LUOJIA Explorer PMS: Panoramic Odometry and Mapping with Structural Information

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Abstract:
Accurate dense reconstruction of unknown spatial environments is crucial for applications such as underground exploration and planetary missions. Existing methods face challenges like observing blind spots and the difficulty of edge feature extraction in point clouds with non-repetitive scanning LiDARs. This paper first uses a novel odometry and mapping system integrating two solid-state LiDARs and an IMU to obtain distortion-compensated point clouds and corresponding poses, which are utilized to generate submaps. Our approach then leverages these accumulated submaps to efficiently extract edge features. Experimental results demonstrate that our submap-based method effectively identifies edge features within point clouds, which can be used for association with panoramas for joint optimization in the future.

1. Introduction

Dense reconstruction of unknown spatial environments has become a major focus of current research due to its broad applicability and significant importance. Utilizing robots for exploring and reconstructing unknown spaces plays a crucial role in various domains such as underground exploration, planetary exploration, and autonomous driving.

Robots equipped with advanced sensors can leverage Simultaneous Localization and Mapping (SLAM) technology to achieve rapid localization and map construction even in GNSS-denied environments. This is accomplished through multi-sensor fusion, which typically involves the integration of Light Detection and Ranging (LiDAR) sensors, cameras, and Inertial Measurement Units (IMUs). Each of these sensors contributes unique capabilities to the SLAM system.

LiDAR sensors determine position and distance by emitting laser pulses and measuring the time taken for their reflections to return. One of the significant advantages of LiDAR technology is its independence from ambient lighting conditions, making it reliable in diverse environments. LiDAR sensors can be broadly categorized into two types: traditional spinning LiDARs with repetitive scanning patterns and solid-state LiDARs with non-repetitive scanning patterns. Both types have their own advantages and applications depending on the requirements of the mapping task. Cameras, on the other hand, offer a cost-effective means of capturing detailed texture information of the environment. They can capture high-resolution images that provide valuable visual context, which is essential for tasks such as object recognition and scene understanding. Additionally, IMUs measure acceleration and angular velocity at high frequencies, which helps in compensating for motion distortions. The fusion of these three types of sensors, LiDARs, cameras, and IMUs, enables the system to utilize the complementary strengths of each sensor. This multi-sensor fusion approach is essential for achieving robust and rapid mapping of unknown spaces, providing comprehensive environmental perception that is critical for successful navigation and reconstruction.

However, many existing methods (Lin and Zhang, 2022; Zheng et al., 2022) rely on combining cameras with small field of view (FOV) and single LiDAR to achieve localization and mapping. These approaches often fail to capture the full extent of the environment, resulting in blind spots. The integration of cameras and LiDARs with larger FOV can effectively address these limitations, significantly expanding the robot's perception range and improving the completeness of the generated maps.

Recent advancements, such as the PanoVLM method (Tu et al., 2023), have demonstrated the potential of using panoramic cameras and LiDAR for cost-efficient and dense mapping. However, their approach to edge feature extraction, which is similar to the method used in LOAM (Zhang and Singh, 2014), is optimized for traditional spinning LiDARs and is not suitable for the non-repetitive scanning patterns of solid-state LiDARs. Furthermore, their system does not incorporate high-frequency IMUs, making it less effective in scenarios involving rapid motion where precise motion compensation is critical.

To address these challenges, this paper employs a novel multi-LiDAR odometry and mapping system integrating two solid-state LiDARs and an IMU. As depicted in Figure 1, the system is also equipped with a panoramic camera to provide a wide FOV, capturing more comprehensive environmental information. Inspired by the method introduced by (Yuan et al., 2021), our approach utilizes accumulated submaps to overcome the difficulties associated with extracting edge features from the sparse scans of non-repetitive solid-state LiDARs.

By integrating multiple LiDARs and an IMU, we can obtain real-time poses and point clouds of the robot, which are then accumulated into sub-maps for subsequent edge extraction. This method effectively addresses the challenge of edge extraction from sparse point clouds in single frames by leveraging the combined data from multiple sensors. Our experimental results demonstrate that the submap-based edge extraction method is capable of efficiently identifying edge features within point clouds. These features can be associated with those in panoramic images for joint optimization in the future.

