Markerless Point Cloud Matching Algorithm Based on 3D Feature Extraction

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Abstract: Since 3D scanners can only scan in a limited range and the scanning process is prone to occlusion and other problems, a complete 3D model cannot be obtained from a point cloud scanning result. Therefore, point cloud matching is necessary for most 3D scanning projects. We propose a point cloud registration algorithm based on a comprehensive approach, and the research contents include a new curvature-based point cloud feature extraction method, a three-dimensional spatial structure classifier of feature points, and an unmarked point cloud-matching algorithm based on three-dimensional feature extraction. The experiments are based on the simulation data and real data to verify the algorithm and evaluate the accuracy. The experimental results show that the matching accuracy reaches the millimetre level, and the fully automated and high-precision label-free point cloud matching based on 3D features is realized, which can provide innovative and breakthrough help for 3D reconstruction.

Keywords: Point cloud feature extraction, feature point classifier, point cloud matching.

Introduction

In the past few decades, 3D scanning technology has developed rapidly, and many methods have been proposed for 3D scanning devices to collect information such as the shape and color of objects. Because the 3D reconstruction information obtained by 3D scanners is more accurate than 2D images, 3D scanning technology is widely used in many fields such as robot navigation, terrain survey, and movie and game creation (Akbar Qureshi et al., 2022). The general data type obtained by the 3D scanner is a point cloud. Through the scanning process, a laser beam is emitted to the surface of the object, and it is reflected back to the laser point containing information such as azimuth and distance. A large number of laser points are aggregated to form point cloud data. With the rapid development of 3D scanning sensors such

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as lidar, the collection speed of point cloud data is faster, the cost is lower, and the data accuracy is higher. The related research on 3D point clouds has become a hot spot (Wang et al., 2022).

Because the 3D scanner can only scan in a limited range and the scanning process is prone to occlusion and other problems, a point cloud scanning result cannot obtain a complete 3D model (Sun et al., 2022). Therefore, it is necessary to perform point cloud registration, that is, by solving the rotation matrix and translation matrix between the point cloud data obtained by scanning, so as to transform the multi-view scanning point cloud into the same coordinate system, and then obtain the complete three-dimensional point of the scanning scene (Suwoyo & Harris Kristanto, 2022). Point cloud registration has a wide range of applications in unmanned driving, robotics, underground mining, and other fields. For example, in the field of unmanned driving, point cloud registration can help the self-driving car to find its own position, and at the same time, it can combine the three-dimensional scene to plan the next route for the self-driving car; in the field of robotics, point cloud registration can be obtained by obtaining the three- dimensional scene as it navigates, or plans a grasping path for the robotic arm by judging its location in real-time; in the field of underground mining, point cloud registration can help engineers survey site conditions in real-time (Delaram et al., 2021; Elias et al., 2023).

To sum up, point cloud registration has become the basis and important technology in various fields, and the point cloud registration algorithm that takes into account high precision and high efficiency has become a research hotspot for many scholars or teams. We propose an unmarked point cloud matching method based on 3D feature extraction (Guo et al., 2023; Suwoyo, Abdurohman, et al., 2022). We need to design a new point cloud feature point extraction algorithm based on curvature feature, feature point 3D spatial structure classifier, and feature point automatic matching algorithm (Du et al., 2023). A series of tasks, such as algorithm design, data acquisition and processing, algorithm verification, and algorithm effect evaluation. Our contributions are as follows:

1. A new curvature-based point cloud feature point extraction method is proposed, which takes into account the extraction accuracy and efficiency.
2. A three-dimensional spatial structure classifier of feature points is proposed, which improves the automation and accuracy of classification.
3. An automatic feature point matching algorithm is proposed, and experimental tests are carried out on the basis of simulation data and real data to achieve millimeter-level accuracy.

The paper is structured as follows. First, we present related work in point cloud registration. In Section 3 we present the proposed matching pipeline. Section 4 presents the methodology of the experiments and the results, and Section 5 concludes the paper and suggests directions for future work.

Research Method

In this paper, a markerless point cloud matching algorithm based on 3D feature extraction is proposed, which first extracts the point cloud features and filters out the feature points. Second, the feature points are classified by using the three-dimensional spatial structure classifier of feature points (Jia-ning, 2022). Thirdly, row point cloud matching is achieved using a markerless point cloud matching algorithm (Shi et al., 2023).

Point cloud feature extraction

The first step is to preprocess the point cloud data: first remove the sparse outliers through the pcdenoise function of Matlab. Then, the variable resolution point cloud simplification method is used to realize voxel division, multi-Skip space construction, and Skip-tree construction (as shown in Fig.1), thereby simplifying the storage access and calculation process of point clouds (Ma et al., 2022).

