Real-time high-precision location and mapping system based on NDT of the large scene

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Abstract: The traditional lidar registration algorithm has good stability and high precision when carrying out large-scale simultaneous localization and mapping. However, in complex and changeable environments such as outdoor, severe occlusion, or electronic interference, the signal is easily affected, and the positioning accuracy cannot be guaranteed. To solve the above problems, a high-precision localization method based on laser-point cloud NDT (Normal Distributions Transform) is proposed in this paper, which makes full use of the mean and variance characteristics of NDT registration of the midpoint cloud, and the proposed method is added into the complete framework of SLAM (Simultaneous Localization and Mapping). The algorithm proposed in this paper was verified on the ”Wuling Electric Vehicle” platform. The experimental results were showed that the proposed algorithm could effectively avoid the influence caused by signal weakening, which improved the positioning accuracy. It also had stronger robustness and better tracking performance.

1. Introduction
With the development of the computer, artificial intelligence, and related technologies, mobile robots have been widely used in industrial manufacturing, aerospace, transportation, military, medical treatment, and many other aspects [1]. In the research of mobile robots, the realization of reliable and stable autonomous positioning is one of the key technologies for the robot to realize intelligent and fully autonomous work, which is a hot spot in robot research. Positioning technology is widely used in various fields, such as collection, navigation, and position in life, aircraft and missile positioning in military applications, ship position in navigation, etc. GPS (Global Positioning System) is used to complete the positioning method [2].

In terms of positioning technology under a specific environment, due to the relatively structured indoor environment and prominent environmental characteristics, SLAM technology based on two-dimensional laser has been widely adopted and widely used. However, the outdoor scene is complex and changeable, so the technology cannot be applied to the outdoor environment. In the outdoor environment, all kinds of mobile robots, such as intelligent cars, mainly adopt GPS for accurate positioning, while vision and laser radar are used for obstacle avoidance. GPS sensor positioning based on satellite has the advantages of simple, stable, and high precision. However, in the outdoor environment, heavy shielding or electronic interference GPS signal is easy to be affected, which cannot be guaranteed positioning accuracy [3].

With computer vision technology development, visual odometer began to appear, usually based on image feature matching to achieve accurate positioning [4]. The existing visual odometer, such as MSCKF and ORB-SLAM2, has high positioning accuracy under certain conditions, and the error rate
can be controlled within 2%-3%. Many scholars at home and abroad have conducted extensive research on the comparative positioning method based on a visual odometer. However, the visual odometer has a high computational cost, is sensitive to camera parameters, and has low robustness in some scenes, such as weak texture scene, motion blur scene, and lighting change scene. LOAM is a current laser odometer based on point cloud features, which has good positioning accuracy and robustness. However, the method based on feature points is easy to fail in scenes where some feature points are not apparent [5]. Some other scholars, based on ICP and its improved algorithm which based on three-dimensional laser relative positioning [6], find the corresponding relationship between two point clouds through a point, and the ICP algorithm aligns the two groups of point clouds repeatedly until the stop condition is met. Therefore the ICP density larger point cloud registration problems computational complexity, and the estimate of the point of dependence is extreme, and the robustness is not high.

The mobile robot's localization problem is actually to find out the current position of the mobile robot on the map. SLAM technology can realize navigation and positioning without mapping. However, it is challenging to realize the SLAM of mobile robots truly. Recently, pure SLAM can not meet the requirements of accuracy and reliability for autonomous positioning. It is challenging to realize online mapping and positioning of mobile robots in current research [7]. Therefore, it is more realistic and straightforward to locate mobile robots based on having a high-precision map. In this paper, the NDT algorithm is applied based on the existing high-precision map and real-time measurement data of lidar, which can complete the robot's precise positioning in the unstructured outdoor environment without relying on GPS positioning information.

