Research on mapping technology of laser navigation robot without reflector

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Abstract. In view of the problems existing in the construction of large sparse environment map for laser navigation robot without reflector, an incremental SLAM algorithm based on multistage ICP matching is proposed. This method constructs a new image according to the pose of the robot, and develops a regional closed-loop algorithm combined with incremental optimization method based on the graph optimization algorithm. Experimental results show that due to the low amount of environmental information, the algorithm can effectively avoid falling into local minima, eliminate the cumulative error of mapping, reduce the computational complexity, and realize accurate mapping and real-time application.

1. Introduction

In recent years, the technology of simultaneous localization and mapping (SLAM) based on 3D LIDAR sensor has become an important topic in the field of robot. The establishment of map is the basis for autonomous mobile robot to complete detection, autonomous navigation and other tasks in harsh environment.

Although SLAM has been deeply studied, there are still many problems to be solved, including the computational complexity after increasing from two-dimensional to three-dimensional[1]; how to ensure the consistency of the map in sparse environment and make reliable data association with less information[2]. This paper aims to solve the following two problems:

(1) In sparse environment, the scarce environmental information and uneven road sensed by 3D LIDAR sensor easily lead to data association falling into local minimum. In particular, when the robot returns to the region it has previously explored, it cannot obtain a reasonable attitude estimation, resulting in inconsistent maps.

(2) In large-scale environment, with the expansion of robot trajectory and the expansion of pose from 3-DOF to 6-DOF, how to ensure the robustness of data association and reduce the computational complexity of graphic optimization.

In order to solve these problems, we propose an incremental SLAM algorithm based on multistage ICP matching method.
2. Problem analysis

In large-scale outdoor environment, it is more complex to create environment map with laser ranging sensor than indoor environment. Generally speaking, the outdoor environment has a large range and few features, and the sensor can perceive limited information. 3D laser SLAM technology usually uses point cloud map as the storage format. On the one hand, with the expansion of the scene range, point cloud map will inevitably lead to a surge in memory, so it is necessary to find a more suitable data structure; on the other hand, when the robot returns to the previous place after a long path, the cumulative error of data association is inevitable. Inconsistent maps, as shown in Figure 1, are estimated by the loam algorithm by extracting feature points in the scene. However, with the increase of map capacity, it is difficult to build a closed-loop map. From the diagram, we can see that in the red circle, when the map is closed-loop detected and updated, the map has obvious deformation and cannot be closed effectively.

![Figure 1. Map without closed loop optimization](image)

3. Methods of resolution

This algorithm divides slam into front-end and back-end, and proposes a robust matching algorithm from coarse to fine for the front-end data association problem, which can generate scene map with high consistency even without back-end optimization. The back-end includes Closed-loop Detection and incremental optimization process, in which a good solution is given for the effectiveness of the mapping.

3.1. Matching algorithm

By using the coarse to fine matching algorithm, the current map is matched with the global map to generate more accurate robot pose. In coarse matching, generalized ICP (an ICP variant of plane to plane) is used to improve the robustness and accuracy of inter frame matching (with wheel odometer as initial value). There are several variations of ICP generalized based on ICP matching, the matching accuracy of generalized ICP is the highest.

![Figure 2. Variation of ICP with different matching methods](image)
The fine matching process considers the following situations

![Figure 3. Matching process between current frame and map](image)

Among them, $\mathcal{Q}_k$ is the point cloud map established at k time, $\mathcal{Q}_{k+1}$ is the current frame converted to the world coordinate system at $k + 1$ time, $T_k^w$ is the pose of the robot in the world coordinate system at k time, and $T_{k+1}^w$ is the pose increment of the robot at $k + 1$ time (that is, the output in the coarse matching process in the previous step). As shown in the figure above, it is obvious that there is a deviation between the robot pose generated by rough matching and the real pose, which shows that $\mathcal{Q}_k$ and $\mathcal{Q}_{k+1}$ do not coincide. The precise matching steps are as follows:

1. Describe $\mathcal{Q}_k$ by k-d tree, find the nearest point in $\mathcal{Q}_k$ for each laser point in $\mathcal{Q}_{k+1}$ (FLANN algorithm), and establish pairing;
2. Establish a nonlinear equation, to minimize the distance between all pairs;
3. Use L-M method is to solve nonlinear optimization problems $T_{opt} = (R, t)$;
4. Then the pose of the robot at $k + 1$ is $T_{k+1}^w = T_{k+1}^L \cdot T_{opt}^w$.