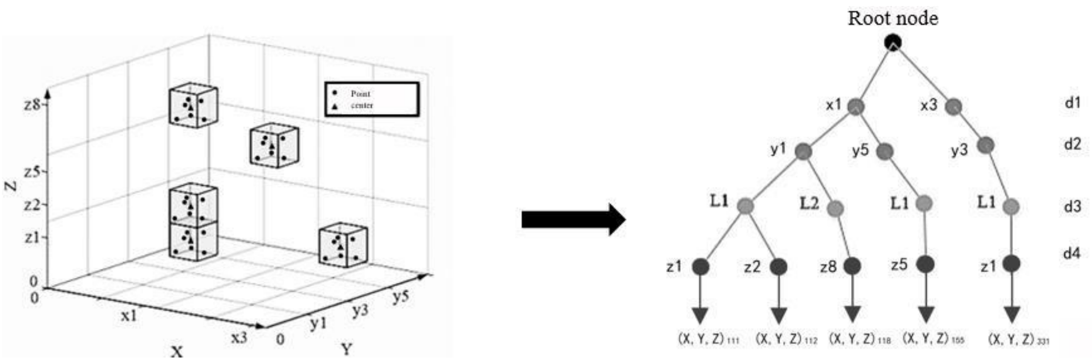

Figure 1 Multi-Skip space and Skip-tree construction

In the second step, the principal component analysis (PCA) method is used to numerically estimate the local curvature of the effective volume elements, and the map composed of the effective voxels and their curvature values is called a Ski-map, as shown in Fig.6. Among them, each point represents the geometric center point of an effective volume element, and the color of the point represents the curvature value. The area with a color closer to dark blue has a smaller curvature value, and the area with a color closer to bright yellow has a larger curvature (Shi et al., 2022; Suwoyo, Hidayat, et al., 2022).

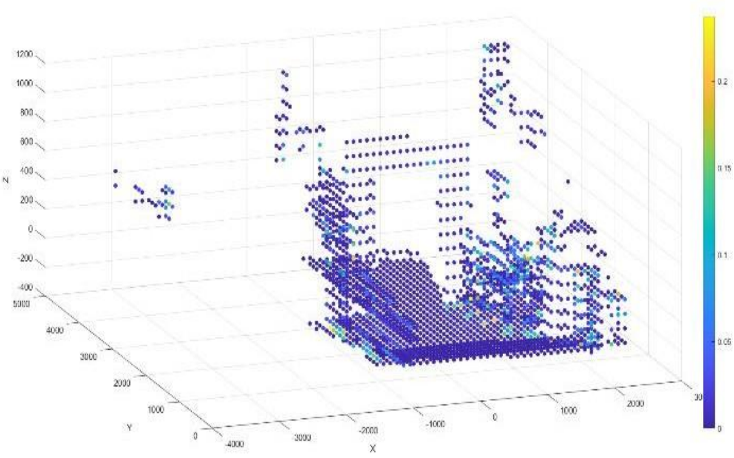

Figure 2 Skip Map

The third step is to carry out feature definition and feature point screening: a new point cloud feature that combines curvature features and the structure of the point cloud. The curvature feature is directly reflected by the curvature value. Specify category semantic labels to reflect. The visualization result of the feature point is shown in Fig.3. The left image is the distribution map of all the point clouds in the effective voxels of the feature point, and the color represents the curvature information; the right image is the structured visualization result of the point cloud. Finally, the screened feature points are divided into five types: first-class corners, second-class corners, other corners, edges, and planes.

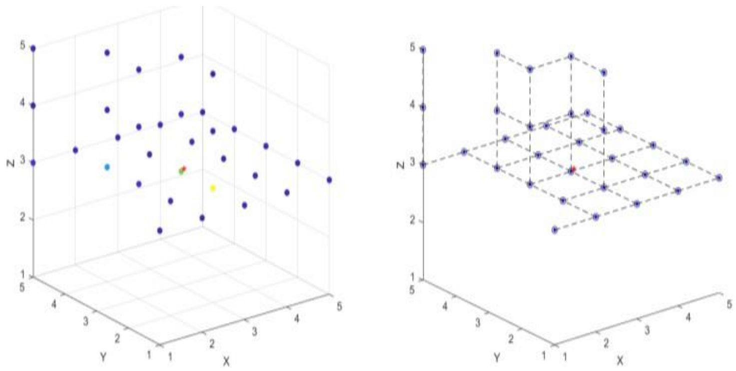

Figure 3 Feature point visualization results

Feature point three-dimensional spatial structure classifier

After the point cloud feature extraction is completed, feature point classification needs to be performed. The manual classification process is cumbersome and time-consuming. Therefore, in order to automate the feature point classification process, a three-dimensional spatial structure classifier of feature points is designed, and the classifier function is realized through network construction, training, performance evaluation, and optimization.

