Online Collaborative 3D Mapping in Forest Environment

Yufeng Yue[1], Chule Yang[1], P.G.C.N. Senarathne[2], Jun Zhang[1], Mingxing Wen[1] and Danwei Wang[1]

***Abstract*— Fusion of local 3D maps generated by individual robots to a globally consistent 3D map is a key challenge in multi-robot missions. Online collaborative mapping has mainly been addressed for robots equipped with cameras or 2D LiDARs. However, in unstructured and ill-light forest environment, 3D Lidars provides more accurate representation. In this paper, we propose a probabilistic framework to address the integrated 3D map fusion problem, which can be factorized into a product of relative transformation estimation and global map estimation. Moreover, a distributed communication strategy is employed to share map information among robots. The proposed approach is evaluated in the forest environment, which shows its utility in 3D map fusion for multi-robot mapping missions.**

I. INTRODUCTION

Utilizing a group of robots is much more robust and efficient in complicated environments than a single robot [1]. A key challenge is that each robot only has partial information of the environment due to limited sensing ability. Therefore, sharing and fusing data perceived by each robot among all robots is necessary [2], which enables each robot to make decisions and plan tasks from a holistic viewpoint. In the challenging forest environment (see Fig. I), GPS, communication bandwidth and computational power are limited. Hence, a compact 3D probabilistic map generated by compressing raw sensor data is preferred. In general, map fusion is composed of estimating the relative transformation and map merging, which are usually tackled separately. The majority of the existing approaches focus on estimating relative transformation and directly applying the transformation to stitch the partial maps, and place less emphasis on how to merge the maps.

The novelty of the work is the proposal of an online probabilistic framework to address the integrated map fusion problem, which is independent of sensor types and SLAM algorithms. Moreover, a distributed communication architecture is proposed and validated with real-time forest experiment under limited communication bandwidth and computational power.

II. DISTRIBUTED COLLABORATIVE MAP FUSION

A. Problem Formulation

Given a group of robots $\gamma = \{a, b, c, \cdots\}$ (the number of robots is r) in an environment, m_i stands for the partial map generated by robot $i \in \gamma$. For robot i, the map fusion problem is to estimate a set of relative transformation matrices $T_{i,1:r}$ (map matching) and generate the global map M_i conditioned on all available partial maps (map merging), where $T_{i,1:r} = \{T_{i,j},\ \ j \in \gamma \cap j \neq i\}$ and $T_{i,j}$ indicates the relative transformation between partial maps m_i, m_j. The joint distribution of $T_{i,1:r}$ and M_i is formulated in Eq. (1):

$$p(M_i, T_{i,1:r}|m_{1:r}). \tag{1}$$

The formulation of the joint distribution enables us to combine the map matching and map merging as an integrated problem. To solve the joint estimation distribution, Eq. (1) is factorized into a product of relative transformation posterior and the global map posterior, where Eq.(1) is written as $p(T_{i,1:r}|m_{1:r}) \cdot p(M_i|T_{i,1:r}, m_{1:r})$.

B. Relative Transformation Estimation

Instead of simply considering $T_{i,j}$ as a fixed unknown parameter, $T_{i,j}$ is modeled as a 6D multivariate Gaussian distribution and solved by MAP estimation, where $T_{i,j} \sim (\hat{T}_{MAP}, \hat{T}_{\Sigma_{MAP}})$. Since the relative transformation T_{ij} is pairwise independent, the posterior of relative transformation $p(T_{i,1:r}|m_{1:r})$ can be factorized into a product of the posterior of relative transformation between each pair in Eq. (2):

$$p(T_{i,1:r}|m_{1:r}) = \prod_{j=1}^{r} p(T_{i,j}|m_{1:r}) = \prod_{j=1}^{r} p(T_{i,j}|m_i, m_j) \tag{2}$$

To solve the MAP estimation problem, we apply Bayes rule to factorize Eq. (2) into Eq. (3), which is the product of maximum likelihood estimation and prior estimation:

$$p(T_{i,j}|m_i, m_j) = p(m_i|T_{i,j}, m_j) \cdot p(T_{i,j}), \tag{3}$$

where term $p(m_i|T_{i,j}, m_j)$ is a maximum likelihood estimation (MLE) problem that aims to find the most likely relative transformation $T_{i,j}$ by matching the two partial maps m_i, m_j. To establish voxel-wise correspondences for map merging, a novel map registration algorithm called occupancy iterative closest point(OICP) [2] is applied to solve MLE.

Fig. 1. The collaborative robots in forest environment

*The research was partially supported by the ST Engineering NTU Corporate Lab through the NRF corporate lab@university scheme.

