Point Cloud Registration Method for Pipeline Workpieces Based on RANSAC and Improved ICP Algorithms

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Abstract. Aiming at the registration problem of laser-scanned workpiece point cloud data, a point cloud registration method based on RANSAC algorithm and improved ICP algorithm is proposed. Firstly, feature points are selected according to the variation law of the normal vector in the original point cloud data, and the initial matching point set is obtained by establishing the histogram (FPFH) of feature points. Then a random sampling consensus (RANSAC) algorithm is applied to the initial data matching. At last, the nearest point iterative algorithm (ICP) accelerated by k-d tree is used for accurate matching, and the quaternion method is used to obtain the registration parameters. The new algorithm and PCA+ICP algorithm are tested and the experimental results are compared. The results show that the new algorithm can achieve registration, and improve the speed and accuracy of registration, which provide a reference for similar problems.

1. Introduction

With the development of laser scanning technology, point cloud data obtained by laser scanning has attracted widespread attention [1]. Three-dimensional point cloud registration technology is widely used in various fields. In recent years, industrial robots have become the mainstream of development. Recognition of workpiece posture on assembly line is one of the key technologies of industrial robot sorting. Therefore, how to apply point cloud registration technology to the recognition of workpiece posture has become a hotspot for more and more scholars.

At present, many experts and scholars have proposed many solutions for point cloud registration. Among them, the nearest point iteration algorithm proposed by computer vision researcher Besl [2, 3] is the most widely used, and many experts and scholars have improved it on this basis; Chen et al. [4] solved coordinate transformation by calculating the minimum distance from the point to the tangent plane of the corresponding point; Guskov extracted the local shape descriptor of the point cloud to define an approximate transformation, and extracted subsets from the point cloud as the source point cloud set; H. Alt et al. proposed registration based on Hausdroff distance and Frachet distance. These algorithms have high requirements for point cloud data and hardware equipment, and the registration time is too long compared with the industrial pipeline to meet the actual production needs.

In order to solve this problem, a new point cloud automatic registration algorithm based on RANSAC algorithm and improved ICP algorithm is proposed. Firstly, the points whose normal vectors change regularly in the region are selected as feature points, and the initial registration point pairs are selected by establishing the feature histogram of the feature points. Then, the initial registration points are...
roughly registered by RANSAC algorithm to obtain the accurate registration point pairs. Finally, the point clouds are accurately registered by ICP algorithm optimized by k-d tree, and the registration parameters are calculated by quaternion method.

2. Select feature point set based on FPFH

Because the number of point clouds in the original point cloud data is too large, direct rough registration of the original point cloud will greatly prolong the registration time, and will produce a certain degree of error. Therefore, the point cloud should be streamlined before rough registration. Feature points are stable, distinguishable, single and rich in feature information. The set of these points is called feature point set. If only one of the eigenvalues (such as normal vectors) is used to describe point clouds, the description information of feature points will be relatively small, and it will not be able to describe feature points comprehensively. In order to solve this problem, the feature point histogram (FPFH) is used to describe the normal features of point clouds, so that the feature points can be described to a greater extent, and the point clouds can be distinguished better.

FPFH calculates the spatial difference between each query point \( p_q \) and its K neighbourhood points by using the normal feature of point cloud, and parameterizes it to get the description form of feature points. The specific steps are as follows.

1) Calculate the characteristic representations \( h_1, h_2, h_3 \) between each query point \( p_q \) and the nearest point normal, and call them SPFH.

\[
\begin{align*}
    h_1 &= \text{acsc} < n_i \cdot v_k > \\
    h_2 &= < n_i \cdot (s_k - p_q) > \\
    h_3 &= \left\| s_k - p_q \right\|
\end{align*}
\]

In the formula, \( n_i \) is the normal vector of point \( p_q \), \( v_k \) is the normal vector of point \( p_q \), \( s_k \) is the three-dimensional coordinate of point \( p_q \), and \( h_1 \) is the angle between the normal vector of a point and the normal vector of its adjacent point; \( h_2 \) is the product of two vector points, one is the normal vector of a point, the other is the vector between the point and its adjacent point. \( h_3 \) is the Euclidean distance between a point and a point in its vicinity.

