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Improvement of Particle Filter based on Fusion Method of Gmapping Algorithm Based on 2D Environment

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Abstract

As an important algorithm of SLAM, the Gmapple algorithm is based on particle filtering. In order to solve the problem of slow drawing and particle loss in repeated iterations based on RFTP particle filtering algorithm, an improved fusion method for particle filtering is proposed, and a corresponding weighted fusion model is established. Through the simulation environment experiment, the Gmapping graph obtained by this algorithm is significantly more accurate than the proposed Gmapping graph and the Gmapping graph with simple particle filtering.

Keywords

Gmapping, particle filtering, fusion method, map construction.

1. INTRODUCTION

In the wide application of driverless technology, various types of self-driving vehicles, robotic equipment, etc. often need to obtain map information by themselves to determine their position. At the same time, real-time location and map construction (SLAM) [1] [2], as the core algorithm of autonomous driving, has gradually become an important part of the field of robotics research. The particle filter-based Gmapping algorithm is used as a branch of the SLAM algorithm [3]. The distance data is measured according to the laser feedback, and the distance between the robot and the obstacle is determined. Finally, the grid map needs to be established. However, because the Gmapping algorithm relies heavily on the odometer, the lack of loop detection [4] will result in misplacement of the map. Therefore, previous studies usually proposed proposed distribution or selective resampling based on particle filtering to reduce the impact of particle degradation to enhance the accuracy of mapping [5].

In the improvement of the proposed distribution, relatively simple resampling is generally adopted, which will eventually lead to a decrease in the number of key particles, which will eventually lead to excessive deviation of the results of the mapping. To solve this type of problem, various improved particle resampling methods have been proposed. The simple adaptive particle resampling proposed by Moral et al. [6] will cause serious misalignment when the construction time is too long. The particle resampling method based on Kalman filter proposed by Feng Zhang et al. [7] can solve the problem of particle degradation within a certain range. However, due to the complicated calculation, the construction efficiency is slow when the construction scope is large. The key points are prone to errors and other conditions.

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In the simpler particle filtering, the traditional method is based on RBpf [8] [9] for simple mapping and positioning separation. Li T et al. [10] proposed an algorithm for collecting particles based on simple particle filtering. The map information carried by the particles was normalized, but it was only applicable due to the significant increase in the calculation amount in the later stage of construction. Construction of a smaller environment. Novian Habibie et al.[11] presented a particle filtering algorithm based on tree recognition based on the simulation environment. However, due to the large loss rate of particle information, the late construction of the image was ghosted.

The most commonly used particle filter algorithm is the resampling iterative method, which estimates the pose of the robot at each moment by iterating. In the process of continuous resampling of particle filters, accumulated errors are formed due to particle errors. Previous various particle processing algorithms have not solved such problems well. Therefore, in view of the shortcomings of the above-mentioned basic particle filter Gmapping algorithm, an improved fusion particle filter algorithm is proposed. Compared with the Gmapping proposed by the distributed processing and the Gmapping based on the RBpf particle filter, the image accuracy is established. Significant improvement, and the efficiency of mapping is also higher.

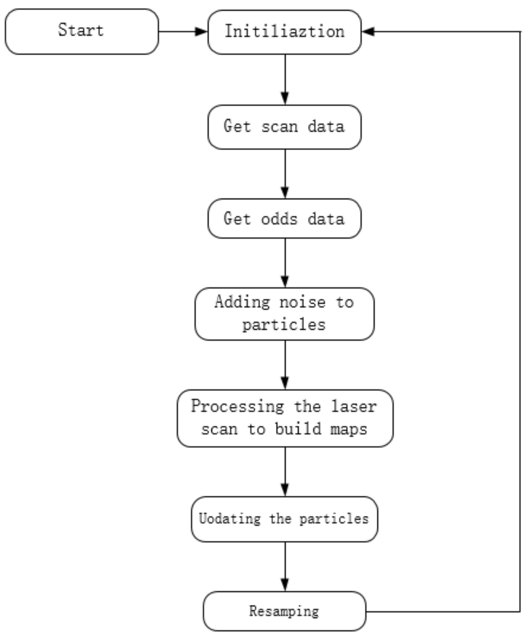

Figure 1. The basic principle of Gmapping

2. PROPERTIES

The core method of laser SLAM construction mainly estimates the probability function of representative map information based on the observation value and its odometer information, including the key points and the trajectory of the robot [12]. RBpf is an effective method to solve the problem of simultaneous positioning and mapping. It can separate the positioning and mapping, so that the particles factorize the joint probability density function when estimating the pose of the probability density:

$$p(x_{1:t}, m \mid z_{1:t}, u_{0:t}) = p(m \mid x_{1:t}, z_{1:t})\, p(x_{1:t} \mid z_{1:t}, u_{0:t}) \tag{1}$$