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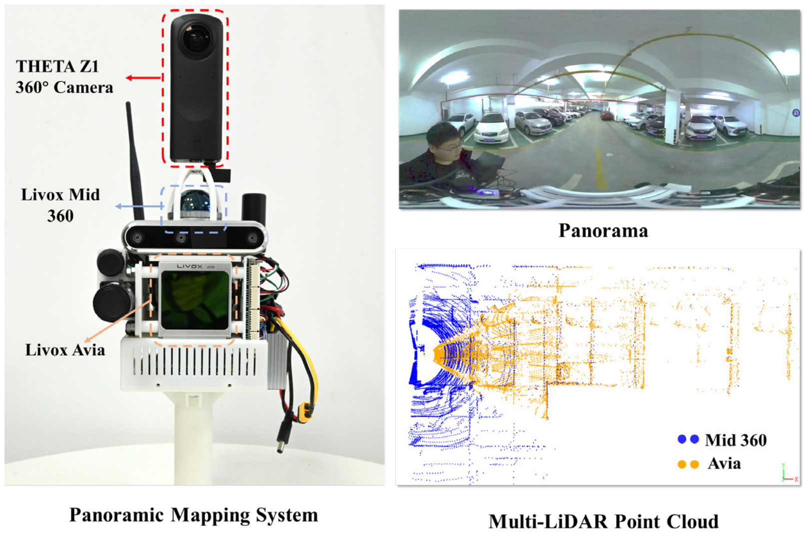

Figure 1. LuoJia Explorer-panoramic mapping system. Left: Photo of the system. Right: Panorama from a panoramic camera and multi-LiDAR point cloud data.

2. Related Work

For LiDAR Odometry (LO) methods, the LOAM method (Zhang and Singh, 2014) extracts edge features in real-time from point clouds by calculating and sorting local curvature. Many subsequent 3D LiDAR Odometry methods (Cong et al., 2023, 2022; Shan and Englot, 2018) have built upon and improved LOAM. Specifically designed for LiDARs with small FOV and irregular sampling patterns, the LOAM Livox method (Lin and Zhang, 2020) addresses challenges in feature extraction and selection within a limited FoV, robust outlier rejection, moving object filtering, and motion distortion compensation. This approach registers the point cloud to a local map within a specific range, achieving real-time LiDAR odometry. To mitigate matching degeneration caused by the limited number of features due to small FoV and point selection, LOAM Livox not only integrates the LOAM methodology but also identifies edge feature points by detecting differences in LiDAR reflectivity.
In the realm of LiDAR-Inertial Odometry (LIO) methods, the LiLi-OM method (Li et al., 2021) addresses feature extraction for the irregular scanning pattern of the Livox Horizon LiDAR. This method unfolds a scan frame and segments it based on time to filter valid points. Subsequently, it performs eigendecomposition on the valid points. By comparing the three eigenvalues, it extracts edge and plane features. Then, LiLi-OM integrates LiDAR and IMU measurements through hierarchical keyframe-based sliding window optimization. The Fast-LIO series methods (Xu et al., 2022; Xu and Zhang, 2021) employ a tightly-coupled iterated Kalman filter (iEKF) to fuse LiDAR points with IMU data, utilizing a back-propagation process to compensate for motion distortion. They also introduce a new method for computing the Kalman gain, which reduces the computational load caused by a large number of LiDAR points. Fast-LIO2 directly registers the raw point cloud to the map and updates it using the ikd-Tree data structure to manage the map efficiently. The AFLI-Calib method (Wu et al., 2023) enhances the accuracy of extrinsic self-calibration for LiDAR-IMU systems by dynamically adjusting the LiDAR frame length based on sensor motion state and scene matching stability.
For LiDAR-Inertial-Visual Odometry (LIVO) methods, the R3live series methods (Lin and Zhang, 2022) couple a LIO subsystem with a VIO subsystem. These subsystems jointly and incrementally build a 3D map of the environment in real-time. The LIO subsystem reconstructs the geometric structure by registering new points from each LiDAR scan to the map, while the VIO subsystem recovers radiance information by rendering pixel colors from each image onto the map points. The Fast-LIVO (Zheng et al., 2022) method consists of two tightly-coupled odometry subsystems: the VIO subsystem and the LIO subsystem. To avoid the feature extraction, triangulation, or optimization, the VIO subsystem aligns new images and solves for pose by minimizing the direct photometric error, leveraging the point cloud map built by the LIO subsystem.

