Simultaneous Localization and Mapping of Mobile Robot with Research and Implementation

Chen Du[1, a] and Yu Du[2, b, *]

[1]Beijing Key Laboratory of Information Service Engineering, Beijing Union University, Beijing 100101, China;

[2] College of Robotics, Beijing Union University, Beijing 100101, China.

[a]xueshdch@163.com, [b, *] duyu@buu.edu.cn

Abstract. In the process of autonomous navigation, mobile robots need to build maps of the surrounding environment and simultaneous localization. The Rao-Blackwellzed particle filter algorithm is one of the methods to efficiently solve the problem that simultaneous localization and mapping of mobile robots. At present, Mapping of inconsistent have long been the focus of research. In order to solve this problem, this paper provides an algorithm which uses high-precision Laser data to correct the proposed distribution based on odometer readings, focus sampling on the possible areas of observation information, reduces the error of proposed distribution, and establish a more accurate map environment. Finally, the experimental verification was carried out on the Bulldog mobile robot platform equipped with a 16-line Laser sensor. The results show that the optimized method of performance is more stable, can improves the diversity of particles and creates high-precision environmental maps online in real time.

Keywords: Sensor technique; Simultaneous localization and mapping; Rao-Blackwellized particle filter; Robot operating system.

1. Introduction

With the rapid development of science and technology society and the vigorous development of artificial intelligence, mobile robot technology, which is condensing many scientific and technological achievements such as control engineering technology, computer technology, sensor technology, material science, mechanical manufacturing technology, signal processing, has entered a new upsurge. It is an important basis and symbol for intelligence to be able to identify and locate the environment autonomously, so as to be able to move, judge and act autonomously. Therefore, among the many research of mobile robots, simultaneous localization and mapping (SLAM) has become a very important part of many research [1, 3].

Simultaneous Localization and Mapping consists in the simultaneous estimation of the state of the robot and the map of the environment according to the environmental characteristics observed by its sensors, such as Laser and odometer. It includes simultaneous estimation of robot state and environment map [4]. In simple instances, the robot state is the representation of its position, direction and speed, which can also include other quantities, such as sensor biases and calibration parameters. The map, on the other hand, is a representation of robot operating environment, such as landmark position, obstacles and so on. The establishment of high-precision maps facilitates the execution of other robot tasks and is a very important part of the research of mobile robots.

After many years, many improved algorithms about RBPF-SLAM have emerged. Wang Tian Orange [5] introduced a kind of region Particle Swarm Optimization (PSO) method into RBPF-SLAM algorithm to adjust the particles' proposal distribution. All particles are clustered into several regions and the weighted central position of each region is calculated. Luo Yuan [6] designed an RBPF-SLAM algorithm based on annealing parameters to optimize the hybrid proposed distribution. The annealing parameters were used to control the proportions of the mixed proposed distributions, so that the improved proposed distribution estimates were closer to the real state. Goran [7] proposed a grid-based modification method of Rao-Blackwellized particle filter, which relies on the floor plan of the indoor environment to provide a priori information for simultaneous localization and mapping, so as to have stronger robustness.

Based on the Rao-Blackwellized particle filter method, this paper uses high-precision Laser data to correct the proposed distribution based on the odometer readings. In order to verify the effectiveness of the algorithm, based on the Bulldog mobile robot platform, relevant experiments were carried out.

2. SLAM based on Rao-Blackwellized

The problem of Simultaneous localization and mapping can be understood as: when the initial state of the robot is known, that is, the initial map m_0 and the initial pose x_0, the sensor observation information $z_{1:t} = z_1,\ldots,z_t$ from the initial to the moment, and the control information $u_{1:t-1} = u_1,\ldots,u_{t-1}$ of the odometer, the joint posterior probability $p(x_{1:t}, m \mid z_{1:t}, u_{1:t-1})$ of the robot's trajectory $x_{1:t} = x_1,\ldots,x_t$ and the environmental map m_t can be estimated. As shown in formula 1:

$$p(x_{1:t}, m \mid z_{1:t}, u_{1:t-1}) = p(m \mid x_{1:t}, z_{1:t})\, p(x_{1:t} \mid z_{1:t}, u_{1:t-1}) \tag{1}$$

This formula divides the joint posterior distribution into products of two posterior distributions. On the one hand, the posterior probability estimation of the robot's posture is obtained by collecting and processing the observation and control information of each particle; on the other hand, the posterior probability estimation of the map is obtained under the condition that the robot's posture estimation and the observation information of external sensors are known.