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The above formula shows the basic rules of particle filtering. Among them, $p(x_{1:t} \mid z_{1:t}, u_{0:t})$ Indicates the initial position of the robot. $p(m \mid x_{1:t}, z_{1:t})$ Represents the key particles of the map. The particle filter algorithm is mainly divided into the following four steps:

(a)Particle estimation: Through the state transfer function, a large number of samples are generated by existing particles, and the particle information of these samples is weighted to enhance the probability density.

(b)Observation correction: With the pose coordinates sequentially obtained, the weight of each corresponding particle is calculated. By analogy, each particle has a weight description that corrects the existing particle population to get the most representative particle.

(c)Particle resampling: A redistributed approximately continuous distribution of key particles based on previously assigned weights. However, due to the lack of such particles, it is necessary to use the state transition equation again to process the resampled particles to obtain new predicted particles.

(d)Map creation: Using the new particles obtained by resampling, the corresponding map estimates are constructed by sampling the trajectories.

3. PROVED RBPF FUSION PARTICLE FILTER

The algorithm based on RBpf particle filter carries a large amount of map information for each key particle. Therefore, in the process of iterative iteration, the calculation is slow, the particle is lost, and the distortion of the image is caused [13]. It is now proposed to use the fusion method adaptive resampling method to eliminate the particle degradation problem in Gmapping particles. The purpose of adaptive resampling is to establish the normalized weights of key particle points, which are obtained by the following formula:

$$N_e = \frac{1}{\sum_{i=1}^{N} (\omega^{(i)})^2} \tag{2}$$

Solving the sample variance to measure the stability of the sample weights:

$$SV = \frac{1}{M} \sum_{m=1}^{M} (N_t^{(m)} - N w_t^{(m)})^2 \tag{3}$$

Through the basic principle of particle filtering, the optimization of weights can be obtained:

$$\begin{aligned} \omega_t^{(i)} &= \frac{p(x_{1:t}^{(i)} \mid z_{1:t}, u_{1:t-1})}{q(x_{1:t}^{(i)} \mid z_{1:t}, u_{1:t-1})} \\ &= \frac{p(z_t \mid x_t^{(i)}, u_{t-1}^{(i)}) p(x_t^{(i)} \mid x_{t-1}^{(i)}, u_{t-1})}{q(x_t^{(i)} \mid x_{1:t-1}^{(i)}, z_{1:t}, u_{1:t-1})} \omega_{t-1}^{(i)} \end{aligned} \tag{4}$$

Since the weight optimization process cannot find a certain analytical expression, two sampling points are found at the optimal position of the robot, and the position estimation is used to find K sampling points in the vicinity. And the weighted mean and variance of the obtained K sample points are taken as the mean of the Gaussian distribution:

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$$\begin{cases} \mu_t^{(i)} = \dfrac{1}{\eta^{(i)}} \sum_{j=1}^{K} x_j \bullet p(z_t \mid m_{t-1}^{(i)}, x_j) \\ \bullet\, p(x_j \mid m_{t-1}^{(i)}, u_{t-1}) \\ \delta_t^{(i)} = \dfrac{1}{\eta^{(i)}} \sum_{j=1}^{K} x_j \bullet p(z_t \mid m_{t-1}^{(i)}, x_j)\, p(x_j \mid m_{t-1}^{(i)}, u_{t-1}) \\ \bullet (x_j - u_t^{(i)})(x_j - u_t^{(i)})^T \end{cases} \tag{5}$$

Get a fusion of information based on sample points:

$$\eta^{(i)} = \sum_{j=1}^{K} p(z_t \mid m_{t-1}^{(i)}, x_j)\, p(x_j \mid x_{t-1}^{(i)}, u_{t-1}) \tag{6}$$

After that, the fusion information is equalized with the weight formula of the key particle points to obtain the RPTF-based fusion particle filter:

$$M^{(i)} = \sum_{j=1} \frac{p(z_t \mid m_{t-1}^{(i)}, x_j)\, p(x_j \mid x_{t-1}^{(i)}, u_{t-1})}{N_e} \bullet \omega^{(i)} \tag{7}$$