3. Method

Our method is divided into three main parts: data inputs, multi-LiDAR-inertial odometry, and submap-based edge extraction, as illustrated in Figure 2.

3.1 Multi-LiDAR-Inertial Odometry and Mapping

In this section, we build upon our previous work PMLIO (Xu et al., 2023), employing it as the multi-LiDAR-inertial odometry and mapping algorithm to achieve robust pose estimation. The global frame $(\cdot)^G$ is defined by the first frame of the IMU, while the body frame $(\cdot)^B$ is defined by the IMU frame.
Firstly, the method employs spatial-temporal fusion to combine the point cloud P_L obtained by LiDAR mid and the point cloud P_A obtained by the LiDAR avia. This fusion ensures that data from different LiDARs is integrated seamlessly, providing a comprehensive point cloud for further processing. Subsequently, the algorithm compensates for motion distortion, which is beneficial for more accurate pose estimation. Through the use of an iterated extended Kalman filter, observations from both the IMU and the LiDARs are fused. This process results in a distortion-compensated and fused point cloud $P_M = \{p_0^B, p_1^B, \dots p_i^B\}$ within the body frame. Additionally, the corresponding set of poses in the global coordinate system $(\cdot)^G$ is denoted as $\mathrm{T}^G = \{t_0^G, t_1^G, \dots t_i^G\}$.
This approach not only integrates data from multiple LiDAR sensors but also ensures that the resulting point cloud is accurate from motion-induced distortions. By fusing IMU and LiDAR data, the method provides robust and reliable pose estimation, crucial for applications requiring precise navigation and mapping.

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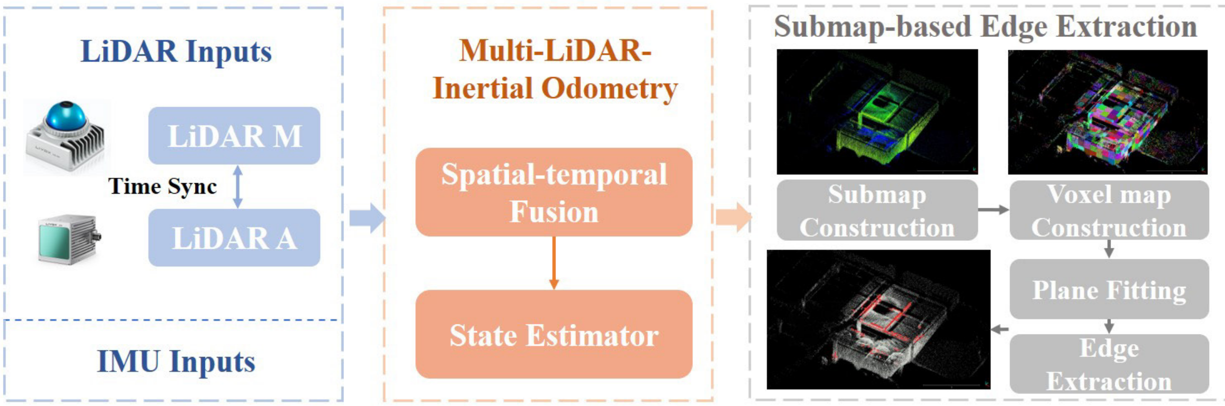

Figure 2. The workflow of the proposed method.

3.2 Submap-based LiDAR Edge Extraction

Due to the sparsity of point clouds in each frame scanned by solid-state LiDAR, robustly extracting edge features for data association between images and point clouds proves challenging. Therefore, this paper utilizes the distortion-compensated and fused point cloud P_M and the corresponding poses T^{G} to accumulate submap S. The method employs Equation 1 to accumulate point clouds from frame i to frame $i+n$ to form submap.

$$S = \sum_{j=i}^{i+n} t_j^G p_j^B \quad (1)$$

The presence of phenomena such as fake points and bleeding points in depth-discontinuous edges can significantly affect the accuracy of data association. These issues arise due to the inherent limitations of LiDAR's scanning and reflection mechanisms. To address these challenges and ensure precise association, we employ the method (Yuan et al., 2021) to focus on extracting the depth-continuous edge feature from the accumulated submap S through a detailed four-step process:

Voxel map construction: The submap is segmented into fixed-size voxels based on the specific scene requirements. This step facilitates efficient processing, and reduces computational complexity.

