Proceedings of the 38th Chinese Control Conference
July 27-30, 2019, Guangzhou, China

Point Cloud Registration Algorithm Fusing of Super4PCS and ICP Based on the Key Points

Jun Lu[1], Wei Wang[1], Hongxu Shao[1], Li Su[1]

1. College Of Automation, Harbin Engineering University, Harbin 150001, China
E-mail: 348359423@qq.com

Abstract: A point cloud registration algorithm fusing of Super 4PCS and ICP based on the key point is proposed to solve the problem that the traditional Super 4PCS algorithm is time consuming and has poor registration accuracy for point clouds with low-overlap region. Firstly, by using the voxel grid method, point cloud is down-sampled to reduce the amount of the computation data. In order to reduce the search range of consistent four-point sets, key points are extracted by using ISS(Intrinsic Shape Signature) method. Then the optimal consistency four-point sets is obtained by Super4PCS based on extracted key points. We use each point in this four-point sets as the center to establish a neighborhood ball, and the overlapping regions is obtained by calculating the intersection of the neighborhood balls. Finally, registration is performed by using ICP within obtained overlapping regions. The experimental results show that the proposed method can improve the registration speed while improve the registration accuracy.

Key Words: point cloud registration, ISS (Intrinsic Shape Signature), Super4PCS, overlapping region, ICP (Iterative Closest Point)

1 Introduction

Point cloud registration is a vital process for integrating multiple partial point clouds into a complete 3D model, and has been widely used in many 3D scanning systems. In these 3D scanning systems, due to the shape and size of the object and the limitation of the viewing range of the 3D laser scanning equipment, one time scan cannot obtain complete 3D model information of the object. In order to obtain a complete 3D model, combining several datasets into a global consistent model is usually performed using a technique called registration. The key idea is to identify corresponding points between the data sets and find a transformation that minimizes the distance (alignment error) between corresponding points. This process is repeated, since correspondence search is affected by the relative position and orientation of the data sets. Once the alignment errors fall below a given threshold, the registration is said to be complete. At present, these algorithms are mainly classified into two categories, i.e., global feature based and local feature based algorithms.

In local feature-based methods, local feature descriptors play a crucial role in feature matching. In general, a good feature descriptor should be highly descriptive, in order to provide a comprehensive and unambiguous representation of local shape geometry. To ensure accurate and efficient feature matching, the feature descriptors should also be computationally efficient, compact, and robust to common nuisances such as noise and point cloud resolution variation. At present, numerous local feature descriptors have been proposed. In 1998, Johnson and Hebert[1][2] proposed a spin image by spinning a plane around the normal and computing the number of points falling into the image bins. Similarly, Chen and Bhanu[3] proposed a local surface patch (LSP) by integrating normal angles and curvature-based quantities into a 2D histogram. Both of these methods use the point-normal as the local reference axis (LRA), while the descriptiveness of LRA-based local feature descriptors is greatly limited because only the surface normal is used as a reference; there is a gauge of freedom in the rotation around the axes that must be eliminated. Niloy J. Mitra[4] introduced a second-order curvature feature, which can effectively improve the convergence speed, but this algorithm consumes a lot of time . Bingwei He[5] et al. proposed a registration algorithm based on curvature partial overlaps. However, this algorithm is generally proposed for gridded point cloud and cannot be directly applied to scattered point cloud. Besides, Jiaqi Yang[6] et al. proposed a local feature descriptor, called a local feature statistics histogram (LFSH). Baowei Lin[7] et al. proposed a method for encoding scale invariant 3D point features. Although the above mentioned registration methods can generally provide satisfactory point cloud registration results, they still have some common limitations. First, the existing 3D feature descriptors still suffer from low descriptiveness, and weak robustness. Second, most of the pairwise registration algorithms are time-consuming especially for large-scale point clouds with a huge amount of data.

The objective of global feature based algorithms is to construct a set of features to encode the geometric properties of the entire 3D object. Such as ICP(Iterative Closest Point) and 4PCS (4-Points Congruent Sets), etc. . ICP, which is one of the most classical registration algorithms, was proposed by Besl and McKay et al.[8] in 1992. Although the ICP method is a powerful algorithm for registration, it has obvious shortcomings, e.g., it may converge to a local minimum or even be non-convergent without a priori alignment of the point clouds. Therefore, the researchers first use the geometric features for coarse registration, and fine registration is performed by using ICP algorithm.