2) The nearest neighbors of each point are redistributed, and the value of FPFH is weighed by SPFH value, as shown in Formula (4)

\[
\text{FPFH}(p_q) = \text{SPFH}(p_q) + \frac{1}{k} \sum_{i=1}^{k} \frac{1}{\omega_k} \cdot \text{SPFH}(p_k)
\]

In the formula, the weight \( \omega_k \) denotes the distance between query points and adjacent points. The weights of the combination is very important, it is said that the K neighborhood effects range to the query point \( p_q \) as the center, from the query point nearer the larger weight line is coarse. Therefore, given a point \( p_q \), the algorithm first evaluates the value of SPFH and creates a match between the point and its neighbors. This process is repeated all the time, and the weight is constantly changed by the value of adjacent SPFH, and finally the FPFH [5] of \( p_q \) is generated. The FPFH calculation process is shown in Fig.1.
In this paper, Stanford dragon point cloud data is selected as the experimental model, and the point cloud model is processed to simulate the target point cloud. The feature points selected by FPFH are shown in Fig. 2, and the points with larger geometric variation in the visible point cloud are observed and retained.

![Figure 1. K-domain computational schematic diagram of FPFH](image)

![Figure 2. Feature Point Set Obtained by FPFH](image)
3. Rough registration based on RANSAC algorithm

RANSAC is a method of random sampling detection [6]. Specifically, three non-collinear matching points selected from $P_t$ are used as "basis" to search corresponding non-collinear points in $Q_t$ and the Euclidean distance transformation matrix is estimated by using these three pairs of points. Then, the remaining point pairs in the sample are substituted into the rigid body transformation matrix, and the consistency of corresponding points is determined under the limit of error threshold (the size of error threshold is generally determined according to experimental experience). The selected corresponding points are called inner points, and all inner points become the point set of this sampling. The upper limit of sampling frequency is updated at any time according to the number of inner points, and when the sampling frequency of any point set reaches the upper limit, the corresponding transformation matrix is regarded as the optimal solution. The selected point set is the final exact matching point pair; otherwise, the sampling steps need to be repeated until the optimal solution is found. The key to registration is that the selected "basis" must be in the overlapping area of the two point cloud models. However, in the actual application process, the target point cloud and the reference point cloud obtained in the collection of point cloud are partially contained, partly exist in points $P_t$ and $Q_t$, and no corresponding matching point exists in $Q_t$. Based on the feature that the Euclidean distance is invariant when the point cloud performs rigid body transformation in space, the points of $P_t$ and $Q_t$ are selected again.

Euclidean distance is to calculate the straight-line distance between two points in space by using the Pythagorean Theorem. Assuming that there are two correct matching point pairs in $P_t$ and $Q_t$, respectively $(p_{t1}, p_{t2})$ and $(q_{t1}, q_{t2})$, the distance between the matching point pairs is equal.

$$
\rho_{t1} = \sqrt{(x_{p_{t1}} - x_{q_{t1}})^2 + (y_{p_{t1}} - y_{q_{t1}})^2 + (z_{p_{t1}} - z_{q_{t1}})^2}
$$

In the formula $\rho_{t1}$ is the distance between $p_{t1}$ and $q_{t1}$, and the coordinates in space are $(x_{p_{t1}}, y_{p_{t1}}, z_{p_{t1}})$ and $(x_{q_{t1}}, y_{q_{t1}}, z_{q_{t1}})$ respectively. Similarly, the distance $\rho_{tj}$ between $p_{tj}$ and $q_{tj}$ is known. There is a relationship between the two pairs of correct matching points.

$$
\rho_{t1} = \rho_{tj}
$$

However, in reality, it is relatively difficult to find matching point pairs completely satisfying the above formula in two discrete point cloud data. Therefore, if the point pairs satisfy $\rho_{t1} \approx \rho_{tj}$, the corresponding point pairs will be regarded as the correct matching point pairs, where $\varepsilon_2$ is the threshold value greater than zero, and $\varepsilon_2 = 0.001$ is selected here.