Plane fitting: Within each voxel, the RANSAC algorithm is used to fit planes to the point cloud data. RANSAC is effective in dealing with noisy data and outliers, making it suitable for plane detection.

Intersecting planes selection: Only planes that intersect at defined angles are considered for edge extraction. This selective process evaluates the angular relationships between planes to filter out those that do not contribute meaningfully to edge formation.

Plane intersection lines computation: The intersections of these selected planes are computed to produce depth-continuous edge lines.

This method is adaptable to various scanning modalities, expanding its applicability to different types of LiDAR sensors.

3.3 Panorama Line Extraction

For common feature-based methods used to associate LiDAR and camera data, edge features are one of the most commonly used types due to their prevalence in structured environments. This section introduces a method for line extraction from panoramas captured by panoramic cameras.

Due to the severe distortion present in panoramas, traditional line extraction methods designed for frame cameras perform poorly. This paper utilizes the method proposed by (Tu et al., 2023) to extract line features, which involves four main steps: First, LSD (Line Segment Detector) method is used to extract initial lines from the panoramas. Next, for each extracted line, its two endpoints are transformed onto the unit sphere and a plane is formed with the camera center. Then, lines are fused if they are adjacent, have an angle difference of less than 2 degrees, and the minimum Normalized Cross Correlation (NCC) value between their endpoints is greater than 0. The angle difference is determined by the angle between the previously formed planes. Finally, lines shorter than 1/20 of the image height are filtered out.

Future work might explore the PanoVLM method (Tu et al., 2023) to associate panoramas and point clouds using these line features. By leveraging the complementary strengths of panoramas and LiDAR point clouds, it is possible to achieve joint optimization, leading to more accurate and comprehensive dense reconstructions. This integrated approach has the potential to improve the performance of robotic systems in complex environments.

4. Experiments

4.1 Experimental Data Collection and Setup

The data for the experiment were collected using the LuoJia Explorer panoramic mapping system, which is equipped with multiple sensors including the Livox Mid360, Livox Avia, and a panoramic camera, as illustrated in Figure 1. The system's specific parameters are listed in Table 1. The Livox Mid360 is a solid-state LiDAR with a wide horizontal FoV of 360°, so we placed it at the top of the system. The Livox Avia, in contrast, has a smaller horizontal FoV of 70.4° but a longer observation range. To take advantage of this, we positioned the Livox Avia facing forward to focus on objects directly ahead, supplementing the coverage of the Livox Mid360. As shown in Figure 1, the overall point cloud distribution validates our strategy. The Livox Mid360's point cloud (blue) is sparse at long distances but covers a wide area, while the Livox Avia's point cloud (yellow) is denser, more concentrated, and extends further. Our placement effectively leverages the strengths of each LiDAR sensor. Additionally, we positioned a panoramic camera at the top of the device, which provides a 360-degree FoV to thoroughly observe the surrounding environment and offers visual texture information. The panoramic images obtained from this camera are shown in Figure 1.

Hardware	Parameters					
	Scanning pattern	FOV	Points	Frequency	Range	Built-in IMU
Livox Avia	Non-repetitive	Vertical:77.2° Horizontal: 70.4°	240,000/s (first or strongest return)	10 Hz	190 m@10%	BMI088
Livox Mid360	Non-repetitive	Vertical:59° Horizontal: 360°	200,000/s	10 Hz	0.1m-40m@10%	ICM40609, 200Hz, 6axis
360° Camera	Model: THETA Z1 360° Camera					

Table 1. Sensor Configurations of LuoJia Explorer-panoramic mapping system.

In the experiment, we used the built-in IMU from the Livox Mid360 as the IMU input for our method. The external parameters between the IMU and LiDAR were obtained from the factory settings. The external parameters between the LiDARs had been calibrated in advance, following the calibration method described in our previous work (Xu et al., 2023). Moreover, time synchronization was performed between the multiple LiDARs and the panoramic camera.