2. Theory

2.1. Real-time construction of point cloud maps for specific large scenes

The mobile robot can freely explore the surrounding environment like human beings, so it needs to know where it is and understand the appearance of the surrounding environment, which requires the robot to locate and map itself [8]. This article uses the LIO-SAM algorithm to realize the construction of mass point cloud maps. It is known that LIO-SAM algorithm is a using laser radar real-time attitude estimation and mapping method through the calculating point in its roughness to extract the characteristics of the local area. It is used to choose high edge roughness value point as characteristics, point as plane characteristics of lower roughness, matching the edge, and features complete registration [9].

The specific process of LIO-SAM is as follows:

1) Projecting a point cloud into a depth map is used to break up, which needs to correct point cloud data. SAM is based on the assumption of uniform motion, and the actual laser sensor in motion at a constant speed is not necessary. Therefore, it is used IMU (Inertial Measurement Unit) unless the error is caused by uniform motion part to meet the assumption of uniform motion.

2) Feature points extraction. There are two kinds of feature points extracted from SAM, namely Edge Point and Planar Point. The maximum curvature is Edge Point, and the minimum curvature is Planar Point. The specific curvature calculation formula is as follows:

\[
c = \frac{1}{|S|} \left| \sum_{i,j} \left( X^L_{(i,j)} - X^L_{(i,j)} \right) \right|
\]

Five points are selected to the left and right of the current point for calculation, respectively.

3) After calculating the curvature, the feature points can be selected, but we need to remove some unreliable points before selecting the feature points. Unreliable points can be divided into two kinds: one is the point that is close to parallel with the laser line, and the other is the point that the laser line may block. These two kinds of points cannot be guaranteed to be seen in the next frame of data, which cannot be matched and need to be removed. Firstly, the depth difference between two adjacent points is
calculated, and the side with a more considerable depth difference may occlude. Then, the angle difference between the two points is calculated. If the angle difference is less than the set threshold, it is considered that occlusion may occur. Five points on the side where this happens need to be removed.

4) Use the lidar odometer to match the current frame with the previous frame to obtain the odometer data. Matching here includes time synchronization of laser frames and point cloud matching. Since a laser frame takes a long time, the laser point cloud data will undergo drastic changes due to the laser’s movement in a scanning interval, so the two frames of the laser before and after should be converted to the same time.

5) The current frame is matched with the sub-map to obtain more accurate mileage information and update the map through radar mapping.

6) The final attitude estimation is obtained by integrating the attitude estimation from the lidar odometer and radar mapping with the integration module.

The specific process of the LIO-SAM algorithm is shown in Fig. 1:

2.2. VoxelGrid down-sampling method and filtering function

The computational complexity of the NDT algorithm is positively correlated with two factors: the input point cloud's density and the deviation of the initial attitude estimation. The denser the input point cloud, the greater the computational complexity required for NDT registration. The worse the initial attitude estimation is (the more it deviates from the real attitude), the greater the corresponding computational complexity will be, and the NDT cannot even converge in the case of too low initial attitude. Autonomous positioning has high requirements for real-time performance, and the less time it takes for point cloud registration, the better. Therefore, the input point cloud can be de-sampled to improve NDT registration speed, and the VoxelGrid de-sampled method can be used to reduce the density of the input point cloud.

The downsampling principle of VoxelGrid implemented by PCL (Point Cloud Library) is to create a series of three-dimensional voxel grids through input point cloud data, which is similar to collecting a
small three-dimensional cube in space. In each voxel, the barycenter of all points in the VoxelGrid is used to display other points in the voxel approximately\(^\text{[10]}\). The specific process is as follows:

1) According to the coordinate set of point cloud data, the maximum values \(x_{\text{max}}, y_{\text{max}}, z_{\text{max}}\) and the minimum values \(x_{\text{min}}, y_{\text{min}}, z_{\text{min}}\) on the three coordinate axes of X, Y, and Z are obtained.

