ISSN: 2664-9640

Real time and high-precision point cloud map construction algorithm and application based on LiDAR

Yujiao Shi [a],Tongmei Wang [b], Mingyang Ma [c]

Tianjin Binhai Vocational Institute of Automotive Engineering, School of Information Engineering, China

[a]shiyujiaoyx@163.com, [b]wangtongmeitqzy@163.com, [c]mamingyangmond@163.com

Abstract

Lidar is one of the important sensors for the development of unmanned driving technology. It can construct point cloud maps by scanning the surrounding environment, and high-precision positioning of vehicles can be achieved based on the constructed point cloud maps. Therefore, it is particularly important to construct real-time and high-precision maps. Therefore, this article proposes a real-time construction scheme based on lidar data. Firstly, perform adaptive calibration of the LiDAR based on the ICP (Iterative Closest Point) algorithm; Secondly, perform point cloud keyframe extraction on LiDAR data; Finally, based on the similarity of point cloud strength and the normal distribution transformation algorithm NDT (Normal Distribution Transform), multi feature inter frame point cloud matching is performed to achieve fast and accurate lidar slam (Simultaneous Localization and Mapping). The experimental results show that the real-time and high-precision map construction is completed based on the data after Lidar adaptive calibration.

Keywords

Lidar, driverless, data fusion, point cloud mapping.

1. Overview

LIDAR (Light Detection and Ranging) is the abbreviation of Laser Detection and Ranging System. The data obtained by scanning with LiDAR is called LiDAR point cloud data. Vehicle mounted LIDAR is a new remote sensing technology that has developed in recent years and is widely used for 3D ground information collection. Compared with traditional photogrammetry technology, vehicle mounted LIDAR can automatically and quickly obtain high-precision and high-density surrounding 3D coordinate information, and has important applications in urban 3D reconstruction, terrain surveying, and other fields. With the development of unmanned vehicle technology, LIDAR, as one of the important sensors in the perception field of unmanned vehicles, has important research value in obstacle detection and SLAM (Instant Localization and Mapping) technology for unmanned vehicles.

LIDAR SLAM technology has important research significance in unmanned vehicles. Reference [1] proposed a method for positioning and mapping based on visual laser point clouds. Reference [2] proposed a method for low drift real-time LiDAR positioning and map construction. Reference [3] proposed a method for 2D point cloud registration and map construction based on normal distribution transformation, Reference [4] proposed a method for 3D point cloud registration and map construction based on closed loop detection using normal distribution transformation. Reference [5] proposed an indoor positioning and map construction algorithm based on Inliers tracking statistics. Reference [6] introduced particle swarm optimization ideas into the robot human simultaneous positioning and map construction algorithm. At present, the relatively mature SLAM algorithm [7-8] has high requirements for the initial state of LiDAR point cloud data. The initial state of point cloud data also determines the accuracy of SLAM algorithm in unmanned vehicle positioning. Therefore, LiDAR point cloud data preprocessing is an important technology in the field of unmanned vehicle perception. Due to the large amount of point cloud data returned after laser radar scanning, including ground point information and non ground point information, the most important step in data preprocessing is point cloud data filtering. The research on point cloud data filtering algorithms mainly includes the following categories: mathematical morphology based filtering algorithms [9-11], clustering or segmentation methods [12], fitting methods [13], slope based filtering methods [14], etc.

This article mainly studies the unmanned mapping technology based on LiDAR data. Firstly, the LiDAR is calibrated adaptively using the ICP algorithm; Secondly, perform point cloud keyframe extraction on LiDAR data; Finally, based on the similarity of point cloud strength and the normal distribution transformation algorithm NDT, multi feature inter frame point cloud matching was performed, achieving fast and accurate lidar slam, and achieving the information rich point cloud map construction required by unmanned vehicles.

2. Adaptive calibration

LiDAR is an important sensor for the development of unmanned driving technology. Commonly used in vehicle LiDARs are 16 wire, 32 wire, and 64 wire LiDARs. This article adopts the method of 32 line LiDAR point cloud data fusion to study the construction of point cloud maps.

This article uses the ROS (Robot Operating System) mechanism to receive LiDAR point cloud data, based on the ICP adaptive calibration method, as follows:

The essence of the ICP algorithm is to solve the spatial transformation between two sets of point cloud data P and Q, so as to minimize the distance between the two point cloud models. In the overlapping area of the two sets of point cloud data to be registered, two point sets are selected to represent the source point set and the target point set, where P and Q are point cloud sets with different lidars, and n represents the number of point clouds in the two point sets. Let the rotation matrix be R, the translation matrix be t, and $E(R,t)$ be used to represent the error between point set P and point set Q under the transformation matrix (R,t). The problem of solving the optimal transformation matrix can be transformed into an optimal solution that satisfies $\min E(R,t)$.

