quantified, and a degeneracy detection threshold is set. When degeneracy is detected in the LiDAR, inertial measurement unit, or visual odometry, the state error function in the fusion process is dynamically adjusted by removing the residual terms corresponding to the degraded sensor, while retaining its observation data for subsequent map updates. Experimental results on the M3DGR public dataset and real data collected from the Second Jiaozhou Bay Submarine Tunnel in Qingdao show that, in degeneracy-prone sequences such as corridors and elevator shafts, the maximum values of the degeneracy metric of the proposed method are lower than those of mainstream algorithms including LVI-SAM, R3LIVE, and FAST-LIVO2. The method effectively suppresses degeneracy in specific directions and significantly improves the system's robustness and localization accuracy in extremely feature-poor environments.

Introduction

Current LiDAR-inertial-visual SLAM algorithms utilize various tightly-coupled fusion frameworks to match and fuse feature points such as edges and corners extracted by the visual system with the echo point clouds acquired by LiDAR. Xu et al. [1] extract planar, linear, and point features and group stable geometric features to better represent environmental attributes; they then analyze feature matching errors and constraint consistency to ensure the stability and reproducibility of feature constraints. Zheng et al. [2] employ an Error-State Iterated Kalman Filter (ESIKF) method, using inertial measurement unit (IMU) data as the prediction model, while LiDAR point clouds and camera-extracted features serve as observation models for front-end tracking. The geometry of the map is updated by allowing the error state to converge.

Although these methods design complex front-end and back-end optimization procedures to improve accuracy and robustness, the approach of Xu et al. relies heavily on the number of feature points extracted from the visual system. When the extracted features are sparse, only a limited number of LiDAR feature points can participate in the fusion process. This also results in many voxel blocks in the constructed voxel map lacking accurate RGB and depth information and being filled through estimation, such as by simulated ray casting. The greater the number of such estimated voxel blocks, the worse the mapping accuracy, making degeneracy more likely to occur. Zheng et al.'s ESIKF passively weakens updates in degraded directions via Kalman gain, but cannot explicitly detect the degeneracy direction or dynamically adjust the data fusion weights accordingly.

In the experiments of the aforementioned methods, varying degrees of map degradation occurred in feature-sparse scenes such as underground parking lots and corridors. Ultra-long submarine tunnels represent an even more extreme case of feature-sparse environments, where the internal environment is highly repetitive and the mapping distance is very long, making the degradation problem more severe. Therefore, building upon the work of Zheng et al., we have made the following improvements specifically for the extreme scenario of an ultra-long submarine tunnel:

1. In the front-end tracking and observation stage, explicit sensor degeneracy detection is added, and the fusion threshold is adaptively adjusted based on the detection results, thus improving the system's robustness and localization accuracy.
2. We evaluate our work through experiments in scenes where both LiDAR and visual odometry are degraded, and we conduct comparative tests specifically for the ultra-long submarine tunnel scenario. The results show that our work significantly enhances the anti-degeneration capability when facing feature-sparse environments.

