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Optimal Parameter Analysis of Two 2D Lidar SLAM

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Abstract

At present, the mainstream SLAM (simultaneous localization and mapping) algorithm based on laser radar has Gmapping and Cartographer. This paper mainly studies the mapping effect of two algorithms using laser radar in the same environment. With the open source robot operating system (ROS), map construction of two algorithms in different configurations is implemented on a mobile robot equipped with lidar. The experiment indicates the direction of parameter optimization, which proves that the Cartographer algorithm is better than Gmapping.

Keywords

SLAM, ROS, Gmapping, Cartographer, parameter optimization.

1. INTRODUCTION

The Lidar SLAMalgorithm mainly includes Gmapping algorithm based on particle filtering method and Cartographer algorithm based on graph optimization method [1-3]. The Gmapping algorithm mainly adopts RBPF (Rao-Blackwellized Particle Filtering) (RBPF) particle filtering method, and uses the odometer and sensor to estimate the pose of the robot [4]. The algorithm preserves the excellent particles according to the particle weight, and solves the problem. The problem of particle poverty [5]. The Cartographer algorithm is divided into two parts, namely local optimization and global optimization [6]. The local optimization uses the least squares method to match the lidar scanning frame with the sub-map to obtain a locally optimized sub-map. The global optimization is closed-loop detection. Map progressive optimization.

At present, most related researches are theoretical, and the advantages and disadvantages of various algorithms under different parameter configurations are insufficient. The effect of map construction is closely related to the algorithm, but the choice of parameters plays a crucial role in the accuracy of the resulting map. In this paper, by comparing the effects of two algorithms in the same environment, the advantages and disadvantages of the two algorithms are clearly defined.

2. ALGORITHM ANALYSIS

2.1. Planning

Gmapping is an RBPF-based SLAM algorithm that uses lidar data and odometer data to improve the proposed distribution and introduce a selective resampling mechanism to reduce the number of particles and prevent particle degradation, improving computational efficiency.

A. RBPF SLAM algorithm

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The RBPF SLAM algorithm uses the observation information $z_{1:t} = z_1, z_2, \cdots, z_t$ of the external sensor and the odometer information $u_{1:t} = u_1, u_2, \cdots, u_t$ to calculate the joint posterior probability distribution of the environment map m and the robot trajectory $x_{1:t} = x_1, x_2, \cdots, x_t$, Equation (1) is

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

Equation (1) separates the location problem from the map estimation problem. Estimate the posterior probability $p\left(x_{1:t} \mid z_{1:t}, u_{1:t-1}\right)$ of the robot pose using observation data and odometer data, and estimate the posterior probability of the map using the estimated pose and observation data of the robot $p\left(m \mid x_{1:t}, z_{1:t}\right)$.

B. Optimize the proposed distribution

Conventional RBPF SLAM uses the odometer motion model as the proposed distribution. The advantage is that the motion model is easy to obtain and the calculation is simple. However, when the robot is equipped with a high-precision lidar sensor, the reliability of the observation model is far greater than that of the odometer motion model. If only the motion model is used, the accuracy of the lidar data is sacrificed, so the odometer is used as the proposed distribution. Sub-optimal. At the same time, because the particles cover the entire space of the odometer state, and only a small part of the particles are positively consistent with the target distribution, the weight of the particles will change greatly when calculating the weight. However, there are only a limited number of particles to simulate the state distribution, so it is necessary to discard the particles with small weights, and let the particles with significant weights replicate to achieve the convergence of the particles to the real state. However, this causes frequent resampling, which causes particle degradation in RBPF.

In order to improve the proposed distribution, the most recent observation is used, so the optimal proposal distribution is:

$$p\left(x_t \mid x_{t-1}^{(i)}, m_{t-1}^{(i)}, z_t, u_{t-1}\right) = \frac{p\left(z_t \mid x_t, m^{(i)}\right) \cdot p\left(x_t \mid x_{t-1}^{(i)}, u_{t-1}\right)}{p\left(z_t \mid x_{t-1}^{(i)}, m^{(i)}, u_{t-1}\right)} \tag{2}$$

When using raster maps to characterize the environment, since the observed probability distribution is not available, the approximate form of the accurate target distribution is not available, so sam ples can be sampled to simulate the proposed distribution.

To obtain an improved proposed distribution, particles are collected from the motion model and the particles are weighted using observations to select the best particles. These weighted particles are then used to simulate the improved proposed distribution. However, if the observation probability is sharp, more numbers of particles are needed to cover the observation probability. This causes the same problem as sampling from the odometer.