Among them, $E(R,t)$ is called the objective function, which represents the degree of difference between two point sets. The objective function can be represented by the following formula:

$$E(R,t)=\sum_{i=1}^{n}\|Q_i-(P_i\cdot R+t)\|^2 \tag{1}$$

Solve the optimal transformation matrix, namely R and t, by minimizing the objective function.

(1) Calculate the corresponding nearest point of each point in point cloud P in point set Q;

(2) Find the transformation that minimizes the average distance between the corresponding points, and use SVD decomposition to obtain the rotation parameter R and translation parameter t, so as to minimize $E(R,t)$;

(3) Use the rotation parameter R and translation parameter t obtained in the previous step for P to obtain a new set of transformation points P';

(4) If the transformed point set P' and point set Q meet the objective function requirements, that is, the average distance between the two point sets is less than the given threshold, the iterative calculation will be stopped. Otherwise, the new P' will be recalculated as the new P to continue the iteration until the convergence conditions are met.

ISSN: 2664-9640

The calibration of lidar was completed through the above algorithms, providing effective data for subsequent algorithms.

3. Point cloud keyframe extraction

The selection of keyframes is of great significance for optimizing point cloud maps. During real-time positioning and mapping in autonomous driving, the front-end calculates the pose transformation between adjacent frames, and the back-end constructs a point cloud map. However, due to the current computational performance of the computer itself not being able to handle projects similar to SLAM, before creating a point cloud map, select key frames to create a point cloud map to improve computational efficiency. The present invention proposes to achieve adaptive keyframe extraction of point clouds based on dynamic speed changes and heading angle changes, which compensates for the selection of keyframe point clouds in traditional methods such as Euclidean distance and time. The selection of key frames for point clouds not only improves computational efficiency, but also provides necessary scene data for point cloud mapping on the Lidar SLAM backend. Therefore, the strategy for selecting key frames in the present invention is as follows:

(1) When the speed of the unmanned vehicle v_0 =0 (instantaneous speed), the unmanned vehicle is in a stationary state and accumulates a large amount of point cloud data over time. Therefore, the closest point cloud data is selected based on the timestamp and added to the keyframe sequence;

(2) When the speed of the unmanned vehicle is 0< v_1 <60 (km/h, the average speed of a certain distance), model it based on the speed at this time and the curvature yaw of the heading angle change that occurs during movement, and select the point cloud keyframe through timestamp:

$$t = k\frac{1}{v_1} + u\frac{1}{yaw} \tag{2}$$

Among them, k is the inverse coefficient of velocity and u is the inverse coefficient of heading angle. As the velocity and heading angle change, point cloud keyframes are selected in the timestamp sequence based on the time interval t.

4. 3 Matching Algorithm between Adjacent Point Clouds Associated with Multiple Features

The core of Lidar SLAM front-end odometer is to calculate the transformation relationship between adjacent frames, including the translation and rotation relationship between the current frame point cloud and the previous frame point cloud data. Due to anomalies in real-time point cloud data, the transformation relationship between adjacent point clouds is incorrect, resulting in inaccurate mapping. Therefore, the present invention proposes a matching relationship between adjacent point clouds based on NDT algorithm and multi feature correlation of point cloud strength information.

The NDT algorithm represents a dataset of a large number of discrete points within a cube as a piecewise continuous differentiable probability density function.

Firstly, divide the point cloud space into several identical cubes, and ensure that there are at least 5 point clouds within the cube. Calculate the mean q and covariance matrix Σ of each point within the cube:

$$q = \frac{1}{n}\sum_i X_i \tag{3}$$

$$\Sigma=\frac{1}{n}\sum_{i}(X_i-q)(X_i-q)^T \tag{4}$$

Among them, $X_{i=1,2,\dots,n}$ is the point cloud collection, and n is the number of point clouds.

Then, the discrete point cloud is segmented and continuously differentiable in the form of probability density, and the probability density of each point in the cube is represented using the NDT algorithm:

$$p(X)\sim\exp\left(-\frac{(X-q)^T\Sigma^{-1}(X-q)}{2}\right) \tag{5}$$

By using the Hessian matrix method to solve the registration between adjacent frames of point cloud data scanned by vehicle mounted LIDAR, the essence of point cloud registration is to obtain the pose relationship between adjacent frame point clouds based on the point cloud data collected by unmanned vehicles at different positions.

