Localization and Mapping Algorithm for the Indoor Mobile Robot Based on LIDAR

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Abstract. In order to realize the autonomous Localization and navigation of indoor robots, this paper designs an indoor mobile robot positioning and mapping system based on LIDAR, and proposes a kind of localization and mapping task based on the improved RBPF-SLAM algorithm. This method mainly solves the deficiency in the original RBPF-SLAM algorithm from the aspect of improving the proposed distribution and limiting the number of resampling, making it more suitable for indoor mobile robot localization and mapping. Finally, the accuracy and rationality of the robot localization and mapping based on the RBPFS-LAM algorithm based on LIDAR are verified by experiments.

1. Introduction
With the development of science and technology, the mobile robot autonomous navigation technology has developed rapidly, and now there are many kinds of navigation methods that have been widely used, such as magnetic navigation, inertial navigation, GPS navigation, laser navigation and visual navigation [1-5]. At present, the most widely used non-contact sensors in the field of robot positioning and navigation are mainly cameras and LIDAR [6,7]. The visual navigation based on the camera mainly relies on the camera to collect the environment information, through a series of image processing technology such as feature recognition matching to realize the navigation of mobile robot. The realization method is relatively simple, but is susceptible to environmental lighting, and the camera field of view is limited, so the algorithm requirements are higher. Laser navigation uses LIDAR sensors to collect distance information from the environment, realize the robot's autonomous navigation, the accuracy is relatively high, can achieve 360 degrees of information capture, and not affected by environmental lighting and other factors, can run day and night, and better night effect, therefore, the technology has been the auto pilot car. The most central sensor device in areas such as drone driving.

The LIDAR-based SLAM algorithm obtains a series of scattered point cloud data with accurate angle and distance information collected by LIDAR, then matches it by ICP (iterative nearest neighbor algorithm), and finally calculates the distance and attitude change of LIDAR relative motion by matching point cloud data at different times to complete the localization of the mobile robot itself [8,9]. Researchers at Tokyo University first used particle filter (PF) to complete SLAM in 2006, and successfully realized the application of FastSLAM in AUV navigation and positioning [10]. Because PF uses sample form instead of function form to estimate the system state and does not consider the statistical characteristics of noise,
the prediction model in practical application is inaccurate. The traditional FastSLAM chooses the prior distribution as the recommended distribution [11,12], which results in the serious degradation of particles without considering the latest measurements. Resampling reduces the degree of particle degradation but results in particle dilution.

Based on previous research and the shortcomings of the traditional LIDAR localization and mapping algorithm based on particle filtering algorithm, a laser SLAM algorithm based on improving the proposed distribution and limiting the number of resampling is proposed. It mainly includes: using LIDAR to collect 3D (three-dimensional) point cloud data in environment, and obtaining the position parameters of adjacent moment robots according to ICP calculation; According to the motion model of the actual robot, the proposed distribution of particle filtering algorithm and the calculation of particle weight update map, and finally limit the number of resampling to maintain the diversity of particles makes it more realisti.

2. Indoor mobile robot positioning algorithm based on LIDAR
The mobile robot localization algorithm based on laser SLAM mainly includes: LIDAR data acquisition, relative position estimation based on ICP data matching and particle filtering. The algorithm flow chart in Figure 1.

![PF-SLAM algorithm flow chart based on LIDAR.](image)

![Pibot Mobile Robot System Block.](image)
2.1. Laser-based mobile robot and its localization system scheme design
According to the structure of the tire, the mobile robot can be divided into track-type mobile robot and wheel-type mobile robot. Considering that the robot mentioned in this paper is carried out in indoor environment, the choice of circumference technology PIBOT specifically for ROS development of the mobile differential two-wheeled car, which is suitable for indoor flat ground walking.

The PiBot mobile robot system frame diagram shows as shown in Figure 2, removing some of the expansion peripherals, mainly consisting of four parts: mobile robot platform, LIDAR sensor, the upper machine Arduino development board and control system (ROS host).

3. Robotic LIDAR localization and mapping based on improved RBPF-SLAM algorithm
In indoor robot localization problems with particle filtering frames, each particle only needs to represent a possible attitude. But in SLAM, attitudes and maps are the status variables, so a particle needs to hold the position of a moving robot at the same time for all historical moments as well as the entire map. According to the condition Bayesian law, there are:

\[ p(x_{t}, m | z_{t}, u_{t-1}) = p(m | x_{t}, z_{t}) \cdot p(x_{t} | z_{t}, u_{t-1}) \]  \hspace{1cm} (1)

This decomposition actually divides SLAM into two steps of localization and mapping, which greatly reduces the complexity of SLAM problems. This treatment is called Rao-Blackwellized Particle Filtering (RBPF). The simple principle of its algorithm is to use the map and motion model of the previous moment to predict the position of the current moment, and then calculate the weight, resampling, update the particle map, loop operation [13].

