AMCL based Map Fusion for Multi-robot SLAM with Heterogenous Sensors *

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Abstract - This paper proposes an efficient adaptive Monte Carlo Localization (AMCL) based approach to align the occupancy grid maps built by a multi-robot system. Map alignment plays an important role for the map fusion of multi-robot simultaneous localization and mapping (SLAM), especially for the SLAM with heterogenous sensors. Two robots equipped with a laser and Kinect respectively are executing FastSLAM 2.0 in the same environment but at different starting point; the motion and measurement information is recorded with timestamps. To merge the maps built by different robots, one robot is first relocated in the map built by the other robot by using the recorded motion sequences and measurement information. With the relocation result, the transformation matrix between the two different maps is calculated; the matrix is further used as the initial relative pose information for ICP process to obtain precise alignment result. Experiments are finally performed to demonstrate the effectiveness of the proposed approach.

Index Terms - AMCL; map fusion; multi-robot SLAM; heterogenous sensors.

I. INTRODUCTION

SLAM is the problem of the robot acquiring a map of its unknown environment while localizing its pose in the map simultaneously. It is a basic requirement in autonomous navigation, path planning, and obstacle avoidance, etc. In the last two decades, great success has been achieved on the challenging SLAM problems including data association, computation complexity and loop closure in single robot SLAM. There are a lot of mature methods based on probabilistic theory [1] including extended Kalman filter SLAM (EKFSLAM) [2], Graph based SLAM ([3], [4]) and FastSLAM [5], etc.

Developments in single robot SLAM have significantly promoted the research on multi-robot SLAM. Multi-robot SLAM has great advantages in efficiency, accuracy, robustness, etc. For example, multiple robots are more efficient than a single robot because robots can parrellly implement the SLAM task, and also the robots equipped different sensors can share the overlapped map information to augment the map size and enrich the map information. Furthermore, multi-root system can still work even one robot is broken; this is very important in the practical application.

However, multi-robot SLAM problem is significantly more difficult than single-robot SLAM because of unknown relative robot poses, map fusion, scalability issues, etc. Different sensor technologies have been developed in the past decades, such as 2D laser scanner[5], 3D scanner [6], monocular vision system [2], stereo vision system [7], and RGB-D cameras [8]. Maps fusion becomes very important in multi-robot SLAM because different maps are built distributed in several independent robots. The two key problems, i.e., the calculation of the relative poses between robots and the map alignment, are the focus of the present paper.

This paper aims to align two 2D occupancy grid maps which are built by two robots equipped with Kinect and a laser individually. Motivated by the AMCL approach with KLD-sampling [9], the proposed approach is implemented in a similar way to deal with the relocation problem and implement the fusion of two different maps. First, two different 2D occupancy grid maps are built by using FastSLAM 2.0 [10] in different robots. The robots’ motions and measurements are recorded simultaneously. One robot is then relocated in another robot’s map by using the AMCL algorithm based on the recorded motions and measurements. The relocation result and the robot’s recorded localization information are further integrated to calculate the primary estimation for the relative pose between the two robots.

Finally, the iterative closest point algorithm (ICP) [11] is utilized to obtain better relative pose estimation, where the primary estimation is treated as the starting point for the iterations. Experiments show that the proposed algorithm performs much better than the pure ICP method.

II. Related Work

Multi-robot SLAM arouses great interest in the SLAM field. Integrating different characteristics in sensors to build

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different types of maps is an important issue in multi-robot research. The relative issues have received considerable attention over the past years.

Grisetti et al. [5] presented an innovative technique to reduce the particle number in the Rao-Blackwellized particle filter. The proposed algorithm can get the distribution of robot and environment map by taking not only the movement of the robot but also the most recent observation, thus it can greatly increase the accuracy of the distribution. Nicola Fioraio et al. [12] proposed a real-time visual and point cloud SLAM. In the algorithm, a map alignment is accomplished by optimizing the accumulating constraints in the sparse graph. And a solution for loop closure problem is also presented by map alignment. Xun et al. [13] presented a new approach to the multi-robot map alignment problem that enables teams of robots to build joint maps without initial knowledge of their relative poses. S. Thrun[14] developed a technique that combines fast maximum likelihood map growing with a Monte Carlo localizer which implemented on distributed multiple robot system.