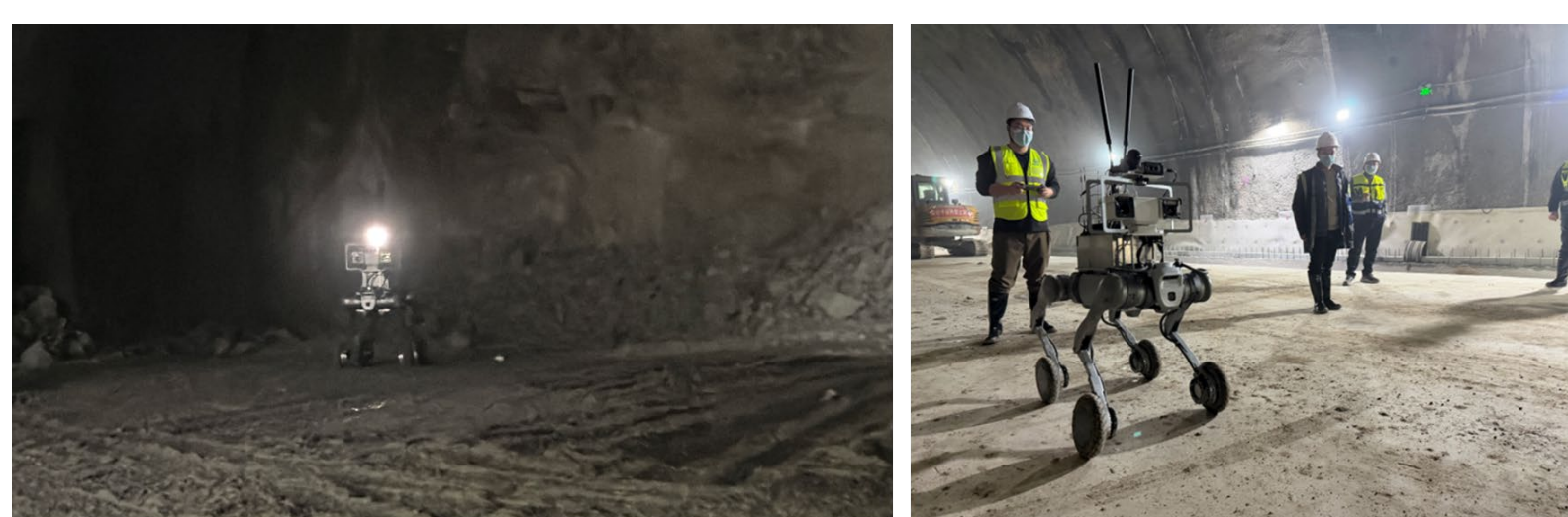


Figure 1. Inspection robots are undergoing field testing at the Second Jiaozhou Bay Submarine Tunnel in Qingdao..

Methods

In long tunnels or mines, due to a lack of constraints in the forward direction, LiDAR systems may exhibit performance degradation in at least one degree of freedom. The ESIKF method employed in [2] essentially solves a nonlinear optimization problem. Therefore, according to the theory in [3], the most difficult-to-observe direction can be determined by computing the Hessian matrix of the state matrix, thereby identifying the direction most prone to degeneracy. Subsequently, one can quantitatively determine whether degeneracy has occurred based on a pre-set threshold. Then, by introducing a new parameter, the degeneracy factor, the confidence weights of LiDAR and IMU can be dynamically adjusted to suppress degeneracy in specific directions. The overall algorithm structure is shown in Figure 2.

At each time step k , in the process of computing the posterior distribution, the ESIKF requires the Jacobian matrix of the prior distribution, $\mathbf{H}^k$, which is the Hessian matrix. By performing eigenvalue decomposition on $\mathbf{H}^k$, the maximum and minimum eigenvalues and their corresponding eigenvectors can be obtained, denoted as λ_{max} , λ_{min} , and $\mathbf{p}_{max}$, $\mathbf{p}_{min}$, respectively. The degeneracy degree value is defined as shown in Equation (1):

$$\lambda_D = \log \frac{\lambda_{max}}{\lambda_{min}}$$

where λ_D is a value greater than 0. A larger value indicates more severe degeneracy in the direction of $\mathbf{p}_{min}$. Therefore, a degeneracy detection threshold λ_H can be specified. When λ_H exceeds the threshold λ_H , it can be determined that degeneracy has occurred in the direction of $\mathbf{p}_{min}$, thus providing a basis for adjusting the weights in the ESIKF state update process in the next step.

