Research on Improved Localization and Navigation Algorithm for Automatic Guided Vehicle

Xiaohui Liu¹, Wu Wei¹, Yong Gao¹,* and Xiaoqin Wei¹

¹School of Automation Science and Engineering, South China University of Technology, Guangdong, China

*Corresponding author

Abstract. Aiming at the problem of inaccurate positioning caused by the wheel slippage or "kidnapping" movement of the robot in the positioning navigation, an improved autonomous positioning navigation strategy based on the robot operating system (ROS) is proposed. Firstly, combined with adaptive Monte Carlo localization (AMCL) algorithm and laser-based point-and-line iterative closest/corresponding point (PLICP) pose estimation algorithm, the accuracy and robustness of positioning are effectively improved. Then, based on the path planning strategy combining A* algorithm and dynamic window algorithm (DWA), an improved navigation failure recovery method is proposed and integrated into the ROS navigation framework, which can effectively improve the efficiency of robot positioning navigation and task execution. Finally, the mobile robot model TurtleBot is used as the experimental platform. The simulation experiment and field test demonstrate that the improved algorithm is superior to the original algorithm. The improved algorithm can adapt to the inaccuracy of the odometer and can achieve accurate localization and navigation in long-distance environment.

1. Introduction

The automatic guided vehicle (AGV) is widely used in military, transportation, logistics and other fields due to its good environmental adaptability and anti-interference ability. It is an important branch of mobile robot technology development. With the rapid development of flexible manufacturing, the demand of AGV is also growing in China [1]. Under the premise that the environmental map is known, the positioning and navigation technology is the core issue for the development of AGV, and on which domestic and foreign scholars have carried out extensive research.

AGV navigation means that the AGV controls its speed and angle according to the path offset to ensure that the AGV can reach the target point accurately [2]. AGV navigation can be transformed into path planning and obstacle avoidance problems. In literature [3], a magnetic nail positioning and navigation method based on Kalman filtering and PD control is proposed which has high accuracy but large limitation on complex paths. In literature [4], an improved Markov localization algorithm based on Gaussian kernel function is proposed. Although it can solve the abduction problem of robots, it has a large amount of computation and great restrictions on AGV positioning in non-structural environment.

Fox D and Burgard W [5] proposed the dynamic window algorithm, which has better obstacle avoidance effects for obstacles in static environments.

Aiming at the above problems, this paper proposes an improved positioning and navigation algorithm based on ROS framework by using laser, and verifies its effects through simulation experiments and field tests.
2. Improved Positioning Algorithm

Based on the known map, the purpose of the positioning is to determine the current position of the robot in the map, and the positioning accuracy directly affects the accuracy of subsequent navigation. Commonly used positioning methods are mainly divided into relative positioning and absolute positioning. Relative positioning determines the current pose by measuring the distance and direction of the robot relative to the initial position. Time drift may occur, however, because the relative positioning is based on the accumulation of measured values to achieve accurate positioning, which is not suitable for long-distance and long-time positioning. Therefore, this paper adopts the commonly used probability-based absolute positioning method-adaptive Monte Carlo localization method, and proposes corresponding improvement methods.

2.1. Adaptive Monte Carlo Localization Algorithm

Guided by probability statistics theory, Monte Carlo localization (MCL) method is based on particle filtering [6]. The method uses the distribution of particle samples to represent the confidence of pose, and continuously updates the particles and their weights according to the motion and observation model of the robot to realize the particle filter estimation, the algorithm process is shown in Figure 1. However, with the continuous iteration, the conventional MCL method will have more serious particle degradation, particle shortage and other phenomena, so it can’t solve the abduction problem of the robot. For these problems, AMCL emerges as required [7]. Many scholars have proposed different improved methods, one of which is to combine the conventional MCL with the Kulbback-Leibler Divergence (KLD) sampling method to adjust the size of the particle set over time to form adaptive Monte Carlo localization algorithm.

![Figure 1. Process of Monte Carlo localization algorithm.](image1)

2.2. Improved Adaptive Monte Carlo Localization Algorithm

During the experiment, it was found that when the robot moved, the odometer data error would be large if the ground is uneven or the wheels slips, bringing difficulties to the robot positioning. In order to avoid the above problems and improve the positioning accuracy, a positioning method based on PLICP pose estimation and AMCL method is proposed, as shown in Figure 2.