The 4PCS (4-Points Congruent Sets) registration algorithm is an efficient algorithm based on the global search strategy. The rigid transformation matrix can be calculated from three pairs of point correspondences. Therefore, a simple registration algorithm is to select three random points in the source point cloud and search for all possible corresponding three-point sets in the target point cloud. This search method has the complexity of O(N3), where N is the number of points in the target point cloud. Aiger et al. [9] proposed the '4-point congruent sets' (4-PCS) algorithm that extends the search method based on three points to four points in 2008. Firstly, the algorithm randomly selects three points from the source point cloud data by RANSAC to form a surface, and then selects a point that can be approximately coplanar with the surface. According to the length proportion between the four points, select approximately congruent four-point set in the target point cloud, then find the corresponding relationship based on a certain objective function to complete registration. The complexity of the algorithm is reduced to O(N2). Experiments show that the 4PCS algorithm is more efficient and robust. In 2011, based on the 4PCS algorithm, the D4PCS algorithm[10] (Dynamic 4PCS) was proposed. The algorithm estimated the overlap range of point cloud in each iteration process and dynamically selected consistent four-point sets, which accelerated the convergence rate of the algorithm. The Super4PCS algorithm was proposed by Mellado et al.[11] in 2014, which reduces the complexity from quadratic to linear time through some improvements in the search stage. Carolina Raposo et al.[12], proposed a global 3D registration method based on the improvement of Super4PCS called 2PNS (2 Point + Normal Sets) in 2017, in which the author did not look for coplanar four points, but look for the correspondence according to a pair of points and their normal vectors. Because the traditional Super 4PCS algorithm takes all the points in the original point cloud data into account when searching for the four-point set, which consumes a lot of searching time. If the traditional Super 4PCS algorithm is used directly, the calculation speed is slow and the precision is low, it is difficult to achieve the effect of real-time acquisition and matching.

In this paper, we proposed a point cloud registration algorithm fusing of Super 4PCS and ICP based on the key points. The results of the experiment indicate that the proposed method not only reduces the amount of calculation, speeds up the calculation rate, but also improves the registration accuracy.

2 Point Cloud Registration Algorithm Fusing of Super4PCS and ICP Based on the Key Points

In this paper, we perform voxelization of the stereo box of point clouds. The point clouds are under sampled by using the voxel center of gravity to represent all the points in the entire voxel. In order to reduce the search range of consistent four-point sets, key points are extracted by using ISS(Intrinsic Shape Signature) method. Then the optimal consistency four-point sets is obtained by Super4PCS based on extracted key points. We use each point in this four-point sets as the center to establish a neighborhood ball, and the overlapping regions is obtained by calculating the intersection of the neighborhood balls. Finally, registration is performed by using ICP within obtained overlapping regions. Fig. 1 shows the overall workflow of the algorithm.

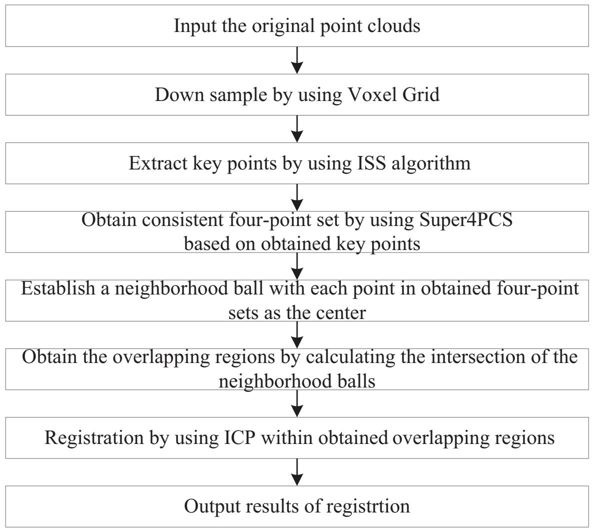


Fig. 1: Point cloud registration framework

2.1 Down Sampling by Using Voxel Grid Method

In the point cloud registration process, the transformation matrix can be calculated from three pairs of point correspondences. In generally, the number of original point clouds used for registration is large and the points is dense. Therefore, it is necessary to under sample the point clouds while maintaining the surface features of the point clouds. We use the voxel grid under sample method to under sample the global point cloud data. The specific steps are as follows:

