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A Survey of Map Merging Techniques for Cooperative-SLAM

Heon-Cheol Lee[1], Seung-Hwan Lee[1], Tae-Seok Lee[1], Doo-Jin Kim[1] and Beom-Hee Lee[1]
[1] School of Electrical Engineering and Computer Sciences, Seoul National University, Seoul, 151-742, South Korea
(Tel : +82-2-880-6487; E-mail: {restore98, leeyiri1, felix84, djkim00, bhlee}@snu.ac.kr)

Abstract - This paper presents a survey of map merging techniques for cooperative-SLAM. The recently proposed map merging techniques are classified into two categories: direct map merging and indirect map merging. In each category, several techniques are briefly described. Then, their advantages and disadvantages are discussed in the context of accuracy and computation time. The description and discussion can contribute to realizing and improving cooperative-SLAM.

Keywords - Map merging technique, Distributed robot system, Cooperative-SLAM.

1. Introduction

SLAM (Simultaneous Localization and Mapping) is one of the fundamental problems of robotics when a robot performs tasks autonomously without any knowledge of its own pose and surrounding environments. C-SLAM (Cooperative-SLAM) [1] is an efficient framework to solve the problem of SLAM, which is based on the cooperation of multiple robots to estimate the robot poses and build a map of the environments. In C-SLAM, the individual maps built by the multiple robots should be merged to obtain a global map. Map merging is performed by acquiring the map transformation matrix (MTM) between the individual maps. Recently, various map merging techniques for C-SLAM have been developed.

This paper presents a survey of the map merging techniques which have been applied to C-SLAM. This survey can be very helpful for the implementation of C-SLAM. This paper is organized as follows: Section 2 introduces the general formulation of C-SLAM. Section 3 and Section 4 describes respectively two categories of map merging techniques: direct map merging techniques and indirect map merging techniques. Finally, in Section 5, their advantages and disadvantages are discussed in the context of accuracy and computation time.

2. Cooperative-SLAM

For two robots with unknown initial correspondences, C-SLAM [2] can be formulated as follows:

$$\begin{aligned} &P(x^1_{1:t}, x^2_{1:t}, M \mid z^1_{1:t}, u^1_{0:t-1}, x^1_0, z^2_{s:t}, u^2_{s:t-1}, \Delta^{21}_s) \\ &= P(M \mid x^1_{1:t}, z^1_{1:t}, x^2_{s:t}, z^2_{s:t}) \\ &\quad P(x^1_{1:t} \mid z^1_{1:t}, u^1_{0:t-1}, x^1_0) P(x^2_{s:t} \mid z^2_{s:t}, u^2_{s:t-1}, x^1_s, \Delta^{21}_s) \end{aligned} \tag{1}$$

where M is the merged map, and Δ^{21}_s is the relative pose between two robots at the time s. $x^i_{k:t}$ is the trajectory for robot i at times k, k+1, …, t. $z^i_{k:t}$ is the corresponding sequence of observations, and $u^i_{k-1:t-1}$ is the sequence of actions executed by robot i. The conditional dependency between the robot trajectories is ignored to estimate the posterior efficiently. Because the robot trajectories are treated as independent variables, each term of the posterior probability can be estimated independently, and then the full posterior can be obtained by using the estimated terms.

C-SLAM can be realized by various hardware systems and software architectures. Figure 1 shows an example of the hardware system for C-SLAM, which consists of three mobile robots and a wireless router for communication among the robots. Each mobile robot is equipped with a laptop computer for data processing, a camera to recognize visual objects and a laser scanner to acquire range information on surrounding environments. An example of the software architecture for C-SLAM is shown in Fig. 2. One of the mobile robots is a leader robot which has the cooperation module. The unit for multiple map merging is included in the cooperation module.

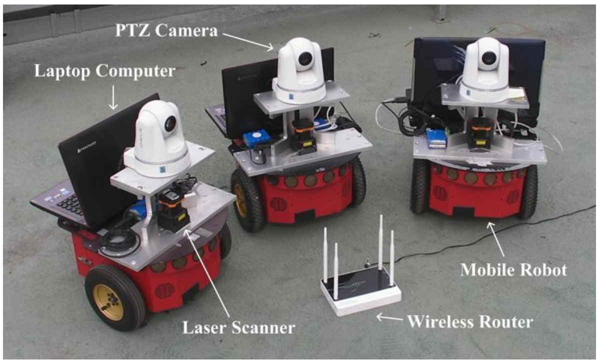

Fig. 1. A hardware system to realize C-SLAM.

