MULTI-ROBOT COOPERATIVE LiDAR SLAM FOR EFFICIENT MAPPING IN URBAN SCENES

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ABSTRACT:

We first use the multi-robot SLAM framework DiSCo-SLAM to evaluate the performance of cooperative SLAM based on the complicated dataset in urban scenes. Besides, we perform comparisons of single-robot SLAM and multi-robot SLAM to explore whether the cooperative framework can noticeably improve robot localization performance and the influence of inter-robot constraints in local pose graph, utilizing an identical dataset generated via the Carla simulator. Our findings indicate that under specific conditions, the integration of inter-robot constraints may effectively mitigate drift in local pose estimation. The extent to which inter-robot constraints affect the correction of local SLAM is related to various factors, such as the confidence level of the constraints and the range of keyframes imposed by the constraint.

1. INTRODUCTION AND RELATED WORK

1.1 Introduction

For unknown and unlocatable environments, simultaneous localization and mapping (SLAM) (Cadena et al., 2016)is a fundamental technology that can help the robot navigate and build maps in the environment. Multi-robot has the potential to be more effective and efficient than single-robot in some tasks such as localization and mapping (Huang et al., 2022; Trusheim et al., 2021; Xie et al., 2022). To accurately merge the map, the main goal of the multi-robot SLAM is to find the transformation between different robots. The key components of this task are composed of using perception-derived descriptors to detect the inter-loop closure effectively, establishing accurate inter-robot measurement constraints, and optimizing the transformation from any robot frame to the base frame. Moreover, inter-robot constraints in multi-robot cooperative SLAM can also be used in local pose optimization to reduce the local drift of the individual robot due to the accumulation of errors. More importantly, the multi-robot cooperative LiDAR SLAM would lead to significantly increased computational load, efficient feature extraction and data exchange between robots are important for the real time multi-robot SLAM.

1.2 Recent works

Collaborative Simultaneous Localization and Mapping (C-SLAM) is a vital component for successful multi-robot operations in environments without an external positioning system, such as indoors, underground or underwater. In recent years, the field of multi-robot SLAM has witnessed significant advancements. These recent works highlight the growing body of research focused on distributed multi-robot SLAM, with particular attention paid to lidar-based systems and cooperative strategies. Expanding on multi-robot SLAM, Zhou et al. (2022) introduce an online system that merges range measurements provided by UWB sensors with lidar data from multiple mobile robots. The result is a globally-consistent map comprising individual point cloud maps and trajectory estimations for all robots. Huang et al., (2022) proposes a novel framework for distributed multi-robot SLAM that employs 3D LiDAR observations. Furthermore, Zhong et al., (2022) presents DCL-SLAM, a fully distributed collaborative LiDAR SLAM framework designed for robotic swarms operating in unknown environments with minimal information exchange. Wu et al. (2022) contributes a map merging method for collaborative lidar-based SLAM that relies on GPS measurements and an improved Iterative Closest Point (ICP) algorithm. In a recent development, Lajoie et al. (2023) introduces Swarm-SLAM, an open-source C-SLAM system that emphasizes scalability, flexibility, decentralization, and sparsity—key properties in swarm robotics. As these frameworks continue to mature, they hold great promise for applications in a wide range of challenging environments.

Detecting inter-robot loop closures to estimate the relative pose is a highly effective method for merging the robots' trajectories into a common frame, without relying on external positioning infrastructure. In addition, compensating for the front-end odometry drift is crucial for improving the accuracy of trajectory estimates. In a multi-robot SLAM algorithm, particularly in distributed multi-robot SLAM with limited communication bandwidth, it is crucial to create precise inter-robot measurement constraints. While single-robot SLAM often relies on odometry measurements for an accurate initial estimate, multi-robot SLAM requires deriving inter-robot constraints from perceptual information. Feature descriptors are used to find potential data association because they are easy to transfer and query among different robots.

