Research on SLAM of Large-scale Space Point Cloud Topological Robot

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Abstract: This paper focuses on the cutting-edge and difficult issues in the field of navigation and positioning of service robots. By exploring the technical approach to practical service robot environment modeling and positioning, a new topology SLAM method is proposed. This paper focus on the key technologies involved in 3D SLAM of robots based on large-scale spatial point clouds, including back-end optimization and closed-loop, high-precision sensor calibration technology. Further propose topological map construction strategies, and focus on designing map-generating algorithms based on graphs or tree structures. The research results will provide innovative ideas and practical solutions for environmental modeling and navigation control of service robots, and strongly support technological advances in related research fields based on three-dimensional environmental perception.

1. Introduction
In the mobile robot navigation system, due to the constant changes of the dynamic environment, the limitation of the measurement accuracy of the sensors, and the errors in theoretical modeling, the positioning and mapping errors during the SLAM process cannot be completely eliminated, and to some extent over time Has a cumulative trend. In recent years, front-end optimization methods have matured. Therefore, it is necessary to conduct in-depth research on back-end optimization to improve the accuracy of SLAM state estimation[1].

The purpose of modeling the robot environment is to plan and control the subsequent paths. The metric environment map is more intuitive, but it is not suitable for path planning and has a high storage cost[2]. Topological map is a compact environment representation method, which usually represents the connectivity of an environment in the form of a graph structure, thus greatly reducing the severe dependence of environment modeling on computer storage and computing resources[3]. How to build a concise and effective environmental topology model to better serve the path planning of robots is an urgent problem.

2. SLAM Front-end and Back-end Optimization
In the field of mobile robot navigation, although environmental modeling methods such as topological maps and emerging semantic maps have demonstrated incomparable superiority at a higher level, they still rely on the basic environment description of metric maps at the bottom[4]. For relatively complicated tasks, the robot must inevitably complete the modeling of the three-dimensional environment[5]. Laser radar based simultaneous localization and mapping (SLAM) technology provides...
an effective solution for creating a globally consistent environment map, but it is limited to two-dimensional maps and is difficult to handle more complex robot tasks.

In order to build an accurate three-dimensional metric map, a feasible method is to use two-degree-of-freedom lidar to collect 3D environmental data, and realize the full estimation of the robot's 6 DOF pose through the registration between real-time laser point cloud data and the established map. Create a 3D environment map in the SLAM framework. The laser-based method has the significant advantage of high accuracy, but lacks the necessary textures, making subsequent recognition processes based on grayscale textures limited; and 3D lidar sensors require higher development costs. In recent years, the rapid development of machine vision technology has created sufficient technical conditions for this, but the measurement accuracy and noise level of the vision system have largely restricted the improvement of 3D map performance[6].

The mainstream method for 3D point cloud spatial registration is still the iterative closest point algorithm. If the two point cloud data have at least partially overlapping common space parts, an optimal solution that meets the conditions can be found through an iterative optimization process. Besl et al. Gave the convergence theorem of the ICP algorithm: For the objective function of the mean square distance, the ICP algorithm always monotonically converges to a local minimum. Nuchter et al. Applied it to the matching of 3D lidar data, and some scholars applied it to reverse engineering.

The Levenberg-Marquart method is a n improvement on the first-order Newton iterative algorithm, and its main purpose is to provide a fast-convergent regularization method for large parameterized problems[7]. This method can be regarded as a combination of the first-order Newton iterative method and the steepest descent method, and some scholars have applied this nonlinear optimization process to the ICP algorithm. Back-end optimization includes cluster adjustment, Bayesian networks, and graph optimization.

The use of a new type of active depth-sensing sensor to implement the robot's environment modeling and navigation is an effective technical approach. However, in the domestic and foreign scientific and technological literature, there have been no reports of successful implementation of ADMS-based robot SLAM. The fundamental reason is that it is restricted by technical factors such as sensor calibration methods and point cloud matching efficiency, especially the lagging research on the calibration methods suitable for it, which makes ADMS technology with wide application value not yet successfully applied in the field of robot SLAM.

3. Closed-loop Detection Method Based on Random Ferns

Study the 3D SLAM back-end optimization method and reliable closed-loop detection method based on factor graph to improve the uniform convergence of the metric map. The front-end links of SLAM, such as point cloud matching, have become more and more mature in academia and industry in recent years[8]. From the perspective of back-end optimization, this article improves the accuracy of SLAM state estimation and improves the consistency of the map. The factor graph is an undirected graph evolved from the Dynamic Bayes Network (DBN). Unlike the Bayesian network, the variable nodes in the factor graph correspond to the parts to be optimized in SLAM. That is, the pose and map of the robot, and the observation and control quantities are used as factor nodes. The incremental factor map efficient optimization method and the random fern-based closed-loop detection method are adopted to improve the uniform convergence of the metric map.
In order to effectively identify the areas that have reached the area and complete the final global closed-loop, random ferns are used to achieve closed-loop matching, that is, the random fern model is used in the optimized camera pose model, and the incremental metric map is based on this Perform overall optimization to improve the consistency of the maps you build[9].