The point cloud intensity feature information represents the degree of correlation between adjacent frame point cloud data, and determines the relationship between adjacent frames by calculating the covariance and correlation coefficient between adjacent frames. The strength information between adjacent point clouds is:

$$A=[a_1,a_2,\dots,a_n] \tag{6}$$

$$B=[b_1,b_2,\dots,b_n] \tag{7}$$

Calculate the covariance function using point cloud intensity information as follows:

$$\mathrm{cov}\_ba=F(dev\_B*dev\_A) \tag{8}$$

Where dev_B and dev_A are the dispersion matrices, respectively. Covariance can simply reflect the correlation between two sets of statistical samples. If the covariance difference is positive, it is a positive correlation; If the value is negative, it is a negative correlation. The larger the absolute value, the stronger the correlation.

By calculating the correlation coefficient to represent the degree of correlation between adjacent frame point clouds, the calculation is as follows:

$$K=\frac{\mathrm{cov}\_ba}{std\_b*std\_a} \tag{9}$$

Among them, cov_ba is the covariance of point cloud intensity information, std_a is the standard deviation of point cloud sample A intensity, std_b is the standard deviation of point cloud sample B intensity, and K is the correlation coefficient. A trend towards 1 indicates a positive correlation.

The specific algorithm for Lidar SLAM front-end odometer is as follows:

(1) Calculate the NDT of the LIDAR scan point cloud for the first frame;

(2) Initialize coordinate transformation parameter T:

$$T=\begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix} \tag{10}$$

Where R is a 3 * 3 rotation matrix and t is a 3 * 1 translation matrix;

(3) Map the second frame laser scanning point cloud set to the first frame coordinate system based on the initial matrix T, and obtain the mapped point cloud set $X_i^{'}$;

(4) Calculate the NDT of each point after mapping transformation;

$$p(X_i^{'})\sim\exp\left(-\frac{(X_i^{'}-q_i)^T\Sigma_i^{-1}(X_i^{'}-q_i)}{2}\right) \tag{11}$$

(5) Calculate the sum of probabilities of corresponding points falling into the corresponding cube:

ISSN: 2664-9640

$$s(p)=\sum_{i}\exp[-\frac{(X_i^{'}-q_i)^T\sum_i^{-1}(X_i^{'}-q_i)}{2}] \tag{12}$$

According to the Newton optimization algorithm, the objective function$-s(p)$ is optimized by finding the transformation parameter p to maximize the value of $s(p)$.

Introducing multi feature data association to determine the correlation between adjacent point clouds. When K approaches 1 infinitely, it indicates that the intensity of the current adjacent frame point cloud is positively correlated, with α and β being 0.6 and 0.4, respectively:

$$H=\alpha * s(p)+\beta * K \tag{13}$$

Jump to step 3 to continue execution, where $H>=\frac{s(p)+K}{2}$ returns the coordinate transformation parameter T of the optimal solution.。

At this point, based on point cloud strength similarity and normal distribution transformation algorithm NDT, multi feature inter frame point cloud matching is performed to achieve a fast and accurate lidar slam front-end odometer.

5. Experimental results and analysis

As shown in Figure 1, this experiment relies on a small unmanned vehicle as a platform to conduct a LiDAR map construction experiment and conduct actual complex park environment testing. The unmanned vehicle is equipped with a 32 wire RSlidar lidar, as shown in Figure 1.

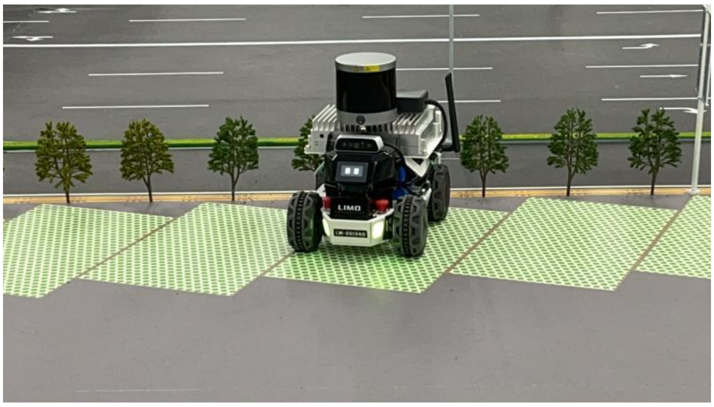


Figure 1 Small Unmanned Vehicle

This article uses LiDAR for map construction, and the experimental results include LiDAR adaptive calibration. LiDAR utilizes matching algorithms between adjacent point clouds associated with multiple features to construct the map.