We utilized the system to gather data from the underground parking garage at Wuhan University, which served as the experimental validation site. As shown in the panoramic image in Figure 1, the parking garage is a structured environment with edge features that are suitable for experimental validation.

4.2 Results

The point cloud map of the experimental site obtained by the method clearly reflects the structure of the parking garage without any stratification, as shown in Figure 3. The edge features in the complete point cloud map are clearly visible. This demonstrates the effectiveness of integrating data from multiple LiDARs and the IMU, providing reliable point cloud and pose estimations for subsequent submap-based edge extraction.

To fully validate the effectiveness of submap-based edge extraction method, we tested multiple submaps with $n = 20$. As shown in Figure 4, the first column displays the results after voxel segmentation of the submaps. It can be observed that voxel segmentation is well-executed in dense areas of the point cloud, providing a solid foundation for subsequent edge extraction.

The second column highlights edge features extracted from the submaps, represented in red. It can be seen that the edge features extracted from the point cloud are mostly accurate, especially in dense areas of the point cloud. However, some edge features in sparse areas of the point cloud were not effectively extracted.

The third column displays the corresponding panoramic image and the line features extracted, shown in color. It is evident that line features in the panoramic images have been successfully extracted.

These experimental results qualitatively validate the effectiveness of the proposed method. It is evident that most edge features have been successfully extracted, thereby confirming the efficacy of the method.

4.3 Discussion

Although the proposed method effectively extracts edge features from point clouds, there are still some limitations. For instance, edge features in sparse areas of the point cloud are not effectively extracted, and the results show a relatively low number of edge features. Future work will explore using a sliding window to accumulate submaps. Experimental results indicate that edge feature extraction is more successful in areas with well-performed voxel segmentation. Currently, a fixed-size voxel segmentation method is used and adopting an adaptive voxel segmentation method may improve the effectiveness of edge feature extraction.

Following the completion of edge extraction from both point clouds and images, future research could investigate the PanoVLM method (Tu et al., 2023) to associate panoramas and point clouds using these line features, and then achieve joint optimization to obtain more accurate and comprehensive dense reconstructions.

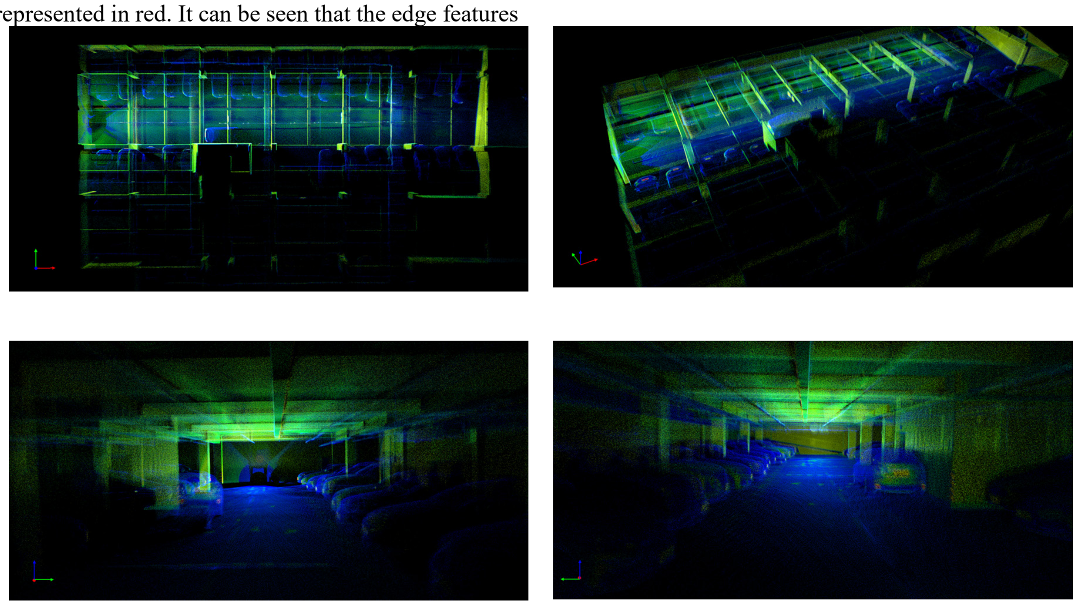

Figure 3. The point cloud map of the underground parking garage.

