Acta Technica 62 (2017), No. 5B, 921–930

An Improved Point Cloud Registration Method Based on Iterative Closest Point algorithm

Wang Yujian[2], Wu Mingming[3], Lian Tengfe[2], Gao Qian[2]

Abstract. An improved Iterative Closest Point algorithm is reported for the shortage of 3D point cloud registration. The search speed is improved by building KD-tree index on the basis of Iterative Closest Point algorithm. The sampling points are determined by the 3D voxel grid algorithm. The corresponding points of the point cloud are weighted by the normal vector. The point pairs whose weight is larger than the given threshold eliminated. The influence of the noise points is reduced in use of the method mentioned above. Finally, the outlier data are eliminated by introducing M-estimation to the objective function. The experimental results show that the proposed method can shorten the time of registration effectively and achieve high registration accuracy.

Key words. point cloud registration, Iterative Closest Point algorithm, voxel grid, KD-tree.

1. Introduction

Multi-slice cloud data is stitched to get a set of 3D data points in one coordinate system through point cloud registration. Firstly, it is necessary to find the correspondence between the two points of cloud data sets. Secondly, the point cloud data in one coordinate system is transformed into another coordinate system. Point cloud registration can be regarded as the process of solving transformation matrix. According to the characteristics of the sample model, Gai, Y. (2014) thinks that the registration process can be divided into rigid registration and non-rigid registration. According to the accuracy of registration, the registration process can be divided into rough registration and fine registration.

[1]Acknowledgement - The study was financially supported by National Natural Science Foundation of China (NSFC) (No. 61271369), and Beijing Natural Science Foundation (No. 4152018).

[2]Workshop 1 - School of Information, Beijing Union University, Beijing 100101, China

[3]Corresponding author: Wu Mingming; e-mail: `xxtyujian@buu.edu.cn`

The most common rough registrations used by principal component analysis (PCA), minimum bounding box method, RANSAC registration algorithm, etc. The RANSAC registration algorithm is used in Yuan, L. (2010). PCA and the minimum bounding box methods are used in Yang, X. H. et al. (2010). The results of the rough registration cannot meet the requirement of registration accuracy, so the registration method needs to continue.

At present, the most widely used fine registration algorithm is the iterative closest point (ICP) algorithm proposed by Besl, P. J. & McKay, N. D. (1992). ICP algorithm is more applicable. The registration accuracy is high

when the initial conditions of the iteration are satisfied. However, it is large of the computational complexity of the algorithm, and it is low of the algorithm's registration efficiency. Therefore, researchers have proposed a variety of improvement schemes at home and abroad for the deficiency of traditional ICP algorithm (Li, Y., 2014; Xiong, H.C., Szedmak, S. & Piater, J., 2013). Dai, J. L. et al. (2014) found the nearest point by means of curvature feature points and KD-tree.

This method improves the efficiency of the ICP algorithm. Wang, X. et al. (2012) introduces M-estimation of the objective function to remove the anomaly points. This method improves the accuracy of the algorithm.

2. Classic ICP Algorithm

The number of points were *Np*, Nx in the point cloud P and point cloud X. To represent a rigid body transformation by $q=[q_R \mid q_T]$. The process of the ICP algorithm is shown in Fig.1, the main process is as follows (Zhang, X. J. et al.2012):

(1)Initialize the operation: $P_0=P$, $q_0=[1\ 0\ 0\ 0\ 0\ 0\ 0]^T, k=0$;

(2)For each point in the point cloud Pk, the corresponding point set X_k is obtained by calculating the nearest point of the point cloud X in the model;

(3)The sum of squares dk of the corresponding points is calculated. The rotation matrix q_R and the translation vector q_T (that is, the vector q_k) are calculated;

(4)The new position of P_k is obtained after the transformation $P_{k+1}=q_k(P_k)$;

(5)The sum of squares d_{k+1} between P_{k+1} and X_k is calculated;

If d_k-$d_{k+1}<$, the algorithm is terminated and the iteration result is returned. Otherwise, back to step (2) to continue.