2) Side lengths \(l_x, l_y, l_z\) of the point cloud minimum bounding box are obtained according to the maximum and minimum values on the three coordinate axes X, Y, and Z, as shown in Formula (2):

\[
\begin{align*}
    l_x &= x_{\text{max}} - x_{\text{min}} \\
    l_y &= y_{\text{max}} - y_{\text{min}} \\
    l_z &= z_{\text{max}} - z_{\text{min}}
\end{align*}
\]  

(2)

3) The voxel small grid's side length cell is set, and the three coordinate axes X, Y, and Z are equally divided into M, N, and L parts. Then the minimum bounding box is divided into \(M \times N \times L\) voxel small grid, as shown in Equations (3) and (4):

\[
\begin{align*}
    \text{sum} &= M \times N \times L \\
    M &= \left\lfloor \frac{l_x}{\text{cell}} \right\rfloor \\
    N &= \left\lfloor \frac{l_y}{\text{cell}} \right\rfloor \\
    L &= \left\lfloor \frac{l_z}{\text{cell}} \right\rfloor
\end{align*}
\]  

(3)

(4)

4) Among them, the \(\left\lfloor \right\rfloor\) said integer down, the total number of voxel small grid.

5) The small grid number of each voxel is (i, j, k). Determine the small voxel grid to which each data point belongs, as shown in Equation (5):

\[
\begin{align*}
    i &= \left\lfloor \frac{(x-x_{\text{min}})}{\text{cell}} \right\rfloor \\
    j &= \left\lfloor \frac{(y-y_{\text{min}})}{\text{cell}} \right\rfloor \\
    k &= \left\lfloor \frac{(z-z_{\text{min}})}{\text{cell}} \right\rfloor
\end{align*}
\]  

(5)

6) Point cloud streamlining. The center of gravity of each small voxel grid is calculated, and the center of gravity replaces all points in the small grid. If the center of gravity does not exist, the data point closest to the gravity center in the small grid is used to replace all small grid points. Thus, the whole simplification process is completed, as shown in Formula (6):

\[
c_{i,j,k} = \frac{1}{k} \sum_{i=1}^{k} p_i
\]  

(6)

Where \(c_{i,j,k}\), \(p_i\), \(k\) is the center of gravity, data points, and points of the small voxel grid.

Flowchart of Voxel Grid down-sampling method is shown in Fig. 2:
2.3. **High precision positioning based on NDT registration algorithm**

NDT algorithm is a registration algorithm applied to the statistical model of multi-dimensional points. The surface is represented by a set of local probability density functions, which describes a portion of the surface. When using NDT for scan timing, the goal is to find the current scan location to maximize the likelihood that the current scan point is on the reference scan surface. The optimized parameters are the attitude estimation of the current scan, including the rotation matrix and translation matrix. The best attitude estimation is to maximize the likelihood function and correspondingly minimize the probability of its negative logarithm function. In the registration process, the algorithm does not use the corresponding point features to calculate and match, so the time is faster than other methods, which improves the algorithm's running efficiency. For point clouds with different resolutions, the registration effect is also good.

The basic idea of the NDT algorithm is not to compare the difference between two-point clouds and point clouds, but to convert the reference point cloud (high-precision map) into the normal distribution of multi-dimensional variables. If the transformation parameters can make the two-laser data match well, then the probability density of the reference frame's transformation point will be large. Therefore, the optimization method can be used to calculate the transformation parameter that maximizes the sum of the probability density, and then the two laser-point cloud data will match best\(^{[11]}\).

The specific process of the NDT registration algorithm is shown in Fig. 3:
Fig. 3 Flowchart of the NDT registration algorithm

The NDT algorithm can meet the requirement of precision for autonomous positioning of mobile robots and meet the requirement of real-time for autonomous positioning because of its short computation time.

