

Super-Resolution Reconstruction of LIDAR Point Cloud Image on Mobile Platform

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Keywords: Super-resolution reconstruction, target recognition, 3-Dpointcloudregistration, ICPalgorithm.

Abstract: Target recognition technology based on 3D LIDAR scanning technology provides important significance for vehicle and missile-borne systems. In view of the low resolution of existing 3D LIDAR the combination of LIDAR scanning technology and image processing technology is proposed. ICP algorithm is mainly used to reconstruct dense point cloud images through sparse laser point cloud image sequence, and to improve low resolution three-dimensional point cloud images. Super-resolution reconstruction is beneficial to target detection and recognition and other subsequent processing. Firstly, we focus on the application of ICP algorithm in three-dimensional laser point cloud registration, and use ICP algorithm to reconstruct three-dimensional point cloud image with super-resolution. Secondly, a simplified model is proposed to quantitatively evaluate the performance of point cloud reconstruction algorithm.

1. Introduction

At present, LIDAR has been more and more widely used in military affairs. For example, in UAV missile-borne system and motor platform vehicle-borne system, it has become a trend of modern warfare that the missile is controlled and navigated by UAV or combat vehicle equipped with LIDAR to strike ground or sea targets accurately. The technology of LIDAR in our country started late and its development is limited. There is still a certain gap between the technology level of LIDAR and the advanced level of the world. Since the 1960s, the United States has been studying lidar imaging, which represents the most advanced level in the world in theory and application. In 1978, the first heterodyne laser imaging radar was developed in the United States, and in 1980s, a multifunctional CO₂ laser coherent imaging radar was developed. Through a series of experiments, it was proved that the laser imaging radar has the ability to detect and recognize targets in complex background. The laser imaging radar was solved by the diode-pumped solid-state laser imaging detection system, which was developed in the mid-1980s. Miniaturization and uncooling. From 1986 to 2006, the American Air Force Research Laboratory (AFRL) developed practical lidar seekers for submunition guidance, low-cost autonomous attack system (LOCAAS), small smart bomb (SSB), cruise missile and other weapon systems, which realized autonomous guidance, target automatic identification, aiming point selection, guidance fuze integration and other functions. The maximum detection distance and range resolution of S laser imaging seeker can reach 10 km and 0.15 M. In 2004, the US Air Force Research Laboratory also developed a non-scanning focal plane array lidar with a resolution of 128*128, a detection distance of 1 km, a range resolution of 0.05 M and an imaging frequency of 30 Hz, which makes the application of lidar in missiles more extensive. The research of domestic area array three-dimensional laser imaging radar technology began in the "Tenth Five-Year Plan". At present, the area array radar can be used with resolution of 64 x64, range resolution of 0.1M and scanning angle of 4 X4. It has been basically used in military affairs, but the technical level of resolution still needs to be improved. Due to the low resolution of LIDAR in China, the number of point clouds taken at long distance is too sparse, which brings great difficulties to the

subsequent target detection and recognition, thus affecting the subsequent military process of flying object navigation and ground-to-air target tracking. Therefore, dense reconstruction of sparse point cloud sequence is of great significance and can provide guidance for subsequent technology. And preconditions.

Because the laser scanning equipment may receive the influence of visual field, noise and illumination in the process of measuring three-dimensional objects, it is impossible for the scanning equipment to obtain all point cloud information of the object to be measured from the same perspective. Three-dimensional image registration is to unify the three-dimensional point cloud images of the same object obtained by different sensors from different perspectives into a coordinate system. At present, most of the commonly used three-dimensional point cloud registration methods use iterative closest point (ICP) algorithm. This algorithm uses point (point surface) distance to find adjacent points, and then calculates rotation and translation matrix between multi-frame point clouds by means of mean square error function to achieve the purpose of registration. In essence, it is an iterative convergence algorithm. At present, there are many algorithms derived from point cloud registration, but basically based on the classical ICP algorithm, this paper uses the classical ICP algorithm to register the three-dimensional point cloud, uses the SVD algorithm to solve, and finally obtains a dense and clear three-dimensional point cloud image.