![Figure 2. Improved PLICP-AMCL algorithm flow chart.](image2)

PLICP is a point-to-line match method, which means minimizing the Euclidean distance from a point to the straight line rather than from a point to a point [8]. The core idea of the improved PLICP-AMCL positioning method is: based on the AMCL method, when the odometer error of the robot exceeds the
set threshold, the positioning estimation no longer uses the odometer positioning data, but uses PLICP for relocation. This can improve the robustness of positioning. Since the improved algorithm is a linear fusion of AMCL and PLICP methods, the improved algorithm will not change the convergence of the original algorithm [9, 10].

3. Improved Navigation Algorithm

The navigation of the robot can be transformed into the path planning problem. The path planning is further divided into global path planning based on prior information and local planning problem based on sensor information.

3.1. Improved Navigation Failure Recovery Method

When the robot deviates from the navigation path and the positioning is lost, the original navigation failure recovery method is to let the robot rotate in place, then let the sensor acquire the surrounding environmental information and match the map until the relocation is successful. However, this method may cause the robot to continuously rotate in place, not only wasting time, but also usually making the robot unable to reach the target point from the lost navigation.

Therefore, this paper proposes an improved navigation failure recovery method: when the robot navigation is lost (positioning failure), let the robot rotate a few turns in place to update the local cost map, then move the robot to a small distance in the direction without obstacles. After stopping, let the robot get global positioning and re-plan a path to the target point. The method can effectively improve the efficiency of the robot positioning navigation and performing tasks.

3.2. Integrated Localization and Navigation Frame

This paper builds the navigation framework to realize the laser-radar-based navigation experiment based on the ROS platform which includes the navigation algorithm package configuring global and local path planning. In this paper, A* algorithm, which combines the advantages of Dijkstra algorithm and Breadth-First Search (BFS) algorithm [11], realizes global path planning, and DWA, which is suitable for unstructured static environment, realizes local path planning [12]. The input of the navigation algorithm package includes: target setting, raster map, RPLIDAR laser data, robot positioning, coordinate transformation, odometer information. The improved ROS navigation framework is shown in Figure 3. After the robot's initial pose is determined, the robot's navigation target can be determined on the map via the "2D Nav Goal" button in RVIZ.

![Figure 3. Improved ROS navigation framework.](image)

4. Simulation and Experiment

4.1. Simulation Analysis

This paper uses the Gazebo platform and the RVIZ visual interface to simulate the robot positioning navigation. The open source TurtleBot model, equipped with a virtual laser sensor, is introduced into
Gazebo as a robot experiment platform, which can realize omnidirectional scanning in a 2D plane with a scan radius of 8m, as shown in Figure 4(a). The bottom of the robot is equipped with two left and right driving differential wheels and two front and rear driven universal wheels. The photoelectric encoder is mounted on the differential wheel, which can calculate the displacement of the robot by the number of measured pulses per unit time. The robot’s experiment environment built in Gazebo is shown in Figure 4(b), including five obstacles. The grid map created through its own laser sensor is displayed in RVIZ, as shown in Figure 4(c). The small green arrow in the figure indicates the orientation of the 500 particle samples distributed around the robot.

![Figure 4](image)

**Figure 4.** The initial position of the navigation.

After setting a target point for the robot in the grid map (the red five-pointed star logo in Figure 5), the RVIZ automatically plans an excellent navigation path for the robot (the green curve in Figure 6). When the robot moves to the target point, the navigation effect of using the original and improved positioning navigation algorithm is respectively shown in Figure 5 and Figure 6.

![Figure 5](image)

**Figure 5.** The navigation effect of the robot obtained by the original algorithm at (a) starting point, (b) path point and (c) target point.

![Figure 6](image)

**Figure 6.** Navigation effect diagram of the robot obtained by the improved algorithm at (a) starting point, (b) path point and (c) target point.

4.2. **Field Test**

The robot platform used in this paper is the TurtleBot mobile robot developed by YUJIN Company, as shown in Figure 7(a). Its mechanical structure and hardware configuration are similar to the simulation model. The laser-borne radar sensor is the RPLIDAR A2 developed by SLAMTEC, which enables 360-degree rotational scanning in the plane. The environment in which the robot is located consists of a laboratory and the outside corridors, as shown in Figure 7(b)-(h). Since the RPLIDAR laser radar can only scan 2D plane, a 2D raster map is constructed, as shown in Figure 8. The initial position of the robot is set at the turning aisle (d). Its logo on the grid map is shown by the black dot in Figure 9(a). The small green arrow indicates the particle distribution and the corresponding pose. Three target points (red five-pointed star in Figure 9(b)-(d)) are set in the grid map, and the robot sequentially reaches the specified target point and moves along the path by using the positioning
navigation algorithm.