3. The Improved ICP Algorithm

3.1. basic idea

Random sampling method relies on the random function, and feature sampling method requires that the point cloud data have obvious characteristics. A point cloud data sampling method based on 3D Cartesian grid voxels is proposed. The method can streamline the point cloud data, and it is simple and fast. The cloud data is greatly reduced after streamlining, and the KD tree index is built to simplify the point cloud, so that it can accelerate the speed of searching corresponding points

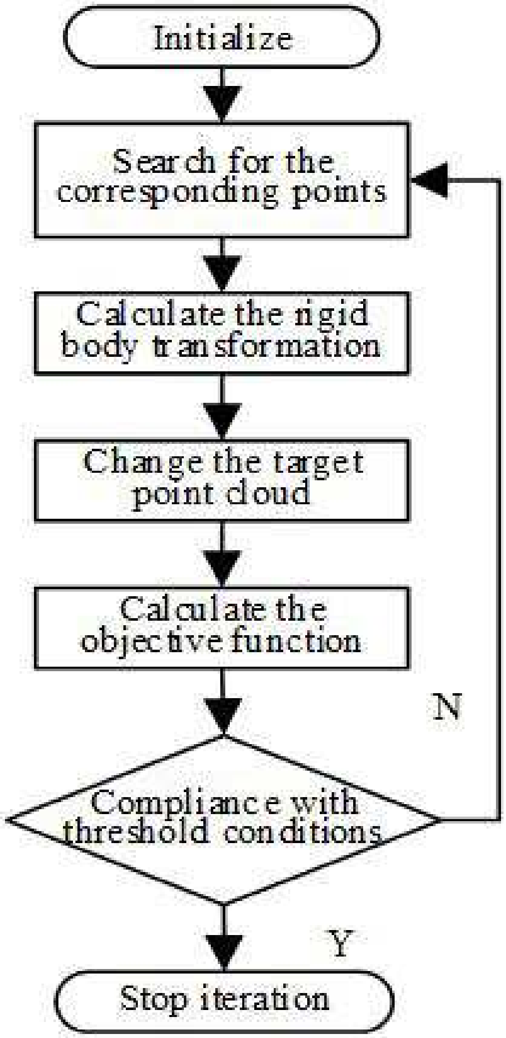

Fig. 1. The flow chart of ICP algorithm

and adjacent points.

A large number of error matching results may occur in the determination of the matching point pair. In order to eliminate the influence of this mismatch, the method of normal weighting is adopted. In order to improve the registration accuracy further, the standard threshold method is adopted to remove the false point pairs.

For any point pi in point cloud set P, the points in its neighborhood are obtained through the KD-tree index of P, and then the surface is fitted, finally, a least squares surface is constructed. The normal vector of the least squares surface is taken as the normal vector of point pi. For each point pi in the point cloud, the corresponding covariance matrix C can be obtained by the formula (1).

$$C = \frac{1}{n}\sum_{j=1}^{n}(p_{i,j} - \overline{p_i})(p_{i,j} - \overline{p_i})^T \tag{1}$$

In the formula, n represents the number of adjacent points. $\overline{p_i} = \frac{1}{n}\sum_{i=1}^{n} p_{i,j}$. It obtains the eigenvector corresponding to the minimum eigenvalue of C, and this vector is the normal vector of the least squares plane at point p_i, (Xie, Q. P., 2015; Wang, Y. J., 2016).

Give the weights of point pairs in use of formula (2).

$$weight = n_p \cdot n_x \tag{2}$$

In the formula (2), n_p and n_x represent the unit normal vector corresponding to point p and point x, respectively.

This method can further reduce the impact of outliers on the registration results and improve the robustness of the algorithm.

3.2. Point Cloud Data Sampling Based on 3D Cartesian Raster Voxels

The method of 3D Cartesian grid voxel is used to complete the sampling of point cloud data. Firstly, a cube can be built around block clouds. Secondly, the cube is evenly divided into a series of small cubes. It determines the points in each small cube, and calculate the center of gravity. It uses the center of gravity to replace points in a small cube. As shown in Fig.2, the hollow circles represent the point cloud data in the small cube. The solid circle represents the center of gravity based on all the hollow circles. That is, the solid circle represents the sampling point selected in a small cube.