4. EXPERIMENT AND ANALYSIS

4.1. Robot Motion Model

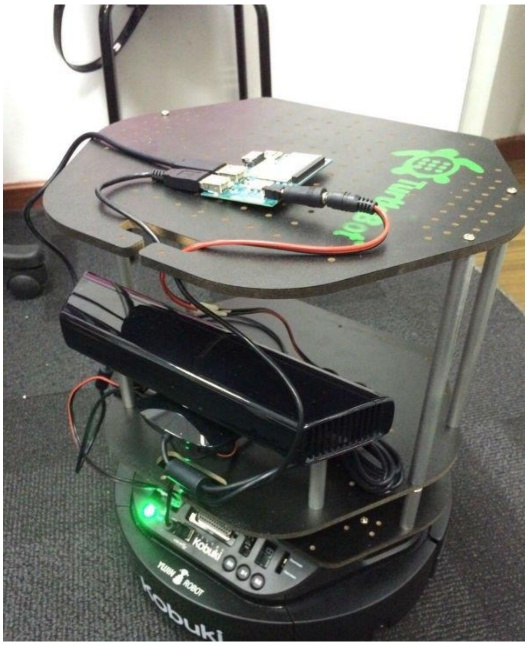

Figure 2. Turtlebo robot

The prototype of the robot used in this paper is Turtlebot. Turtlebot relies on double rear wheel drive, and the steering is differential steering. It is equipped with laser sensors, image sensors and other equipment. It can realize the construction and positioning based on the basic principle of Gmapping algorithm, and the construction and positioning results. Transfer to the

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host computer. The ROS system provides a virtual model of the turtlebot in the Gazebo simulation environment, which can basically simulate the motion state of the Turtlebot. Turtlebot's equation of motion equation is as follows [14]:

$$P_k = L_{k-1} + T_v = \begin{bmatrix} l_x + Tv_k \cos(\theta + \alpha_k) \\ l_y + Tv_k \sin(\theta + \alpha_k) \\ l_\theta + \sin(\frac{\beta_k}{B}) \\ l_s + S_k \end{bmatrix} \tag{8}$$

Among them, $L_{k-1} = [l_x, l_y, l_\theta, l_s]$ represents the position description of the robot at the moment of $k-1$,the matrix T_v represents the transformation relationship from time $k-1$ to time k , the four parameters contained in L_k are represented as: X axis coordinate direction change, Y axis coordinate direction change, angle change size, key beacon point difference, respectively.

The observation matrix of the robot motion process is as follows:

$$Y_k = \begin{bmatrix} D \\ \theta \end{bmatrix} = \begin{bmatrix} \sqrt{(d_{Xi} - d_k)^2 + (d_{Yi} - d_k)^2} \\ \tan^{-1}(\frac{d_{Xi} - d_k}{d_{Yi} - d_k}) - \theta_k \end{bmatrix} \tag{9}$$

D Indicates the distance of the robot device from the beacon point, d_{Xi} and d_{Yi} respectively indicate the horizontal and vertical coordinate values of the current device, θ indicates the angle between the current velocity vector direction and the coordinate point direction. Through the robot motion description matrix, real-time positioning and mapping of the robot device can be realized.

4.2. Experiment Environment

The experimental simulation was carried out in a robot operating system (ROS) environment based on the embedded operating system of Ubantu 16.04, and the simulation world model was built using the Gazebo simulation tool that comes with the ROS system. The Gmapping laser SLAM map established by the robot equipment is obtained through the visual observation software (Rviz) provided by the ROS system.

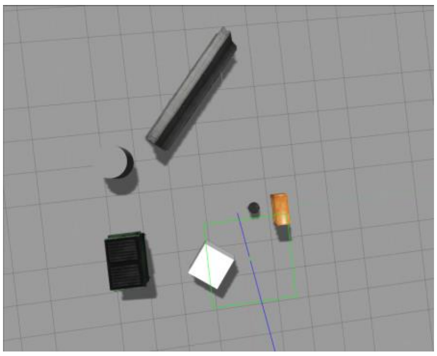

Figure 3. Turtlebo robot

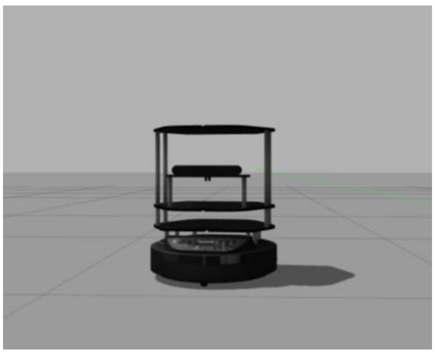

Figure 4. Turtlebot model in Gazebo simulation

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4.3. The Drawing Effect of Gmapping

