Part point cloud segmentation method based on model registration

Lei Si¹, Han Yang², Zhongming Li³, Liming Duan*¹,
¹ ICT Research Center, Key Laboratory of Optoelectronic Technology and Systems of Education Ministry of China, Chongqing University, Chongqing, 400044 China
² College of Mechanical Engineering, Chongqing University, Chongqing, 400044 China
*Corresponding author’s e-mail: duanliming@cqu.edu.cn

Abstract. In order to analyze the machining errors of parts more accurately, a point cloud segmentation method based on model registration was proposed for mechanical parts. First, the surface information of the standard model of the part is extracted from the Initial Graphics Exchange Specification (IGES) file; then, the part point cloud is registered to the standard model using the method of the moment principal axis method and the Iterative Closest Point algorithm (ICP); then, by calculating the distance between each point in the point cloud and each surface in the standard model, it is used to determine the corresponding relationship between the model surface and the point cloud, and then the point cloud is segmented; finally, the segmentation results are surface-fitted and benchmarked to obtain a segmentation with better alignment quality. The experimental results show that this method can automatically segment the part point cloud according to the surface features of the part when only the IGES model and the point cloud model are input, without setting any empirical parameters, and obtain the segmentation result with clear boundaries.

1. Introduction
Digital inspection technology is a high-precision and high-efficiency means of error detection [1], and how to analyze the size and distribution of tolerances more accurately from its inspection results is an important research direction. When designing mechanical parts, different surfaces often have different accuracy requirements, and the manufacturing error of parts can not be reflected in the accuracy difference using the traditional method of calculating the machining error of parts [2]. In order to better reflect the pertinence of error analysis, it is necessary to segment the part point cloud obtained from 3D measurement.

Commonly used point cloud segmentation methods include surface-based methods and clustering-based methods. The surface-based region segmentation method is to segment points belonging to the same basic geometric features into the same region, the main steps include the selection of seed points and region growth. Jagannathan and others partitioned the point cloud into several regions by calculating the curvature value of each vertex in the point cloud, and the curvature values of points in the same region are similar, and the curvature values of points in different regions are more different, so as to achieve the point cloud segmentation[3]. The key point of the surface-based point cloud segmentation method is the selection of seed points and growth criteria, thus requiring strong a priori knowledge and the edges it produces are prone to distortion. The clustering-based point cloud segmentation method considers the essence of area segmentation to be the classification of data points.
with similar local geometric feature parameters. Wang et al combined the social particle swarm optimization algorithm with the fuzzy-C Means (FCM) algorithm, which effectively avoids the shortcomings of local convergence that can easily fall into the clustering process, but the segmentation is not very effective when targeting sparse point clouds[4]. In general, the above methods basically need to establish the neighborhood of the data points, and then, according to the information of the neighborhood data points, calculate the normal vector, curvature and other relevant quantities of each data point, and then do the next processing. In this process, strong a priori knowledge is required, so the algorithm is not automated enough and the segmentation results are not easy to control.

To address the above problem, a point cloud segmentation method is proposed. Taking advantage of the surface rules of the standard model of the part, which is easy to identify and has clear boundaries, we first align the point cloud of the part with the standard model, then establish the correspondence between the point cloud and the surface, and finally divide the point cloud of the part according to the surface characteristics of the standard model of the part and optimize it.

2. Point cloud registration

To ensure accurate registration of the 3D measurement model and the original design model, the number of sampling points and the number of point clouds in the measurement model need to be similar [5], and the number of sampling points is determined according to formula (1).

\[
1.0 \leq \frac{\text{card}(F) n_i}{\text{card}(H)} \leq 1.2
\]

where \( F \) is the surface set of the original design model, \( \text{card}(F) \) is the number of surfaces \( F \), \( n_i \) is the number of points on the \( i \)-th surface, and \( H \) is the point set of the point cloud in the 3D measurement model, \( \text{card}(H) \) is the number of point clouds.

The point cloud registration is the basis for establishing the correspondence between the point cloud model and the standard model. In this paper, the initial position of the ICP algorithm [6] is determined using the moment principal axis method [7], and then the ICP algorithm is used to accurately align the part point cloud with the IGES model.

Let \( X \) denote the point cloud set of the original design model and \( P \) denote the point cloud set of the sampled point clouds. Calculating the principal axes of a point cloud requires calculating the inertia matrix \( I \). The characteristic vector of the inertia matrix \( I \) is the primary direction of the point cloud. Arranging the principal direction vectors as third-order squares according to the magnitude of the corresponding eigenvalues and unitized as \( E_p \) and \( E_x \), then the rotation matrix \( R \) and translation vector \( T \) are as follows:

\[
R = E_x \cdot E_p^{-1}
\]

\[
T = \bar{u}_x - \bar{u}_p
\]

Performing the above rotational and translational transformations on the point cloud \( P \), the transformed point cloud \( V = R \cdot P + T \).