However, there are two fatal problems with the above algorithm. First, the map has high requirements for the robot attitude, for any one particle, only rely on the results of motion model sampling to build a map, the error will be very large. If there were enough particles, there might be several particles that got an accurate map, but overall, the proposed distribution swayed through motion models is too dispersed and too far apart from the actual distribution. Second, frequent resampling results in particle dissipation. Each particle needs to hold the position of the moving robot at all historical moments, as well as the entire map, and frequent resampling can cause the diversity of positional postures that were long ago.

3.1. Improved PF-SLAM algorithm based on LIDAR
In view of the two major problems of the conventional PF-SLAM algorithm, based on the enlightenment of Gmapping algorithm, this paper adopts the method of improving the proposed distribution and limiting the number of resampling, can use the fewer particles to estimate the state, reduce the computational complexity, and effectively solve the phenomenon of particle degradation.

3.2. Improve the distribution of proposals
RBPF uses the odometer motion model as the proposed distribution, causing most of the particles to deviate from their real positions. In contrast to motion models, the observational model of LIDAR can give a relatively concentrated distribution. As shown in Figure 3, if the particle sampling range is changed from a flat and wide area to the peak region L represented by the LIDAR observation model, the new particle distribution can be closer to the real distribution.
The scheme is to make a scan match of the prediction as the initial value after the prediction is given by the odometry motion model. The purpose of scanning matching is to find a position profile that best fits the map for the current observation. After scanning the match, we find the peak region represented by L and determine the mean and variance of the Gaussian distribution represented by the peak region. According to the literature [13], the best approximation of the true distribution is obtained by random sampling of K points in L and calculating the mean and variance according to the k-point odometry and observation model.

$$\mu_i^{(i)} = \frac{1}{\eta_i^{(i)}} \sum_{j=1}^{K} \eta_j p\left(z_i | m_{k_{j-1}}^{(i)}, x_j \right) \cdot p\left(x_{j} | x_{k_{j-1}}^{(i)}, u_{k-1}\right)$$  \hspace{1cm} (2)

$$\Sigma_i^{(i)} = \frac{1}{\eta_i^{(i)}} \sum_{j=1}^{K} \eta_j p\left(z_i | m_{k_{j-1}}^{(i)}, x_j \right) \cdot p\left(x_{j} | x_{k_{j-1}}^{(i)}, u_{k-1}\right) \left(x_j - \mu_i^{(i)}\right) \left(x_j - \mu_i^{(i)}\right)^T$$  \hspace{1cm} (3)

$$\eta_i^{(i)} = \sum_{j=1}^{K} \eta_j p\left(z_i | m_{k_{j-1}}^{(i)}, x_j \right) \cdot p\left(x_{j} | x_{k_{j-1}}^{(i)}, u_{k-1}\right)$$  \hspace{1cm} (4)

Therefore, the new particles are sampled from the Gaussian distribution. Each particle is given a weight for subsequent resampling steps. The weights are calculated as follows [11]:

$$w_i^{(i)} = w_i^{(i)} \cdot p\left(z_i | m_{k_{j-1}}^{(i)}, x_{j}^{(i)}, u_{k-1}\right) = w_i^{(i)} \cdot \int p\left(z_i | m_{k_{j-1}}^{(i)}, x^{(i)}\right) \cdot p\left(x_{j}^{(i)} | x_{k_{j-1}}^{(i)}, u_{k-1}\right) dx$$

$$= w_i^{(i)} \cdot \sum_{j=1}^{K} p\left(z_i | m_{k_{j-1}}^{(i)}, x_j \right) \cdot p\left(x_{j} | x_{k_{j-1}}^{(i)}, u_{k-1}\right)$$  \hspace{1cm} (5)

The upper formula is a full probability formula that takes into account the positions of K that may appear at the current moment, and calculates the weighted average of their contribution to the current observation.

3.3. Limit the number of resampling

To avoid particle dissipation, the number of resampling should be limited. The diversity and accuracy of particles are maintained at a high level as the robot continues to move towards unknown areas. Particles in the local region maintain a high accuracy, but the cumulative error is always superimposed, if frequent resampling, the diversity of particles will disappear, the longer-term position attitude will become more and more single.