$$
\frac{|\rho_{t1} - \rho_{tj}|}{\rho_{t1} + \rho_{tj}} < \varepsilon_2
$$

Find out the matching point pairs that meet the distance constraints as shown in Fig 3, and then resample the data with Random Sampling Consistency (RANSAC) algorithm to complete the initial registration.
Because the unit quaternion algorithm has high accuracy and robustness, the unit quaternion method is chosen to solve the problem. The unit quaternion algorithm is as follows: suppose there is a unit quaternion vector \( q \) with \( q_0 \geq 0 \) and meet \( q_0^2 + q_1^2 + q_2^2 + q_3^2 = 1 \). The relationship between rotation matrix \( R \) and rotation unit quaternion is as follows:

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

Assuming the existence of target point cloud A and reference point cloud B, the centroids \( \bar{\mu}_a \) and \( \bar{\mu}_b \) of the two groups of point clouds are obtained, and their specific relations are as follows:

\[
\begin{aligned}
\bar{\mu}_a &= \frac{1}{N_A} \sum_{i=1}^{N_A} A_i \\
\bar{\mu}_b &= \frac{1}{N_B} \sum_{i=1}^{N_B} B_i
\end{aligned}
\]

(9)

Taking the obtained centroid into equation (8), the movement parameters of three directions in the translation matrix space are obtained by the relationship between the rotation matrix \( R \) and the centroid and the translation matrix \( T \). The specific relations are as follows.

\[
T = \bar{\mu}_b - R\bar{\mu}_a
\]

(10)

By using matching parameters, each point \( p_i \) in the target point cloud is transformed into the coordinate system where the reference point cloud is located. The new point set composed of \( p_i' \) is used as the new position of the target point cloud in precise registration. The specific relations are as follows:

\[
p_i' = R \cdot p_i + T
\]

(11)

4. Precise registration based on improved ICP

The specific steps of the traditional ICP algorithm are: assuming that the point set and the point set are mutually matched. Firstly, the nearest point of each point in the center is computed; then, the rigid body transformation with the smallest average distance between the corresponding points is obtained to obtain the translation and rotation parameters; secondly, the new set of transformation points is obtained by using the rigid body transformation parameters calculated in the previous step; if the average distance
between the new set of transformation points and the reference point set is less than a given threshold, the iterative calculation is stopped and registration is completed. Otherwise, the new set of transformation points will be iterated as a new continuation until it meets the requirements of the objective function. It can be seen that the calculation of corresponding points is the longest time-consuming step in the whole registration process, and it is particularly important to speed up the search of k-d tree [7].

The core of k-d tree searching for the nearest point is to establish the topological relation of the point based on the coordinate axis segmentation of the binary tree [8]. Firstly, the node to be searched is compared with the value of the determined splitting dimension. If the value of the splitting dimension is less than or equal to, it will enter the left subtree branch. If the value of the split dimension is greater than, it will enter the branch of the right subtree. In this way, it will loop to the leaf node of the binary tree and find the nearest similar point in the same subspace as the point to be searched along the search path. Then, if the node in the search path is closer to other subspace nodes, then the node in the subspace can be searched for the closest point. Repeat the above steps until the search path is empty and the search is complete.

5. Experiments and analysis
In order to verify the effectiveness and registration performance of the proposed algorithm, a simulation comparison experiment is designed. The registration experiment is carried out using dragon model provided by Stanford University website as template point cloud. The improved algorithm in this paper is compared with the classical ICP algorithm. The point cloud model is processed according to the experimental needs. The experiment was carried out on the computer of Core (TM) i7-5500U CPU, 8GB memory and Windows 7 64-bit operating system using the software of MATLAB R2016b. After processing, the position relationship of the two point cloud models in the spatial coordinate system is shown in Fig. 4

![Figure 4. Diagram of reference point cloud and target point cloud.](image1)

![Figure 5. Using PCA Rough Registration Result Diagram.](image2)

After rough registration, the point clouds are shown in Fig.5. The results show that after rough registration, the target point clouds and reference point clouds have a better location relationship.