The real-time multi-robot SLAM framework has been successfully implemented by using lightweight feature descriptors to detect inter-robot loop closure and distributed optimization. Feature descriptors are used to find potential data association because they are easy to transfer and query among different robots. Vision based methods extract features on images and then build Bag of Words (BoW) (Chang et al., 2021; Deutsch

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et al., 2016). Recent research also extracts point features to scale down the data such as transforming the LiDAR point cloud into a descriptor and then comparing the similarity of the descriptors. Scan Context (Kim & Kim, 2018)encodes egocentric visible information as a 2D matrix by projecting the scan onto a plane, which is then divided into grid cells according to a specified number of sectors and rings. Since scan context is lightweight and easy to be searched by KD tree, so it is widely integrated into many frameworks. However, this method is not robust enough and finds many false loops closure. Dr. Tixiao Shan (Shan et al., 2021)using image-quality high resolution 3D point clouds to obtain an intensity image and encode the ORB feature descriptors into a bag-of-words vector. This proposed method is more robust and combine the benefit of both camera and lidar-based method. Zhong et al. (2022) integrates LiDAR-Iris(Wang et al., 2020), a lightweight global descriptor, to describe laser scans and identify loop closures without exchanging extra raw data. This descriptor captures the altitude data of each bin, extracts distinctive features without any prior training, and remains rotation-invariant without requiring brute-force matching.

Although features descriptors are robust in many cases, they are unreliable in repeated scenes. Recent works address this issue through selectivity in accepting inter-robot loop closure and outlier rejection procedure to detect erroneous loop closure. In this case, robots only exchange the messages when they meet. However, this rendezvous approach relies on the overlap timestamp of multi-robots. A widely used outlier rejection procedure in multi-robot SLAM named pairwise consistent measurement set maximization (PCM) (Mangelson et al., 2018)checks the consistency of inter-robot measurements, which allows us to robustly merge trajectories. After obtaining the inter-robot measurement constraints, the optimization of the constraints is critical for the fuse. In the commonly adopted distributed Gauss-Seidel (DGS) (Choudhary et al., 2016) approach, each robot independently optimizes its own graph and only takes into account the overlapping constraints with other robots. Recently, the work from DiSCo-SLAM (Huang et al., 2022)adopted a two-stage optimization approach and the initial global optimization step solves the transformation among robots. Next, the local graph optimization step is performed utilizing the local odometry, intra-robot constraints, and inter-robot constraints.

1.3 Research gap

Unfortunately, previous studies mostly were tested on specially designed routes and relatively simple environments. Since researchers usually lack multi-robot observations, sequences of the single robot are always modified into a synthetic multi-robot dataset. However, the performance of real multi-robot cooperative LiDAR SLAM in complex urban scenes and the effectiveness of inter-robot constraints on local pose graph optimization still need to be tested.

1.4 Contributions

- We first use the multi-robot SLAM framework DiSCo-SLAM proposed in (Huang et al., 2022) to compare the performance of the single and cooperative LiDAR SLAM based on the same dataset generated using the Carla simulator('Dosovitskiy et al., 2017).
- We found that inter-robot constraints are transformed to intra-pose constraints in local SLAM and the effectiveness of inter-robot constraints in improving local SLAM in this experiment is limited.
- We found that the extent to which inter-robot constraints affect the correction of local SLAM is related to various factors, such as the confidence level of the constraints and the range of keyframes imposed by the constraint.
- To obtain similar positioning accuracy but with a lower computational load, we use feature selection in the LiDAR odometry part.

2. ALGORITHMS

2.1 Overview of the architecture of DiSCo-SLAM

Huang et al., (2022)proposes a distributed multi-robot SLAM framework intended for real- time use with 3D LiDAR. Once the system receives the LiDAR scan, the local SLAM thread and each map fusion thread are activated simultaneously. The multi-robot SLAM adopts LIO-SAM(Shan et al., 2020) as local SLAM framework. In this framework, it will launch the local SLAM node to estimate the individual robot pose transformation first and then the information of key frame will be sent to the fusion node of each robot. The point cloud information of key frames includes pose estimation and full scan, which is transferred to the map fusion node.

The map fusion node will use the cloud information of key frame to publish the lightweight spatial feature descriptor named Scan Context(Kim & Kim, 2018). Scan Context messages are published by projecting the LiDAR scan onto a 2D plane. The resulting 2D scan image is then divided into grid cells according to a specified number of sectors N_s and rings N_r. To obtain a ring key feature, the value of each grid cell is computed as the maximum intensity of all the points captured in the cell. Then, for each ring, a ring key feature of dimension N_r is extracted by counting the non-zero values of each cell. A ring key KD tree is built to search for nearest neighbour search and get a list of nearest indices of descriptors. The SC features are shifted along the sector axis to ensure rotation invariance. The shifting angle also serves as an initial rotation guess for the ICP scan-matching process in cases where there is no coordinate transformation history available. The Pairwise Consistent Measurement Set Maximization (PCM) technique has been introduced to mitigate the risk of accepting erroneous loop closures. Such inaccuracies may arise from distinct environmental regions that exhibit similar appearances or from objects within the environment arranged in repetitive patterns.