3. Experimental results and analysis

3.1. Introduction to the experimental platform
The framework proposed in this paper is validated using data sets collected from ouster lidar. Take "Wuling Electric Vehicle" as the experimental platform, as shown in Fig. 4. Data acquisition and testing were carried out on the vehicle. The ouster lidar was fixed on the vehicle's front, and the IMU was fixed on the vehicle. The differential GPS antenna was fixed on the roof. Data collection was carried out at night when there were few people and vehicles to avoid the interference of dynamic objects on the algorithm. The vehicle speed was kept at about 20km/h, and multiple groups of data were collected.

Fig. 4 Experimental platform -- Wuling electric vehicle
The experimental environment was selected in an industrial park with uneven distribution of tall buildings and trees and weak GPS signals. The unmanned car's driving route is about 800 meters, and its starting point and endpoint form a closed. This environment can better test the performance of the algorithm for the loop return.

3.2. Large scene positioning and composition experiments

The traditional GPS positioning system consists of three parts: space satellite, ground monitoring, and user reception \[13\]. The monitoring station on the ground is responsible for observing each satellite and provides the observation data to the master control station. After receiving the data, the master control station calculates each satellite's precise position at every moment and transmits it to the satellite through the injection station. The satellite then transmits the data to the ground via radio waves to the user's receiving device. Through this operational mode, the GPS positioning system can help the car accurately locate the current position, calculate the journey according to the established destination, and guide the car to the destination through the map and other ways.

Laser, IMU, and differential GPS data are collected to ensure that the vehicle is driving in a closed-loop so that the algorithm can complete the closed-loop detection of the corrected cumulative error. LIO-SAM algorithm is used to fuse the collected data of lidar, IMU, and differential GPS, and the point cloud map is constructed. The construction process of the point cloud map is shown in Fig. 5.

![Fig. 5 The construction process of point cloud map](image)

In the process of map construction, the experimental platform collects laser, IMU, and differential GPS data, combines the lidar information and IMU information, uses the NDT algorithm to locate the vehicle, and obtains high-precision pose information. Fig. 6 presents the positioning trajectory of the NDT algorithm corresponding to Fig. 5. As shown from the Fig. 5, the experimental platform car drives smoothly, and the error is always small and stable in the pose estimation process. Therefore, the overall performance of the NDT algorithm in locating the trajectory is good.

![Fig. 6 NDT algorithm localization trajectory](image)

When the mapping is built for SLAM, registration between two frames is carried out with the starting point as the origin of coordinates to transform the new point cloud into the local coordinate system and realize incremental map creation \[12\]. The established point cloud map is shown in Fig. 7.
Fig. 7 Point cloud map of an industrial park

To verify the superiority of the algorithm, the value of differential GPS is taken as the control value in the same scene. The positioning result is compared with the GPS trajectory. The value of differential GPS was taken as the control value, and the positioning result was compared with the GPS trajectory, as shown in Fig. 8.

Fig. 8 Comparison of NDT algorithm and GPS location trajectory

It can be seen from the above Fig 8, compared with the traditional GPS positioning trajectory, the trajectory of the NDT algorithm is more stable under the steering condition of the experimental platform car. According to the calculation, the NDT algorithm's horizontal error and rotation error have been kept in a small range. The GPS method has a larger jump. The high precision pose estimation based on the NDT algorithm shows good performance, and the positioning trajectory with high accuracy can be obtained.

4. Conclusion

To solve the problem of low precision in large-scale simultaneous localization and mapping when GPS signals are weak, a high-precision localization method based on laser point cloud NDT is proposed in this paper is applied to complete the SLAM framework for experiment and analysis. LIO-Sam is used to build the map of the collected data, and the point cloud map with high precision can be obtained. On the basis of the map, the point cloud registration algorithm of the NDT is used to realize the autonomous positioning. By comparing the location trajectory with the GPS trajectory, it can be determined that the NDT algorithm can achieve accurate positioning in the absence of GPS signals, thus solving the autonomous positioning of mobile robots in the absence of GPS signals. Using the physical platform for data acquisition, algorithm verification, and error analysis successfully proved that the system could successfully complete the positioning and navigation tasks without GPS signals and achieve the expected goals.

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