Finally, the improved ICP algorithm is used to further precisely register the point clouds after rough registration, and the results shown in Fig. 6 (a) are obtained. Results Compared with PCA + ICP algorithm (as shown in Fig. 6 (b)), the registration result of point cloud in this algorithm is better, and the degree of coordination is high, which can meet the registration requirements. Because the PCA+ICP algorithm is not streamline the point-cloud registration before registration, and k-d tree is not used for
improvement, the registration time of the point-cloud model is quite different. The time, number of iterations and MSE mean square registration errors of the two algorithms are detailed in Table 1.

![Accurate registration results of the proposed algorithm](image1)

![The registration results of PCA + ICP algorithm](image2)

**Figure 6.** Results of point cloud data registration

|                      | PCA + ICP algorithm | The new algorithm in this paper |
|----------------------|---------------------|---------------------------------|
| The number of iterations | 40                  | 25                              |
| The elapsed time /s   | 19.211278           | 5.197549                        |
| MSE/mm               | 0.112               | 0.028                           |

Table 1. Experimental comparison data of two algorithms

Through the observation and analysis of Fig. 6 and Table 1, the following results can be obtained: In terms of registration time, the running time of the improved algorithm in this paper is 1.116s, which is obviously better than PCA + ICP algorithm. The number of iterations is less, and the MSE mean square registration error is smaller. As for registration results, PCA + ICP algorithm does not deal with point clouds, resulting in unsatisfactory registration results. Aiming at the shortcomings of PCA+ICP algorithm this algorithm is optimized, thus get a better registration results. The results of rotation matrix R and translation matrix T obtained by the two algorithms are shown in Fig. 7.
6. Conclusion

This paper presents a new automatic registration algorithm for point cloud based on RANSAC algorithm and improved ICP algorithm. The algorithm selects initial registration point pairs by establishing feature point histogram (FPFH). Then RANSAC algorithm is used to complete rough registration of target point cloud and reference point cloud. K-d tree is used to improve the classical ICP algorithm and complete accurate registration of point cloud data. At the same time, the registration parameters are calculated by four-element method, and the point cloud data with partial inclusion relation is automatically registered. Compared with PCA + ICP algorithm, the results show that the new algorithm reduces the number of iterations, speeds up the running speed, and improves the registration accuracy, which show the effectiveness of the new algorithm.

References

[1] Jian Liu, Di Bai. Three-dimensional point cloud registration algorithm based on feature matching [J]. Journal of Optics, 2018, 38 (12), 240 - 247.
[2] Haijie Tao, Feipeng Da. An automatic registration method of point cloud based on normal vector [J]. China Laser, 2013, 40 (8): 179 - 184.
[3] Besl P J, Mckay N D. A method for registration of 3-D shapes [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 1992, 14 (2): 239 - 256.
[4] Chen Y, Medioni G. Object modeling by registration of multiple range images [J]. Image and Vision Computing, 1992, 10 (3): 145- 155.
[5] Lei Zhang, Zhihang Ji, Jixin Pu. Constrained improved ICP point cloud registration method [J]. Computer Engineering and Application, 2012 (18): 197 - 200.
[6] Luhao Gan, He Saixian. Research on Point Cloud Mosaic Method with Low Overlapping Degree [J]. Laser Magazine, 2019, 40 (03): 84-90.
[7] Junhui Guo. Application of improved ICP algorithm based on KDTree in point cloud registration [J]. Microcomputer and application, 2015, 34 (14): 81 - 83+86.
[8] Zhiqiang Tu, Kai Zhang, Chenglong Yang, Xiaopeng Zhu, Jie Huang. Improvement of ICP mosaic algorithm for point cloud in three-dimensional model reconstruction [J]. Journal of Welding, 2013, 34 (01): 97 - 100+118.