



Application of SLAM Algorithm in The Construction of 2-D Maps

Liu Zhongwei, Li Jinyan, Wu Wei, Pan Mingtao, Liu Kao, Yang Hang

College of Engineering, Zunyi Normal University, Honghuagang District, Zunyi City, Guizhou Province, China, 563006

Corresponding to: Yang Hang

Abstract: In today's society, maps, as an important tool for human spatial cognition and spatial thinking, solidify and abstract the results of spatial cognition to complete the visual expression and information transmission of geographic information, and provide auxiliary decision-making for people to understand the urban pattern, formulate travel routes, take a taxi or self-drive navigation and other geospatial activities. The role of this is obvious, human beings have more strict requirements for maps, and the algorithms that can draw maps are also blooming. The purpose of this paper is to study the application of SLAM algorithm in the construction of simple 2-D maps, analyze the advantages of SLAM algorithm in the construction of 2-D maps, and analyze the role of closed-loop detection and trajectory optimization in the process of building 2-D maps. SLAM includes lidar data mapping, which has high measurement accuracy and stable measurement performance, and is now more widely used in industry.

Keywords: SLAM Algorithm; 2-D Map; Lidar; Closed-Loop Detection; Trajectory Optimization

1 INTRODUCTION

The technology in which an unmanned device realizes autonomous positioning and navigation through a series of operations such as data acquisition by its own sensors in an unknown environment is called even positioning and mapping technology.

SLAM has been around for 30 years, and was proposed in 1986 by Smith and Cheeseman, who were the first to raise the issue of SLAM. Its development process can be divided into three stages: in the traditional era (1986-2004), the SLAM problem was proposed, and the problem was transformed into a state estimation problem, which was solved by means of extended Kalman filter, particle filter and maximum likelihood estimation; In the era of algorithm analysis (2004-2015), the basic characteristics of SLAM were studied, including observability, convergence and consistency. Robustness-Analytical Era (2015-) Robust, high-level scenario understanding, computing resource optimization, and task-driven environment awareness. Visual SLAM is developed on the basis of traditional SLAM, and in the early days, visual SLAM mostly used extended Kalman filter and other means to optimize the accuracy of camera pose estimation and map construction, and later with the improvement of computing power and algorithms, BA optimization and pose optimization have gradually become the mainstream. With the popularization of artificial intelligence

technology, SLAM based on deep learning has attracted more and more attention from researchers.

The mainstream of SLAM systems is mainly divided into laser SLAM, visual SLAM, and multi-sensor fusion SLAM technology for various sensor-assisted laser/vision. In this experiment, laser SLAM is used, which can solve the shortcomings of the visual SLAM system that needs to process a large amount of image data, and because the camera is sensitive to light and cannot be directly measured. LiDAR can directly measure the distance, perceive the environment more accurately, obtain the spatial position and shape information of objects, build high-precision maps for accurate positioning, and make the SLAM system more reliable and stable for long-term operation. It is widely used, such as indoor navigation, 3D reconstruction and autonomous driving, and is a research hotspot in the era of artificial intelligence.

LiDAR is mainly divided into 2D laser SLAM and 3D laser SLAM. There are also two types of laser line analysis. They are single-line lidar and multi-line lidar. The 2D laser SLAM used in this paper is more suitable for the experimental research in this chapter, which can only be used for real-time navigation in the navigation area, and the two-dimensional imaging lacks height information and cannot be imaging.

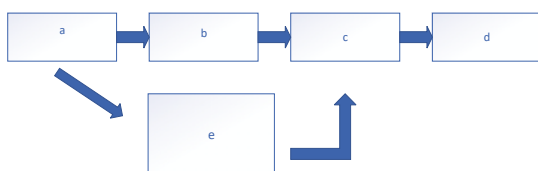
2 EXPERIMENTAL PRINCIPLE

SLAM algorithms are implemented on a series of 2D lidar scans using scan processing and attitude map optimization (PGO), with the goal of estimating the robot's trajectory and building a map of the environment. In this experiment, a two-dimensional offline SLAM algorithm will be used to construct a 2D map of a set of robot trajectory data scanned by 2D lidar. In the process of building the map, the estimated robot trajectory drifts over time, which can be due to three reasons: noisy scanning of sensors, without sufficient overlap; lack of significant features in the environment; The initial conversion is inaccurate, especially when rotation is important. In 2D mapping, the drift of the estimated trajectory can lead to inaccurate environment maps. In this experiment, the 2D map will be optimized through the above two steps, and the application of SLAM algorithm in the process of constructing 2-D map will be studied

3 EXPERIMENTAL PROCESS

3.1 ESTABLISHMENT OF ROBOT TRAJECTORY ENVIRONMENT MAP

The SLAM algorithm was used to load the laser scan and estimate the robot trajectory. Data collected in an indoor environment using Clearpath Robotics™ Jackal™ robot. The robot is equipped with a TiM-511 laser scanner from SICK™ and has a maximum range of 10 meters. Load the file containing the laser scan into the workspace, which is denoted as a in Figure 1; In the process, the front-end visual odometer b is responsible for estimating the movement of the camera between adjacent images and the appearance of the local map; The back-end nonlinear optimization c is responsible for accepting the camera pose measured by the visual odometer at different times, as well as the information of loop detection, and optimizing them to obtain a globally consistent trajectory and map. Loopback detection e is responsible for determining whether the robot has ever reached the previous position, and if it detects loopback, it will provide the information to the backend for processing; Based on the estimated trajectory, map D establishes a map corresponding to the mission requirements.