The process can be summarized by the following four steps [8]:

1) Sampling: According to the proposed distribution, and obtaining the next generation particle set $\{X_t^{(i)}\}$ from the previous generation particle set $\{X_{t-1}^{(i)}\}$. The motion model of the system is typically used as a proposal distribution.

2) Weight: In order to better estimate the proposal distribution and reduce the error with the target distribution, the importance weight of each particle needs to be calculated, as shown in formula 2:

$$\omega_{\mathrm{t}}^{(\mathrm{i})} = \frac{p(x_{1:t}^{(i)} \mid z_{1:t}, u_{1:t-1})}{q(x_{1:t}^{(i)} \mid z_{1:t}, u_{1:t-1})} \tag{2}$$

3) Resampling: Resampling the particles of the system according to the set threshold. After resampling, all the particles have the same weight.

4) Map Estimation: For each particle, its motion trajectory $x_{1:t}^{(i)}$ and observation information $z_{1:t}$ can be used to calculate the corresponding map $p(m^{(i)} \mid x_{1:t}^{(i)}, z_{1:t})$.

3. Implementation based on Optimized RBPF-SLAM

ROS (Robot Operating System), a robot operating system, is a distributed processing framework. ROS are divided into: node, manager, message, and topic. The core is a node that is used to perform a relatively simple task or process. Multiple nodes pass messages to each other and can independently initiate or terminate. A node can issue messages or provide services for specific titles to other nodes [9].

All experiments were performed on the ROS system, and the main node simplified diagram is shown in Fig.1.

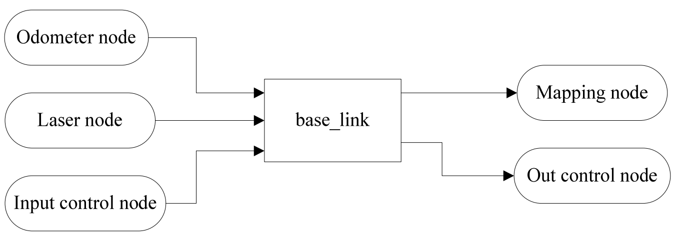

Fig. 1 Main nodes running on the ROS

The odometer node, the laser node and the control node publish messages to the base_link topic, the base_link interacts with the message, the information issued by the control output node is used to control the movement of the robot, and the mapping node extracts the message of the base_link topic for map construction.

The experimental platform is a Bulldog robot with a length of 90cm, a width of 70cm and a height of 80cm. The picture is shown in Fig. 2. The robot is equipped with a Rslidar laser sensor and an internal PC connected by a serial cable. The internal PC is a ROS system running on Linux (Ubuntu 14.04), which enables real-time online map construction. The external PC connects to the Bulldog route and communicates via the HTTP protocol. In addition, this experiment also uses a handle for controlling the Bulldog robot during the map construction process.

Fig. 2 Picture of mobile robot

First, the experimental scene is approximately 2.5m × 5m. Figure 3 shows the RBPF-SLAM algorithm using only the odometer motion model and the high-precision laser data to correct the high-precision map based on the proposed distribution of the odometer readings.

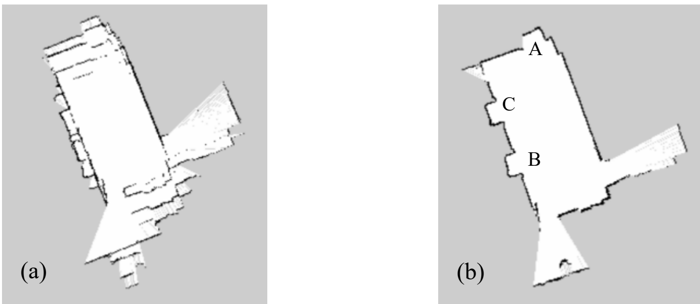

Fig. 3 Mapping with different proposed distributions

As time goes on, the error of odometer becomes larger and larger, and the phenomenon of map inconsistency becomes more and more obvious, as shown in the edge of in Figure 3 (a). Point A, B, and C in Figure 3 (b) can accurately reflect the map environment.