Fenwicket et al.[15] presented a cooperative concurrent mapping and localization (CML) probabilistic algorithm that merges sensor and navigation information in multi-robot system. Montemerlo et al. [10] proposed a FastSLAM2.0 algorithm which incorporates the most recent measurement in the pose prediction process. AMCL is a useful probabilistic approach for mobile robot localization which is applicable to both local and global localization problems. Upon probabilistic method, robot’s belief can be represented by numbers of weighted samples, which can then be updated in later movement. In order to use a small number of samples to represent the belief of robot, Kullback–Leibler distance sampling (KLD-sampling) was proposed by Dieter Fox [9]. The key idea of KLD-sampling is generates samples until the number of particles is enough to guarantee that the KL-distance between the estimate and the posterior does not exceed a specific bound. By using this adaptive statistical method in state estimation based on particle filters, the computation complexity can be greatly reduced while having a high accuracy.

Although our work is based on the algorithms of FastSLAM 2.0 and AMCL, we focus on the map fusion problem for multi-robot SLAM with heterogenous sensor information. And this is our main contribution to use AMCL method in the map fusion process. The unknown relative pose between robots and the heterogenous sensor-based maps both promote the challenge of the problem.

III. ALGORITHM

Efficient map fusion is the focus of the present paper; however, several algorithms, i.e., FastSLAM and adaptive sampling, are necessary for the distributed robots to build their own maps about the environments. FastSLAM has been proved to be effective to solve SLAM problems in practical applications. In FastSLAM 1.0 [16], the proposal distribution built only upon the motion prediction is just suboptimal. To address this problem, FastSLAM 2.0 integrated both the motion prediction and the measurement uncertainty distribution in the proposal distribution, and thus can obtain a more accurate and robust SLAM performance. In addition of the integration, the scan matching technology [17] can be further used to improve the accuracy of the proposal distribution. FastSLAM is based on Rao-blackwellized particle filter, and therefore too frequent sampling may lead to the failure. The adaptive resampling technology [18] based on the value of Neff is used to control the resampling frequency. The method can greatly improve the robustness of the FastSLAM. All these technologies have been programmed into the GMapping Package in Robot Operating System. Note GMapping can only process 2D sensor measurements, and output 2D occupancy grid maps. However, the Kinect camera provides 3D point clouds about its surrounding environment. To enable the map fusion between Kinect and laser based maps, the Kinect measurements with the same height are used in the FastSLAM for map building; the camera is equipped horizontally, and thus the selected measurements consist of a horizontally layer. However, the heterogenous sensors are distributed at different robots with different equipping height relative to the ground, and thus it becomes a problem to find the correct layer of the Kinect point cloud to fit the laser measurements. To simplify the problem, it is assumed that the operating environments are vertically homogenous; the assumption is trivial for indoor environments but not outdoor environments. Based on the assumption, the middle layer of the Kinect measurements is selected in the experiments.

By using the FastSLAM algorithm, maps with different accuracies are obtained individually in the robots. During the SLAM process, all the motions and measurements are recorded. Although the robots move in the same environment, there are no landmarks equipped the robots for the calculation of relative poses when they meet each other. The absence of initial relative pose is a great challenge for the map fusion process. To obtain the relative pose, an AMCL based approach is proposed in the paper. Because the map from laser measurements is more accurate than that from Kinect, it is used as the map for AMCL process; the robot with Kinect sensor is relocated in the laser-equipped robot’s map by using the recorded motion sequence and measurements. The main AMCL algorithm is illustrated below in Table I.

It is a good idea to maintain a short-term average of the measurement likelihood, and relate it to the long-term average when determining the number of random samples in lines 24 and 25. The probability of adding a random sample takes into consideration the divergence between the short and the long term average of the measurement likelihood. If the short-term likelihood is better or equal to the long-term likelihood, no random sample is added. However, if the short-term likelihood is worse than the long-term one, random samples are added in proportion to the quotient of these values. In this way, a sudden decay in measurement likelihood induces an increased number of random samples. Line 27 plays a crucial role in the statistical bound to determine the number of particles in KLD-sampling.
These two ideas determine the number of random samples and the size of the particle set respectively.