A: SENSOR DATA B: FRONT-END VISUAL ODOMETER C: BACK-END NONLINEAR OPTIMIZATION D: MAPPING E: LOOPBACK DETECTION

FIGURE 1 WORKFLOW DIAGRAM

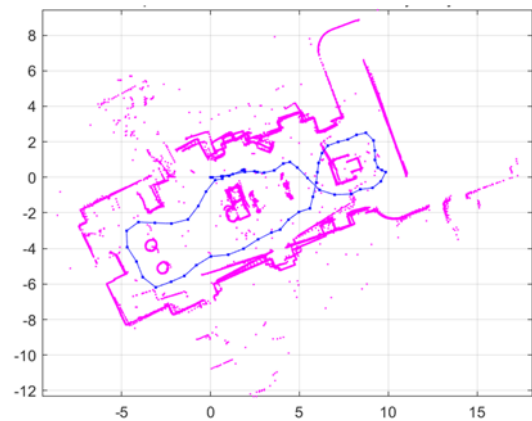


FIGURE 2: MAP OF THE ROBOT TRAJECTORY ENVIRONMENT

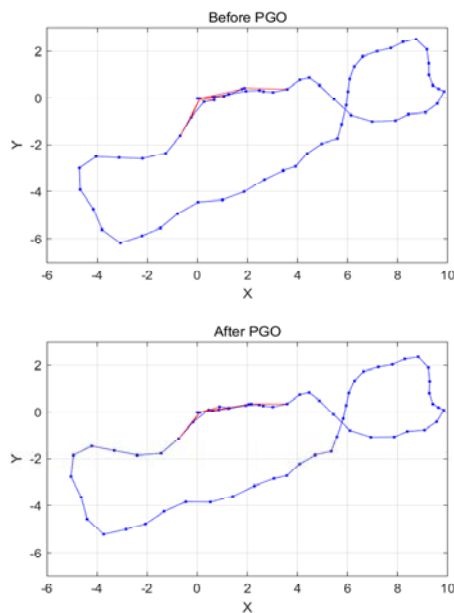
3.2 DRIFT CORRECTION OF THE ROBOT TRAJECTORY ENVIRONMENT MAP

For a well-established map of the robot's trajectory environment, this experiment will correct for trajectory drift by accurately detecting loops that are where the robot returns after a previous visit. Closed-loop edges are added to the robot trajectory environment map to correct for trajectory drift during attitude map optimization.

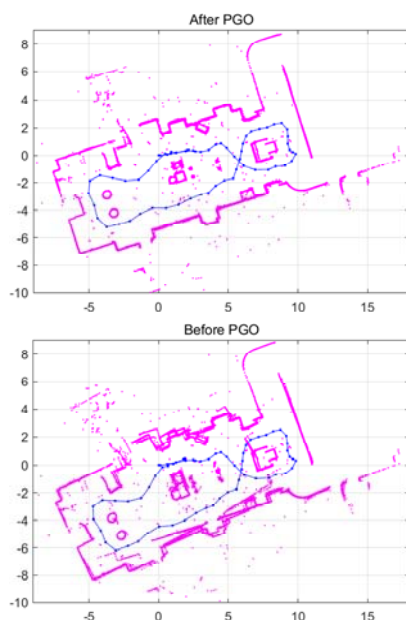
The first step is to perform closed-loop detection to determine whether the robot has previously visited the current location in a given scan, and the search consists of matching the current scan with previous scans around the robot's location within the specified radius. If the match score is greater than the specified threshold, the scan is accepted as a match. Use the detectLoopClosure function to detect closed loops and add them to the map object using the addLoopClosure function.

In the second step, the trajectory is optimized, and the poseGraph function is used to create a gesture map object from the drift-corrected lidar scan map. Use the optimizePoseGraph (Navigation Toolbox) function to optimize the pose diagram. The nodeEstimates (Navigation Toolbox) function is then used to extract the optimized absolute pose from the pose map and update the trajectory to build an accurate map of the environment.

The third step is to visualize the environment map of the robot's trajectory, and the changes in the trajectory of the robot before and after the visualization attitude map optimization can be obtained. Select the red line to represent the edge of the closed loop.

**FIGURE 3 COMPARISON BEFORE AND AFTER PGO**

3.3 VISUALIZE THE ENVIRONMENT AND ROBOT TRAJECTORY BEFORE AND AFTER OPTIMIZATION.

**FIGURE 4 ROBOT TRAJECTORY BEFORE AND AFTER OPTIMIZATION**

4 CONCLUSION

Laser SLAM can greatly improve the accuracy of the constructed map, and for the error caused by the time of laser

SLAM in the robot trajectory movement, the proposed drift correction and visualization processing can correct the error and correct the trajectory drift by accurately detecting the loops, which are the places where the robot returns after the previous visit. Add a closed-loop edge to `lidarscanmap` object, to correct the trajectory drift during the optimization of the pose map. Visualize the change of the robot trajectory before and after the attitude map optimization. The edge of the closed loop is indicated by a red line. It has made a significant improvement in the field of high-speed mobile vehicle equipment such as autonomous vehicles and drones.

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