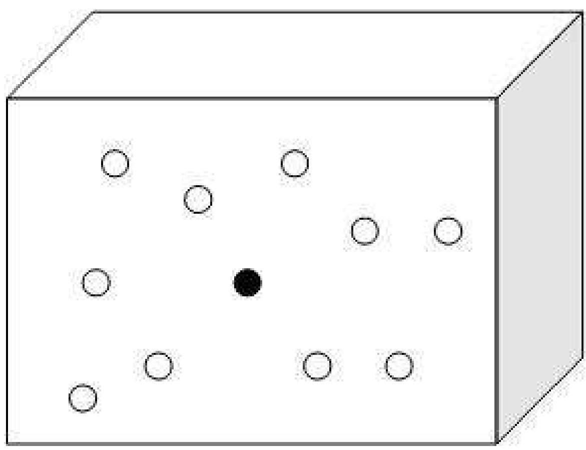

Fig. 2. Sample through the 3D voxel grid algorithm

The main algorithm of the sampling method is as follows:

(1) It determines the range of values for the cloud data on the three axes. It builds a large cube that can surround the whole point cloud.

(2) The width of the small cube is set to m. The big cube is evenly divided. In the three coordinate axes, it determines the number of layers of the small cubes by the formula (3).

$$\begin{cases} a = ceil((X_{\max} - X_{\min})/m) + 1 \\ b = ceil((Y_{\max} - Y_{\min})/m) + 1 \\ c = ceil((Z_{\max} - Z_{\min})/m) + 1 \end{cases} \tag{3}$$

(3) For any point in the point cloud, $p_i = (x_i,\ y_i,\ z_i)$. According to the formula (4), it obtains the index of the grid to which p_i belongs.

$$\begin{cases} x_{index} = ceil((x_i - X_{\min})/m) \\ y_{index} = ceil((y_i - Y_{\min})/m) \\ z_{index} = ceil((z_i - Z_{\min})/m) \end{cases} \tag{4}$$

(4) It determines the points in each small cube, and calculates the center of gravity. It uses the center of gravity to replace points in a small cube.

3.3. KD-tree

The KD-tree method is used to establish the topological relations of points. This is a method of coordinate axis segmentation based on binary trees. It can describe the construction process of the KD tree as follows. Firstly, the dividing line is searched along the X-axis, and the average of the x values of all points is determined. The closest point of the value of x to the average is taken as the division point. The space is divided into two parts according to the x value of the split point. The dividing lines are respectively searched in the two subspaces along the Y-axis. The two subspaces are divided into two parts. The dividing lines are found in the new subspace along the Z axis, and so on. It divides until there is only one point in the area (Zhou, Ch. Y. et al., 2011).

In general, it need calculate the k-nearest neighbor points of the point p. Firstly, it need compute the Euclidean distance between p and the rest of the points. Then, these points are sorted by the size of the distance. The first k points are taken out and are regarded as the k neighbors of point p. However, this method is less efficient. By establishing the KD-tree index, the search leads to finding the k-nearest neighbor points. This method can effectively shorten the time of finding the nearest point and improve the efficiency of the algorithm.

3.4. Solving Transformation Matrix by Quaternion

It describes the process of solving the transformation matrix by the quaternion method as follows. Firstly, the center of gravity is calculated according to the point set P and X, respectively. $\overline{P} = \frac{1}{N}\sum_{i=1}^{N} p_i$, $\overline{X} = \frac{1}{N}\sum_{i=1}^{N} x_i$. Secondly, the covariance matrix of two point clouds is constructed in use of the center of gravity. As shown in formula (5).

$$\sum_{P,X} = \frac{1}{n}\sum_{i=1}^{n}\left[(p_i - \overline{P})(x_i - \overline{X})^T\right] \tag{5}$$

It simplifies the Formula (5), $\sum_{P,X} = \frac{1}{n}\sum_{i=1}^{n}\left[p_i x_i^T\right] - \overline{PX}^T$.