The target distribution usually has only a few peaks and in most cases only one peak. Therefore, K values are taken near the peak to simulate the proposed distribution. First, scan matching is used to find the region with high probability and then sample. The Gaussian function is usually used to construct the proposed distribution, so after having K data, a Gaussian function can be simulated as the proposed distribution:

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$$\mathbf{\Sigma}_t^{(i)} = \frac{1}{\eta^{(i)}} \cdot \sum_{j=1}^{K} p\left(z_t \mid x_j, m_{t-1}^{(i)}\right) \cdot p\left(x_j \mid x_{t-1}^{(i)}, u_{t-1}\right) \cdot \left(x_j - \mu_t^{(i)}\right)\left(x_j - u_t^{(i)}\right)^{\mathrm{T}} \tag{3}$$

The normalization factor is:

$$\eta^{(i)} = \sum_{j=1}^{K} x_j \cdot p\left(z_t \mid x_j, m_{t-1}^{(i)}\right) \cdot p\left(x_j \mid x_{t-1}^{(i)}, u_{t-1}\right) \tag{4}$$

2.2. Cartographer Algorithm

Cartographer is Google's real-time indoor mapping project. The sensor is mounted on a backpack and can generate a 2D grid map with a resolution of 5 cm. Scan match is used to insert each frame of scan data obtained by the laser radar into a submap at the best estimated position, and scan matching is only related to the current submap. After generating a submap, a partial loop close is performed, using branch positioning and a pre-computed grid. After all submaps are completed, a global loopback is performed.

The entire system consists of two parts. The pose expression of the robot is k, and the pose of the robot is optimized by local optimization and global optimization respectively. The first two parameters represent translation, and the latter parameter represents rotation. The local optimization part is the matching of the lidar scanning frame and the sub-map, and the sub-map is locally optimized. The global optimization part is to perform global map optimization according to the pose relationship between the scan frames after finding the closed-loop scan frame.

A. local optimization

Local optimization is the process of matching the lidar scanning frame with the sub-map, and iteratively aligning the lidar scanning frame and the sub-map reference frame to construct the sub-map. The lidar scan is called a frame, the initial scan frame is at origin $(0,0)$, and the scan point is described as $H = \{h_k\}_{k=1,\cdots,k}, h_k \in R$. In equation (1), the pose transformation of the scan frame to the submap is described as, which can strictly map the scan points from the scan frame to the submap.

$$T_\xi p = \underbrace{\begin{pmatrix} \cos\xi_\theta & -\sin\xi_\theta \\ \sin\xi_\theta & \cos\xi_\theta \end{pmatrix}}_{R_\xi} p + \underbrace{\begin{pmatrix} \xi_x \\ \xi_y \end{pmatrix}}_{t_\xi} \tag{5}$$

Several iterative scan frames create a submap that takes the form of a probability grid with a resolution of r. For each grid point, we define a corresponding pixel. Each time a new scan is inserted into the probability grid, a set of hit grid points and disjoint miss grid points are calculated. For the hit point, we insert the adjacent grid points into the hit set. For the miss points, add all the relevant points on the scan center and scan point join rays to the miss set, except for the points in the hit set. For each point that has not been observed before, and if this has been observed before, then the point probability is updated according to equations (2) and (3).

$$odds(p) = \frac{p}{1-p} \tag{6}$$

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$$M_{\text{new}}(x) = \text{clamp}\left(\text{odds}^{-1}\left(\text{odds}\left(M_{\text{old}}(x)\right)\cdot\text{odds}\left(p_{\text{hit}}\right)\right)\right) \tag{7}$$

Before inserting the scan map into the sub-map, the scan frame pose is optimized with the current submap application ceres, and the mapping of the k scan points is superimposed by the nonlinear least squares optimization (4), and a total of k scan points hit Point, after transforming the pose and pairing with the probability value in the submap, each place corresponding to the display should be a big probability to be hit, then the match is better.

$$\underset{\xi}{\text{argmin}} \sum_{k=1}^{K}\left(1 - M_{\text{smooth}}\left(T_{\xi}h_k\right)\right)^2 \tag{8}$$

Since the least squares problem is a local optimal problem, a good initial value (the initial value of the pose) has a great influence on the solution. Therefore the IMU can be used to provide a scan-matched rotation variable for the initial pose value. In the absence of an IMU, it is necessary to increase the frequency or matching accuracy of the scan match.

