

# Algorithm research of 3D point cloud registration based on iterative closest point<sup>1</sup>

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**Abstract.** An improved Iterative Closest Point (ICP) algorithm is proposed to overcome the shortcomings of point cloud data registration algorithm in 3d reconstruction. The proposed algorithm constructs the kd-tree index to accelerate the searching of neighboring point cloud and the nearest point. The normal spatial sampling method is used to determine the sample point set. The normal weight and normal threshold methods are adopted to eliminate the false matching points and reduce the influence of noise points. The experiments show that the improved algorithm can shorten the registration time and obtain higher registration precision.

**Key words.** 3D reconstruction, point cloud registration, ICP algorithm, kd-tree.

## 1. Introduction

As an important research topic in computer vision field, three-dimensional reconstruction has been widely used in computer graphics application, digital simulation, 3D printing, reverse engineering and so on. Structured light three-dimensional scanners through multiple scanning objects surface, you can get different perspective of the three-dimensional point cloud data. The complete model can be obtained by registering the multiple point clouds. Therefore, the registration of point clouds directly affects the results and accuracy of three-dimensional reconstruction. According to the accuracy of registration, the registration method can be divided into coarse registration and precision registration.

The position relationship is arbitrary by scanning the surface of the object with a three-dimensional scanner to obtain multiple isolated point clouds. Therefore, it

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is necessary to consider the coarse registration and connect the two adjacent point clouds. The most common coarse registration are: principal component analysis (PCA) method, minimum bounding box method, RANSAC registration algorithm based on affine invariant and so on. The RANSAC registration algorithm based on affine invariant is used to estimate the parameters including a large number of external points, and the RANSAC registration algorithm has higher robustness for the smaller 3D data sets with overlapping parts [1]. The PCA algorithm can select a relatively small amount of data to interpret most of the data of the original cloud, reducing the dimension of the data [2]. Although coarse registration provides a good initial value for registration, but the results can not meet the requirements of registration accuracy, so the introduction of fine registration to improve the registration accuracy. At present, the most widely used precision registration algorithm is the Iterative Closest Point (ICP) algorithm proposed by Besl and McKay in 1992 [3].

## 2. ICP algorithm and improved scheme

### 2.1. Algorithm principle and characteristics

The ICP algorithm is an optimal matching method based on least squares method. The method is carried out continuously: the process of determining the corresponding point set and calculating the optimal rigid body transformation until the convergence criterion is satisfied [4]. The ICP algorithm is mainly used to solve the problem of free surface registration. Using the ICP algorithm can solve a variety of free surface registration problems and and it is not necessary to perform surface segmentation and feature extraction for the processing point sets. The algorithm can get more accurate registration results. But the ICP algorithm still has some shortcomings in practical application, the two point clouds need to have a good initial position, otherwise it can influence the rate of convergence and cause the wrong match result. In addition, the amount of calculations when finding the nearest point is larger and the time complexity of the algorithm is higher.

### 2.2. Improved scheme of ICP algorithm

The scholars have proposed a variety of improvements for the shortcomings of the traditional ICP algorithm. An example is an extension of the iterative ICP algorithm that simultaneously registers multiple 3D scans, with the efficient and accurate 3D registration method [5]. For precise registration, an improved ICP algorithm based on feature points generated by curvature is introduced [6]. Literature [7] proposes an improved ICP algorithm based on the single stress of point cloud, which improves the robustness of the algorithm. The dynamic adjustment weighting and the rejection strategy based on the adaptive threshold are proposed to improve the efficiency of the algorithm [8]. There are many ICP improvements [9], [10]. The various improved ICP algorithms can be summarized as follows:

(1) The sampling points can be selected by methods of uniform sampling, random sampling and so on, which can reduce the computational complexity and improve

the operation speed.

(2) The matching point pairs are determined by the methods of nearest point matching, feature matching and so on. The feature matching method can reduce the computational complexity, and the nearest point matching method has strong robustness.

(3) The weights of matching point pairs are determined by the methods of uniform weight, distance weight and so on, which can effectively remove the noise point.

(4) The wrong match point pairs are removed by the methods of distance threshold, distribution excluded and so on.