The ICP algorithm is used to perform fine alignment of \( V \) and \( X \). Set the fine alignment transformation to \( T_{\text{ICP}} \) and the transformed part point cloud is denoted as \( V_{\text{pcf}} \), as shown in formula (4):

\[
V_{\text{pcf}} = T_{\text{ICP}}(V)
\]

3. Point cloud segmentation

In general, the surface corresponding to any point in the aligned point cloud \( V_{\text{pcf}} \) should be the nearest surface to that point in the standard model. However, a point near a surface boundary should be related to the surface boundary by determining the relationship of the point's projection point on the surface to the surface boundary to determine the correspondence between the point in \( V_{\text{pcf}} \) and the surface in the standard model. As shown in Fig.1, surfaces \( \Psi_1 \) and \( \Psi_2 \) belong to plane \( \Psi \), and surface \( \Pi_1 \) belongs to plane \( \Pi \), the distance from point \( t \) to plane \( \Psi \) is \( l_1 \) and the distance to plane \( \Pi \) is \( l_2 \), and \( l_2 < l_1 \), but only the projected point of point \( t \) on surface \( \Psi_1 \) is inside the boundary of \( \Psi_1 \), so it can be determined that
there is a correspondence between point \( t \) and surface \( \Psi_1 \), but there is no correspondence with surface \( \Psi_2 \) and surface \( \Pi_1 \).

![Figure 1. A special case of attribution surface for the point](image)

3.1. Initial point cloud segmentation

The point \( v_i=(x_i, y_i, z_i) \) is one of points in the point set \( V_{pcf} \) and the surface \( f_j \) is one of surfaces in the surface set \( F \) of the original model. Set \( v_{ij} \) be the projection point of point \( v_i \) on surface \( f_j \) and \( l_{ij} \) be the distance from point \( v_i \) to surface \( f_j \). The ascending distance set \( L_i=\{l_{ij1}, l_{ij2}, l_{ij3},\ldots\} \) from point \( v_i \) to all the surfaces in the original design model is calculated, and the sequence of surface set \( F_i=\{f_{ij1}, f_{ij2}, f_{ij3},\ldots\} \) and projection point set \( V_i=\{v_{ij1}, v_{ij2}, v_{ij3},\ldots\} \) corresponding to \( L_i \) are obtained. Two rays are drawn from the projection point to determine the positional relationship between the projection point and the surface. According to the type of surface, it can be divided into two cases:

When the surface is plane: the position of projection point \( v_{ij} \) is outside the out-of-plane contour, on the plane boundary, inside the plane, or inside the in-plane contour, corresponding to (a), (b), (c), (d) in Fig.2. Two rays with opposite directions which takes projection point \( v_{ij} \) as the starting point are drawn. The number of intersections between the two rays and the plane boundary is recorded as \( N_1, N_2 \) respectively. Then determine whether there is an extreme point. If it exists, the number of extreme points is recorded as \( n \), then the number of intersections is updated, that is \( N_1 = N_1 + n \). Similarly, the value of \( N_2 \) is updated.

There are three types of intersections with the plane boundary in the rays leading downward from the projection point \( v_{ij} \), shown as Fig.2(a). In the first case, the intersections are \( P_1, P_2 \) and \( P_3 \), and point \( P_4 \) is an extreme point, so the number of intersections is 4. In the second and third cases, the intersections are \( P_a, P_b, P_c, P_d, P_e \) and \( P_f \), and the number of intersections is 4 and 2 respectively. In the upward rays, three rays have no intersection with the plane boundary. Similarly, the number of intersections can be calculated in (b), (c), (d) in Fig.2.

![Figure 2. Location relationship between projection point and plane boundary](image)

After obtaining the number of intersections \( N_1 \) and \( N_2 \), if any of \( N_1 \) and \( N_2 \) is an odd number, the projection point exists inside the plane, otherwise, the projection point exists outside the plane.
3.2. Point cloud segmentation optimization

The initial segmentation of the point cloud is more dependent on the alignment accuracy of the point cloud. When the point cloud data distribution is uneven or part of the data is missing, the alignment accuracy decreases significantly, and the calculation of the distance from point \( v_i \) to point \( f_j \) will have large errors as well as the boundary determination, resulting in false matches and thus affecting the segmentation effect. To reduce the above effects, after the initial segmentation is completed, a least-squares fit is made to each subset of point clouds according to their corresponding surface types, and the surface with the smallest fit error is chosen as the reference to optimize the alignment of the initial segmentation of the point clouds.

4. Experimental results

In order to verify the effectiveness of the method in this paper, point cloud segmentation of the bearing seat model was performed using the visual studio 2013 platform, the OpenGL (Open Graphics Library) library and the PCL (Point Cloud library) library. The computer used in this experiment is equipped with an Intel Core i5 CPU, 3.30GHz, and 8.00GB of RAM.

![Standard model and 3D measurement model of bearing seat](image1)

Fig. 3 shows the standard model and the 3D measurement model of the bearing seat, the standard model has 27 facets and the 3D measurement model has 8836 points. Fig. 7 shows the results of the alignment of the standard model with the point cloud model.

Due to the sparse distribution of the point cloud perpendicular to the axial hole (which can be interpreted as some missing data), the relative positions of the point cloud models are still skewed significantly after alignment with the standard model. The results of this alignment were used to establish the correspondence between the points in the point cloud and the surfaces in the standard model, as shown in Fig. 4.