B. global optimization

Global optimization is achieved through closed loop detection. Since each lidar scan frame is only matched with a submap containing some recent scan frames, the build error is slowly accumulated. To eliminate the accumulated error, a Sparse Pose Adjustment method is used to optimize all the pose of the scan and submap.

$$\underset{\Xi^m,\Xi^m}{\arg\min}\frac{1}{2}\sum_{ij}\rho\left(E^2\left(\xi_i^m,\xi_j^i;\sum_{ij},\xi_{ij}\right)\right) \tag{9}$$

ρ is a loss function, and the purpose of using the loss function is to reduce the impact of outliers added to the optimization problem on the system. $\Xi^m = \left\{\xi_i^m\right\}_{i=1,\cdots,m}$ and $\Xi^s = \left\{\xi_j^s\right\}_{j=1,\cdots,n}$ are the poses of submap and scan in the world coordinate system, respectively, and are optimized under the constraints of the given relative pose ξ_{ij} and the associated covariance matrix Σ_{ij}. For paired Submapi and scanj, ξ_{ij} represents the relative pose of scan in the matched Submap coordinate system, and the covariance matrix Σ_{ij} can be estimated using the Ceres covariance estimation feature method.

The pose of the lidar scanning frame inserted into the sub-map is stored in the memory. When a sub-map is created, the corresponding scan frame and sub-map are taken into account for closed-loop detection. All scan matches are performed on the back end, and once a good closed-loop match is found, it is added to the global optimization.

3. EXPERIMENTS AND RESULTS

3.1. Experimental Environment and Equipment

This experiment selects the second floor of the electromechanical building as the experimental environment. The mobile robot used in the experiment is a two-wheel differential drive robot bobac, as shown in Figure 1. The installed industrial computer uses the Intel QM77 chipset and integrates the Intel Celeron I5-2430M processor. The bobac mobile robot is equipped with a laser radar of the type Rplidar A2. As shown in Figure. 2, the radar has a measuring range of 0.15m to 12m and a measuring angle of 0 to 270°. The measurement

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accuracy of the measuring object within 1.5 meters is less than 5mm, and the measurement accuracy is less than 1% of the actual distance in all ranges; the resolution of the angle is approximately 0.9°, and the scanning frequency is 10 Hz

Figure 1. Bobac mobile robot

Figure 2. Rplidar A2 Lidar

3.2. Experimental Environment and Equipment

Through the handle, the control command is sent to the bobac mobile robot, and the RVIZ tool under the ROS platform is used to monitor the map construction situation in real time. At the same time, the observed data is recorded by the rosbag, and the remaining experiments are performed by using the recorded data to ensure the data is consistent during the test. In order to maintain the stability of the scan match, the rapid rotation is reduced throughout the process.

A. Gmapping SLAM Algorithm Mapping

First, the Gmapping SLAM algorithm is used to construct the map. According to official data, there are many factors that affect the effect of Gmapping composition. The parameters that play an important role are particles and minimuScore. minimumScore determines a confidence level for the laser. The higher the requirement, the higher the requirement for the laser matching algorithm. The easier the laser matching will fail and the odometer data will be used. If the setting is too low, it will cause a lot of noise in the map. According to the performance of the laser radar, the value is set to 25. Gmapping uses a particle filter algorithm, and the particles are constantly iteratively updated, so choosing a suitable number of particles allows the algorithm to have a higher speed while ensuring accuracy. Through experiments, it is found that in the process of increasing the number of particles from 70 to 90, the quality of the generated map is constantly higher, which is manifested by the decrease of the slope of the corridor in the horizontal direction, and the sawing of the edge features is significantly less; When the number is increased to 110 or more, the map effect is 90 time difference from the number of particles, which is caused by a sudden increase in the calculation load and a decrease in real-time performance. It is therefore determined that the optimal particle number 90 is in this configuration.

