Rapidly Exploring Gmapping

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Abstract.

This paper presents an improved algorithm for the proposal distribution. The proposed algorithm enhances the range of filter values, the precision of re-sampling, and the accuracy of the map building. Additionally, the computational overhead is reduced, thereby optimizing the issue of the particle degeneration. The comparative experiments demonstrate that the proposed algorithm enhances the mapping precision and speed.

Keywords: Path planning, Algorithm optimization.

1 Introduction

Currently, the traditional RBPF (Rao-Blackwellised Particle Filters) algorithm uses particle filtering algorithm to estimate the status of the robot[1],[2].Traditional positioning and environmental map acquisition still requires a lot of human resources to accurately measure the surrounding environment. The process is time-consuming and labor-intensive, with poor results and errors. Therefore, the method of simultaneous localization and mapping (SLAM) is a hot topic in the current research of mobile robots. At present, the implementation of 2D laser SLAM is mainly divided into two methods: filter-based and nonlinear optimization-based. The filter-based method includes the extended Kalman filter (EKF), the unscented Kalman filter (UKF), and the particle filter (PF). The SLAM method based on nonlinear optimization mainly uses the framework of graph optimization to implement SLAM. The Gmapping algorithm is an algorithm for simultaneous localization and mapping of mobile robots. It is widely used in mobile robots, unmanned vehicles, drones and other fields, especially in navigation and exploration tasks in unknown environments. Its real-time and effectiveness make it one of the important tools in the field of SLAM. Gmapping is a SLAM algorithm based on 2D LiDAR using the RBPF algorithm to complete the construction of a two-dimensional grid map. It can build indoor maps in real time, and the amount of calculation required to build small scene maps is small and the accuracy is high. Gmapping is mainly based on the particle filter algorithm, which estimates the position and posture of the robot through LiDAR data and robot motion information. The ability to process sensor data in real time and generate a two-dimensional environment map is very important for mobile robots that need to navigate in unknown environments. This method uses multiple "particles" to represent possible states and updates these states based on sensor data. The advantages of Gmapping are real-time and high efficiency. It can build indoor environment maps in real time, with less calculation in small scenes and higher map accuracy.

Although Gmapping can generate maps in real time with high accuracy, it is inevitable that particles will degrade when estimating the robot's state in large scenes because a large number of particles are needed to estimate the robot's posture. Particles with larger weights will account for a larger proportion, and particles with smaller weights will gradually decrease or even disappear. In addition, frequent resampling steps will cause particles to gradually degrade, which will waste a lot of computing resources and affect the mapping effect. In 2007, Giorgio Griisetti and Cyril Stachniss [3] proposed an improved RBPF mapping algorithm to implement SLAM mapping, that is, an improved Rao-Blackwellised particle filter mapping algorithm using an improved proposed distribution and an adaptive resampling method. This improved RaoBlackwellised particle filter algorithm improves the performance of the algorithm, effectively reduces the computational complexity, and alleviates the particle degradation problem by using a small number of particles for state estimation [4],[5],[6]. However, the algorithm still relies on a high number of particles in an environment with large maps and high local similarity, and errors will occur in mapping. The robustness of the algorithm needs to be improved, and how to effectively limit the spatial range of the Proposal distribution to improve sampling efficiency has not been fully explored.

This paper is structured as follows: the second part describes the Gmapping algorithm; the third part describes the idea of the improved algorithm; the fourth part conducts a reasonable data analysis of the results of the optimization algorithm; and the fifth part summarizes the whole paper.

2 DRP-GMapping Core Idea

In order to overcome the problems of excessive computation and particle degradation in SLAM methods based on conventional particle filters, this paper further optimizes the proposal distribution by optimizing the particle formula of the particle swarm algorithm, restricts the proposal to a small valid area, and dynamically adjusts the proposal distribution in combination with the observation information of the latest frame of the robot, and then samples this valid area. This allows the odometer distribution to match the lidar distribution, greatly improves the sampling accuracy, reduces the number of particles collected, and greatly alleviates the particle degradation problem.The fig.1 shows the comparison of particle filters.

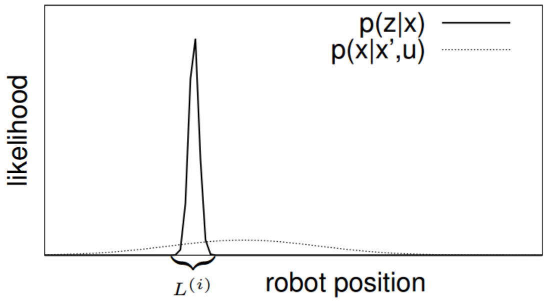


Fig.1 Particle filter comparison

In order to solve the efficiency problem in particle filtering, we proposed a method to improve the efficiency of particle filtering by limiting the effective area of proposal distribution. Specifically, the traditional proposal distribution is generally widely distributed in the entire state space, while we limit the proposal distribution to a narrower effective area.

The specific steps of this method are to dynamically estimate the possible activity range of the robot through the robot's motion model, local map information and sensor data. The range is determined by the robot's current position, movement speed, and obstacle information in the surrounding environment. By restricting particle generation to only this effective region, the distribution range of particles in state space can be significantly reduced. Specifically, at each moment, the current position of the robot is first predicted through the robot motion model (such as the differential drive model), and combined with the status information of the previous moment, an estimate of the current position is obtained. Combined with the observation information of the latest frame, the possible range of activities of the robot is evaluated. For example, by analyzing the location of obstacles in lidar data, the proposal distribution is restricted to areas where obstacles do not exist. Finally, based on the robot's motion estimation and recent observations at the current moment, the size and position of the effective area are dynamically adjusted. The shape of the effective area can be a circle or a rectangle, and the range is adjusted in real time based on the robot's motion status and sensor feedback.