The most important part of this framework is the two-stage global and local optimization. After performing the PCM techniques, the accepted inter-robot loop closures are used to optimize the transformations from local robots to the global coordinate frame. In the global step, the coordinate transformations between robots derived form inter-robot loop closures are regarded as measurements and use GTSAM (the Georgia Tech Smoothing and Mapping library) to optimize the global transformation. Separator poses refer to the key poses in multi-robot system that are used to establish connections between different robots. Upon completing global optimization, the inter-loop closures will be converted to virtual intra-robot loop closures. In order to calculate the relative poses between the virtual intra-robot loop closure, the related poses are multiplied with the inter-robot loop closure's relative transformation.

2.2 Transmission of inter-robot constraints to local SLAM

The **Figure 1** illustrates the transmission between global optimization and local SLAM in two-robots situation. The local SLAM transfers the LiDAR scan and pose estimation to the map fusion node. After detecting the inter-loop closure and optimizing the transformation between different robots, the inter-loop constraints are transferred to local pose graph for further optimization by establishing global to local coordinate transformation. After receiving the virtual intra-robot observation, the local SLAM will add the pose constraints between related key frame and the local pose graph is optimized. The index of related key frame and constraints are derived from the inter-loop queues and sent by the map fusion node.

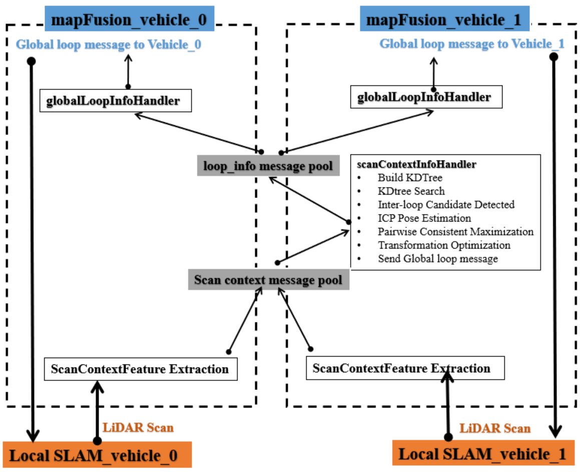

Figure 1. Inter-robot constraints to local SLAM

3. EXPERIMENT

3.1 Experiment setup

To test the cooperative LiDAR SLAM based on complex datasets, the two-robot dataset with 10 Hz 16-line LiDAR and 100 Hz raw inertial measurement unit (IMU) data was recorded in the Carla simulator and configured for compatibility with DiSCo-SLAM. When designing the driving path of two vehicles **(Figure 2**), we let the two vehicles start from different points (presented by triangular shape) and each robot 's trajectory includes intra-robot and inter-robot loop closure. The blue one represents the ground truth trajectory of vehicle_0 and the green one for the vehicle_1. We used the EVO package ('Grupp, 2017) for the evaluation and comparison of odometry and SLAM.

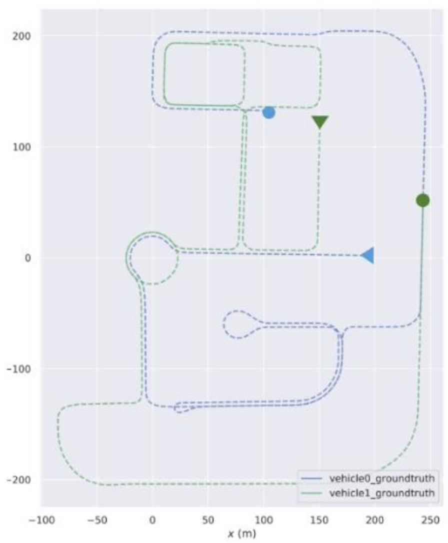

Figure 2. Route design of vehicle_0 and vehicle_1.

3.2 Evaluation method

To evaluate the cooperative SLAM performance, we use the two-vehicle dataset to run the multi-robot SLAM and save their optimized local pose estimations. The optimized transformation from vehicle_1 to vehicle_0 is published by the topic and used to merge the map. We use the absolute pose error (APE) w.r.t translation part to evaluate the overall consistency of trajectory and use Umeyama algorithms(Umeyama, 1991) to transform the estimated merged map to the coordinate system of ground truth **(Figure 3)**. The APE and RPE w.r.t translation part is given in **Table 1**.