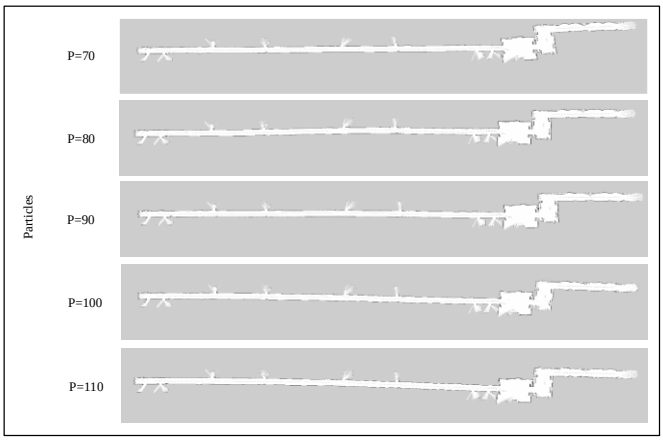

Figure 3. Effect of changing the number of particles on the mapping of Gmapping SLAM

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B. Cartographer SLAM Algorithm Mapping

The Cartographer SLAM algorithm is divided into a local SLAM and a global SLAM, where the local SLAM is responsible for constructing a series of sub-maps, and the global SLAM is responsible for closed-loop constraints. During the experiment, it was found that after the rosbag was played, it still took a certain time to complete the construction of the map. This is because the processor of the mobile robot could not meet the needs of the Cartographer algorithm when looking for closed-loop constraints. It is therefore necessary to adjust the global SLAM to optimize the number of constraints.

The sample rate constant is first set to control the sampling of the closed-loop nodes by the Cartographer algorithm in order to limit the number of constraints and calculations. The sample rate is the ratio of the added constraint to the potential constraint, and if it is lower than this value, the constraint is added. If the sampling result is too small, it will lead to the possibility of missing the constraint and invalidate the closed-loop detection. Too much will result in the global SLAM running too low efficiency and can not achieve real-time closed-loop detection. Since the corridor environment is relatively single and consider the processor performance, set the sampling. Rate parameter POSE_GRAPH. constraint_builder. sampling_ratio=0.1. The threshold of the scan match score, The threshold of the scan matching score is tested POSE_GRAPH. constraint_ builder.min_ scor, and the match between the scan and the map is not considered when the value is below the threshold. The experiment found that when the value is increased from 0.2 to 0.4, the slope of the generated map gradually decreases in the horizontal direction, and the interval between the two larger blank areas on the right side of the map gradually becomes clear, but when the value rises to 0.6, the generation is generated. The map begins to slope in the countryside.

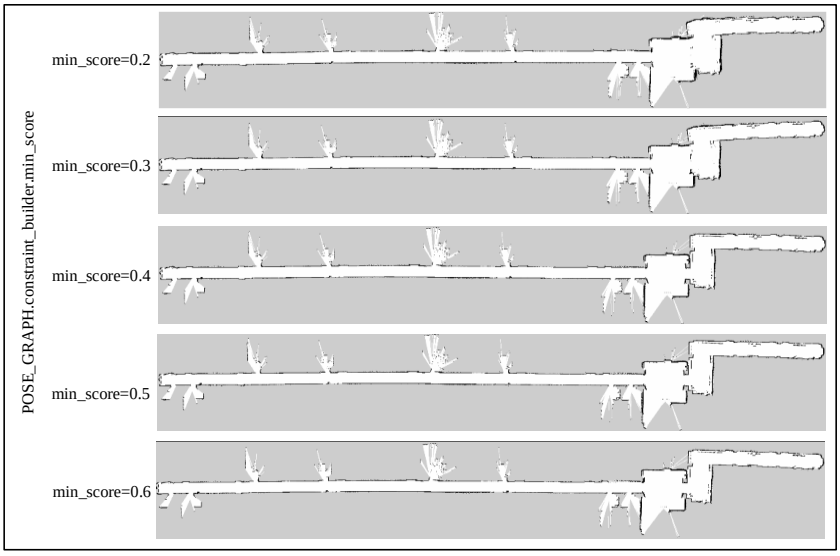

Figure 4. Effect of changing the threshold of scan matching score on Cartographer SLAM mapping

By analyzing Figure. 3 and Figure. 4, the maps constructed by the two algorithms show a certain degree of curvature in the horizontal direction, but the curvature of the cartographer constructed map is slightly smaller than that obtained by the gmapping method. Comparing the maps constructed after optimizing the parameters in Fig. 3 and Fig. 4, it can be seen that under the same input data, the map obtained by the cartographer algorithm is more complete than the map constructed by gmapping, and the map position is more accurate.

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4. AC CONCLUSIONS

The SLAM experiment was carried out using RPLidar A2 laser radar. The composition effects of Gmapping and Cartographer SLAM were compared, and the influence of each parameter on the final map generation was analyzed. The direction of optimal parameter configuration was pointed out. By using the analysis method of this paper, the time for determining the optimal parameters can be greatly saved, and the establishment of the optimal parameters is of great significance for improving the performance of the algorithm.

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