(1) Building a spatial voxel grid

For the point cloud $P=\{p_1,p_2,\cdots,p_N\}$, we can easily determine the maximum and minimum $x_{\max}, x_{\min}, y_{\max}, y_{\min}, z_{\max}, z_{\min}$ in the X, Y, Z directions to build the minimum cubic space bounding box of the point cloud. Set the grid size of each cube as d_0 and divide the X, Y and Z directions to obtain the grids and the number of grids is $m\times n\times l$.

$$\begin{cases} m=\lceil (x_{\max}-x_{\min})/d_0 \rceil \\ n=\lceil (y_{\max}-y_{\min})/d_0 \rceil \\ l=\lceil (z_{\max}-z_{\min})/d_0 \rceil \end{cases} \tag{1}$$

$\lceil\cdot\rceil$ denotes round up

(2) Point index number

After the spatial voxel mesh is established, The grid with the index number for point $p_i(x,y,z)\in P$ is $\lfloor\cdot\rfloor$.

$$\begin{cases} index\_x=\lfloor (x_{\max}-x_{\min})/d_0 \rfloor \\ index\_y=\lfloor (y_{\max}-y_{\min})/d_0 \rfloor \\ index\_z=\lfloor (z_{\max}-z_{\min})/d_0 \rfloor \end{cases} \tag{2}$$

$\lfloor \cdot \rfloor$ denotes round down

(3) Save the index number in the grid, calculate the center of gravity C0 for all points in each grid by neighbor search.

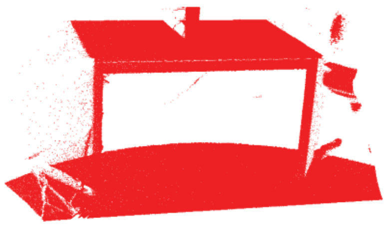
$$C_0 = \frac{1}{k}\sum_{j=1}^{k} p_j \tag{3}$$

The k represents the number of points in the grid.

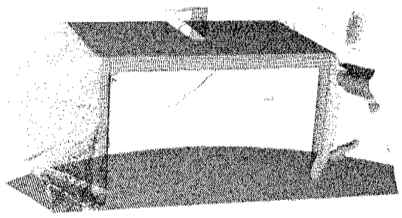
(4) The center of gravity of all points in each voxel grid is replaced by the original points in voxel to reduce the number of points in voxel.

The voxel grid method used the center of gravity of the small voxel to replace the original point by evenly dividing the space. On the one hand, it can effectively reduce the number of point clouds, on the other hand, it can effectively maintain the topological relationship between point cloud data and preserve the original surface shape of the object.

The figure 2 shows the comparison before and after down-sample of a desk point cloud. The original point cloud with 460,400 points remain 41,049 points after down-sample by the voxel grid method. However, the shape feature and spatial structure details of the point cloud are consistent with the original point cloud. In this way, the number of points used for calculation is reduced. And the same shape information as the original point cloud can be effectively extracted.



(a) The original point cloud data



(b) The point cloud data after down sampling

Fig. 2: Down sampling comparison

2.2 Extract Key Points by Using ISS Algorithm

In this paper, the ISS algorithm is used to extract key points. The purpose is to extract points with certain characteristics in point cloud data and then serve as the input of consistent four-point set in subsequent search.

ISS(Intrinsic Shape Signature)[13] is a method to establish a local coordinate system by using neighborhood information and characterize the degree of point features by using the relation between eigenvalues. Its high speed, accuracy and robustness are the advantages of being a key point extraction algorithm. The main steps are as follows:

(1) By establishing spatial kd_tree to obtain the topological relationship of point cloud data, it is convenient to query and traverse points.

