A Review of Research on Point Cloud Registration Methods

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Abstract. The point cloud Registration Method is the Basis for 3D reconstruction and scenes perception. After decades of development, it has been acquired in the fields of reverse engineering, machine vision, CAD/CAM, laser remote sensing, virtual reality, human-computer interaction, and stereo imaging. A wide range of applications. in this paper, the existing registration methods are divided into two types based on the registration process: coarse registration and fine registration. The algorithm principles and processes, and combs the related derivative algorithms. On this basis, the characteristics of various algorithms are compared and analyzed, which provides a reference for selecting suitable algorithms in different scenarios. Finally pointed out the main problems and future research directions.

1. Introduction

With the development of point cloud data acquisition methods and processing capabilities, point cloud data has received more and more attention from researchers in the fields of industrial reverse engineering, SLAM (Simultaneous Localization and Mapping), and surveying and mapping[1]. Different fields have different application requirements for registration algorithms. For example, reverse engineering requires fine product model design. In order to meet industrial design standards, the accuracy of point cloud registration algorithm is higher. Machine vision requires robots to be in an unknown environment. Positioning and composition, in order to meet the needs of the robot to sense the environment in time, so the calculation efficiency of the point cloud registration algorithm is higher; when the map photogrammetry and remote sensing image are collected for large scene data, in order to stably collect accurate information of a large number of data points, Therefore, the registration algorithm is required to be more robust.

Because different fields have different requirements for algorithms, researchers have proposed many different registration algorithms. These algorithms can be classified based on different angles, for example, according to the registration process (or registration accuracy), which can be divided into coarse registration and fine registration [2]. According to the registration feature, the search space can be divided into global registration and local registration. According to the registration primitive, it can be divided into feature registration and featureless registration [3]. According to the registration transformation parameter solution, it is divided into 4]: quaternion method, singular value solution, least squares method, genetic algorithm and so on. According to whether the registration object is
deformed, the registration method is divided into rigid registration and non-rigid registration algorithms [5].

The main systems in this paper summarize the various registration algorithms based on the classification process. Among them, the representative registration methods in the coarse registration class mainly have four-point fast registration method [6], sampling consistency initial registration. Method [7], LORAX registration method [8], normal distribution transformation registration method [9]; representative registration algorithm in fine registration: iterative nearest point method [10], consistency drift point registration Method [11], genetic algorithm registration method [12], DO (Discriminative Optimization) registration method [13]. The algorithm principle and implementation flow are detailed, and the related derivative algorithms are sorted out, which provides convenience for selecting the appropriate registration method in practical work. Finally, this paper summarizes the shortcomings of the existing registration methods and proposes the next research focus of the point cloud registration work.

2. Summary of point cloud registration work

Point cloud registration can be understood as: a perfect coordinate transformation by calculation, and the point cloud data under different viewing angles is uniformly integrated into the specified coordinate system through rigid transformation such as rotational translation. A little more common: two point clouds for registration, which can be completely coincident with each other by rotational translation, etc., so the two point clouds belong to a rigid transformation, that is, the shape size is exactly the same, but the coordinate position is not the same. Point cloud registration is to find the coordinate position transformation relationship between two point clouds.

This section introduces several classical algorithms that are commonly used under the coarse registration and fine matching classification. The principle and process are detailed, and the related derivative algorithms are combed.

2.1. Coarse registration

Point cloud registration is classified into coarse registration and fine registration based on the process. The coarse registration is the initial registration. The main purpose is to get more corresponding point pairs, so that the source point cloud and the target point cloud cluster can overlap in a larger range. Accurate registration is to improve the secondary registration of the coincidence of two points on the basis of coarse registration translation rotation.

2.1.1. 4PCS. In 2008, Dior Arger et al. proposed a four-point fast registration algorithm [6] (4-Point Congruent Sets, 4PCS). The key steps of the algorithm: First, select 3 points in the source point cloud data set to form a plane, in the plane the fourth point is selected according to a specific method, and the four points constitute a standard pair. Then, in the given point cloud data to be searched, find a coplanar four-point pair with approximate affine equals as a candidate point pair. Finally, it is determined whether the candidate coplanar four-point pair and the selected standard coplanar four-point pair can be equal under certain constraints. 4PCS algorithm flow:

1) Selecting a coplanar 4-point pair on the source set;
2) Defining an affine invariant set for a given pair of base points;
3) Determining a transformation matrix and calculating a transformation matrix;
4) Find the transformation matrix according to 3) for different basic point pairs;
5) Find the best transformation matrix according to different transformation matrices.