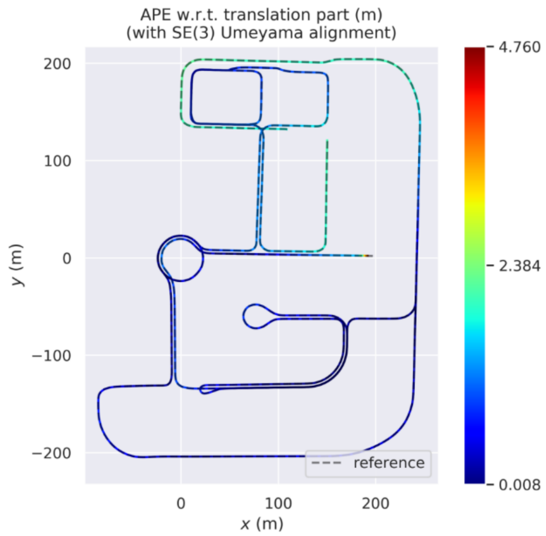

Figure 3. APE w.r.t translation part of cooperative SLAM.

	Min	Max	Mean	RMSE
APE	0.007	4.760	0.850	1.062
RPE	0.001	1.594	0.007	0.039

Table 1. Absolute pose error (APE) and relative pose error (RPE) w.r.t Translation Part(m).

In the second experiment, we divided the two-vehicle dataset into two single-vehicle datasets and still run the DiSCo-SLAM for each vehicle. Using single-vehicle data will result in no inter loop constraints in local pose graph optimization. We perform comparisons of pose error between single-robot SLAM and multi-robot SLAM **(Table 2 and Figure 4)** to explore whether the cooperative framework can noticeably improve robot localization performance and the influence of inter-robot constraints in local pose graph.

Setting	Min	Max	Mean	RMSE
Vehicle_0 (single)	0.062	2.228	0.352	0.565
Vehicle_0 (collaborative)	0.017	4.996	0.300	0.543
Vehicle_1 (single)	0.010	2.139	0.423	0.561
Vehicle_1 (collaborative)	0.013	1.900	0.411	0.538

Table 2. Absolute pose error w.r.t translation part.

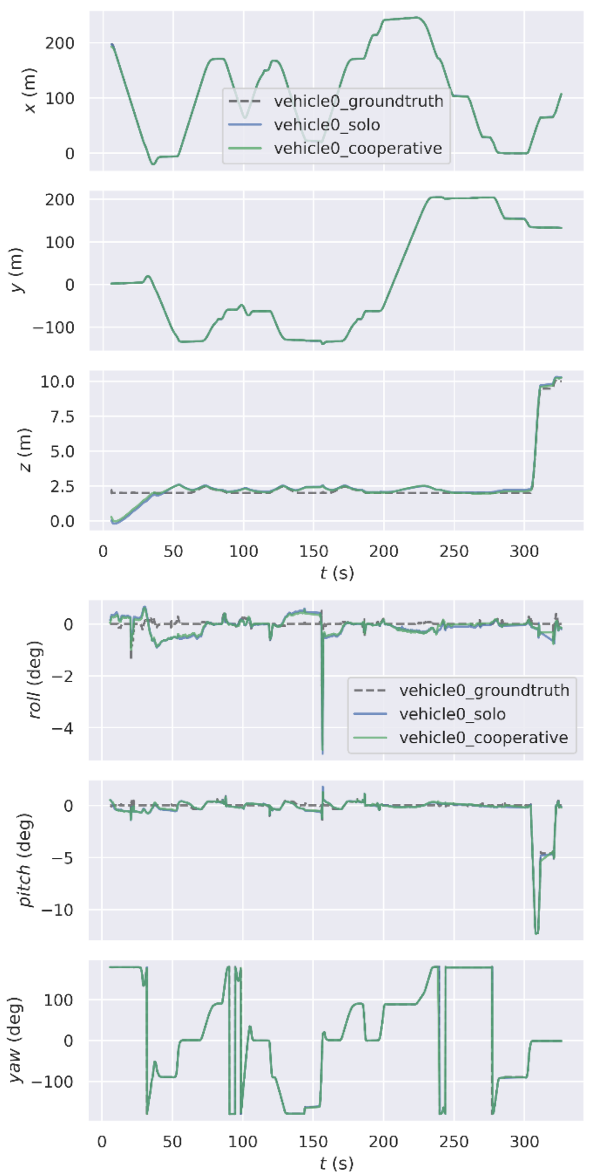

Figure 4. comparisons of pose estimation between single-robot SLAM and multi-robot SLAM