Figure 7. The robot platform used in the field test (a), and the test environment (b)-(h).

Figure 8. 2D map of test environment.

Figure 9. The robot’s initial position (a) and its motion process (b) from start point to target point1; (c) from target point1 to target point2; (d) from target point2 to target point3.

Figure 10. Positioning navigation comparison based on (a) initial algorithm and (b) improved algorithm.

In the navigation process from the target point 1 to 2, the navigation effect of the original algorithm and the improved algorithm of the present invention is compared, as shown in Figure 10. It can be seen that the original algorithm has a high degree of particle dispersion and significant deviation, and the laser scanning does not match the current map, resulting in an error in positioning navigation. The improved algorithm makes the laser scanning and map coincidence degree, the particles are concentrated around the current position of the robot. The positioning is relatively accurate, and the robot can accurately reach the target point.
In the long corridor environment, the robot has been tested many times. It can be found that when the wheels slip or the robot is “kidnapped”, the original algorithm will lead to the positioning drift and the positioning loss phenomenon, and the improved algorithm has strong adaptability. This allows the robot to quickly adapt to long-distance navigation and reach the target point accurately.

5. Conclusion
This paper mainly studies the improved localization and navigation algorithm to improve the localization accuracy of mobile robot and avoid navigation failure. Firstly, This paper combines the traditional AMCL method and the PLICP method to solve inaccurate positioning problem of the robot caused by wheel skidding and collision. Secondly, using the ROS framework integrated with PLICP-AMCL algorithm, A* algorithm, DWA algorithm and improved navigation failure recovery method, the robot is successfully controlled along the path of independent planning, effectively improving the efficiency of positioning and navigation. Finally, the TurtleBot robot is used as the experimental platform for comparative simulation and physical experiments. The results show that the improved positioning and navigation algorithm has better accuracy and robustness. In the future, we can consider the fusion of the algorithm in the text with Inertial Measurement Unit (IMU) sensor information and depth camera information to further improve the autonomy of mobile robots in complex environments’ positioning and navigation.

Acknowledgments
This work was supported by the National Natural Science Foundation of China (61573148), the Science and Technology Planning Project of Guangdong Province (2015B010919007, 2016A040403012, 2017B090901043), and the Science and Technology Planning Project of Guangzhou (201604046015, 201604046014, 2017171201).

References
[1] Sergio R González and Ivan Mondragón 2017 Manufacturing Control Architecture for FMS with AGV: A State-of-the-Art (Advances in Automation and Robotics Research)
[2] Iñigo RM and Alley D 1991 Algorithms for path planning, navigation and guidance of an AGV vol 7 (Robotics and Autonomous Systems) pp 309-326
[3] Song Z and Wu X 2016 A new method of AGV navigation based on Kalman Filter and a magnetic nail localization Int. Conf. on Robotics and Biomimetics (New York: IEEE) pp 952-957
[4] Hao Li and Wenhua Ye 2018 Markov localization algorithm based on Gaussian kernel function in feature map vol 24(Computer Integrated Manufacturing Systems) pp 1081-1088
[5] Fox D Burgard W Thrun S 1997 The dynamic window approach to collision avoidance vol 4 (IEEE Robotics & Automation Magazine) pp 23-33
[6] Rohde J and Jatzkowski I 2016 Vehicle pose estimation in cluttered urban environments using multilayer adaptive Monte Carlo localization Int. Conf. Information Fusion (New York: IEEE) pp 1774-1779
[7] Fengping C and Qiyao F 2018 Research on real-time positioning based on adaptive Monte Carlo algorithm vol 44 (Computer Engineering) pp 28-32
[8] Almeida J and Santos V M 2012 Real time egomotion of a nonholonomic vehicle using LIDAR measurements vol 30 (Journal of Field Robotics) pp 129-141
[9] Censi A 2008 An ICP variant using a point-to-line metric Proc. Int. Conf. on Robotics and Automation (Pasadena) pp 19-23
[10] Thrun S Fox D Burgard W 2008 Robust Monte Carlo localization for mobile robots (Asterdam: Artificial Intelligence) pp 103-104
[11] Yajie Wu and Jingdong Yang 2017 Mobile robot path planning based on A* algorithm vol 30 (Electronic Science and Technology) pp 124-127
[12] Enqiang Zhou 2019 Research on Positioning and Navigation Technology of Mobile Robot based on SLAM Algorithm Int. Conf. Machinery, Materials and Computing Technology (Chongqing) pp 500-505