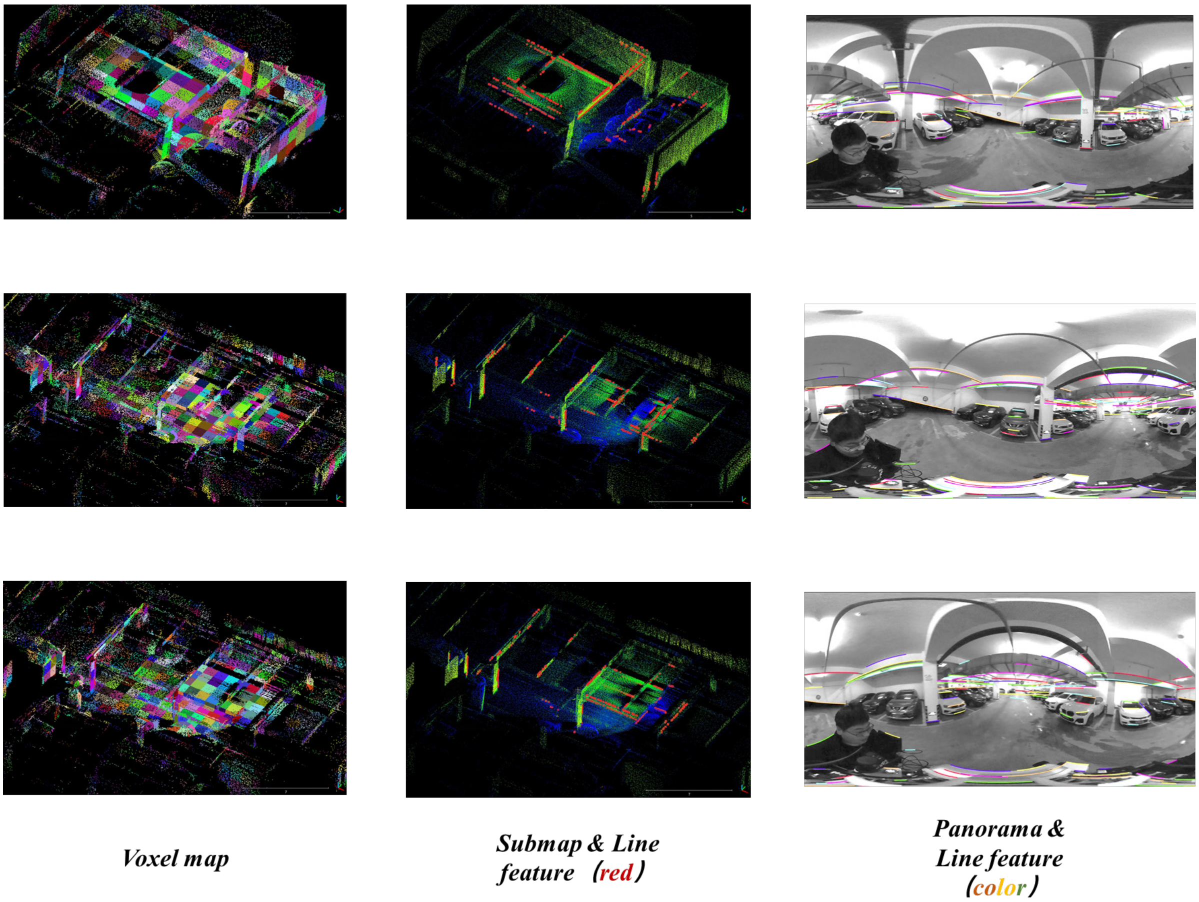

Figure 4. The results of submap-based edge extraction and panorama line extraction.

5. Conclusion

Employing robots for accurate dense reconstruction of unknown environments is crucial. However, existing methods often face challenges, such as the observation of blind spots and difficulties in extracting edge features from point clouds generated by non-repetitive scanning LiDARs. In this paper, we employed a novel odometry and mapping system that integrates two solid-state LiDARs and an IMU to obtain distortion-compensated point clouds and corresponding poses. These are then used to generate submaps, which our approach leverages to efficiently extract edge features. Experimental results have demonstrated that our submap-based edge extraction method effectively identifies edge features within point clouds. These features can potentially be associated with panoramas for joint optimization in future applications.