3.2. Building maps

The incremental optimization method is adopted to construct a new image according to the robot's position and posture; the new computer posture and map are calculated by acquiring the position and posture of the robot at the previous time, the control quantity and the observation quantity at the current time\cite{5}.

The pose of the robot at time $t$ is $x_t$, the sensor observation is $z_t$, the control quantity is $u_t$, if $x_{it} = \{x_{it}, \cdots, x_{iT}\}$ is the trajectory of the robot from the beginning to the time $t$, the SLAM problem is equivalent to posterior probability estimation distribution $P(x_t, m|x_{it}, u_{it-1})$, where $m$ is the environment map.

$$
\begin{align*}
P & (x_{iz}, m|z_{iz}, u_{iz-1}) \\
& = P(m|z_{iz}, x_{iz}, u_{iz-1}) P(x_{iz}|z_{iz}, u_{iz-1}) \\
& = P(m|z_{iz}, x_{iz}) P(x_{iz}|z_{iz}, u_{iz-1})
\end{align*}
$$

(1)

It can be seen from formula (1), the map $m$ depends on the trajectory of the robot and the corresponding sensor observation, then SLAM can be simplified as the problem of robot trajectory estimation:

$$
P(x_{iz}|z_{iz}, u_{iz-1}) = P(x_0) \prod_{i=1}^{t} P(x_i|x_{i-1}, u_{i-1}) \prod_{j=1}^{i} P(z_{ij}|x_j)
$$

(2)

The SLAM method based on pose graph does not directly obtain $P(x_{iz}, m|z_{iz}, u_{iz-1})$, only the maximum likelihood is obtained
Generally, assuming that the noise of kinematic model and observation model satisfies Gaussian distribution, the kinematic model and observation model can be transformed into the following form:

$$x_j - N(x_i \oplus T_y, \Sigma_y)$$

Among them, the $\oplus$ operation represents coordinate transformation. The relative relationship and covariance between $T_{ij}$ and $\Sigma_{ij}$ are $x_i$ and $x_j$ respectively, and can be obtained by the above matching algorithm. In the case of two dimensions, $x = (x, y, \theta)^T$ Then $T$ can be expressed as $(x_T, y_T, \theta_T)^T$, than the concrete form of $\oplus$ operation can be expressed as:

$$x \oplus T = \begin{pmatrix}
  x + x_T \cos(\theta) - y_T \sin(\theta) \\
  y + x_T \sin(\theta) + y_T \cos(\theta) \\
  \theta + \theta_T
\end{pmatrix}$$

Thus, formula (3) can be written as:

$$x_{ij} = \arg\min_{x_i} \sum_{(i,j) \in C} \|x_i \oplus T_{ij} - x_j\|^2$$

Let $f_j(x_i) = x_i \oplus T_y$, which is a nonlinear function. In order to facilitate processing, we need to linearize it:

$$f_j(x_i) = F_j \delta x_i + f_j(x_i^0)$$

Where $F_j = \frac{\partial f_j(x_i)}{\partial x_i}$ is the Jacobian matrix of $f_j(x_i)$. Let $H_y = \Sigma_y^{-\frac{1}{2}}$, formula (6) is simplified:

$$\delta x_{ij} = \arg\min_{x_i} \sum_{(i,j) \in C} \|H_y F_j \delta x_i - H_y f_j(x_i^0) + H_y x_{ij}^0 + H_y f_j(x_i^0)\|^2$$