(5) The objective function is chosen by the methods of the square sum of the corresponding point distance, the square sum of the point and the corresponding tangent plane and so on.

### 3. Improved point cloud registration algorithm

#### 3.1. Basic ideas

In this paper, the registration of point cloud is accomplished by using the combination of coarse registration and precision registration. The coarse registration adopts the main direction sticking method. This method can quickly reduce the translation and rotation dislocation. In order to reduce the error of registration, precision registration is required on the basis of coarse registration. The precision registration method proposed in this paper is an iterative nearest point improvement algorithm based on traditional ICP algorithm.

The improved iterative nearest-point algorithm uses the normal spatial sampling method based on kd-tree index, and utilizes the advantage of the kd-tree index to effectively improve the accuracy and speed of registration [11], [12]. For a point  $p_i$  in the point cloud set  $P$ , the surface of the neighborhood of the kd-tree of  $P$  is used to construct a least squares surface, and then the normal vector is used to fit the surface to construct a least squares surface and the normal vector is used as the normal vector of point  $p_i$ . For each point  $p_i$  in the point cloud, the corresponding covariance matrix  $\mathbf{C}$  is

$$\mathbf{C} = \frac{1}{n} \sum_{j=1}^n (p_{i,j} - \bar{p}_i)(p_{i,j} - \bar{p}_i)^T, \quad \bar{p}_i = \frac{1}{n} \sum_{i=1}^n p_{i,j}. \quad (1)$$

In (1),  $n$  represents the number of neighboring points. The eigenvector corresponding to the smallest eigenvalue of  $\mathbf{C}$  is the normal vector of the least squares plane at point  $p_i$ . The eigenvector corresponding to the minimum eigenvalue of  $\mathbf{C}$  is the normal vector of the least squares plane at point  $p_i$ . The method of normal sampling is to select more points in the area where the normal variation is larger, and fewer points are selected in the area where the normal variation is smaller, as shown in Fig. 1. For the model with obvious characteristics, using the normal sampling method can avoid the wrong match and improve the accuracy and speed of registration.



Fig. 1. Normal space sampling

The nearest-point algorithm is used to determine the match point pair. Firstly, the kd-tree index of the target point set is constructed, and then the kd-tree index is used to query the point closest to the Euclidean distance of the data set as the matching point. Using the nearest-point algorithm can get better robustness, but the efficiency is low. The method based on the kd-tree index can effectively speed up the search speed and improve the efficiency of the algorithm.

The method of normal weight is used to assign weight to point, and the method of normal threshold is used to eliminate the error. Giving point to weight is

$$\text{weight} = n_p \cdot n_x. \quad (2)$$

In equation (2),  $n_p$  represents the unit normal vector corresponding to point  $p$  and  $n_x$  represents the unit normal vector corresponding to point  $x$ . This method can give the point pair with different weights, the larger the normal difference, the smaller the weight, and the smaller the normal difference, the greater the weight. The weights of all points are obtained after giving a threshold and then the point pair whose weights are less than the given threshold is removed. This method can remove the noise point and reduce the point cloud data involved in the iterative calculation. Thus the method effectively improve the speed and accuracy of registration.

The square sum of the distance of the corresponding point is chosen as the objective function, the square of the distance is

$$f(R, T) = \sum_{i=1}^N \|x_i - Rp_i - T\|_2^2. \quad (3)$$

Formula (3) is minimized by the quaternion method, and solves the transformation matrix. Calculating the center of gravity of point set  $P$  and  $X$ , respectively, as shown in the formula

$$\bar{P} = \frac{1}{N} \sum_{i=1}^N p_i, \quad \bar{X} = \frac{1}{N} \sum_{i=1}^N x_i. \quad (4)$$

Then the covariance matrix of the two cloud points is constructed by using the center of gravity

$$\sum_{P, X} = \frac{1}{n} \sum_{i=1}^n [p_i x_i^T] - \bar{P} \bar{X}^T. \quad (5)$$

According to the covariance matrix to construct the symmetric matrix

$$\mathbf{Q}(\sum_{P,X}) = \begin{bmatrix} \text{tr}(\sum_{P,X}) & & \Delta \\ & \Delta^T & \\ & & \sum_{P,X} + \sum_{P,X}^T - \text{tr}(\sum_{P,X}) \mathbf{I}_3 \end{bmatrix}$$

where

$$\Delta = [A_{23} \ A_{31} \ A_{12}], \quad A_{i,j} = \left( \sum_{P,X} - \sum_{P,X}^T \right)_{i,j}. \quad (6)$$

The  $\text{tr}(\sum_{P,X})$  in the formula represents the sum of all elements on the main diagonal of  $\sum_{P,X}$  and  $\mathbf{I}_3$  is the unit matrix of the third order.