According to Equation (1), the degeneracy degree values for LiDAR, IMU, and visual information can be obtained as λ_{LD} , λ_{ID} , and λ_{VD} , respectively. To dynamically adjust the ESIKF based on the degeneracy levels of the three types of data, we modified the state error function to cope with various possible sensor degradation situations. The modified state error function is shown in Equation (2):

$$\min(\|\hat{\mathbf{x}}_k^{k+1} \ominus \hat{\mathbf{x}}_k^k\|, \|\hat{\mathbf{x}}_k^{k+1} \ominus \hat{\mathbf{x}}_k^k\|, \|\hat{\mathbf{x}}_k^{k+1} \ominus \hat{\mathbf{x}}_k^k\|)$$

where $\hat{\mathbf{x}}^k$ is the state of the corresponding sensor type at time k . When λ_{LD} , λ_{ID} , and λ_{VD} all fall below the degeneracy detection threshold λ_H , the state error function in Equation (2) is adopted. If the degeneracy degree value of a certain sensor type exceeds the threshold, its state residual is removed from the equation. However, the corresponding point cloud data is not discarded but is reprojected onto the map using the optimized pose obtained from other sensors. If both the LiDAR and camera sensors fail simultaneously, no state update is performed, and the IMU prediction is directly used as the posterior estimate.

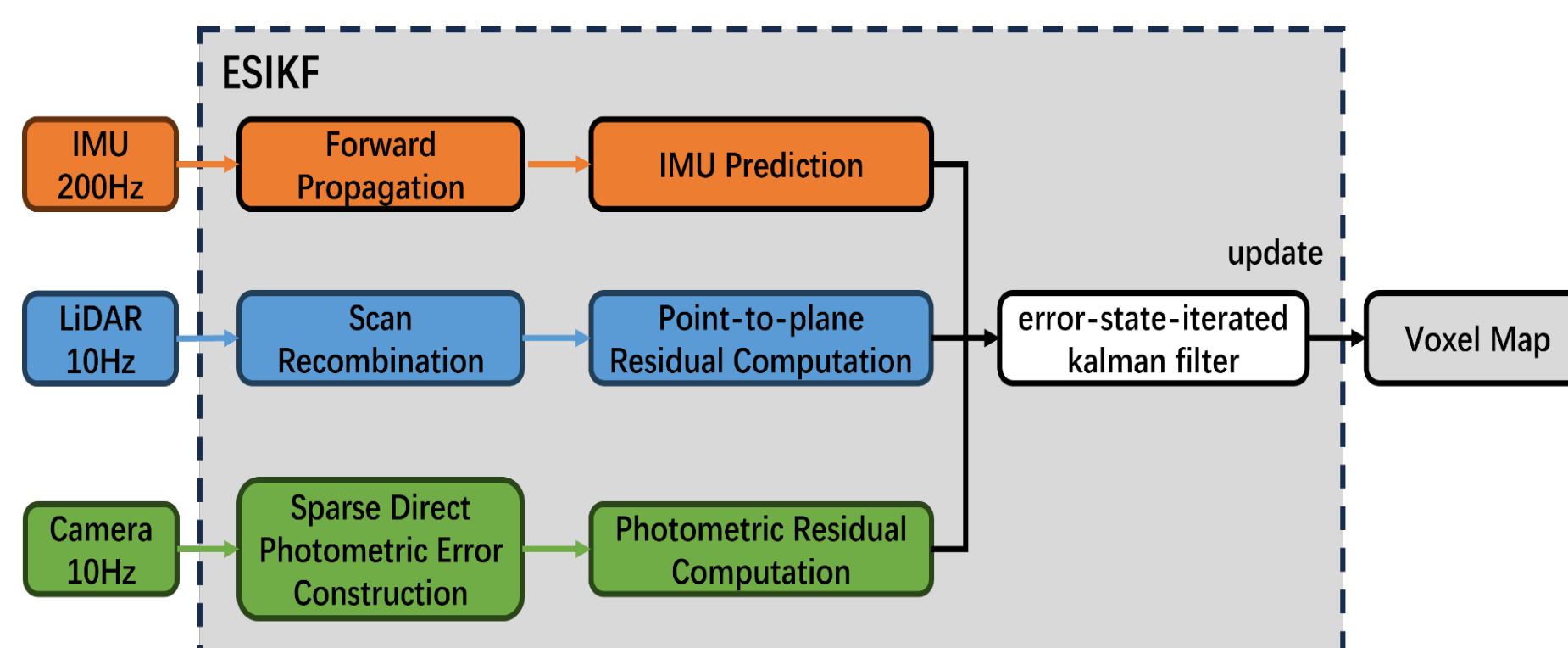


Figure 2. Pipeline of our system.