Record as $X = (\delta x_1^T, \delta x_2^T, \cdots, \delta x_i^T)^T$, the general form is:

$$X^* = \arg\min_{X} \|Q(R \ 0)^T X + (b_1 \ b_2)^T\|^2$$

$$= \min_{X} \|Q(R \ 0)^T X + (b_1 \ b_2)^T\|^2$$

$$= R^T Q^T b_2$$

Among them, $Q(R \ 0)^T$ is the QR decomposition of $A$. In this project, the incremental method is used for QR decomposition. Since $a$ does not change much in each iteration, the givens rotation matrix of QR decomposition at the previous time can be used as the initial value of iteration. At this time, QR decomposition is incremental, and the upper triangular matrix inversion is less complex, so this method can meet the real-time application.

### 3.3. Algorithm implementation

In order to reduce the complexity of the algorithm, online slam process is implemented. The global closed-loop detection algorithm is not adopted, but the key frames adjacent to the current frame in a
certain region are used for Closed-loop Detection (as shown in Fig. 4 and Fig. 5)[6]. The algorithm steps are as follows:

4. Experimental test
To verify the effectiveness of the algorithm, a mobile robot is used to scan the environment and build a map in a large-scale and sparse substation, as shown in Figure 6. The robot is equipped with a 3D LIDAR rs-lidar-16 with a measurement distance of 150m, a measurement accuracy of 2cm, a vertical scanning range of -15 degrees to 15 degrees, and a horizontal scanning range of 360 degrees. It continuously scans the surrounding environment at a frame rate of 10 Hz and a speed of 300000 points per second.

4.1. Algorithm accuracy test
In order to test the accuracy of mapping, loam (LIDAR odometry and mapping) algorithm was compared with generalized ICP algorithm. In the experiment, the robot runs along a 10m long straight line on a flat road at a speed of 0.6m/s.

Table 1 shows the positioning error measured by loam and generalized ICP algorithm in Figure 6 substation environment. It can be seen that the generalized ICP algorithm is more accurate. If there is a closed-loop region in the robot's path, the generalized ICP algorithm is better than the loam algorithm.

| Algorithm       | Trans.Error(m) |
|-----------------|----------------|
| LOAM            | 0.064±0.057    |
| Generalized-ICP | 0.052±0.043    |

Figure 4. Global map update
Figure 5. Local map update

Figure 6. Substation with large scale and sparse environment
4.2. Mapping results
In the substation environment, the robot travels at a speed of 0.6 m / s for about 600 m, and a total of 10080 frames of images are collected by 3D lidar sensor. The plan and environment of the substation are shown in Figure 7. The red line represents the trajectory ABCDA of the robot. Figure 8 shows the point cloud map established by generalized ICP algorithm and loam.

Compared with loam, generalized ICP algorithm has higher map consistency. Due to the existence of cumulative error, when the robot moves from area along the red trajectory shown in Figure 7, and then returns to area a, the estimated attitude deviation is large. At this time, loam cannot effectively process data association, resulting in wrong Association and destroying the established map. The generalized ICP matching method generates a reliable constraint condition between the two attitudes, and uses the incremental optimization method to optimize the global attitude\cite{7}, so the final map has high consistency.

| Rot.Error(deg) |       |
|---------------|-------|
| 1.8±1.2       | 1.6±1.4 |

Figure 7. Route and environment of substation

Figure 8. Point cloud map established by generalized ICP (a) and loam (b) algorithms

5. Conclusion
For large sparse environments, this paper proposes an incremental SLAM algorithm based on multistage ICP matching, which simplifies the SLAM problem to the least square optimization problem. The multistage ICP matching method is used to obtain the attitude constraints, and the Fisher information is used to estimate the uncertainty matrix. Experimental results show that the algorithm...
can effectively avoid falling into local minimum due to the low amount of environmental information. In addition, multistage matching and incremental optimization can reduce the computational complexity and realize accurate mapping and real-time application.

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