Robot SLAM Method Based on Multi-Sensor Fusion

Guan Jiwen
Krirk University, Bangkok, Thailand

Abstract: This study presents an innovative multi-sensor fusion SLAM solution to address the significant error in particle proposal distribution, excessive particle resource consumption, and low algorithm execution efficiency encountered in traditional RBPF-SLAM algorithms in practical applications. The proposed solution aims to optimize the overall performance of the SLAM system by effectively integrating data from laser radar, inertial measurement unit (IMU), and wheel odometer, among other multi-source sensors.

Keywords: Multi-sensor Fusion; Robots; SLAM

1. Introduction

In the current rapidly evolving robotics landscape, Simultaneous Localization and Mapping (SLAM) technology, a key enabler for autonomous navigation and intelligent environmental perception, is increasingly becoming the focus of industry attention. While theoretically, the traditional RBPF-SLAM algorithm based on particle filtering has granted robots the ability to simultaneously localize and map in unknown environments, its performance is often constrained by multiple factors in real-world, complex and variable application scenarios. To address these challenges, this study aims to explore an innovative SLAM solution that leverages multi-sensor fusion technology to achieve a qualitative leap in terms of localization accuracy, system robustness, and computational efficiency by deeply integrating the unique advantages of various sensors. This approach not only has the potential to break through the limitations of existing technologies but also opens up new paths for the future development of robot autonomous navigation and intelligent perception technologies.

2. The Principle of RBPF-SLAM Algorithm

The basic SLAM algorithm can be described as follows: based on the given sensor data, the robot's future pose state is predicted by applying the robot's kinematic model and observation model [1]. The RBPF (Rao-Blackwellized Particle Filter) based SLAM algorithm has successfully solved the state estimation problem in complex robot environments by cleverly utilizing the Monte Carlo method [2]. The core idea behind this approach is as follows: first, the joint posterior probability of the robot's trajectory x1:t and the map m is precisely computed; then, using Bayesian filtering techniques, it is decomposed into the product of independent posterior probabilities for trajectory estimation and map estimation (as shown in Equation 1), which greatly reduces the dimension of the estimation problem and improves computational efficiency and accuracy of the estimate.

$$p(x_{1:t}, m|z_{1:t}, u_{1:t}) = p(x_{1:t}|z_{1:t}, u_{1:t})p(m|z_{1:t}, z_{1:t}) \quad (1)$$

The detailed flow of the RBPF-SLAM algorithm is described as follows:

(1) Particle importance sampling: First, the sampling operation is carried out according to the preset importance suggestion distribution to generate N initial particles$\left\{\{x_{1:t}^i, w_t^i\}_{i=1}^N\right\}$。Each particle is assigned an initial weight that represents the weight of the I-th particle at time t.

(2) Particle weight calculation: According to the basic principle of importance sampling, the weight of the particle is defined as the ratio between the proposed distribution and the target distribution. The purpose of this step is to assess the extent to which each particle contributes to the estimation of the state of the system. The calculation method of particle weights is shown in equation (2).

$$w_{t-1}^i = w_{t-1}^i \cdot \frac{p\left(x_{1:t}^{(i)}\middle|z_{1:t}, u_{1:t}\right)}{q\left(x_{1:t}^{(i)}\middle|z_{1:t}, u_{1:t}\right)} \quad (2)$$

After normalization, we can obtain:

$$\widetilde{w}_t^i = \frac{w_t^i}{\sum_{i=1}^n w_t^i} \quad (3)$$

(3) Resampling process: Resampling operation is performed based on the weight of the particle. The specific method is to eliminate the particles with smaller weights and copy the particles with larger weights to achieve the rescreening of particles. In order to optimize the efficiency of the algorithm and reduce unnecessary resampling times, the effective particle number Neff is introduced as an index to measure the degradation degree of particle weight.

(4) State estimation and map update: Finally, the pose state of the robot is obtained by synthesizing the information of all particles$x_{1:t}^{(i)}$。At the same time, the observation information of the sensor is combined$z_{1:t}^{(i)}$, The environment map is further solved $\mathrm{p}\left(m^{(i)}\middle|x_{1:t}^{(i)}, z_{1:t}\right)$。This process is the core step of RBPF-SLAM algorithm to realize environment modeling and robot localization.