The purpose of resampling is to enhance particles close to the real value and discard particles that are far from the true value. Prior to the loop, even though some particles were far removed from the true value, existing observations were not sufficient to distinguish the correct particles from the wrong particles, so resampling was meaningless at this time. Resampling can only be as effective as it should be if the new observation completes completely widen the weight gap between the correct and the wrong particles after the loop has occurred.
Therefore, it is necessary to determine whether a loop back ring has occurred, as mentioned in the literature [13], and it can be evaluated below to determine whether the loop back ring occurs.

\[ N_{\text{eff}} = \frac{1}{\sum_{i=1}^{N} \left( \bar{w}_i \right)^2} \]  

(6)

If \( N_{\text{eff}} \) is larger, the smaller the particle weight gap. When \( N_{\text{eff}} \) is lowered below a certain threshold, it indicates that there is a large gap between the distribution of particles and the true distribution, showing at the particle level that some particles are very close to the true value, and many particles are far from the true value. This is exactly what happens when the loop is occurring, so choose this time for resampling.

4. Experimental results and analysis

In order to verify the feasibility and measurement accuracy of the laser-based ground robot localization and mapping algorithm proposed in this paper, this paper is carried out through the robot localization and mapping experiment and the robot navigation experiment.

4.1. Robot localization and mapping experiments

In order to verify the accuracy of the robot localization and mapping algorithm proposed in this paper, the proposed algorithm is run on the ROS robot operating system, and the specific steps include:

1) Add LIDAR drive, using Flash LIDAR in this experiment, you can find the corresponding LIDAR drive from the ROS open source Package, and modify the corresponding parameters, baud rate, interface, coordinate system, etc.

2) Add robot start-up node: the mobile robot platform at the time of this experiment has an Arduino development board, which has the Arduino node, connects the mobile robot platform, and completes the PID control parameter setting of the mobile platform, encoder data reading and conversion, communication serial setting.

3) Add the slam-mapping node: Add the node and configure the mapping parameter, where the key parameters are shown in Table 1.

| Name               | Value | Description                          |
|--------------------|-------|--------------------------------------|
| Xmin, ymin, xmax,  |
| ymin               | /     | Initialize the map size              |
| particles          | 8     | Number of particles                  |
| resampleThreshold  | 0.5   | Resampling threshold                 |
| iterations         | 5     | Number of iterations of the ICP algorithm |
| minimumScore       | 280   | Scan match threshold                 |
| map_update_interval| 0.01  | Map update frequency                 |

The environment selected in this experiment is a laboratory, as shown in Figure 4, which shows that the environment is relatively complex and somewhat narrow. According to the map established in Figure 4, we can see that:

1) The algorithm proposed in this paper can accurately establish the environment map. This shows that the positioning algorithm proposed in this paper supports real-time viewing and displaying the position of motion robots.

2) Comparing with the initial position result of moving robot and the position of the actual robot, The
feasibility of positioning and drawing algorithms proposed in this paper is verified.

Figure 4. Rviz view of the initial location of the moving robot

Figure 5. Set five position points and robot motion Trajectories

4.2. Robot navigation experiment
In order to verify the accuracy of the indoor robot navigation algorithm proposed in this paper, this section first uses remote control to control the robot's map of building indoor environment, and then simulates the motion of the moving robot on the map, setting six position points in turn, as shown in Figure 5, the red circle represents the position of the robot. The blue arrow represents the direction of the robot's motion. After completing the localization, the robot uses the algorithm proposed in this paper to independently plan the path to the specified five positions and finally return to the starting point according to the path planning and navigation algorithm in the literature [14]. Running navigation algorithms on robots, mobile robots begin to navigate autonomously, and mobile robots navigate the actual environment as shown in Figure 6. Similarly, the red arrow points in the direction of the robot's motion, which returns to its starting position after a circle of movement along the planned path.

Figure 6. The actual movement of robots in indoor environments

Figure 7 is a view of the Rviz that the robot moves. The red circle in the figure represents the robot, and the blue arrow represents the direction of the robot's motion. The robot starts from the starting point and moves one lap along the predetermined route back to the starting point.
From Figures 6 and 7, it can be seen that:
1) the mobile robot can plan accurate autonomous navigation to the set six position points according to the positioning algorithm proposed in this paper. It is explained that the localization algorithm proposed in this paper has good localization accuracy and can be applied well to navigation applications in complex indoor environment.
2) Qualitatively, the motion trajectory is biased from the design trajectory, mainly because the laboratory environment is complex, and the algorithm in this paper does not consider the loop-back detection process. In summary, the RBPF-SLAM improves the standard in two aspects: suppressing particle degradation and improving particle depletion. It improves the accuracy of navigation, positioning and feature position estimation. It is of great significance for long-range navigation and concealment tasks.

5. Conclusions
In order to realize the autonomous positioning and navigation of indoor robots, LIDAR is used as a data acquisition sensor, an all-in-one mobile robot localization and mapping system is designed and constructed, and an improved laser SLAM algorithm is proposed in combination with the traditional RBPF-SLAM algorithm according to the complex characteristics of indoor environment. The feasibility and accuracy of the algorithm proposed in this paper are verified by localization and mapping experiments and robot navigation experiments.

6. References
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