In order to adapt to different scene applications, the researchers improved the 4PCS algorithm according to the registration characteristics. Some 4PCS derivative algorithms such as S-4PCS [14] in order to solve the shortcomings of 4PCS in the large environment acquisition time, S-4PCS will algorithm Map to "instance issues" and use intelligent index data organization to effectively solve instance problems. The registration algorithm has the advantages of simplicity, high memory efficiency and high speed. K-4PCS [15] proposes key points to refine the point cloud in order to solve.
the problems of low registration area density, large registration scanning angle, low operation and memory efficiency. Point cloud data has high registration accuracy in scenes with obvious geometric features. SK-4PCS [16] proposed to connect feature points with special rules to obtain semantic key points. Improve the registration accuracy and calculation efficiency of K-4PCS. G-4PCS [17], SG-4PCS [18] In order to solve the low efficiency of 4-PCS algorithm, G-4PCS proposed and proved that increasing the separation index can reduce the search space of matching base, and use this property to improve the operation of 4-PCS. Time. The SG-4PCS uses intelligent indexing technology, which reduces the complexity of the 4PCS algorithm and increases the computation time by about 65%.

2.1.2. Sample Consensus registration. The random parameter estimation algorithms similar to the sampling consistency estimation parameter algorithm mainly include: random sampling consistency estimation, maximum natural consistency estimation, minimum median variance consistency estimation, etc. The consistency criterion is applicable to all estimation parameter algorithms [19]. [20] Proposed a RANSAC-based fast image overlay image distance method based on RANSAC (Random sample consensus), which is suitable for noiseless data and featureless data registration. In 2009, Rusu et al. Implement Sample Consistency-Initial alignment (SAC-IA). SAC-IA gives an initial estimated stiffness transformation matrix that provides an initial registration state for more accurate pose estimation algorithms (eg, ICP, etc.) [7]. SAC-IA algorithm steps:

1) Randomly select N sample points from the source point cloud, and the selection rules are set according to the FPFHF (Fast point feature histograms feature, two-point distance);
2) Selecting a point in the target point cloud according to the same set condition to generate a point set M;
3) Randomly selecting one point from M and N as the corresponding point pair;
4) Calculating a rigid transformation matrix between corresponding points;
5) Judging whether the transformation matrix meets the requirements by the judgment condition (distance error and function judgment), and repeating the above process if the transformation matrix does not meet the requirements;
6) If the matrix meets the requirements, the registration is completed.

2.1.3. LORAX. The LORAX is the registration method mentioned in the literature [8] in 2017. This method mainly uses the neural network automatic encoder to complete the registration work. To put it simply, the point cloud is divided into a number of small blocks by a sphere, and each piece is projected into a depth map, and then the depth map is subjected to feature compression using a deep neural network, and finally compressed into a matrix as a feature. Through the location relationship of these feature screening points, the registration can be calculated and the registration work can be completed. LORAX algorithm flow:

1) Set the random ball coverage point set to be set to super point;
2) Selecting a standardized local coordinate system for each super point;
3) Projecting the super point data onto the 2D depth map;
4) Significant detection and super-point filtering;
5) Using a neural network automatic encoder to reduce the size;
6) Finding a candidate matching matrix between the relevant descriptors;
7) Use localized search to complete the registration.

2.1.4. NDT. In 2003, Biber et al first applied the Normal Distribution Transformation (NDT) algorithm to the registration to complete the point cloud registration work. Then researchers continue to improve the algorithm on this basis. For the different scenarios, the main derivative algorithms such as 2D-NDT [21] first proposed normal distribution transformation instead of distance scanning, which can map the unmodified indoor environment reliably and in real time; 3D-NDT [22] introduced the NDT into the three-dimensional space for the first time and verified it using the actual data registration of the mining area. Quantitative qualitative comparison is faster and more reliable than traditional ICP
algorithm; improved 3D-NDT [23] [24] proposed a curvature-based 3D-NDT algorithm to solve the problem of 3D-NDT large number of redundant points, effectively shortening the matching Quasi-time; in order to improve the registration accuracy, the paper proposes a 3D-NDT registration algorithm that combines the improved NARF features; ML-NDT [25] and KL-NDT [26] solve the problem of multi-geometry and fewer matching points. The registration of the data to be registered improves the robustness of the 3D-NDT algorithm and reduces the extra calculations. It solves the problem that the precision in ML-NDT is low and the number of layers is heuristically determined. Table 3 shows: The NDT algorithm is the core of its derived algorithm. The central idea is to construct the normal distribution parameters of multidimensional variables based on the scanned data, and to find the maximum transformation parameters with the sum of the probability densities, and obtain the registration data according to the transformation parameters. 3D-NDT algorithm flow [27]:

1) Setting a normal distribution transformation of the target point cloud;
2) Initializing coordinate transformation parameters;
3) For each sample in the source point cloud, map to the coordinate system in which the target point cloud is located according to the initialized transformation parameters;
4) Calculating a corresponding normal distribution of each mapping point;
5) Evaluating the sum of the probability density distributions of each mapping point as the score value s of each coordinate transformation parameter;
6) Optimize s using the Hessian matrix method;
7) Determine whether the convergence requirement is met. If the completion algorithm is satisfied, turn to 3).