(2) Establish a local coordinate system, set the neighborhood radius r of the query point p_i, the weight is set according to the Euclidean distance between each point in the neighborhood and the query point.

$$w_{ij} = \frac{1}{\| p_i - p_j \|}, | p_i - p_j | < r \tag{4}$$

(3) Construct a weighted covariance matrix in the neighborhood of the query point p_i.

$$\operatorname{cov}(p_i) = \frac{\sum_{|p_i - p_j| < r} w_{ij}(p_i - p_j)(p_i - p_j)^{\mathrm{T}}}{\sum_{|p_i - p_j| < r} w_{ij}} \tag{5}$$

(4) Solve the eigenvalue $\left\{\lambda_i^1, \lambda_i^2, \lambda_i^3\right\}$ of equation (5), and sort them from big to small, The corresponding eigenvector is $\left\{e_1, e_2, e_3\right\}$.

(5) Set the thresholds ε_1 and ε_2 , if $\lambda_i^2 / \lambda_i^1 \le \varepsilon_1, \lambda_i^3 / \lambda_i^2 \le \varepsilon_2$, then the point is considered as the key point. Otherwise iterate over the next point.

(6) Repeat the process until all the points have been traversed.

The eigenvalues obtained by solving the covariance matrix are of certain geometric significance. The magnitude of the eigenvalue can be seen as the length of the ellipsoid axis, and the vector of the eigenvalue can be seen as the axis of the local coordinate system, as shown in Figure (3). The shape of the ellipsoid is an abstract description of the distribution of points within the neighborhood. If the neighborhood points are densely distributed along a certain direction, the direction is the first principal direction of the ellipsoid. The direction in which the point distribution is sparse is the second main direction, and the point distribution in the normal direction is extremely sparse, which is the third main direction.

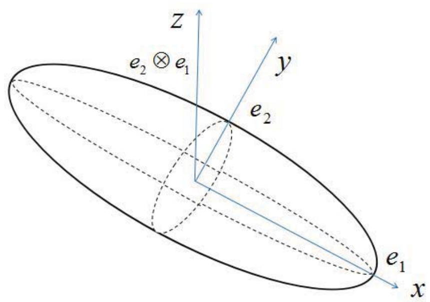


Fig. 3: Geometric significance of eigenvalue and eigenvectors

If a point happens to be at the corner point, the size of the three eigenvalues is nearly equal. Based on this, the threshold is set and key points are selected.

2.3 Point Cloud Registration Algorithm Fusing of Super4PCS and ICP Based on the Key Points

According to the data reduction and key point extraction methods described above, the specific registration process are as follows:

(1) The key point sets of source point cloud and target point cloud obtained by using voxel grid and ISS algorithm are respectively $KP(i)$、$KQ(j)$.

(2) Randomly select four-point basic wide-area base $A_i = \{a_{i1}, a_{i2}, a_{i3}, a_{i4}\}$ in $KP(i)$, and calculate the rigid body transformation invariant $\{d_{i1}, d_{i2}, r_{i1}, r_{i2}, a_i\}$.

(3) Search point pairs with length $\{d_1, d_2\}$ in $KQ(j)$, the candidate consistent four-point set is selected according to the rigid-body invariant.

(4) The rigid transform matrix between the basic wide-domain basis in $KP(i)$ and the candidate consistent point set in $KQ(j)$ is calculated by singular value decomposition.

(5) The rigid transform matrix is applied to the original point cloud P and Q to calculate LCP (Largest Common Pointset). When the LCP is largest, the rigid transform matrix is the optimal transform matrix, and the corresponding A_i and B_i are the optimal four-point set correspondence.

(6) The optimal consistency four-point sets are obtained by Super4PCS based on extracted key points. Each point in obtained four-point sets is used as the center to establish a neighborhood ball, and the overlapping regions is obtained by calculating the intersection of the neighborhood balls.

(7) Registration is performed using ICP within obtained overlapping regions.