The symmetric matrix is constructed according to the covariance matrix. $Q(\sum_{P,X}) = \begin{bmatrix} tr(\sum_{P,X}) & \Delta \\ \Delta^T & \sum_{P,X} + \sum_{P,X}^T - tr(\sum_{P,X}) I_3 \end{bmatrix}$. $tr(\sum_{P,X})$ represents the sum of all the elements on the main diagonal of $\sum_{P,X}$. I_3 is a third-order unit matrix. $\Delta = [A_{23}\ A_{31}\ A_{12}]$, $A_{i,j} = (\sum_{P,X} - \sum_{P,X}^T)_{i,j}$. The transformation matrix q_R=[q_0 q_1 q_2 q_3]^T is expressed in units of quaternions. It obtains the eigenvector corresponding to the largest eigenvalue of the matrix $Q(\sum_{P,X})$. This eigenvector is the rotation vector q_R. Then, it can calculate the rotation matrix R from q_R and formula (6).

$$R = \begin{bmatrix} q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2\left(q_1q_2 - q_0q_3\right) & 2\left(q_1q_3 + q_0q_2\right) \\ 2\left(q_1q_2 + q_0q_3\right) & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2\left(q_2q_3 - q_0q_1\right) \\ 2\left(q_1q_3 - q_0q_2\right) & 2\left(q_2q_3 + q_0q_1\right) & q_0^2 - q_1^2 - q_2^2 + q_3^2 \end{bmatrix} \tag{6}$$

After it obtains the rotation matrix R, the translation vector T can be obtained by the formula$T = \overline{X} - R\overline{P}$.

3.5. Improved ICP Algorithm

The main process of the improved ICP algorithm as follows:

(1) Initialize the operation, k=*0*. It sets the maximum number of iterations K_{max}. The normal threshold V is given.

(2) According to the demand, it determines a reasonable sampling interval. The sampling points are determined by the 3D voxel grid algorithm. It obtains the two sampling points of P_k and X_0. The KD-tree indexes of the two sample points are constructed separately.

(3) For each point in the point cloud P_k, the KD-tree index of X is used to calculate the corresponding point of point cloud X in the model. Hence, it obtains the corresponding point sets X_k.

(4) The least squares plane is constructed based on the KD-tree index. The normal vector of the sampling point is calculated, and then the formula (2)is used to give the corresponding points different weights.

(5) It removes all the corresponding points that v_i is less than V.

(6)According to the corresponding point, it obtains the objective function d_k, and then the transformation matrix q_k is obtained by the quaternion method.

(7)The new position of the data point Pk+1=qk(Pk) is obtained by the transformation matrix qk. It can calculate by the new square sum of distance dk+1. If $d_k - d_{k+1} < \tau$, or the number of iterations is greater than the given value Kmax, it stops the iteration. Otherwise, back to step (3), and continue the iteration.

4. Experimental Results and Analysis

4.1. Simplify point cloud data

First of all, we use the method of 3D Cartesian grid voxel to complete the sampling of point cloud data. It can sample the bunny model as shown in Fig.3. (a) is the model before sampling. The model contains34, 835 points. Take the width m of the small cube as 0.4, (b) is the model after sampling. The sampling algorithm used 0.0920s. The model contains 1,946 points after sampling. It can be seen that the sampling point cloud data can respond well to the characteristics of the object from the experimental results.

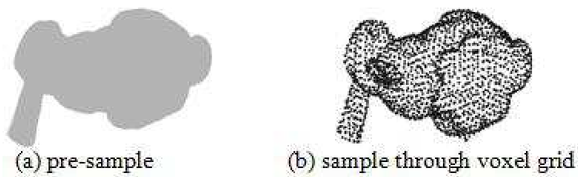

Fig. 3. bunny model

The kitty model is sampled, as shown in Fig.4. (a) is the model before sampling. The model contains 288,316 points. Take the width m of the small cube as 2, (b) is the model after sampling. The sampling algorithm used 0.4357s. The model contains 39,648 points after sampling. Experiments show that it is very good to maintain the surface shape of the object by sampling results.

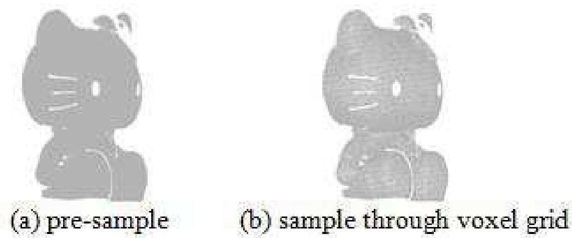

Fig. 4. kitty model

4.2. Point cloud data registration

The first set of experiments by using the famous bunny model, and the experimental results are shown in Fig.5. Figure (a) is the original position model before registration. Figure (b) is the result of the registration in use of the traditional ICP algorithm. Figure (c) is the result of the registration in use of the algorithm (Wang, X. et al., 2012). Figure (d) is the result in use of the improved ICP algorithm. By using the algorithm for registration above, the time used were 80.937s, 20.013s, and 7.685s. It can be seen from the experimental results that we can get a higher registration accuracy and faster registration speed by using the improved

ICP algorithm.