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References

Cong, Y., Chen, C., Yang, B., Li, J., Wu, W., Li, Y., Yang, Y., 2022. 3D-CSTM: A 3D continuous spatio-temporal mapping method. Isprs J. Photogramm. Remote Sens. 186, 232–245. https://doi.org/10.1016/j.isprsjprs.2022.02.005

Cong, Y., Chen, C., Yang, B., Liang, F., Ma, R., Zhang, F., 2023. CAOM: Change-aware online 3D mapping with heterogeneous multi-beam and push-broom LiDAR point clouds. Isprs J. Photogramm. Remote Sens. 195, 204–219. https://doi.org/10.1016/j.isprsjprs.2022.11.017

Li, K., Li, M., Hanebeck, U.D., 2021. Towards High-Performance Solid-State-LiDAR-Inertial Odometry and Mapping. IEEE Robot. Autom. Lett. 6, 5167–5174. https://doi.org/10.1109/LRA.2021.3070251

Lin, J., Zhang, F., 2022. R ^ 3 LIVE++: A robust, real-time, radiance reconstruction package with a tightly-coupled LiDAR-inertial-visual state estimator. arXiv preprint arXiv:2209.03666.

Lin, J., Zhang, F., 2020. Loam livox: A fast, robust, high-precision LiDAR odometry and mapping package for

LiDARs of small FoV, in: 2020 IEEE International Conference on Robotics and Automation (ICRA). Presented at the 2020 IEEE International Conference on Robotics and Automation (ICRA), pp. 3126–3131. https://doi.org/10.1109/ICRA40945.2020.9197440

Shan, T., Englot, B., 2018. LeGO-LOAM: Lightweight and Ground-Optimized Lidar Odometry and Mapping on Variable Terrain, in: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). Presented at the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, Madrid, pp. 4758–4765. https://doi.org/10.1109/IROS.2018.8594299

Tu, D., Cui, H., Shen, S., 2023. PanoVLM: Low-cost and accurate panoramic vision and LiDAR fused mapping. Isprs J. Photogramm. Remote Sens. 206, 149–167. https://doi.org/10.1016/j.isprsjprs.2023.11.012

Wu, W., Li, J., Chen, C., Yang, B., Zou, X., Yang, Y., Xu, Y., Zhong, R., Chen, R., 2023. AFLI-calib: Robust LiDAR-IMU extrinsic self-calibration based on adaptive frame length LiDAR odometry. Isprs J. Photogramm. Remote Sens. 199, 157–181. https://doi.org/10.1016/j.isprsjprs.2023.04.004

Xu, W., Cai, Y., He, D., Lin, J., Zhang, F., 2022. FAST-LIO2: Fast Direct LiDAR-Inertial Odometry. IEEE Trans. Robot. 1–21. https://doi.org/10.1109/TRO.2022.3141876

Xu, W., Zhang, F., 2021. Fast-lio: A fast, robust lidar-inertial odometry package by tightly-coupled iterated kalman filter. IEEE Robot. Autom. Lett. 6, 3317–3324.

Xu, Y., Chen, C., Wang, Z., Yang, B., Wu, W., Li, L., Wu, J., Zhao, L., 2023. Pmlio: Panoramic tightly-coupled multi-lidar-inertial odometry and mapping. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences X-1/W1-2023, 703–708. https://doi.org/10.5194/isprs-annals-X-1-W1-2023-703-2023

Yuan, C., Liu, X., Hong, X., Zhang, F., 2021. Pixel-level extrinsic self calibration of high resolution lidar and camera in targetless environments. IEEE Robot. Autom. Lett. 6, 7517–7524.

Zhang, J., Singh, S., 2014. LOAM: Lidar Odometry and Mapping in Real-time, in: Robotics: Science and Systems X. Presented at the Robotics: Science and Systems 2014, Robotics: Science and Systems Foundation. https://doi.org/10.15607/RSS.2014.X.007

Zheng, C., Zhu, Q., Xu, W., Liu, X., Guo, Q., Zhang, F., 2022. Fast-livo: Fast and tightly-coupled sparse-direct lidar-inertial-visual odometry, in: 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, pp. 4003–4009.