3. SLAM Algorithm based on Multi-Sensor Fusion

The traditional RBPF-SLAM algorithm mainly relies on odometer and lidar, and is used to build motion models and observation models respectively. However, a significant limitation of the algorithm is that it only uses the motion model as the recommended distribution of particle filtering. This processing method inevitably increases the cumulative error of posture estimation, thus causing a large deviation between the posterior distribution of the map and the real environment. In addition, the method also faces a serious challenge, that is, the problem of particle memory explosion, which further limits its breadth and reliability in practical application. In view of this, this paper proposes an innovative multi-sensor fusion SLAM method, aiming to overcome the above problems. Specifically, this method first integrates the data of IMU (inertial measurement unit) and odometer to build a more accurate and comprehensive motion model by integrating the advantages of these two sensors. Subsequently, this method further combines the observation information of lidar for secondary fusion, so as to optimize the recommended distribution function. In addition, in order to effectively alleviate the problem of particle dissipation, this paper also improves the particle resampling strategy. By introducing more reasonable resampling criteria and mechanisms, this method can manage particle resources more efficiently and avoid excessive consumption of invalid particles, so as to further improve the overall performance and stability of the SLAM system.

3.1 Multi-sensor Data Fusion based on Odometer-IMU-Lidar

In the operation scenario, the SLAM (real-time positioning and map construction) algorithm adopted by the robot relies on the accurate measurement of linear and angular velocity by the odometer, so as to realize real-time tracking of its position and attitude information. However, it is worth noting that the odometer often faces the challenge of cumulative error in practice, and this problem needs to be effectively solved. In order to cope with this problem, the IMU (inertial measurement unit) sensor shows the significant advantage of providing high-precision measurement and rapid response in a short time with its integrated high-precision components such as accelerometer, geomagnetic meter and gyroscope. Therefore, this paper explores and applies these unique properties of IMU sensors to accurately correct the accumulated errors of the odometer through scientific methods, so as to ensure the high accuracy of the robot in the process of navigation and positioning [3].

In the data processing of mobile robots, the wheeled odometer data and IMU data collected by them are deeply and accurately modeled and processed. In this process, in order to ensure the accuracy and reliability of the data, the specific expression of the spatial state is clearly defined as follows:

$$x_t = [X_t, Y_t, \theta_t, v_t, \omega_t]^T \quad (4)$$

In the above equation, Xt and Yt represent the displacement of the robot in the X and Y directions respectively, and θt represents the attitude Angle of the robot.

The pose at time t+1 can be expressed by formula (5) :

$$x_{t+1} = [X_t + v_t(cos\theta_t)\Delta t, v_t(sin\theta_t)\Delta t, \theta_t + \omega_t\Delta t, v_t, \omega_t] \quad (5)$$

In the data processing process, a specific threshold of θ0 is set, which is used to evaluate the degree of deviation of attitude Angle between IMU odometers. In the

The mode of movement of the system can be expressed as:

$$x_{t+1} = f(x_t) + w_t \quad (6)$$

implementation process, the attitude Angle difference between the two key sensors is calculated and determined. If the difference exceeds the preset threshold θ0, the attitude Angle provided by IMU is used as the main estimation basis for the robot's current attitude. On the contrary, if the difference value is within the threshold value θ0, the weighted average method will be used to comprehensively consider the attitude Angle information of both IMU and odometer, so as to optimize and obtain a more accurate and reliable attitude Angle estimate. The data fusion process of IMU and odometer intuitively shows the mechanism of the two working together.

The traditional RBPF-SLAM algorithm mainly relies on odometry information when building the robots SLAM motion model 4. However, considering the limitations of odometry being easily disturbed by external environmental factors, this paper proposes an innovative solution that incorporates high-precision LiDAR data into the construction process of the proposed distribution function. This innovative method not only combines the motion model of odometry and IMU data, but also deeply integrates the observation model of LiDAR to achieve the optimization and improvement of the proposed distribution function. The improved proposed distribution function is shown in formula 7.

$$p\left(x_t\middle|m_{t-1}^{(i)},x_{t-1}^{(i)},z_t,u_{t-1}\right)=\frac{p\left(z_t\middle|m_{t-1}^{(i)},x_t\right)p\left(x_t\middle|x_{t-1}^{(i)},u_{t-1}\right)}{p\left(z_t\middle|m_{t-1}^{(i)},x_{t-1}^{(i)},u_{t-1}\right)} \tag{7}$$