![The overall effect](image2)

The point cloud segmentation is basically implemented, with clear boundaries between surfaces. However, due to large deviations in the alignment results, the segmentation results show a number of mis-matches at the surface boundaries. In order to better show the details of the segmentation results, surface A (Fig. 5) with screw holes on the front of the model. It can be seen that surface A contains some of the point clouds (most of the points inside the red circle) that should belong to the base of the bearing support. This is due to a certain skew in the alignment of the point cloud model with the standard model, which changes the relationship between the projected points of some point clouds and the inside and outside of the surface boundaries, resulting in false point-to-surface matching relationships.
In order to improve the above situation, based on the initial segmentation, we optimize the alignment results based on surface A. The results of re-segmentation using the alignment-optimized point cloud are shown in Fig.6.

For any surface, the number of points, maximum positive distance, maximum negative distance, average distance and root mean square error of the set of point clouds corresponding to that surface are also counted. Obviously, the more points, the smaller the maximum distance and the average distance, the more concentrated the error distribution is, and the more accurate the segmentation result corresponding to that surface. Table 1 shows the specific comparison between the segmentation quality of surface A when different methods are used.

| Object  | Method                        | Points included | Maximum forward error (mm) | Maximum negative error (mm) | Average Value (mm) | Standard Error (mm) |
|---------|-------------------------------|-----------------|-----------------------------|-----------------------------|--------------------|---------------------|
| Surface A | Before Alignment Optimization | 651             | 0.143                       | -0.109                      | 0.022              | 0.074               |
|         | After alignment optimization  | 488             | 0.038                       | -0.031                      | 0.017              | 0.025               |
|         | Regional growth method        | 423             | 0.035                       | -0.031                      | 0.016              | 0.024               |

As can be seen from Table 1, the number of points contained in the corresponding point sets of surface A decreased after the alignment optimization, and the average distance did not change significantly, but the maximum positive distance, maximum negative distance and root mean square error were significantly reduced. This indicates that the alignment optimization corrects the alignment skew in the initial segmentation and makes the points in the point cloud fit better with the surfaces in the standard model. The decrease in the number of included points is due to the improvement in the quality of the re-segmentation by removing the mis-match established during the initial segmentation. The region growth method has a significant reduction in error, but this is due to the fact that it does not fully segment the points corresponding to surface A, resulting in too few points corresponding to these two surfaces. In particular, for two surfaces with relatively smooth transitions, the segmentation results of the region growth method produce more serious errors.

5. Conclusion

A method for segmenting part point clouds based on model registration is presented. Unlike other point cloud segmentation methods, this method uses the surface information of the standard model to provide the basis for point cloud segmentation. After the surface type determination and main parameter extraction, the registration of the 3D measurement model with the standard model, and the matching of
the 3D measurement model with the standard model, the correspondence between the points in the point cloud and the surfaces of the standard model is determined, and the point cloud segmentation is finally realized. Compared with general point cloud segmentation methods, this method does not need to calculate the neighborhood information, normal information, curvature information, etc. of each point, nor does it need to set empirical parameters, so it can quickly and automatically complete the segmentation of part point clouds. At the same time, the method is highly reliable, with clear boundaries and small errors, and is also very effective in segmenting sparse point clouds or unevenly distributed point clouds.

From the experimental results, the registration error of this method is 0.065 and the matching coverage reaches 94.7% for the used models. The segmentation results of the specified slices also indicate that this method is superior to the segmentation results of the area growth method and the traditional alignment method.

Acknowledgments
Supported by National Science and Technology Major Project(2017-VII-0011-0106).

References
[1] Li, C. B. Xiao, W. H. Du, Y. B. et al. (2016) Fine registration method for defective parts based on improved ICP algorithm. Computer Integrated Manufacturing Systems, 22: 1021-1028.
[2] Liu, L. S. Zhang, L. Y. Wang, X. F. (2013) A shape registration method considering the regional difference in precision. Journal of Mechanical Engineering, 49: 139-144.
[3] Jagannathan, A. Miller, E. L. (2007) Three-dimensional surface mesh segmentation using curvedness-based region growing approach. IEEE transactions on pattern analysis and machine intelligence, 29: 2195-2204.
[4] Wang, X. H. Wu, L. X. Chen, W. H. et al. (2017) Region segmentation of point cloud data based on improved practical swarm optimization fuzzy clustering. Optics and Precision Engineering, 25: 563-573.
[5] Tian, H. Q. Dang, X. Q. Wang, J. H. Wu, D. M. (2017) Registration method for three-dimensional point cloud in rough and fine registrations based on principal component analysis and iterative closest point algorithm. TDS, 34: 57-75.
[6] He, Y. Liang, B. Yang, J. et al. (2017) An Iterative Closest Points Algorithm for Registration of 3D Laser Scanner Point Clouds with Geometric Features. Sensors, 17: 1862-1863.
[7] Duan, L. Wang, K. Chen, Z. (2013) Improved rough registration algorithm between industrial CT reconstruction model and original CAD model. Computer Integrated Manufacturing Systems, 19: 673-679.