Classifier network construction

Use the Matlab neural network toolbox to build a three-dimensional spatial structure classifier of feature points. The internal structure of the network includes 50 hidden layers and 5 output layers, as shown in Fig.4. The input is all the point cloud data within the valid volume elements, and the output is the categories of valid volume elements, totalling five categories (Zhong et al., 2020).

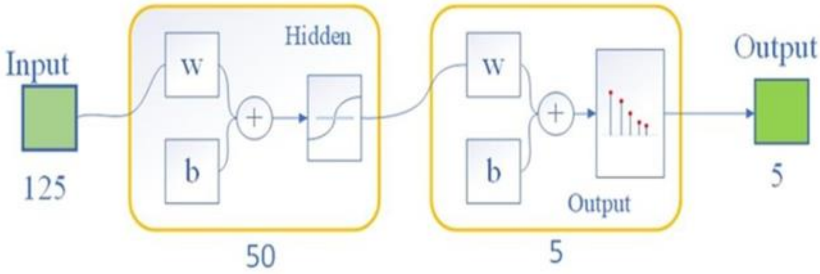

Figure 4 Feature point three-dimensional space structure classifier network structure

Classifier network training

By adjusting the values of connections (weights) between nodes or neurons, a neural network can be trained to perform a specific function so that a specific input produces a specific target output (Guo et al., 2020). 510 sets of training data sets are obtained in the pre-processing, and the point cloud data in voxels is 125 dimensions, so the input is 125 × 510 dimensions, each column represents the point cloud data in a feature point voxel grid; the total number of categories is five, Therefore, the output is 5 × 510 dimensions, and each column represents a category of feature points. The data is divided into three subsets, the proportion of the training set is set to 70%, the proportion of the validation set is set to 15%, and the proportion of the test set is set to 15%. Other specific setting parameters are shown in the following table:

Table1 Network training parameter setting table

Parameter	Defaults	Settings
hiddenSizes	10	50
trainFcn	trainscg	trainscg
trainParam.epochs	1000	1000
trainParam.goal	0.00	1e-11
trainParam.Ir		0.01
divideParam.trainRatio	70/100	70/100
divideParam.valRatio	15/100	15/100
divideParam.testRatio	15/100	15/100

Result and Discussion

After completing the design of the unmarked point cloud matching algorithm based on 3D feature extraction, experimental verification and error analysis are required. The experiment is to compare the unmarked point cloud matching algorithm of the paper, which is first rough and then refined, with the ICP direct registration algorithm, and realize double verification analysis in the simulation and real environment.

Simulation data

We use the software UE4 and the simulation plug-in AirSim to build the simulation scene and simulate the sensor: the simulation scene is built by UE4, and the size is 10m×10m×3m (length×width×height). Three windows plus a wall structure, one side is a structure that simulates two doors plus a wall. In addition, some cubic structures are randomly placed in the simulation scene to simulate indoor cabinets and other objects. The schematic diagram of the simulation scene is shown in Fig.5.

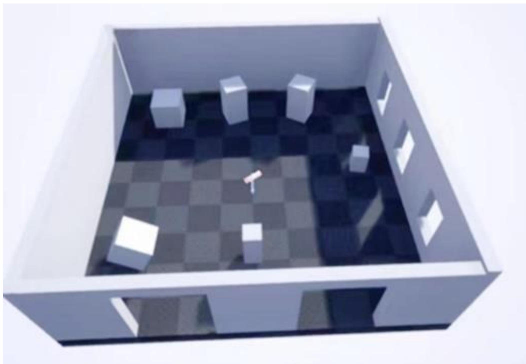

Figure 5 Simulation scene

The laser radar built by simulation is used to scan the simulation scene at fixed points, and two sets of simulation data are obtained by scanning at different positions. The visualization results are shown in Fig.6.