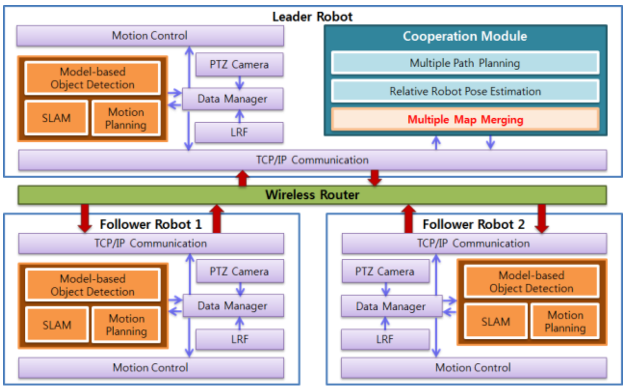

Fig. 2. A software architecture to realize C-SLAM.

Table 1 Map merging techniques for Cooperative-SLAM.

Category	Type	References	Description
Direct map merging	Robot-to-robot measurements	[3], [4], [5]	The visual and range measurements when the robots meet each other at a rendezvous.
	Common regions/objects	[6], [7], [8]	The locations and orientations of the common regions or objects in the multiple maps
Indirect map merging	Point feature matching	[4], [5]	Finding MTM which maximally matches the point features by NNT or PFM
	Application of scan matching	[8], [9], [10]	Applying scan matching algorithms such as ICP, IDC and PSM to map matching
	Spectra-based map matching	[7], [11], [12]	Extracting and matching spectral information on maps instead of geometric information

Map merging is to obtain a global map by merging the individual maps of the different robots using the MTM. The general formation of the MTM is as follows:

$$MTM(\Delta_x, \Delta_y, \Delta_\theta) = \begin{bmatrix} \cos\Delta_\theta & -\sin\Delta_\theta & \Delta_x \\ \sin\Delta_\theta & \cos\Delta_\theta & \Delta_y \\ 0 & 0 & 1 \end{bmatrix} \quad (2)$$

where Δ_θ, Δ_x and Δ_y are relative angle and *x-y* translation amounts, respectively. The map merging techniques to compute the MTM can be classified into two categories: direct map merging and indirect map merging as shown in Table 1.

3. Direct Map Merging

The direct map merging (DMM) is to directly compute the MTM using visual and range sensors, which can be reclassified into two types. One type is to obtain the robot-to-robot measurements when the robots meet each other at a rendezvous. Konolige et al. [3] proposed a two-step map merging framework. The first step called hypothesis is to obtain a MTM using robot-to-robot measurements. Then, for the verification of the hypothesis, the robots move to meet each other at an estimated location. If they fail to meet each other at the estimated location, the hypothesis is rejected. If they succeed, the hypothesis is accepted, which means that their maps are merged. Zhou et al. [4] proposed useful formulations to compute the MTM based on robot-to-robot measurements from omni-directional cameras. However, there was an assumption that the robots should encounter each other. Lee et al. [5] proposed a probabilistic map merging framework for multi-robot SLAM using particle filters. Their framework provided a solution to acquire the most appropriate map merging bases from multiple hypothesis system caused by particle filters. Gaussian processes were used with robot-to-robot measurements.

The other type is to obtain the common regions or objects in multiple maps. In [6], the MTM was computed by overlapped regions detected by ceiling-vision sensors. The image patches collected around observed landmarks were used to find the common regions overlapped by the multiple robots. In [7], the MTM was computed by matching the two-dimensional visual objects recognized by cameras. When the visual objects were recognized, their relative locations and orientations were estimated and used to compute the MTM. Tungadi et al. [8] obtained a coarse MTM by place recognition with omnidirectional vision, which needed a priori process to compute the appropriate size of the bounding box for Haar-based place recognition.

4. Indirect Map Merging

The indirect map merging (IMM) is to compute the MTM by finding and matching the common part of the maps, which can be reclassified into three types. One type is to find and match common point feautres. In [4] and [5], point feature matching was utilized for the features in the maps. Zhou et al. [4] used the nearest neighbor test (NNT) as a point feature matching algorithm after coarse map merging by DMM. But, the performance of the NNT degenerates in dense feature maps. Lee et al. [5] proposed the probabilistic feature matching (PFM) algorithm as a point feature matching algorithm.

Another type is to apply scan matching algorithms to map merging. Tungadi et al. [8] used the polar scan matching (PSM) algorithm to compute the more accurate MTM. León et al. [9] utilized an extension of iterative dual correspondence (IDC) with laser scan sensors. Wang et al. [10] integrated a visual feature matching technique and iterative closest points (ICP) for map merging. However, these techniques based on scan matching algorithms need a sufficiently small portion of occlusions. Moreover, the iteration property to find the optimal solution in scan matching algorithms may cause time-inefficiency in map merging.