The relative offset is given as

$$T = \begin{bmatrix} x_1 - x_2 \\ y_1 - y_2 \end{bmatrix}$$

Expressing the relative angle and offset in a transformation matrix, we have

$$H = \begin{bmatrix} \cos \theta & -\sin \theta & x_1 - x_2 \\ \sin \theta & \cos \theta & y_1 - y_2 \\ 0 & 0 & 1 \end{bmatrix}$$

Finally, the map of the Kinect-equipped robot is transformed into the frame of laser-equipped robot for map alignment. Unfortunately, the above procedures are not enough for successful map alignment, because the FastSLAM and AMCL are all particle-based algorithms. To address this problem, the ICP algorithm is employed to obtain accurate map alignment by using the transformation matrix (4) as its starting estimation. Before the ICP algorithm, the maps of the robots are needed to be transformed into point clouds by simply treating the occupied grids as points.

\[ \theta = \text{atan2}(y_2 - y_1, x_2 - x_1) \quad (1) \]

The AMCL algorithm provides the localization information of the Kinect-equipped robot with respect to the laser-equipped robot. It implies that the first robot is localized in two different coordinate frames, i.e., the frame built in the AMCL, and the one built in the FastSLAM as shown in Figure 1. Denote the robot's localized pose as \((x_1, y_1)\) in the AMCL-based frame \(X_1O_1Y_1\), and \((x_2, y_2)\) in FastSLAM-based frame \(X_2O_2Y_2\). Actually, the AMCL-based frame is also the FastSLAM-based frame of the second robot. The relative angle between the two frames is calculated as

\[ \theta = \text{atan2}(y_2 - y_1, x_2 - x_1) \]
Kinect camera. In our experiments, the UBG-04LX-F01 laser was used as the first sensor in the map building process which can detect obstacles from 20mm to 5,600mm accurately with 240° wide angles and 28msec scanning speed. The Kinect was amounted on the middle plate on the TurtleBot as the second sensor to build the occupancy grid map which the depth data in the middle layer along the z orientation is used to match the laser scan in the GMapping. As shown in Figure 2, the laser on TurtleBot 1.0 and the Kinect on TurtleBot 2.0 are not at the same height. Base on the previous assumption in Section III, the two robots’ environmental obstacles were treated as the same.

When building the occupancy grid maps, two robots started at random initial positions of the environment. The robots were controlled to move along paths with loops for the aim of good GMapping performance. While the robots were building the map, their odometry, sensor measurements and the best particles during the SLAM process were recorded using the ROS tool, i.e. rosbag. The recorded data was needed for further AMCL process. The robots were manually stopped when the SLAM was finished. Figures 3 and 4 illustrate the maps built by TurtleBot 1.0 with the laser and TurtleBot 2.0 with the Kinect, respectively; they are denoted as Map 1 and Map 2, respectively. It is seen that Map 1 was more accurate compared to map 2, because of the higher resolution of laser. Map 2 was noisy in some area due to the uncertainty measurement data from Kinect.

With the maps built, the AMCL process was then processed. Firstly, the TurtleBot 2.0 was re-localized in Map 1 by using TurtleBot 2.0’s recorded motion and measurement information. At the beginning, the particles were uniform distributed to perform global localization as shown in Figure 5. As TurtleBot 2.0 was moving on, it was relocalized well, and finally converged to some point as shown in Figure 6. The best particles were recorded with time stamped. Best particle poses in GMapping in Map 2 and the best particle poses obtained Map 1 by using the AMCL were used to calculate the transformation matrix (in our experiment: $\theta = -0.401690, T = [0.331752; -2.765979]$). The calculated transformation matrix was directly used in the map fusion process. As shown in the Figure 7, two maps were fused together but with very poor accuracy.
was applied to the original maps but without any initial estimation, and obviously the performance was very poor.

V. CONCLUSION

In this paper, we presented a novel approach to address the map alignment problem. Two maps are obtained in the same environment by laser and Kinect respectively using the occupancy grid based FastSLAM 2.0. And then, one robot is relocalized in the map built by another robot, by using the first robot’s motion and measurement information; the AMCL localization algorithm is utilized. The transformation matrix between the different maps is calculated based on the localization result. Finally, the ICP algorithm is employed to obtain accurate map alignment by using the calculated transformation matrix as the starting estimation. Experimental results illustrate that the proposed approach is efficient. Our approach will be tested in the situation in the future work that each robot in the team gets to map part of the environment and then merge all the submaps together to a consistent whole one. Because the Kinect can provide much more information beside the laser, the 3D map fusion will be also included. We will compare our approach with pose graph based algorithms to further improve the paper.

REFERENCES