The unit vector quaternion is used to represent the rotation vector  $\mathbf{q}_R = [q_0, q_1, q_2, q_3]^T$ , and the eigenvector corresponding to the largest eigenvalue of the matrix  $\mathbf{Q}(\sum_{P,X})$  is the rotation vector  $\mathbf{q}_R$  and then the rotation matrix  $\mathbf{R}$  can be calculated from  $\mathbf{q}_R$  and formula

$$\mathbf{R} = \begin{bmatrix} q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2(q_1q_2 - q_0q_3) & 2(q_1q_3 + q_0q_2) \\ 2(q_1q_2 + q_0q_3) & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2(q_2q_3 - q_0q_1) \\ 2(q_1q_3 - q_0q_2) & 2(q_2q_3 + q_0q_1) & q_0^2 - q_1^2 - q_2^2 + q_3^2 \end{bmatrix} \quad (7)$$

The translation vector  $T$  can be obtained by the formula  $T = \bar{X} - R\bar{P}$  after obtaining the rotation matrix  $\mathbf{R}$ .

The topological relation of the kd-tree method is essentially a coordinate tree segmentation method based on the binary tree. First, find the dividing line along the  $X$ -axis to find the average of the  $x$  values of all points, and divide the space into two parts with the split point whose  $x$  value is closest to the average point. And then separately in the two sub-space along the  $Y$ -axis to find the dividing line and through the dividing line will be divided into two parts. In the new subspace, find the dividing line along the  $Z$ -axis, and so on until there is only one point left in the area to be divided.

### 3.2. Coarse registration

The coarse registration selects the main direction sticking method. By calculating the eigenvectors of all points in the cloud, the main direction and two sub directions perpendicular to the main direction are obtained in space. For the two similar point clouds, their coordinate systems are adjusted to the same, it can achieve the registration of point cloud. For the two different point cloud, using this method can reduce the error between the point cloud.

Since the main direction has positive and negative directions, the difference between the two points is  $180^\circ\text{C}$ , so it is necessary to establish the minimum bounding box to test the point cloud after the registration. Two point clouds minimum bound-

ing box coincidence degree  $c$  is:

$$c = \frac{V_i^2}{V_P \bullet V_Q}. \quad (8)$$

Here,  $V_i$  is the volume of two point clouds the minimum bounding box intersects,  $V_P$  and  $V_Q$  represent the volume of the minimum bounding boxes of point cloud  $P$  and point cloud  $Q$  respectively.

If  $c$  is greater than a given threshold, then the two point cloud roughly coincide, otherwise reverse the  $X$ -axis or  $Y$ -axis test again. If all kinds of situations are tested, there is no case of  $c$  greater than the threshold, then the difference between the two point clouds is obvious, and the maximum of  $c$  is selected.

### 3.3. Precision registration

The main process of the improved ICP algorithm is as follows:

1. Iterative initialization:  $k = 0$ , set the maximum number of iterations  $K_{\max}$ , set the normal threshold  $V$ , and construct the kd-tree index of point sets  $P$  and  $X$ .
2. Based on the kd-tree index of point cloud data  $P$ , find the neighborhood of each point  $p_i$  in  $P$ , construct the least squares plane, and calculate the normal vector of  $p_i$ . The normal vector of all points in  $P$  is obtained, and the sampling point set  $P_0$  is determined according to the change of normal vector.
3. For each point in the point cloud  $P_k$ , the nearest point in the model point cloud  $X$  is calculated by the kd-tree index of  $X$ , and the corresponding point set  $X_k$  is obtained.
4. Use formula (2) to assign different weights to points.
5. A pair of matched points whose value of ownership  $v_i$  is less than a given threshold  $V$  is rejected.
6. According to the corresponding point pair, we can get the sum of the squares of Euclidean distances  $d_k$  of the corresponding points in data sets  $P_k$  and  $X_k$  by formula (3), and find the transformation matrix  $\mathbf{q}_k$  by quaternion method.
7. The new position  $P_{k+1} = \mathbf{q}_k P_k$  of the data points is obtained by transformation matrix  $\mathbf{q}_k$ , and the new sum of squares of distances  $d_{k+1}$  is calculated.
8. If  $d_k - d_{k+1} < \tau$ , or iteration times is greater than the given value  $K_{\max}$ , stop iteration, otherwise return to step (2) and continue the iterations.