3.3 Performance of cooperative mapping

In general, cooperative LiDAR SLAM in complex environments can achieve similar performance compared to previous studies. From **Figure 3**, we can find good results for collaborative mapping and localization in large urban environments, except for the start and end parts of some trajectories, which show high errors. During the experiment, we found that the effectiveness of inter-robot loop detection between robots is not enough **(Figure 4 and Table2)**. Under the infrequent overlapping between trajectories or the inconsistent moving directions in the overlapping area, the inter-robot loop detection and the cooperative task may fail.

3.4 The influence of inter-robots' constraint

In the local phase of collaborative SLAM, a local graph is refined, which includes: (1) local odometry, (2) intra-robot constrains, and (3) inter-robot constraints relevant to the specific robot. In the single SLAM, the constraints for the local pose graph optimization contain only the first two. The effect of inter-robot constraints on the result can be found by the control variables method. According to the comparison of the collaborative and single SLAM **(Table 2),** the conversion of inter-robot constraints to the virtual intra-robot constraints slight contributed to the performance of the local SLAM. In order to investigate the detailed relationship between the absolute pose error (APE) of key frame pose estimation and the two kinds of loop-closures, we plotted the absolute pose error of the keyframe pose estimation **(Figure 5).** The difference between the two curves reflects the effect of inter-robot constraints. We draw red dashed lines perpendicular to the x-axis on keyframes where intra-robot loop-closure constraints are present, and green dashed lines perpendicular to the x-axis on keyframes where inter-robot loop-closure constraints are present. It can be found that the regions with inter-robot constraints are not able to reduce the error significantly. However, according to the previous researchers' experiments results, it is said that inter-robot constraints can significantly reduce the drift of local pose estimation when there is sufficient overlap among robots. Under that situation, inter-robot constraints can compensate for the cumulative drift caused by the absence of intra-robot constraints.

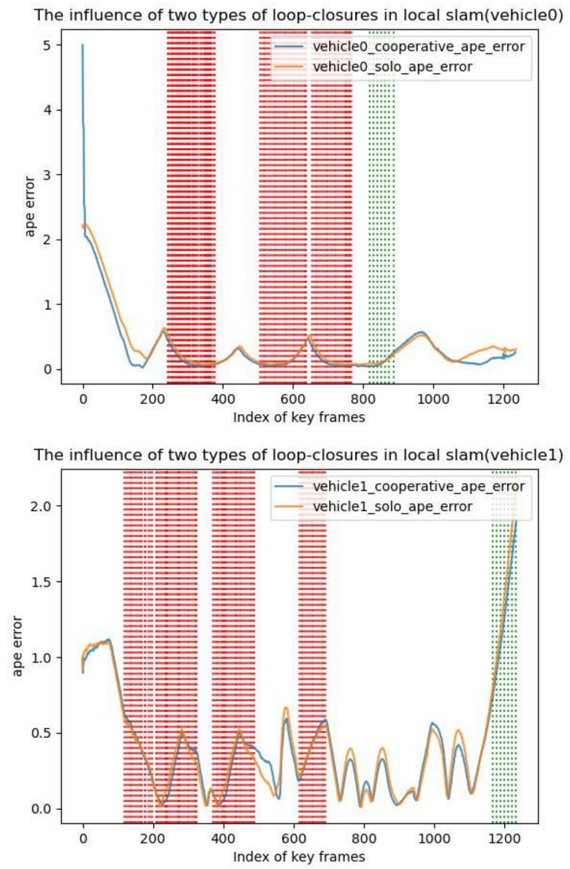

Figure 5. Two types of loop-closures in local SLAM

In different situations, the contribution of inter-robot constraints to the local pose graph varies. Since the inter-robot constraints, which will be converted into virtual intra-robot constraints, are based on the estimation of neighbouring robots' poses and the coordinate system transformation between robots, the extent to which inter-robot constraints affect the correction of local SLAM is related to various factors, such as the confidence level of the constraints and the range of keyframes imposed by the constraint. If the pose estimation of neighbouring robots is inaccurate, this will directly affect the accuracy of inter-robot constraints. This may lead to map inconsistencies and localization errors.

Therefore, accurate pose estimation of neighbouring robots is essential for generating reliable inter-robot constraints. At the same time, by sharing accurate constraints, multi-robot systems can correct each other's localization errors, thereby improving the overall SLAM performance of the system.