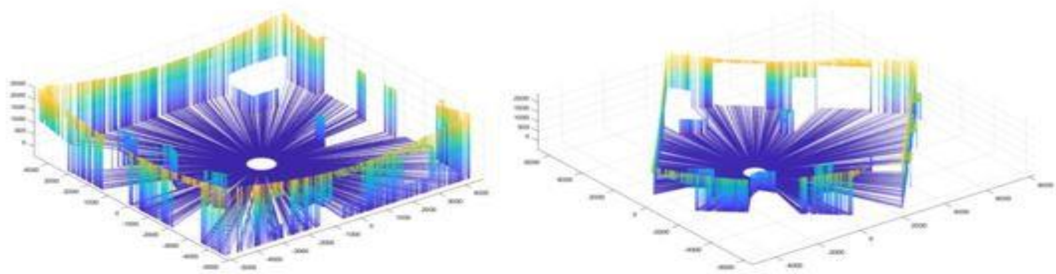

Figure 6 Simulation data visualization results

The scanning center of the first group of simulation data is located in the center of the room, basically scanning the entire simulation scene, but the scanning phenomenon of objects blocking the scanning is obvious, so some walls are missing. The second set of simulation data is based on the first set of scanning position movement and sensor rotation, so that part of the missing data of the first set of point clouds due to occlusion can be obtained. Due to the lack of nodding scanning of the simulated radar, the point clouds near the two sets of data are dense, and the point clouds far away are sparse.

Summary and analysis of real data testing

First, the two sets of simulation data are matched by the algorithm of this paper and directly matched by ICP, and the results are integrated as shown in Fig.27. It can be seen from the visualization results that the matching effect of the algorithm in this paper is significantly better than that of ICP.

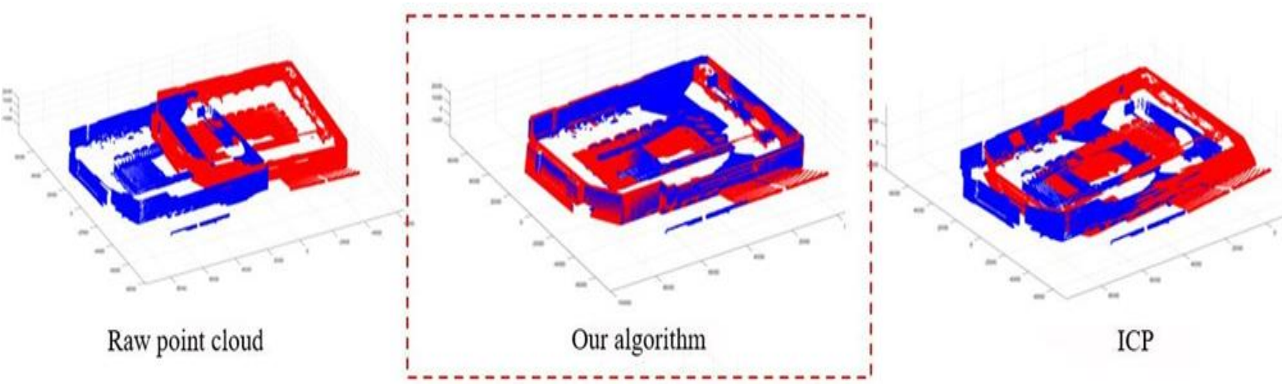

Figure 7 Matching result of real data

Next, compare the time consumption and matching error between the algorithm in this paper and the ICP algorithm in detail, and the integration results are shown in Table4. In order to refine the comparison, the algorithm in this paper is divided into two parts: rough matching and fine matching. From the table, it can be seen that the rough matching link takes 40.42898s in total, mainly because the voxel division and the construction of the variable resolution map take 40.343184s. It takes only 0.085791 s to solve the transformation matrix, and the ICP fine matching time after rough matching is only 8.501487 s, which is greatly reduced compared with direct ICP matching. In addition, from the perspective of the direction error of each axis, the accuracy of rough matching first and then fine matching is significantly improved compared with direct ICP matching.

Table2 Real data matching time-consuming and accuracy comparison

	Time-consuming (s)	X-direction Error (mm)	Y-direction Error (mm)	Z-direction Error (mm)	Average Error (mm)
rough match	**40.42898**	52.767	12.13	63.72	42.872
fine match	**8.501487**	8.943	6.673	10.31	**8.642**
ICP	**665.682670**	1196.863	104.67	606.433	**635.9887**

Conclusions

Based on simulation software and self-designed portable acquisition equipment, this paper studies the 3D point cloud matching algorithm without marker points, and completes a series of works from algorithm design, theoretical analysis, and formula reasoning to data acquisition, algorithm verification, and error analysis. Combining the rough point cloud matching based on 3D features and the fine point cloud matching based on ICP, a point cloud matching algorithm with both high precision and high efficiency is realized. Finally, the algorithm verification and error analysis are carried out through the experiments of two sets of different data in the simulation environment and the real environment, which reflects the robustness of the algorithm. Future work that can be improved includes: further using edge and surface feature points for rough matching, adding an iterative mechanism for obtaining the optimal transformation matrix; increasing the number of experimental verification scenarios, and considering using public datasets for verification.

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