2.4 Registration by Using ICP within Obtained Overlapping Regions

When Super4PCS is used for registration, a certain range of overlapping regions will be constructed according to the optimal consistency four-point set. As shown in Figure 4, the optimal consistency four-point set is $\{a, b, c, d\}$ and $\{a', b', c', d'\}$ after the registration of Super 4PCS. Each point in obtained four-point sets is used as the center to establish a neighborhood ball, and the overlapping regions is obtained by calculating the intersection of the neighborhood balls. Take the point a as an example, the selected area is represented as S_a.

$$S_a = \{p_i \in P, \|p_i - a\| < r\} \tag{6}$$

Similarly, S_b、S_c、S_d、S_a'、S_b'、S_c'、S_d' can be obtained. Fine registration is performed by using ICP within obtained overlapping regions. On the one hand, based on the four-point set, the selection of points in the neighborhood reduces the search ranges of ICP algorithm and improves the efficiency. On the other hand, the overlapping regions can be obtained to improve the accuracy of registration.

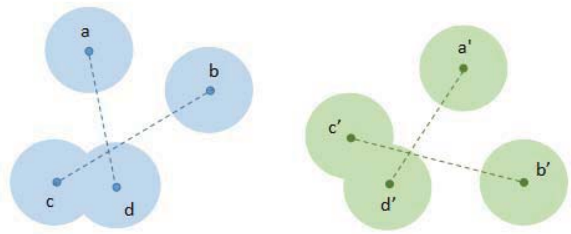
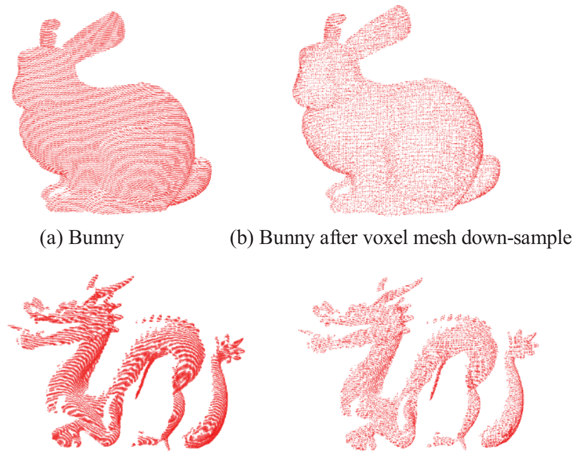


Fig. 4: Overlapping regions are extracted based on consistent four-point sets

3 Experiments and Results

Two sets of point cloud data, Bunny and Dragon, were used in the experiments. Each set of data was obtained from different points of view.

Figure 5 is the result after down-sampling by using voxel grid. It indicates that the density of obtained cloud is reduced, while the shape and geometry of point cloud is preserved.

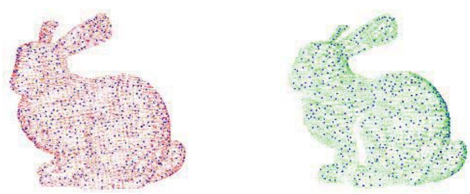


(a) Bunny (b) Bunny after voxel mesh down-sample

(c) Dragon (d) Dragon after voxel mesh down-sample

Fig. 5: Results of voxel mesh reduction sampling

Figure 6 shows the key point distribution obtained by using ISS algorithm from different points of view. For example, Bunny0 is a 0° points of view, and Bunny45 is a 45° points of view. In each figure, the blue point is the key point. These points are selected by using ISS method, which can make the key points more dispersed in the point cloud model, more stable and good distinguishability. At the same time, the selection of key points further reduces the search range of consistent four-point sets in the subsequent registration process, and improves the registration speed and accuracy.

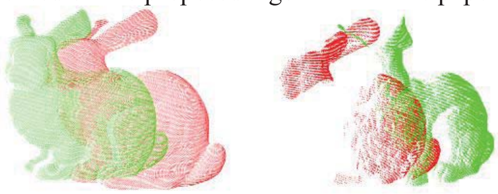


(a)Bunny0 key point distribution (b)Bunny45 key point distribution

(c) Dragon0 key point distribution (d) Dragon24 key point distribution

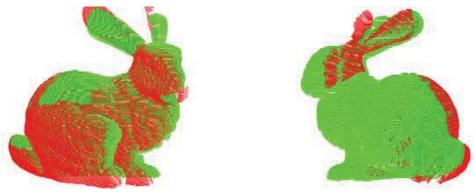
Fig. 6: Key points distribution of different scanning Angle

In order to show the applicability of the algorithm, point clouds with small overlap regions were used. The percentage in the label is an estimate of the overlap rate of the two point cloud datum. Figure 7, 8 and 9 are the registration results of Bunny point clouds by using the original Super4PCS and the proposed algorithm in this paper, respectively. Figure 10, 11 and 12 are the registration results of Dragon point cloud by using the original Super4PCS and the proposed algorithm in this paper. Table 1 and table 2 show the experimental results of the two models based on the proposed algorithm in this paper.