Table 1. Comparison of Various State-of-the-Art Systems on the M3DGR Datasets.

Dataset	M3DGR					
	Corridor01		Corridor02		Elevator01	
	Max	Min	Max	Min	Max	Min
LVI-SAM[5]	7.13	2.30	3.29	1.59	Non	Non
R3LIVE[6]	5.41	1.87	1.79	0.77	7.38	2.80
FAST-LIVO2[2]	1.28	0.21	1.02	0.26	2.63	0.32
Ours	0.93	0.29	0.89	0.33	1.23	0.31

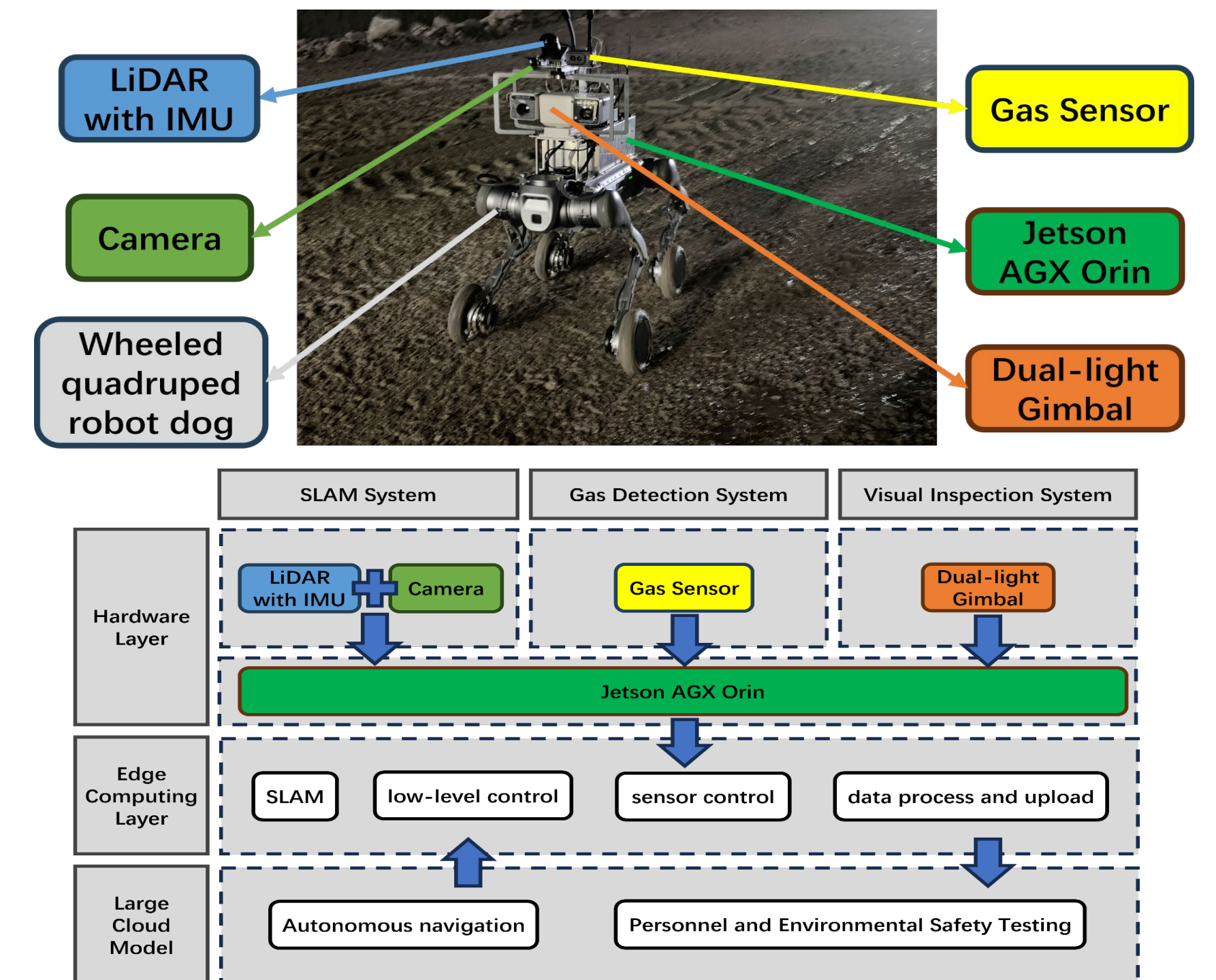


Figure 3. Inspection robot system architecture.

Results

To verify the robustness and localization accuracy of the proposed algorithm, we selected challenging publicly available datasets as well as our self-collected dataset and compared the results with other state-of-the-art algorithms. The public dataset is the M3DGR dataset [4], a sensor-rich benchmark with systematically induced degradation patterns including visual challenge, LiDAR degeneracy, wheel slippage, and GNSS denial; we mainly used the data specifically designed for LiDAR degradation. The dataset we collected targets the primary scenario of this research: an ultra-long submarine tunnel under construction, specifically the Second Jiaozhou Bay Submarine Tunnel in Qingdao, Shandong Province, China. A Hesai JT128 was used for LiDAR, the built-in IMU of the LiDAR served as the IMU, and a RealSense D435i camera was used, employing only its RGB camera. The equipment was mounted on a Unitree B2 quadruped robot dog. Data was collected by remotely controlling the robot dog in the completed sections of the tunnel and stored on a Jetson AGX Orin development board carried on the robot's back. The overall architecture is shown in Figure 3.

In our experiments, we set $\lambda_H=1$ and recorded values of $\lambda_D > 10$ as "Non", indicating extremely severe degeneracy where a correct map could not be constructed normally. The specific experimental data are presented in Table 1.