Second, the approximate map is 6m x 8m, and there are some obstacles, such as desks and chairs, bookcases, long tables, etc. The traditional RBPF-SLAM algorithm and the optimized RBPF-SLAM algorithm can clearly see the outline of points A, B and C in Figure 4 by using different particle numbers.

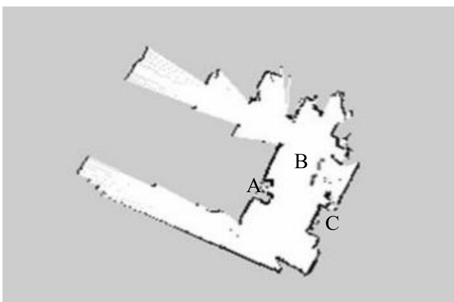

Fig. 4 Experimental scenario

Table 1 shows the two algorithms using different particle numbers to construct the same sharpness map and compare the number of particles.

Table 1. Comparison of particle numbers

Numble	Algorithm	Particle Numbers
1	Traditional Algorithm	38
2	Optimization Algorithm	18

As can be seen from the results of the construction of the map, when the experimental environment is more complicated, it can be obtained from Table 1. When constructing the map with the same definition, the optimized RBPF algorithm uses fewer particles.

4. Summary

Optimizing the Rao-Blackwellized particle filter of simultaneous localization and mapping, using high-precision laser data to correct the proposed distribution based on odometer readings, reducing the error of the proposed distribution, and improving the accuracy and effectively reducing the map inconsistency. Further, the optimized RBPF algorithm uses fewer particles, and it can be seen that the performance of the optimization algorithm is better.

References

[1]. R. Smith, M. Self, P. Cheeseman. Estimating Uncertain Spatial Relationships in Robotics[J]. Machine Intelligence & Pattern Recognition, 2013, 5(5):435-461.

[2]. G. Bresson, Z. Alsayed, L. Yu, et al. Simultaneous Localization and Mapping: A Survey of Current Trends in Autonomous Driving[J]. IEEE Transactions on Intelligent Vehicles, 2017, 2(3):194-220.

[3]. A. A. Panchpor, S. Shue, J. M. Conrad. A survey of methods for mobile robot localization and mapping in dynamic indoor environments[C]// 2018 Conference on Signal Processing and Communication Engineering Systems (SPACES). IEEE, 2018.

[4]. C. Cadena, L. Carlone, H. Carrillo, et al. Simultaneous Localization and Mapping: Present, Future, and the Robust-Perception Age[J]. IEEE Transactions on Robotics, 2016, 32(6).

[5]. T. CH. Wang, Y. F. CAI, Z. M. Tang. SLAM Method Based on Region Particle Swarm Optimi zation and Partial Gaussi an Resampling[J]. Computer Engineering, 2017, 43(11):310-316(in Chinese).

[6]. Y. Luo, Q. Sun, Y. ZHang, et al. simultaneous localization and mapping implementation based on optimized RBPF[J]. Journal of Huazhong University of Sci & Tech (Natural Science), 2016, 44(5): 30-34(in Chinese).

[7]. G. POPOVIć, J. ORšULIć, D. MIKLIć, et al. Rao-Blackwellized Particle Filter SLAM with Prior Map: An Experimental Evaluation[C]// Iberian Robotics conference. Springer, Cham, 2017:14-25.

[8]. G. Grisetti, C. Stachniss, W. Burgard. Improved Techniques for Grid Mapping with Rao-Blackwellized Particle Filters[J]. IEEE Transactions on Robotics, 2007, 23(1):34-46.

[9]. A. Koub. Robot Operating System (ROS) - The Complete Reference (Volume 1) [M]// Robot Operating System (ROS): The Complete Reference (Volume 1). Springer Publishing Company, Incorporated, 2016.