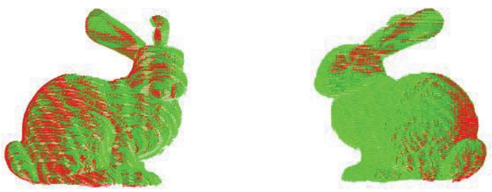
(a)Bunny0&45 (b)Bunny45&90

Fig. 7: Original position of Bunny point cloud



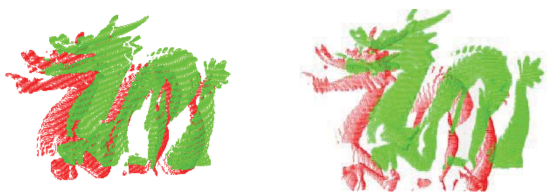
(a)Bunny0&45(80%) (b)Bunny45&90(60%)

Fig. 8: The results by using Original Super4PCS



(a)Bunny0&45(80%) (b)Bunny45&90(60%)

Fig. 9: The results by using proposed algorithm



(a)Dragon0&24 (b)Dragon0&48

Fig. 10: Original position of Dragon point cloud

(a)Dragon0&24 (80%) (b)Dragon0&48(60%)

Fig. 11: The results by using original Super4PCS

(a)Dragon0&24 (80%) (b)Dragon0&48(60%)

Fig. 12: The results by using proposed algorithm

Table 1: The results and parameters using the proposed algorithm for Bunny

Point cloud / Project	Bunny（0&45）	Bunny(45&90)
The number of initial point cloud	40097 40256	40256 30379
Voxel side length (m)	0.001	0.001
The neighborhood radius of the key point	0.0042	0.0042
Key points select thresholds (c_0)	0.995	0.995
The number of key points	475 463	463 459
Registration time (s)	10.05	13.76
LCP	0.929846	0.724851
Registration accuracy (m)	5.3185e-006	2.89394e-005

Table 2: The results and parameters using the proposed algorithm for Dragon

Point cloud / Project	Dragon（0&24）	Dragon (0&48)
The number of initial point cloud	42350 35772	35772 22092
Voxel side length (m)	0.0008	0.0008
The neighborhood radius of the key point	0.0048	0.0048
Key points select thresholds (c_0)	0.995	0.995
The number of key points	372 410	410 244
Registration time (s)	13.858	17.486
LCP	0.805526	0.587175
Registration accuracy (m)	1.075691e-007	8.256112e-007

The algorithms based on 4PCS are global searching methods, which can deal with the registration problem. But from Fig. 8 and Fig. 11, we can see that there are still some deviations between the two point clouds. While from Fig. 9 and Fig.12, the proposed algorithm in this paper can improve the accuracy of registration. Meantime, the registration time is shorten greatly as shown in table 3.

Table 3 shows the comparison of experimental results between the original Super4PCS and the proposed algorithm in this paper. (Before means before the registration, after means after the registration). The LCP (Largest Common Pointset) in the table is a description index of the registration accuracy. It is expressed as $LCP = s/t$. Where s is number of points in the target point cloud, which are closely near to the corresponding points in the source point cloud, t is the number of points in the target point cloud. The greater value of LCP means the higher accuracy of registration. It can be seen from the table 3 that the LCP index using proposed algorithm in this paper is improved.