Inter-robot constraints, when integrated correctly, can potentially improve the local accuracy of individual robots compared to single-robot SLAM without inter-robot constraints. However, this improvement is not guaranteed in every situation and depends on various factors. If the inter-robot constraints are accurate and reliable, they can help correct errors in individual robot's local maps, leading to better local accuracy. On the other hand, if the inter-robot constraints contain significant errors or outliers, they may introduce inconsistencies and negatively impact local SLAM accuracy. Accurate relative pose estimation between robots is critical for establishing useful inter-robot constraints. If relative pose estimation is unreliable or contains significant errors, the local SLAM accuracy may not improve or may even worsen. The effectiveness of inter-robot also depends on the robots' ability to collaborate effectively. Proper coordination, task allocation, and sharing of information among robots are essential for leveraging the benefits of inter-robot constraints. For example. In previous research experiment, the route design and cooperative mechanisms between multiple robots can make use of the more accurate routes to correct for paths with large drift.

3.5 The generation of virtual intra-loop constraints

Figure 6 shows the relationship between the inter-robot loop closures queue and the virtual intra-robot loop closures received by individua robot in this experiment. A valid inter-robot loop closure queue is finally determined by nearest neighbour search for descriptors and outlier rejection. Subsequently, the pose transformation from the keyframe of the vehicle in the first adopted loop to the keyframe of the same vehicle in the next loop at a certain interval is computed one by one. To avoid the timestamp between two key frames is too close, some loops will be discarded. During the calculation of the virtual intra-robot constraints, all separator poses from other robots are transformed to the local coordinate frame according to the latest coordinate transformation matrices. The detailed explanation of this transfer process can explain why inter-robot constraints are not significant for local slam in this experiment. This is because the transformation process of this constraint relies on the accuracy of multiple variables and the imposed ranges of keyframes can be seen to be overlapping.

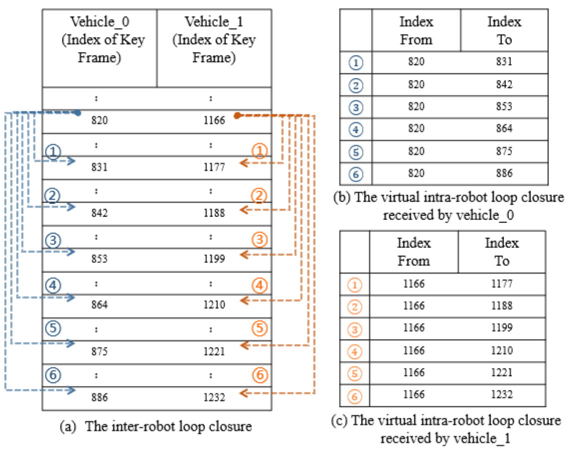

Figure 6. The conversion of inter-loop closures to virtual intra-loop closures

3.6 Future development

In order to improve the flexibility and efficiency of cooperative SLAM in complicated environment, we propose to use another descriptor that can include more environmental information. Shan et al., (2021) uses image-quality high-resolution 3D point clouds to obtain an intensity image and encode the ORB feature descriptors into a bag-of-words vector. This method is more robust and combines the benefits of both the camera and lidar-based methods. To investigate the robust cooperative mapping in urban scenes, we employed the Imaging Lidar to improve the effectiveness of inter-robot loop closure detection. Besides, we propose to perform feature selection in the LiDAR odometry part to improve the efficiency of multi-robot cooperative SLAM. We can expect similar positioning accuracy but with a lower computational load. Moreover, we will explore cooperative mechanisms and conversion algorithms to make the great use of inter-robot constraints. Furthermore, the fusion of SLAM with human mobility data, obtained through GPS-enabled devices and other location-based services, allows for the generation of dynamic and precise maps that reflect the ever-changing nature of urban spaces (Liu et al., 2021; Liu, Shi, et al., 2022; Liu, Wang, et al., 2022; Shi et al., 2022).

4. CONCLUSION

In his paper, we analyse the performance of the single and collaborative LiDAR SLAM based on a complex dataset. In general, we can find good results for collaborative mapping and localization in large urban environments. During the experiment, we found that the extent to which inter-robot constraints affect the correction of local SLAM is related to various factors, such as the confidence level of the constraints and the range of keyframes imposed by the constraint. We may use proper task allocation between robots and route design strategies to leverage the benefits of inter-robot constraints.

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