Therefore, we need to keep the number of particles at a relatively small value to improve the pose quality of proposal distribution sampling. The specific changes are:

$$x_t^i \sim p\left(x_t \mid u_t, x_{t-1}^i\right) \rightarrow x_t^i = \arg\max\left\{p\left(z_t \mid x_t, m\right) p\left(x_t \mid u_t, x_{t-1}^t\right)\right. \tag{1}$$

After optimization, the Proposal distribution is more similar to the Gaussian distribution represented by $\left(\mu, \sum\right)$, so the particle propagation is modified from the kinematic model sampling to the sampling of the Gaussian distribution, and the Gaussian distribution is:

$$u = \frac{1}{n}\sum_{j=1}^{k} x_j p\left(z_t \mid x_j, m\right)$$

$$\sum = \frac{1}{n}\sum_{j=1}^{k}\left(x_j - u\right)\left(x_j - u\right)^T p\left(z_t \mid x_j, m\right) \tag{2}$$

The weight is calculated as follows：

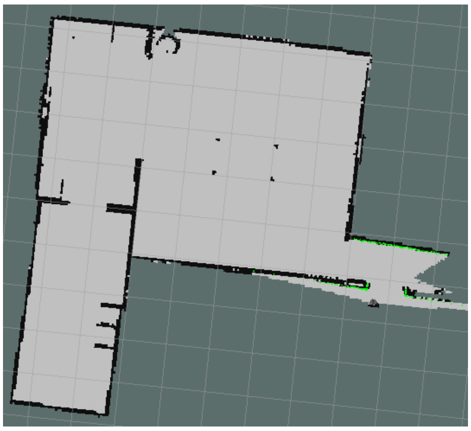
$$w = \eta \frac{p\left(z_t \mid x_t, m\right) p\left(x_t \mid u_t, x_{t-1}^i\right) bel\left(x_{t-1}\right)}{p\left(x_t \mid x_{t-1}, u_t, z_t, m\right) bel\left(x_{t-1}\right)} \tag{3}$$

$$p = \left(x_t \mid x_{t-1}, u_t, z_t, m\right) = \frac{p\left(z_t \mid x_t, m\right) p\left(x_t \mid u_t, x_{t-1}\right)}{p\left(z_t \mid x_{t-1}, u_t, m\right)} \tag{4}$$

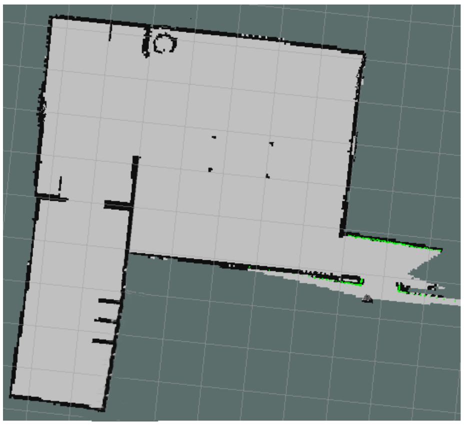
$$\begin{aligned} w &= p\left(z_t \mid x_{t-1}, u_t, m\right) \\ &= \int p\left(z_t \mid x_t, m\right) p\left(x_t \mid x_{t-1}, u_t\right) d\, x_t \\ &= \sum_{j=1}^{j=k} p\left(z_t \mid x_t, m\right) \end{aligned} \tag{5}$$

3 Optimization result analysis

In order to verify the effectiveness of the proposed method, we conducted comparative experiments in various environments. Experimental environments include: Static indoor environment: a standard indoor environment consisting of multiple rooms and corridors. Complex large-scale environments: Large indoor environments with multiple rooms, corridors, and obstacles. In the experiment, we used odometry-based data and compared the performance of the traditional GMapping algorithm and the improved algorithm in terms of positioning accuracy, mapping accuracy, computational efficiency, and robustness. Experimental results show that the optimized GMapping algorithm shows excellent performance in all test scenarios. Compared with traditional methods, the improved algorithm improves positioning accuracy by 15%-25% in static and dynamic environments. In large-scale and complex environments, the maps generated by the optimized algorithm are more accurate, with errors reduced by about 20%. Due to the limitation of particle sampling space, the calculation efficiency is significantly improved, and the processing time is reduced by 10%-15% on average. In a dynamic obstacle environment, the optimized algorithm shows higher robustness, can quickly adapt to environmental changes, and has smaller fluctuations in positioning accuracy.The experimental results are shown in Fig.2.



(a)



(b)

Fig.2.(a) Gmapping algorithm grid map;
(b) improved Gmapping algorithm grid map.

	Simple open environment	Complex obstacle environment
Traditional Gmapping average error (m)	0.23	0.38
Improve the average error of the algorithm (m)	0.18	0.30
Reduction rate (%)	21.7	21.0
Traditional Gmapping is time-consuming (s)	1.00	3.1
Improved algorithm time-consuming(s)	0.85	2.7
Improvement rate (%)	15	12.9

4 Conclusion

This paper proposes a GMapping algorithm optimization method that optimizes the Proposal distribution algorithm in the effective area and combines the observation information of the latest frame. Through this optimization, the efficiency of particle filtering is significantly improved, and the positioning accuracy and mapping accuracy are improved. Experimental results show that this method effectively alleviates the problem of particle degradation, improves the accuracy of resampling, and greatly reduces mapping errors. At the same time, the method in this paper is currently only used in simulation experiments of a single robot. In the future, we will further study the application of this method in actual environments and extend it to collaborative positioning and mapping research on multiple robots.

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