Table 3: Parameters table of the original Super4PCS compared with the proposed method in this paper

Algorithm		Time (s)	LCP	
			Before	After
Original Super4PCS algorithm	Bunny0& Bunny45	80.21	0.521277	0.891298
	Bunny45& Bunny90	88.54	0.241607	0.685854
Algorithm in this paper	Bunny0& Bunny45	10.05	0.521277	0.959846
	Bunny45& Bunny90	13.76	0.241607	0.724851
Algorithm		Time (s)	LCP	
			Before	After
Original Super4PCS algorithm	Dragon0& Dragon24	76.17	0.458221	0.803327
	Dragon0& Dragon48	84.15	0.197855	0.558724
Algorithm in this paper	Dragon0& Dragon24	13.85	0.458229	0.805526
	Dragon0& Dragon48	15.96	0.197853	0.587175

4 Conclusion

A point cloud registration algorithm fusing of Super4PCS and ICP based on the key point is proposed in this paper. The traditional Super 4PCS algorithm searches the whole point cloud when searching for the four-point sets. It has a large amount of calculation and low efficiency and poor registration accuracy for point clouds with small overlapping regions. In order to reduce the amount of the computation data, the voxel grid method is used to under-sample the original point cloud. All points in the grid are represented by the centers of gravity of the grid. In order to reduce the search range of consistent four-point sets, key points are extracted by using ISS method. Then the optimal consistency four-point sets is obtained by using Super4PCS based on extracted key points. We use each point in this four-point sets as the center to establish a neighborhood ball, and the overlapping regions is obtained by calculating the intersection of the neighborhood balls. Finally, registration is performed by using ICP within obtained overlapping regions. Experiments show that the method proposed in this paper has a good improvement in registration accuracy and time compared with the original Super4PCS method.

References

[1] A. Johnson, M. Hebert. Surface matching for object recognition in complex three-dimensional scenes[J]. Image and Vision Computing, 1998, 16(9): 635-651.

[2] A. Johnson, M. Hebert. Using spin images for efficient object recognition in cluttered 3D scenes[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.21, pp.433-449, May 1999.

[3] Chen H C H , Bhanu B B B . 3D free-form object recognition in range images using local surface patches[J]. Pattern Recognition Letters, 2007, 28(10):1252-1262.

[4] Mitra N.J., Nguyen A., and Guibas L. Estimating surface normal in noisy point cloud data[J]. Special issue of International Journal of Computational Geometry and Applications, 2004, 14(4 – 5):261 – 276.

[5] Bingwei He, Zeming Lin, Y.F. Li. An automatic registration algorithm for the scattered point clouds based on the curvature feature[J]. Optics & Laser Technology, 2013, 46:53 – 60.

[6] Yang, Jiaqi, Z. Cao , and Q. Zhang . "A fast and robust local descriptor for 3D point cloud registration." Information Sciences (2016):S0020025516300378.

[7] Baowei Lin a,b,c, Fasheng Wang a,b, Yi Sun.Boundary points based scale invariant 3D point feature[J].J. Vis. Commun. Image R. 48 (2017) 136–148.

[8] Besl P J，Mckay N 13．A method for registration of 3-d shapes[C]．IEEE Transactions on Pattern Analysis and Machine Intelli-genee，1992，14(2)：239—256.

[9] Dror Aiger, Niloy J et al. 4-points Congruent Sets for Robust Pairwise Surface Registration[J]. ACM Transactions on Graphics. 2008.27(3)

[10] Juarez Paulino da Silva Júnior, Díbio Leandro Borges, Flavio de Barros Vidal. A dynamic approach for approximate pairwise alignment based on 4-points congruence sets of 3D points[C]. Proceeding of 18th IEEE International Conference on Image Processing. Los Alamitos: IEEE Computer Society Press, 2011: 889-892.

[11] N. Mellado, D. Aiger, and N. J. Mitra, “Super 4pcs fast global pointcloud registration via smart indexing,”Computer Graphics Forum, vol. 33, no. 5, pp. 205 – 215, 2014.

[12] Carolina Raposo and Jo ˜ ao P. Barreto.Using 2 Point+Normal Sets for Fast Registration of Point Clouds with Small Overlap[J]. IEEE International Conference on Robotics and Automation (ICRA).2017.5652-5658.

[13] YU ZHONG . Intrinsic Shape Signatures: A Shape Descriptor for 3D Object Recognition.2009 IEEE 12th International Conference on Computer Vision Workshops . 2009: 689-696 . DOI: 10 . 1109 / ICCVW. 2009. 5457637.