The adaptive calibration of LiDAR is shown in Figures 2 and 3.

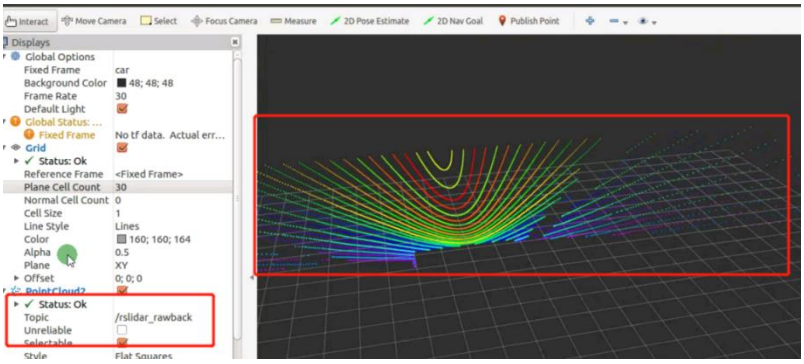


Figure 2 Point Cloud Display before LiDAR Data Calibration

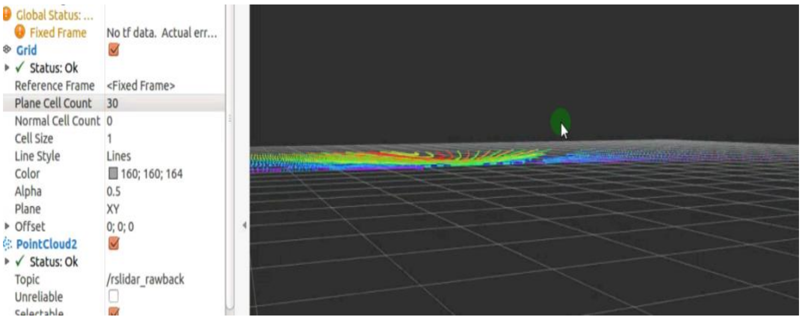
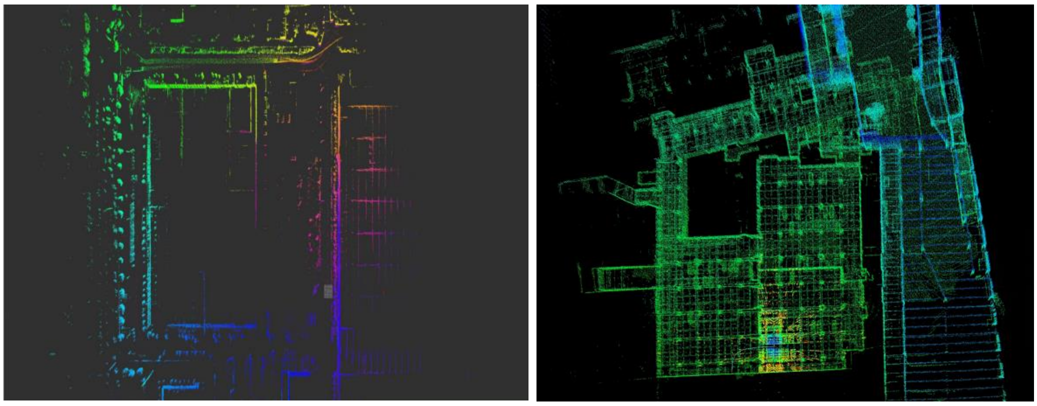


Figure 3 Point Cloud Display after LiDAR Data Calibration

As shown in Figure 2, the radar data before calibration is displayed based on the installation position as the origin, with a slight error between the ground or the reference object. The point cloud calibration of the LiDAR is carried out using an ICP based adaptive calibration method, which is consistent with the ground, vehicle body, and radar to complete the point cloud calibration.



(a) Experiment 1 Map Construction Results (b) Experiment 2 Map Construction Results

Figure 4 Matching between adjacent point clouds associated with multiple features

As shown in Figure 4, (a) is a map construction completed by matching algorithms between adjacent point clouds associated with multiple features in an open environment, and (b) is a map construction completed by matching algorithms between adjacent point clouds associated with multiple features in an underground parking car environment. The experimental results show that the real-time and high-precision point cloud map construction algorithm based on LiDAR in this paper can complete map construction in different complex environments. It can be seen from Figure (b) that, on the basis of the point cloud map, the rapid completion of positioning function can enable unmanned vehicles to conduct more effective autonomous navigation based on the point cloud map.

