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

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Abstract. Aiming at the registration problem of point cloud data obtained by laser scanning workpiece, a new automatic registration algorithm of point cloud based on PCA algorithm and improved ICP algorithm is proposed. Firstly, the feature points are selected according to the change rule of normal vectors in the original point cloud data, and the initial matching point set is obtained by establishing the histogram of feature points (FPFH); then the principal component analysis (PCA) is used to match the initial data; Finally using the k-d tree to accelerate the improved iterative method is closest point (ICP) precise matching, and using quaternion method of registration parameters are obtained. Experiments are carried out on the proposed new algorithm and PCA+ICP algorithm, 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

In recent years, intelligent industrial robots have become a research hotspot. As the core area of "Made in China 2025" strategy, it is one of the key factors to realize "Industrial 4.0" and "Intelligent Manufacturing". Workpiece pose recognition is a key technology in the sorting process of industrial robots. Through the registration of three-dimensional point cloud of the workpiece scanned by laser, the position and pose of the workpiece in the workpiece coordinate system can be obtained.

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 [5] 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 of geometric structure shape based on Hausdorff distance and Frachet distance [6]. These algorithms have higher requirements for point cloud data and hardware devices, and the registration time is too long for the industrial pipeline to meet the actual production needs.

To solve this problem, a new point cloud automatic registration algorithm based on PCA algorithm and improved ICP algorithm is proposed in this paper. Firstly, a point with a large variation of the normal vector of the point cloud in the region is selected as the feature point, and the initial registration point pair is selected by establishing a characteristic histogram of the feature point. Then, the initial
registration point is roughly registered by PCA algorithm, and the precise registration point pairs are obtained. Finally, the point cloud is accurately registered by the ICP algorithm optimized by k-d tree, and the registration parameters are calculated by quaternion method.

2. Select the 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) [7] 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.

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

In the formula, \( n_i \) is the normal vector of point \( p_i \), \( v_k \) 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)

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

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 of \( p_q \) is generated. The FPFH calculation process is shown in Fig.1.
In this paper, Stanford Bunny 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

Figure 2. Feature Point Set Obtained by FPFH
3. Rough registration based on PCA algorithm

PCA is an effective simplified analysis method for detecting data sets, which is used to reduce the dimension of data sets while maintaining the maximum contribution of data sets to the difference. For point sets \( P_t = \{x_1, x_2, x_3, \ldots, x_n\} \), among them, \( x_i \) is \( n \)-dimensional data, and the mean and covariance matrices are respectively:

\[
\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{5}
\]

\[
cov = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})(x_i - \bar{x})^T \tag{6}
\]

The eigenvector of covariance matrix \( \text{cov} \) is the principal axis of point set \( P \). For three-dimensional point cloud data, the three feature vectors obtained by PCA correspond to X axis, Y axis and Z axis, and the reference coordinate system of point cloud is established. Because PCA reflects the greatest difference contribution of data sets, the initial registration can be achieved by adjusting the reference coordinates of two point clouds with large similarity. Because the two directions of coordinate axes may differ by 180°, it is necessary to establish a minimum bounding box to test whether the two point clouds adjust and coincide. By coordinate transformation, the data point cloud bounding box can be transformed into the model point cloud reference coordinate system, so that the spatial positions of the two bounding boxes are basically the same. Calculate the overlap volume of the bounding box. If it is larger than the set tolerance, the two point clouds roughly coincide. If it is smaller than the set tolerance, reverse the reference coordinate axis of the data point cloud and try again. By adjusting the coordinate system, the initial registration of point clouds can be achieved, which provides a better initial value for the next step of accurate registration.

Because the unit quaternion algorithm [8] 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 \( \vec{q}_R = [q_0, q_1, q_2, q_3]^T \), among them \( q_0 \geq 0 \) 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:

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

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:

\[
\begin{align*}
\bar{\mu}_a &= \frac{1}{N_A} \sum_{i=1}^{N_A} \bar{A}_i \\
\bar{\mu}_b &= \frac{1}{N_B} \sum_{i=1}^{N_B} \bar{B}_i
\end{align*} \tag{8}
\]

Taking the obtained centroid into equation (7), 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:

\[
T = \bar{\mu}_a - R\bar{\mu}_b \tag{9}
\]

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:
\[ p_i' = R \cdot p_i + T \] (10)

4. Precise registration based on improved ICP

The position of point cloud after initial registration is taken as the initial position of accurate registration. In this paper, the improved ICP algorithm is used for accurate registration. Compared with the classical ICP algorithm, the improved ICP algorithm adds k-d tree, which improves the efficiency of the algorithm and reduces the registration time.

K-d tree search at the heart of the closest point is based on the binary tree coordinate division point of topological relations. Firstly, the nodes to be queried are compared with the values of the splitting dimension. If the value is less than or equal to the splitting dimension, it enters the branch of the left subtree. If the value is larger than the splitting dimension, it goes to the branch of the right subtree. This way, it loops to the leaf node of the binary tree, finds the nearest neighbor similar point in the same subspace as the query point along the search path, and then carries on the back-and-forth operation to the point. If the other subspace nodes on the search path have closer points, it jumps to the subspace node to search for the nearest point. The above steps are repeated until the search path is empty and the search is completed. Because the calculation of corresponding points is the longest time-consuming step in the whole registration process of ICP, when ICP joins k-d tree, the algorithm can search corresponding points faster, thus greatly reducing the registration time.

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 Bunny 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. 3.

![Figure 3. Diagram of reference point cloud and target point cloud](image)

After rough registration, the point clouds are shown in Fig.4. 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. 5 (a) are obtained. Results Compared with PCA + ICP algorithm (as shown in Fig. 5 (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.

|                      | PCA + ICP algorithm | The new algorithm in this paper |
|----------------------|---------------------|---------------------------------|
| The number of iterations | 25                  | 10                              |
| The elapsed time /s   | 12.443851            | 1.116785                        |
| MSE/mm               | 0.112               | 0.028                           |

Through the observation and analysis of Fig. 5 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. 6.

![Image](image.png)

(a) The results obtained by PCA+ICP algorithm                 (b) The results obtained by this algorithm

Figure 6. Rotation matrix $R$ and translation matrix $T$ obtained by the two algorithms and time result diagrams

6. Conclusion

This paper presents a new automatic registration algorithm for point cloud based on PCA algorithm and improved ICP algorithm. The algorithm selects initial registration point pairs by establishing feature point histogram (FPFH). Then PCA 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] Zhongren Wang, Qingyan Lu, Haisheng Liu. Random workpiece visual recognition and location method based on CAD model [J]. Infrared and Laser Engineering, 2015, 44 (S): 230-235.
[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] Jie Duan, Tsinghua Hu, Lingjun Zhang, et al. Multi-label classification feature selection algorithm based on neighborhood rough sets [J]. Computer research and development, 2015, 52 (1): 56 - 65.
[6] Lei Zhang, Zhihang Ji, Jixin Pu. Constrained improved ICP point cloud registration method [J]. Computer Engineering and Application, 2012 (18): 197 - 200.
[7] Luhao Gan, Saixian He. Research on Point Cloud Mosaic Method with Low Overlapping Degree [J]. Laser Magazine, 2019, 40 (03): 84 - 90.

[8] Yuan Huang, Feipeng Da, Haijie Tao. An automatic point cloud registration algorithm based on feature extraction [J]. China Laser, 2015, 42 (03): 250 - 256.

[9] Qiang Li, Paulo Gao, Mingliang Dou. Point cloud registration algorithm based on multiple feature matching [J/OL]. Computer application research: 1-7 [2019-04-17].

[10] 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.