2.2. Fine registration
In order to minimize the errors between point clouds, they need to be accurately registered. The most common registration methods are as follows.

2.2.1. CPD. In 2010, Andriy and Xubo Song proposed the Coherent Point Drift CPD [11]. The CPD algorithm applies the problem of probability density estimation to point cloud registration, and sets the source point cloud to the centroid of the Gaussian mixture model. The target point cloud is the set of data points generated by the source point cloud, and the reset centroid is continuously searched by the posterior probability. The position is matched to the data point set to obtain a transformation matrix. Registration steps:
1) Calculate the points in the source point set and the target point set to obtain the point cloud set M, N;
2) Initialization parameters: transformation parameters, rotation variables, translation vectors, scale parameters;
3) Calculating the posterior probability and the correlation probability matrix;
4) Solving parameters;
5) Judging whether the calculated probability is converged, and repeating the above steps if convergence is performed;
6) apply the solution parameters to the data registration;
7) Complete the registration work.
8) Registration algorithm based on CPD algorithm [28]: Consistent drift point registration algorithm based on projection transformation (P-CPD) solves the problem of low degree of freedom of CPD transformation model and improves the accuracy of CPD algorithm. And robustness; the local feature-based Consistent Drift Point Registration Algorithm (F-CPD) solves the convergence and accuracy of the CPD algorithm, improving accuracy and robustness.

2.2.2. ICP. In 1992, Besl and McKay proposed the Iterative Closest Point (ICP) algorithm. The ICP selects key point data for matching according to a certain geometric characteristic, and sets these matching points to imaginary corresponding points. Then, the motion parameter model is solved
according to this correspondence. Then use these motion parameter models to transform the data, and use the same geometric features to determine the new correspondence. Repeat the above process until the mean square error is less than a certain value, complete the registration parameter determination, and find the transformation [29]. The ICP algorithm flow is divided into the following steps:

1) Take a point cloud of the registration point, and find the closest point in the reference data point to form a corresponding point pair set;
2) calculating a rotational translation transformation matrix according to the nearest point pair set;
3) Applying a transformation matrix to the target point set data;
4) judging whether the point cloud data after applying the matrix transformation meets the requirements;
5) Objective function calculation and threshold judgment, if the requirements are not met, repeat the above steps;
6) If the requirements are met, the registration work is completed.
7) Based on the ICP algorithm, many improved algorithms are continuously derived. The main ICP-derived algorithms such as Point to Line [30] propose an improved ICP algorithm based on point-to-line metric to solve the infinite number of iterations, which improves the registration accuracy and reduces the accuracy. The number of iterations; Point to Plane [31] solves the computational complexity of the registration algorithm and affects the practical application problem. An improved ICP algorithm based on point-to-cut plane is proposed. Point to Projection [32] solves the problem of selecting multiple points in featureless regions. Slow convergence, misregistration or divergence problems, an improved ICP algorithm based on point-to-see-point is proposed to improve the registration accuracy under noise or improper calibration. Plane to Plane [33] is to solve the problem of ICP being susceptible to local minima. An improved Go-ICP algorithm is proposed to ensure the global optimization while speeding up the algorithm and solving the outlier robustness problem.

2.2.3. Discriminative optimization. In 2017, Jayakorn Vongkulbhisal et al. proposed the Discriminative Optimization (DO) algorithm [13] to be applied in point cloud registration. The algorithm is a method of learning the search direction from the data without the need for a cost function. The DO learns in the space, and solves the corresponding problem according to a series of updates of the fixed points. The three-dimensional rotation and translation transformation are completed according to the exponential mapping and logarithmic mapping relationship between Lie group and Lie algebra. The DO algorithm registration steps are as follows:

1) Define an update rule to define a target point set, a source point set, and a feature function set as a training set;
2) training data according to the feature function, so that the target point cloud set in the training set is transformed into a source point set;
3) update the training set and calculate the coincidence degree of the two points;
4) If the requirements are not met, the two points will have a low degree of coincidence and return to execution 2);
5) If the requirements are met, the rotation translation matrix is calculated to complete the registration work.