[1] Yufeng Yue, Chule Yang, Jun Zhang, Mingxing Wen and Danwei Wang are with School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore

[2] P.G.C.N. Senarathne and Diluka Moratuwage are with ST Engineering-NTU Corporate Laboratory, Nanyang Technological University, Singapore

C. Map Merging

The process of combing the information of common objects from partial maps to form a global enhanced map is usually referred to map merging and is formulated in Eq. (4):

$$p(M_i|T_{i,1:r}, m_{1:r}). \tag{4}$$

The merging process should preserve all valuable information of the partial maps while decreasing the uncertainty of the fused map. Since the same object is observed in different viewpoint with various robots, the voxels representing the same object have different occupancy probabilities in separated maps. Hence, it is vital to consider the dissimilarities when fusing them into a global map. Here, the relative transformation is evaluated based on Mahalanobis distance. Then, a relative entropy filter based on Kullback-Leibler divergence is applied to measure the difference between partial maps, which integrates the measurements and decreases the uncertainty of the global map.

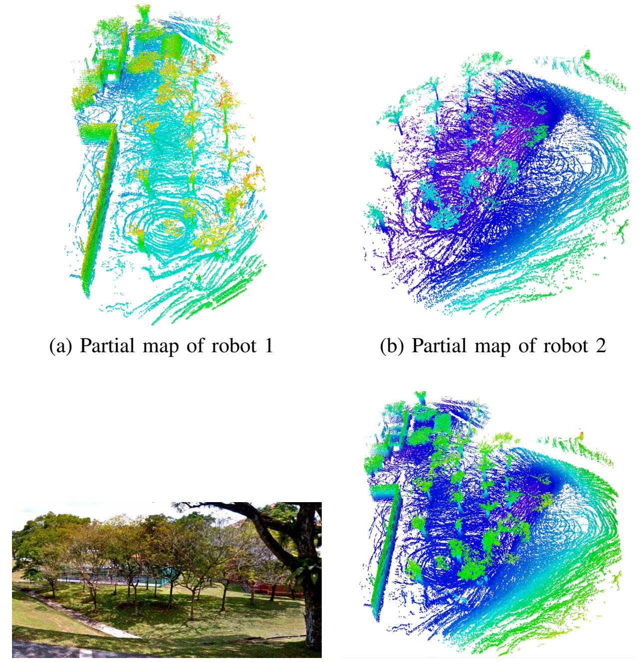
D. Distributed Communication

In the challenging dense forest, the communication bandwidth and computational resources are limited. Hence, it is more feasible for the robots to communicate and transfer data directly with each other rather than transmitting to a central station. Instead of transferring the raw sensor data which requires significant communication bandwidth, we opt to transfer local partial maps which contain the following information: 3D volumetric map in compressed form (i.e. Octree), the time stamp of the map. When robot i receives the partial maps $m_{N_i(t)}$ from neighborhood robots $N_i(t)$, the probabilistic map fusion algorithm described above will be performed to generate global map M_i. Each robot i will preserve its own global map M_i, which increases the robustness to unexpected robot breakdown.

III. Experimental Results

Experiments conducted in the forest environment is presented in this section. Each robot was equipped with a Velodyne VLP-16 Lidar for pose estimation [3] and 3D map [4]. The resolution of the 3D occupancy grid map was set to be 0.1m. The forest is in the university (NTU) with full 3D environment that contains trees and slope (see Fig. 2c), while the communication between robots was established by long range wifi with limited bandwidth. As presented in Fig. 2, the algorithm combines the map information from partial maps to generate an enhanced and more consistent global map.

Here, we present the performance of matching accuracy and merging result for the experiment. As a baseline for comparison, standard ICP based map matching is implemented. Our algorithm produces more accurate results in the experiments in Tab.I. The entropy of the resultant maps after applying different merging algorithm is summarized in Tab. II, which shows the decreased uncertainty by applying relative entropy filter. The experiments indicate that our map fusion strategy is able to combine probabilities of individual maps effectively to decrease the uncertainty.



(a) Partial map of robot 1 (b) Partial map of robot 2

(c) The forest environment (d) Fused global map

Fig. 2. The results of collaborative mapping in the forest. The map produced by robot 1 is semi-structured, while robot 2 produces fully unstructured forest map. The partial maps are fused into a consistent global map.

TABLE I

QUANTITATIVE ANALYSIS OF MAP MATCHING ACCURACY

	Translation Error (meter)		Rotation Error (degree)	
	ICP	Our Algorithm	ICP	Our Algorithm
Forest	2.1496	1.2710	4.0915	2.9587

TABLE II

AVERAGE ENTROPY OF FUSED MAP FOR DIFFERENT UPDATE RULE

	Taking Average	Our Algorithm
Forest	0.278	0.218

IV. Conclusion

This paper proposes a general distributed map fusion framework, which combines map registration and merging into an integrated problem. The accurate relative transformation is calculated by applying map matching algorithm. The map merging is then achieved with a relative entropy filter and decreases the uncertainty of the global map. Experiments validates the proposed method produces enhanced and consistent global 3D maps with high accuracy.

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