## 4. Experiment and analysis

The first group of experiments uses the famous bunny model. All models are shown in Fig. 2. On the basis of rough registration, the time required for precision registration and averaging using traditional ICP algorithm is 150s, and the time of using this improved algorithm for precision registration is 33s. It can be seen from the experimental results that using this algorithm can get higher registration accuracy and faster registration speed.

In the second experiment, a David 3D scanner was used to scan a cup and obtain

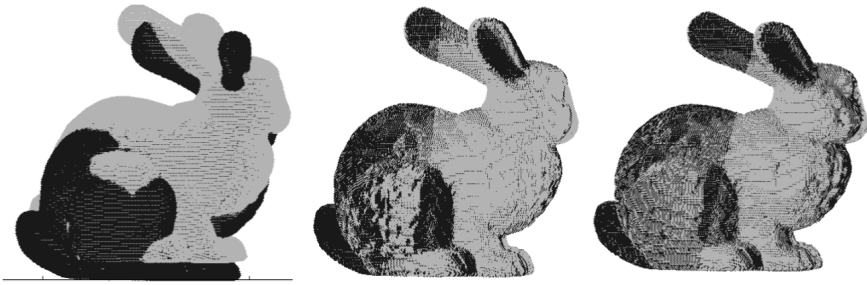


Fig. 2. Bunny: left–bunny model, middle–registration result of bunny model using traditional ICP, right–registration result of bunny model using improved ICP

the point cloud data. All models are shown in Fig.3. Calibration can be carried out before the calibration parameters: the vertical triangulation angle of  $3.12^\circ$ , the horizontal triangulation angle of  $17.12^\circ$  and the full triangulation angle of  $17.41^\circ$ . Scanning the surface of the object by the scanner to obtain the obj format data, and then the two point cloud data obtained by scanning at different angles are registered. On the basis of coarse registration, the traditional ICP algorithm and the improved algorithm are used to achieve the precision registration and uses MATLAB to carry on the programming realization. The experimental results show that the average time of the traditional ICP algorithm is 320s and the average time of the improved algorithm is 62s. Experiments show that the improved point cloud registration algorithm in this paper has better speed and precision.

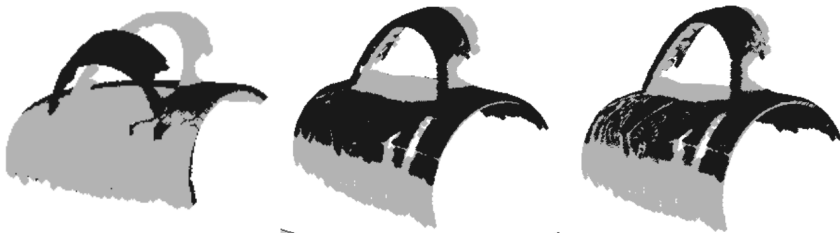


Fig. 3. Cup: left–cup model, middle–registration result of cup model using traditional ICP, right–registration result of cup model using improved ICP

## 5. Conclusion

By describing the advantages and disadvantages of the traditional ICP algorithm and summarizing various improvements of the ICP algorithm, an improved ICP algorithm is proposed. Finally, two sets of experiments show that the method of rough registration and precise registration can improve the speed and accuracy of registration, and prove the feasibility and effectiveness of the algorithm. The improved ICP algorithm is suitable for point cloud data registration with obvious normal features, and it has good application in the accurate registration of point cloud.

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