3. Registration feature summary
In the convergence domain of the registration method, the degree of noise influence, algorithm calculation speed, algorithm robustness, algorithm accuracy, etc., the characteristics of the four coarse registration methods are summarized and summarized in Table 1:

The four coarse registration algorithms are compared in terms of convergence domain, noise impact, running speed and robustness. The 4-PCS algorithm is least affected by noise and is more suitable for point cloud data registration with more noise. The 4-PCS algorithm and the LORAX algorithm run fast, and are more suitable for scenes with a large amount of point cloud data. The 3D-
NDT and LORAX algorithms are more robust and more suitable for environments where the data to be registered is incomplete.

Table 1. Three Scheme comparing.

| Registration method | Convergence domain | Noise effect | Operating speed | Robustness | Accuracy impact |
|---------------------|---------------------|--------------|-----------------|------------|----------------|
| 4-PCS               | /                   | small        | express         | general    | Point-to-point threshold |
| SAC-IA              | large               | high         | general         | good       | Feature extraction   |
| 3D-NDT              | general             | higher       | fast            | better     | Voxel size         |
| LORAX               | small               | general      | express         | better     | Input depth map     |

In order to compare the advantages and disadvantages of the three accurate registration methods, this paper uses the rabbit data model in the Stanford classic point cloud database to perform the registration experiment. According to the simulation results, the performance comparison is performed. The programming environment of the algorithm is CUPi7-4790. The frequency is 3.60Hz, 16GB memory, and the algorithm is simulated using MATLAB. The experiment first calculates the time and success rate of the number of data point clouds in the range of 100-4000 when there is no noise. The result is shown in Figure 1.

![Initial position](image1)

![ICP](image2)

![CPD](image3)

![DO](image4)

Figure 1. Noiseless data registration.

Secondly, the time and success rate of the registration of the noise standard deviation in the range of 0-0.1 are calculated, as shown in Fig. 2. From the figure 2 simulation results, we can see that the CPD algorithm has the longest registration time and the registration success rate is the most affected by noise in these three algorithms, and the ICP algorithm is matched in the presence or absence of noise. The quasi-calculation time is relatively stable and does not change suddenly with the number of points. Considering the calculation time and success rate of the registration, the DO algorithm is optimal compared with the other two algorithms, and the comprehensive experimental results are
analyzed. For the case where the number of point clouds in the point cloud data is small, the three algorithms can better complete the registration work. The DO algorithm is more suitable for noise-free data registration, and the CPD is more suitable for data registration with large noise deviation.

![Initial position ICP CPD DO](image)

**Figure 2.** Noisy data registration.

4. Problems and trends

With the advent of depth cameras and the rapid decline in the price of scanners, more and more researchers are making it easier to acquire 3D point cloud data, while also based on scanning point clouds (depth images such as Kinect, structured light scanning, laser scanning, LiDAR scanning). The registration modeling method has been unprecedentedly developed. The work of registering 3D point cloud data to register and reconstruct 3D models is common in Siggraph (Asia) in recent years. However, the current point cloud registration modeling still has shortcomings such as low precision, poor stability and large computational complexity, and it is far from meeting the actual needs. The specific problems are as follows:

1) For point cloud data with noise points, the registration algorithm is poorly robust;
2) For the point cloud data with large initial angle, the success rate of the registration algorithm is low;
3) For point cloud data with more external point data, the registration algorithm has low computational efficiency;
4) For the missing point cloud data, the success rate of the registration algorithm is low;
5) For drift point cloud data, the registration algorithm has low precision.

According to the above problem, the registration algorithm still has room for improvement. The related problems of point cloud registration will be driven by intelligent and automation in the direction of advanced technologies such as AI and deep learning. The development of VR/AR and network informationization will expand the point cloud registration modeling from specialized applications to popular and consumer applications to meet the needs of network services. Finding new, highly efficient and robust registration methods for different scenarios will be the focus of future research.
5. Conclusion
This paper first introduces the fine registration and coarse registration under the classification of registration process, as well as the iterative nearest point registration method under fine registration, DO algorithm registration method, consistent point drift registration method; positive under coarse registration State distribution transformation registration method, four-point fast registration method, sampling consistency initial registration method, LORAX algorithm registration method. The seven registration algorithm principles and registration process, as well as related derivative algorithms, are sorted out and the characteristics of the algorithm are listed. Then, the advantages and disadvantages of four coarse registration algorithms in convergence domain, noise impact, running speed and robustness accuracy are compared. The success of three fine registration methods under noisy data and noiseless data is compared by experiments. Rate and calculation efficiency. Finally, the problems in point cloud registration are put forward, and the future development trend is forecasted.

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