4.3.1 Mapping experiment

The established simulation world is used in the Gazebo simulation environment, and the simulated Turtlebot robot is controlled in the Gazebo environment to realize the Gmapping process. Viewed by the visualization platform Rviz, the established laser SLAM map is as follows:

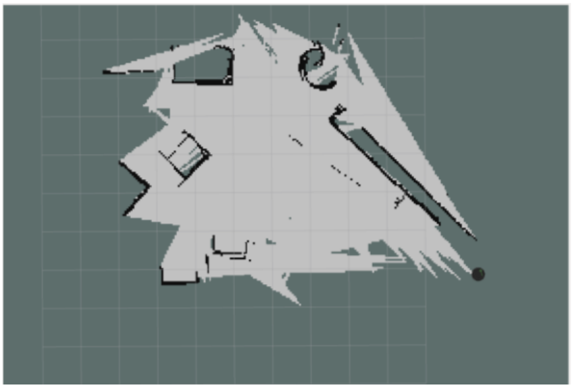

Figure 5. Gmapping processed by proposed distribution

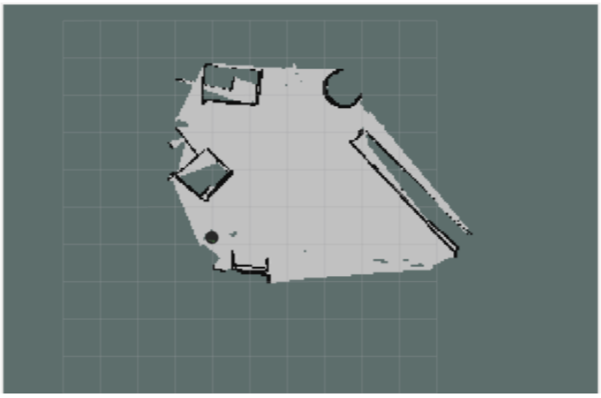

Figure 6. Gmapping mapping of RBpf particle filtering

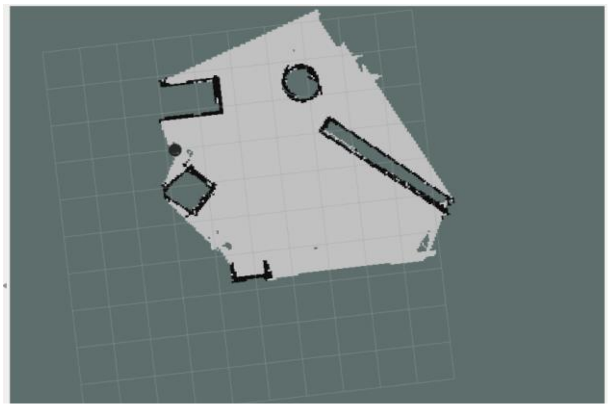

Figure 7. Gmapping mapping based on RBpf fusion particle filter

Through comparison of the three mapping experiments, it can be clearly seen that the Gmapping algorithm of distributed processing and the gmapping algorithm of simple particle filtering can cause obstacle loss, object ghosting or misalignment during laser mapping. situation. The laser SLAM construction based on the RBpf-based fusion particle filtering method

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proposed in this paper can obviously find that the established map is more accurate and delicate than the above two algorithms.

4.3.2 Time comparison

Table 1. Time spending in creating a map

Algorithm	Time (s)
Gmapping processed by proposed distribution	352.62
Gmapping mapping of RBpf particle filtering	426.44
Gmapping mapping based on RBpf fusion particle filte	290.71

Define the map size of 10 units established in the virtual environment as the experimental time. Through the time comparison of several algorithms, it can be seen that the proposed algorithm uses the fused particle filtering scheme, and the construction time is significantly less than the other two algorithms.

5. CONCLUSION

Aiming at the mapping distortion phenomenon of traditional particle filter Gmapping, the fusion particle filter algorithm used in this paper improves the laser mapping quality of Gmapping algorithm and has certain advantages in mapping efficiency. As a stable and simple robot positioning and mapping method, laser SLAM can still exist for a long time in the development of robot equipment and will complement the visual SLAM. Better improve the automatic driving task of robot equipment. The improved algorithm used in this paper provides a new method for Gmapping laser mapping, which makes the map perceived by the robot device more accurate.

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