Substitute formula 7 into the particle weight formula to get:

$$w_t^{(i)}=w_{t-1}^{(i)}\frac{\eta p\left(z_t\middle|m_{t-1}^{(i)},x_t\right)p\left(x_t\middle|x_{t-1}^{(i)},u_{t-1}\right)}{p\left(x_t\middle|m_{t-1}^{(i)},x_{t-1}^{(i)},u_{t-1}\right)}=w_{t-1}^{(i)}\cdot p\left(z_t\middle|m_{t-1}^{(i)},x_{t-1}^{(i)},u_{t-1}\right) \tag{8}$$

3.2 Improving Particle Resampling Strategy

Within the framework of the optimized proposal distribution function, a new set of particles is carefully extracted from the designed distribution function based on the estimation results. In order to effectively suppress particle dissipation, this paper improves the original particle resampling strategy. The core of this strategy is to first construct a new distribution function and calculate the corresponding distribution function values for each particle one by one. Then, a screening mechanism is adopted to retain only those particles with distribution function values falling within a specific range of 0, 1/2, as the components of the new particle set, with special emphasis on selecting the top three particles with the highest weights. Finally, accurate resampling operations are performed within the limited range, with the specific process as follows:

(1) Arrange the weights of all particles in descending order.

(2) Construct the distribution function H(wk) and accurately calculate the value of the distribution function for each particle. Under this framework, the particle weight is inversely related to its corresponding distribution function value, i.e., the smaller the weight, the larger the distribution function value. Since particles with distribution function values in the range of 1/2 to 1 have lower weights and larger deviations from the actual pose of the robot, it is decided to retain only particles with distribution function values less than 1/2, while eliminating particles with distribution function values in the range of 1/2 to 1. The constructed function is shown in formula (9).

$$H(w_k)=\frac{\sum_{i=1}^{k}w_k}{\sum_{i=1}^{N}w_i} \tag{9}$$

(3) Based on the distribution function value, the particles with the top three weights are accurately extracted. Then, a particle is randomly selected and its position in the new particle set is set as A. At the same time, the position of the particle with a distribution function value exactly equal to 1/2 in the new particle set is set as B. Finally, the resampling operation is performed within the interval [A, B].

4. Experiment and Analysis

4.1 Simulation Environment Experiment and Analysis

An open-source simulation dataset is used to measure algorithm performance, and two SLAM technologies are tested through simulation. The simulation scenario is a virtual space of 300m×300m, ensuring consistent experimental conditions. In this environment, the maximum movement speed of the robot is set to 4m/s, and the maximum observation distance of the LiDAR is 20m, simulating the sensor capabilities in practical applications. At the same time, error elements such as speed error of 0.3m/s, distance error of 0.1m, and angle error of 1 are added to better reflect the complexity and uncertainty of the real world. All these simulation experiments are conducted on a standardized hardware platform, which is a computer equipped with a 64-bit Intel i5-8300 processor and 8GB of memory. MATLAB 2016a, a widely recognized scientific computing software, is used to process and analyze data to ensure the accuracy and repeatability of experimental results.

In the simulation mapping experiment, the traditional algorithm exhibited an average mapping time of 375 seconds and relied on at least 40 particles. In contrast, the algorithm innovatively proposed in this paper has achieved significant performance improvements, reducing the average mapping time to 302 seconds and successfully reducing the minimum particle count threshold to 15. After a deep analysis of the experimental results, it was found that under long-term operation and high particle number conditions, the map generated by the traditional algorithm is prone to deviations and has poor accuracy. However, the algorithm in this paper, by maintaining particle diversity and effectively reducing particle dispersion, not only improves the operational efficiency of the algorithm but also captures and presents the accurate posture of the robot in real time, thereby achieving significant improvements in map accuracy.