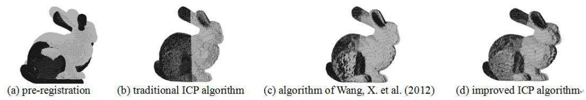

Fig. 5. The registration of bunny model

The first set of experiments by using the kitty model, and the experimental results are shown in Fig.6. Figure (a) is the original position model before registration. Figure (b) is the result of the registration in use of the traditional ICP algorithm. Figure (c) is the result of the registration in use of the algorithm (Wang, X. et al., 2012). Figure (d) is the result in use of the improved ICP algorithm. By using the algorithm for registration above, the time used were 247.268s and 53.175s. The experimental results show that the improved registration algorithm has a better improvement in speed and accuracy.

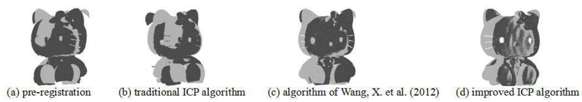

Fig. 6. The registration of kitty model

In the Table 1, it shows the results of the registration of different sizes of point cloud data using the above three methods. We can see the registration speed in the Table 1, Wang, X. et al. (2012) points out that his method is faster than the traditional ICP algorithm. However, the improved ICP algorithm is faster than the other two algorithms.

Table 1. The registration of point cloud in different scales

The amount of data	The average time required for registration/s		
	traditional ICP algorithm	algorithm of Wang, X. et al. (2012)	improved ICP algorithm
5618	7.723	1.659	1.135
11759	22.382	6.327	4.818
34835	80.937	20.013	7.658
288316	247.268s	53.175s	20.528s

5. Conclusion

The registration method of point cloud data is studied in this paper. It introduces the precision registration algorithm, and analyzes the advantages and disadvantages of the traditional ICP algorithm. This paper summarizes the various improvement schemes to the ICP algorithm. Finally, an improved ICP algorithm is put forward according to the actual situation. The algorithm improves the speed and efficiency of point cloud registration. The experimental results show that the algorithm can improve the registration speed and accuracy. It proves the feasibility and effectiveness of the algorithm. The improved ICP algorithm has a good application in the fine registration of point cloud.

References

[1] P. J. Besl, N. D. McKay: *A method for registration of 3-d shapes.* IEEE Transactions on Pattern Analysis and Machine Intelligence *14* (1992), No. 2, 239–256.

[2] J. L. Dai, Z. Y. Chen, X. Z. Ye: *The Application of ICP Algorithm in Point Cloud Alignment.* Journal of Image and Graphics *3* (2007), 517–521.

[3] Y. Gai: *3D Face Registration Based on Surface Deformation.* Computer Science *41* (2014), No. 11, 116–118.

[4] Y. Li: *Research of Automatic Registration and Fusion Technology with Multi-angle 3D Data for 3D Scanning System.* Jilin University (2014).

[5] X. Wang, M. Zhang, X. Yu, X. Zhang: *Point Cloud Registration based on Improved Iterative Closest Point Method.* Optics and Precision Engineering (2012), 2068–2077.

[6] Y. J. Wang, T. F. Lian, S. W. Tan: *A Study of Normal Vector Estimation Method for Three Dimensional Point Cloud.* Journal of Residuals Science & Technology (2016).

[7] Q. P. Xie, H. Y. Yu, P. L. Yu, X. P. LU: *Research on Registration Method of Subway Tunnel 3D Laser Scanner Data.* Science of Surveying and Mapping (2015), No. 98, 101–166.

[8] H. C. Xiong, S. Szedmak, S. Piater: *A study of point cloud registration with probability product kernel functions.* 2013 International Conference (2013), 207–214.

[9] X. H. Yang, H. N. Wang: *Application Research of ICP Algorithm in 3D Point Cloud Alignment.* Computer Simulation *27* (2010), No. 8, 235–238.

[10] L. Yuan: *Research on Point Clouds Registration in 3D Model Reconstruction Pipeline.* Xidian University (2010).

Received November 16, 2017