The other type is to utilize spectral information on maps. Carpin [12] proposed a novel map merging algorithm which utilizes the spectral information on maps. First, the map rotation angle was estimated by finding the most correlated angle in the spectral information extracted by Hough transform. Then, the map translation amounts were estimated by finding the most correlated amounts in the translational spectra. His technique was applied to [7] for the more accurate MTM after coarse map merging based on visual objects. Lee et al. [12] proposed a feature map merging algorithm based on the spectral information extracted by virtual supporting lines (VSLs) generated by connecting the features around a selected host feature.

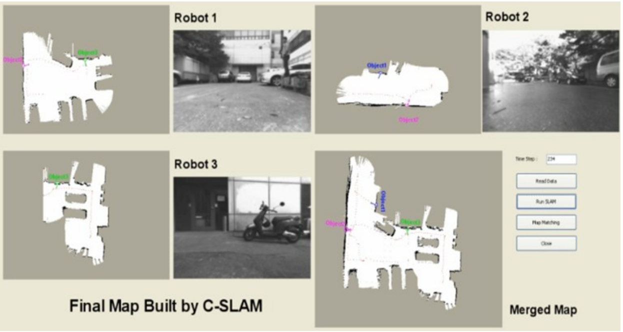

Fig. 3. A result of C-SLAM in an outdoor environment.

5. Discussion

The DMM and IMM have their own advantages and disadvantages. The DMM can be quickly performed as soon as the robot-to-robot measurements or the common objects are obtained. However, the measurements for robots and objects included the inevitable errors caused by imperfect sensors. Thus, the performance of the DMM highly depends on the quality of the measurements. The IMM can improve the coarse result of the DMM. However, since the computation time of the IMM increases generally according to the size of the search space for the MTM, it is not practical to solely use the IMM. Moreover, the IMM may find the local maximum.

For the trade-off between the DMM and the IMM, some researchers have developed the combination of the DMM and the IMM, which is shown in [4,5,7,8]. The combined approach needs many implementation techniques, but its performance is remarkable in the context of computation time and accuracy. The example of the hardware system shown in Fig. 1 and the software architecture shown in Fig. 2 to realize C-SLAM is also a combination of the DMM with common objects and the IMM with spectra-based map matching. Its result in an outdoor environment is shown in Fig. 3. There were three different visual objects which were used to acquire a coarse MTM. Then, a fine MTM was computed by the spectra-based map matching technique. Finally, the three maps built by three different mobile robots were successfully merged.

In future work, the problem of data communication for the more efficient map merging should be addressed. Especially, for active C-SLAM, the problem becomes more important and challenging because the performance of data communication among robots affects directly the performance of map merging.

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References

[1] A. I. Mourikis and S. I. Roumeliotis, "Predicting the Performance of C-SLAM," *International Journal of Robotics Research*, Vol. 25, pp. 1273-1286, 2006.

[2] A. Howard, "Multi-Robot SLAM using Particle Filters," *International Journal of Robotics Research*, Vol. 25, pp. 1243-1256, 2006.

[3] K. Konolige et al., "Map Merging for Distributed Robot Navigation," *IEEE/RSJ International Conf. Intelligent Robots and Systems*, Las Vegas, NV, 2003.

[4] X. S. Zhou and S. I. Roumeliotis, "Multi-Robot SLAM with Unknown Initial Correspondence: the Robot Rendezvous Case," *IEEE/RSJ International Conf. Intelligent Robots and Systems*, Beijing, China, 2006.

[5] H. C. Lee et al., "Probabilistic Map Merging for Multi-Robot RBPF-SLAM with Unknown Initial Poses," *ROBOTICA*, Vol. 30, pp. 205-220, 2012.

[6] H. S. Lee and K. M. Lee, "Multi-robot SLAM Using Ceiling Vision," *IEEE/RSJ International Conf. Intelligent Robots and Systems*, St. Louis, MO, 2009.

[7] H. C. Lee et al., "Implementation of a Network-based Robot System for Cooperative Recognition and Localization of Multiple Objects," *IEEK Summer Conference*, Jeju Island, South Korea, 2012.

[8] F. Tungadi et al., "Robust Online Map Merging System using Laser Scan Matching and Omnidirectional Vision," *IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, Taipei, Taiwan, 2010.

[9] A. León et al., "SLAM and Map Merging," *Journal of Physical Agents*, Vol. 3, No. 1, 2009.

[10] K. Wang et al., "Research on Map Merging for Multi-robotic System Based on RTM," *IEEE Int. Conf. Information and Automation*, Shenyang, China, 2012.

[11] S. Carpin, "Fast and Accurate Map Merging for Multi-Robot Systems," *Autonomous Robots*, Vol. 25, pp. 305-316, 2008.

[12] H. C. Lee and B. H. Lee, "Improved Feature Map Merging using Virtual Supporting Lines for Multi-Robot Systems," *Advanced Robotics*, Vol. 25, No. 13-14, pp. 1675-1696, 2011.