At the front end, feature points and matching relationships are obtained by performing SIFT feature detection and matching on the image, and mismatched points are eliminated using the RANSAC algorithm, and then three-dimensional corresponding feature points are obtained from the mapping relationship, and the mismatched points are further eliminated using the voting method. Then the initial relative position and attitude relationship of the point cloud was obtained by the quaternion method, and the ICP algorithm based on improved kd-tree search was used to achieve accurate registration.

Because the discrete poses of the robots in SLAM are sparse, the state estimation problem can represent the numerical relationship between the estimated quantities in the form of a factor graph at the back end, that is, the product of the probability distribution of multiple factors is used to estimate the joint probability distribution. If the estimated state quantity (ie, the position and attitude of the robot) is expressed as $X = \{xk\}$ and the constraint between the factors is expressed as $U = \{uk ukj\}$, the conditional probability model can be expressed as follows:

$$
P(X|U) = \prod_{k} P(x_k, u_k) \prod_{u} P(x, u|u_j)$$

The maximum posterior optimization result $X^*$ of the robot is the maximum value point of the probability distribution $P(X|U)$, that is:

$$
X^* = \arg \max_{X} P(X|U) = \arg \min_{X} \{- \log P(X|U)\}
$$

$$
= \arg \min_{X} \left\{ \sum_{k} \|f(x_k, u_k) - x_k\|^2 + \sum_{u} \|f(x, u_j|u_j) - x_j\|^2 \right\}
$$

This problem is solved by a non-linear least square method. The loop optimization model is composed of random ferns in the loop optimization model[10]. Random ferns are a classifier with independent features. The core idea is to use image coding to determine the similarity between two frames. In the random fern model, each individual is established based on the correlation between the pixels of the image block where the keypoints are located, and then establishes a relationship between different keypoint regions, so that a feature classifier of spatial relationships between different regions is established.

As shown in Figure 2, the research course progresses layer by layer, interlocking, forming a rigorous and organic whole.
Figure 2. Flow chart of point cloud registration algorithm guided by SIFT

4. Topological Map Architecture combining Graph and Tree
Based on the research of 3D visual metric reconstruction, a more detailed map description inside the topology layer is used to create a topology map architecture combining layered graphs and trees, and the topology node is constructed using the improved B-RRT* algorithm. The generalized room graph structure is extracted at the upper level, and the concept of accessible space tree is introduced at the lower level. Guided by the RRT series of planning algorithms, the currently available passable nodes, that is, the set of candidate sub-target points are selected. Further, in view of the weaknesses and shortcomings of the B-RRT* algorithm in important links such as sampling and expansion, an intelligent
sampling function is introduced instead of the random sampling function in the original algorithm, and the optimal fixed point is sampled between the starting point and the target point as the target point between the two trees, so that the random tree has a certain directional guidance in the expansion and maintenance, thereby avoiding the inefficiency and low precision caused by blind expansion.

Figure 3. Schematic diagram of B-RRT* algorithm

In the process of topological mapping, in order to more effectively explore the environment of the robot, the center point where the robot can reach the farthest passable area is selected as the current possible target point. At the same time, two issues need to be considered logically, namely the deletion of possible target points and the identification of the same possible target point.

5. Parallel Processing Based on Cuda
Due to the large amount of single-frame point cloud data provided by ADMS, the real-time contradiction of online processing is bound to be more prominent, which has become a technical bottleneck restricting its practicality to a certain extent. On the one hand, based on the idea of parallel tracking and mapping, a parallel processing algorithm for robot 3D SLAM is proposed. On the other hand, for functional modules with large computational overhead such as ICP iterative optimization, based on CUDA’s parallel computing technology, on the TX1 or TX2 hardware platform, the parallelization of its algorithm is implemented in the ROS development environment to ensure the entire system operating efficiency[11].

The parallel tracking and mapping ideas are used to separate the camera tracking module from the map generation module, and two independent threads are established during the computer operation, which can achieve parallel visual tracking and map creation, which greatly improves the operation efficiency[12]. CUDA is a potential parallel computing architecture. Based on the powerful computing capabilities of the GPU, a more efficient dense data computing solution is established. In the process of solving the depth map, according to the advanced CUDA technology in computer science, on the TX1 or TX2 hardware platform, the operation speed of the algorithm is increased in parallel.

ROS 2.0 uses a more advanced distributed architecture and entire system, which has higher reliability, real-time performance, and better support for embedded devices. Therefore, this article was developed in the ROS 2.0 environment.

6. Conclusion
This paper proposes a robust, fast, and accurate back-end optimization strategy for service-oriented robot SLAM, and solves the key technologies of efficient robot topology environment modeling based on autonomous metric mapping.

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