It can be observed that in the Corridor scenes of the M3DGR dataset, which are specifically designed for anti-degeneration performance testing, our method effectively suppresses the amplitude of degeneracy when significant degradation occurs, achieving the lowest maximum λ_D value in all scenarios. Figure 5 illustrates a situation after passing a corner and entering a new corridor segment where FAST-LIVO2 suffered degeneracy in the x-axis direction, causing the motion estimation direction to be opposite to the actual forward direction, whereas our method did not exhibit this problem.



Figure 5. Comparison of mapping results between our system and Fast-LIVO2 in the Corridor01 sequence. (a) Fast-LIVO2. (b) Ours.

Conclusions

This paper addresses the challenge of multi-sensor SLAM systems being prone to degradation in extremely feature-sparse environments such as ultra-long submarine tunnels by proposing an adaptive fusion strategy based on degeneracy awareness. The method utilizes Hessian matrix eigenvalue analysis to detect the degree of degradation of each sensor in real time and dynamically adjusts the observation constraints in the ESIKF update accordingly, avoiding the introduction of erroneous information in the degraded direction and thereby reliably suppressing the divergence of pose estimation. Experiments on the M3DGR dataset with systematic degradation patterns and in real submarine tunnel scenarios both confirm that the proposed method offers significant advantages over the state-of-the-art LVI-SAM, R3LIVE, and FAST-LIVO2 in terms of controlling the degeneracy metric and maintaining pose estimation consistency. Future work will focus on applying this method to the mapping and navigation of embodied intelligent inspection robots in ultra-long submarine tunnels.

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