4.2 Physical Environment Experiment and Analysis

4.2.1 Mobile robot hardware platform

The experimental platform described in this paper is 45cm*38cm*30cm in size, and the platform is equipped with a two-wheel differential chassis, which enables it to have all-round mobility. The sensor system integrates LiDAR, IMU (Inertial Measurement Unit) and wheeled odometer, where the liDAR has a scan radius of 12 meters and supports user-set frequency scan matching to meet the needs of different application scenarios. IMU is responsible for providing real-time acceleration and angular velocity data to provide key information for attitude control and positioning of the platform [5]. The wheel meter is responsible for recording the distance traveled by the platform and calculating its motion trajectory through the algorithm. In terms of control system, the platform adopts the architecture of the combination of micro industrial computer and motor drive controller. The industrial computer is equipped with the Ubuntu 16.04 operating system and the Kinetic version of ROS (robot operating system) to realize real-time perception of the environment and map construction, and intuitive display through Rviz tool. The motor drive controller adopts the STM32F1 chip, which is responsible for driving the motor and collecting the information of some sensors, ensuring the efficient and stable operation of the platform.

4.2.2 Robot software system

The robot operating system (ROS) is a comprehensive software platform designed for robot applications. Its architecture is rigorous and is clearly divided into three levels: file system level, computational graph level and open source community level. In the architecture of ROS, nodes constitute the most basic and critical execution units. They are not only producers of data, but also consumers of data, working together to complete diversified tasks including the collection, transmission and distribution of sensor data. It is particularly worth mentioning that SLAM technology realizes the effective transmission of sensor data to the map construction module through the ROS node. This process is the core step for the robot to achieve accurate location determination and map construction function.

4.2.3 Experiment and Analysis

In the actual operation scenario of robots, due to the complex and changing environment, there are often many uncertain factors. The experiment adopted a multi-sensor fusion SLAM algorithm and compared it with the traditional RBPF-SLAM algorithm. The test environment was set in a laboratory and its connected office area.

According to the data presented in Table 1, the multi-sensor fusion SLAM algorithm proposed in this paper has shown significant advantages in the process of map construction. Specifically, the algorithm requires fewer particles and significantly reduces the time for map construction, resulting in a significant improvement in overall efficiency. In contrast, the traditional RBPF-SLAM algorithm mainly relies on odometry information, which leads to accumulated errors during long-term operation. Especially after the robot makes a detour, the integrity of the map is easily affected, resulting in errors such as map loss and false walls. The multi-sensor fusion SLAM algorithm achieves a more comprehensive and accurate perception of the environment by integrating data from multiple sensors. This feature enables the algorithm to maintain high stability and accuracy in the process of map construction, providing a more reliable basis for the autonomous navigation and path planning of robots.

Table 1. Parameter List of Two Algorithms for Building a Consistent Map

experimental map	algorithm	particle number	running time
Laboratory map construction	Traditional RBPF-SLAM	30	105
	Multi-sensor fusion SLAM	15	78
Office area map building	Traditional RBPF-SLAM	30	30
	Multi-sensor fusion SLAM	15	15

5. Conclusion

This article proposes a new method of multi-sensor fusion SLAM for mobile robots. This method effectively improves the accuracy of the motion model by fusing odometry data with IMU data. In the proposed distribution, the observation information from LiDAR is further integrated, resulting in a reduction of particle numbers. Additionally, the particle resampling strategy has been improved to alleviate the dissipation problem. Mapping experiments have been conducted in both simulated and physical environments. The experimental results show that the proposed method can guarantee high-precision mapping while reducing the time taken.

References

[1] Feng Jinhua, Yuan Bo, Zhu Fumin. SLAM diagram of multi-sensor positioning and fusion of mobile robot [J]. Industrial control computer, 2024,37(3):78-80.

[2] Cai Mingzhu, Liu Xiaoyan, Tang Zhiwei. Research on ROS service robot based on multi-sensor fusion SLAM [J]. Laboratory research and exploration, 2024,43(2):65-70.

[3] Tang Yuanwen, Liu Zuoshi. Research on multi-sensor fusion SLAM of mobile robots in complex environments [J]. Manufacturing Automation, 2023,45(8):108-112,166.

[4] Ma Guoli, Zhu Xiaochun, Chen Zitao. A new SLAM method for multi-sensor fusion of mobile robots [J]. Manufacturing Automation, 2022,44(5):70-74.

[5] Xu Shuping, Yang Dingzhe, Xiong Xiaodun. Multi-sensor fusion indoor robot SLAM[J]. Journal of Xi'an University of Technology, 2024,44(1):93-103.