6. Conclusion

This article is based on the ICP adaptive calibration algorithm used in lidar for point cloud calibration, and the map construction is completed using the matching algorithm between adjacent point clouds associated with multiple features. The adaptive calibration based on ICP algorithm solves the problem of some errors between the feedback point cloud data and the real data due to different installation positions of the LiDAR. Through calibration, high-quality point cloud data is provided for subsequent algorithms; Secondly, point cloud keyframe extraction is performed on LiDAR data to avoid problems such as low computational efficiency caused by large, repetitive, and invalid data participating in calculations; Finally, the map construction was completed based on the matching algorithm between adjacent point clouds associated with multiple features, achieving fast and high-precision Lidar SLAM, and achieving the information rich point cloud map construction required by unmanned vehicles.

ISSN: 2664-9640

References

[1] Ji Z, Singh S. Visual-lidar odometry and mapping: low-drift, robust, and fast[C]// IEEE International Conference on Robotics & Automation. 2015.

[2] Zhang J, Singh S. Low-drift and real-time lidar odometry and mapping[J]. Autonomous Robots, 2017, 41(2):401-416.

[3] Biber P , Strasser W . [IEEE 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453) - Las Vegas, Nevada, USA (Oct. 27-31, 2003)] Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453) - The normal distributions transform: a new approach to laser scan matching[C]// IEEE/RSJ International Conference on Intelligent Robots & Systems. 2003:2743-2748.

[4] Magnusson M, Andreasson H, Nüchter A, et al. Automatic appearance-based loop detection from three-dimensional laser data using the normal distributions transform[J]. Journal of Field Robotics, 2010, 26(11-12):892-914.

[5] Xiaoning,Niu,Hongzhe,et al.RGB-D Indoor Simultaneous Location and Mapping Based on Inliers Tracking Statistics[C]//2019:62023-62023.DOI:10.1088/1742-6596/1176/6/062023..

[6] YuanCheng, CaiZixing, ChenBaifan. Simultaneous localization and mapping method for particle swarm optimization [J] Computer Engineering, 2009, 35(11):175-177.

[7] Qingshan Wang, Jun Zhang, Yuansheng Liu, and Xinchen Zhang.Point Cloud Registration Algorithm Based on the Combination of NDT and ICP [J]. Computer Engineering and Application, 2020, 56(07):88-95.

[8] Qingshan Wang, Jun Zhang, Yuansheng Liu, and Xinchen Zhang, "High-Precision and Fast LiDAR Odometry and Mapping Algorithm," J. Adv. Comput. Intell. Intell. Inform., Vol.26, No.2, pp. 206-216, 2022.

[9] Li-Chun S . Processing of Laser Scanner Data and Extraction of Structure Lines Using Methods of the Image Processing[J]. Acta Geodaetica et Cartographica Sinica, 2004, 33(1):63-70.

[10] LiangXinlian, ZhangJixuan, LiHaitao. An adaptive morphological filtering method applied to urban areas [J] Journal of Remote Sensing, 2007, 11(2):276-281.

[11] Li Pengcheng, Wang Hui, Liu Zhiqing, Liu Zhongbin, Shi Bin. A mathematical morphology LiDAR point cloud filtering method based on scanning lines [J]. Journal of Surveying and Mapping Science and Technology,2011,28(04):274-277+282.

[12] Jiang Jingjue, Zhang Zuxun, Ming Ying Airborne Lidar point cloud filtering for complex urban environments [J] Journal of Wuhan University · Information Science Edition, 2007, 32(5): 402-405. JIANG Jingjue, ZHANG Zuxun, MING Ying. Filtering of Lidar Point Clouds for Complex Cityscapes. GEOMATICS AND INFORMATION SCIENCE OF WUHAN UNIVERS, 2007, 32(5):402-405.

[13] Zhang Xiaohong, Liu Jingnan Airborne laser scanning altimetry data filtering [J] Science of Surveying and Mapping, 2004, 29(6):50-53.

[14] Pfeifer N, Filin S. Segmentation of airborne laser scanning data using a slope adaptive neighborhood[J]. Isprs Journal of Photogrammetry & Remote Sensing, 2006, 60(2):71-80.