As the number of point clouds detected by area array radar is less in the process of farther detection distance, the less information it can get, and only sparse point cloud sequence can be obtained, which brings difficulties for subsequent recognition and navigation detection. Therefore, the densification of sparse point cloud sequence becomes necessary. At present, one of the methods to improve the resolution of point cloud image is to improve the resolution technology of imaging equipment, i.e. the research of radar principle. However, the research cost is high, the technology is difficult, and the transmission performance of image is easily affected, which is not conducive to practical application. Secondly, the point cloud image itself is studied. At present, the commonly used methods are reconstruction-based method and learning-based method. For the learning method, although it can achieve better results, it needs a large number of samples for training, and the computational complexity is high and depends on its own similarity. On the basis of understanding and deeply analyzing the point cloud registration algorithm based on reconstruction method, this paper has done a lot of research on reconstructing dense point cloud image sequence, proposed a method of super-resolution reconstruction using image matching technology to improve the resolution of point cloud image, and proposed a simplified mathematical model to evaluate the registration effect, which has been proved by experiments. Good practicability and high feasibility.

2. Laser point cloud matching and super-resolution reconstruction

This paper mainly uses ICP and SVD algorithm to solve the point cloud image and image registration. In this paper, the registration results of three registration methods are compared by using registration experiments, including sequential matching, inverse matching and global matching, in which sequential matching is performed in the order of sparse to dense point clouds. Similarly, inverse matching matches point clouds in the order from dense to sparse. Overall matching does not match all clouds one time in sequence.

2.1 ICP, SVD Principle and Algorithms

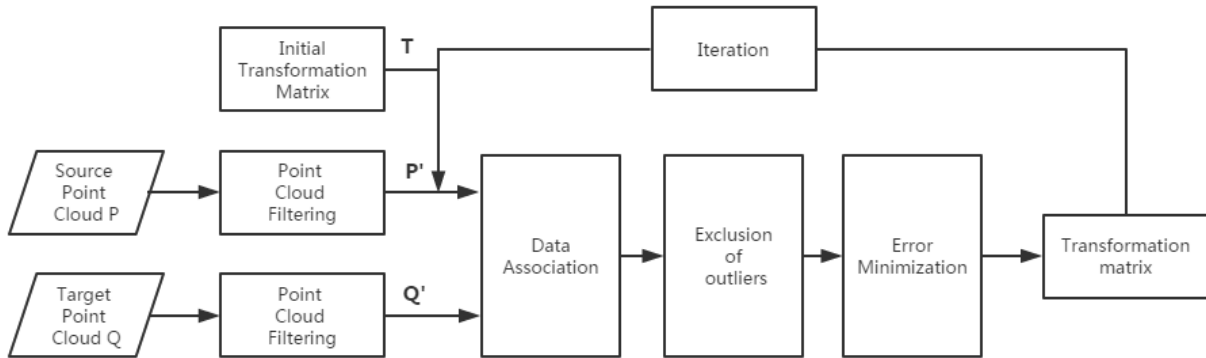


Figure 1. Flow chart of ICP algorithm

The image above shows the registration process of ICP algorithm. The registration process of point clouds is to find a rotation translation matrix (rigid transformation or Euclidean transformation) between two groups of point clouds, and transform the source point clouds into the same coordinate system of the target point clouds. The registration principle of three-dimensional point cloud can be expressed as equation: $P1 = R*P2+t$, where $P1$ and $P2$ are the corresponding points between the target point cloud and the source point cloud. Among them, R is a rotation matrix and t is a translation matrix. The implementation of ICP algorithm can be realized by the following five steps:

1. Obtain two sets of point cloud data P and Q , where P is the point cloud data to be registered and Q is the standard point cloud data. Set the transformation matrix T as the unit matrix I . Firstly, transform the point cloud data to be registered through the transformation matrix T to get a new matrix P' ;

2. Establish the correlation between P' and Q of new point set, and use point cloud association algorithm to find the nearest point Q_i of p_i from Q .

3. Establish the least squares constraint equation

$$\Delta T = \operatorname{argmin} \left(\sum_{i=1}^L \| T(P_i) - q_i \|^2 \right) \quad (1)$$

4. Solving the transformation matrix and superimposing it with the initial matrix to form a new transformation matrix.

5. Return to step 1 and repeat the above steps until the convergence condition is satisfied and the iteration is stopped.

Svd algorithm is used to solve ICP with ICP algorithm, as follows: Given two corresponding point sets:

$$X = \{x_1, \dots, x_n\}; \quad (2)$$

$$P = \{p_1, \dots, p_n\}; \quad (3)$$

Translation t and rotation R that minimize the sum of the squared error:

$$E(R, t) = \frac{1}{N_p} \sum_{i=1}^{N_p} \| x_i - R p_i - t \|^2 \quad (4)$$

Where x_i and p_i are corresponding points.

$$u_x = \frac{1}{N_x} \sum_{i=1}^{N_x} x_i \quad \text{and} \quad u_p = \frac{1}{N_p} \sum_{i=1}^{N_p} p_i \quad (5)$$

Are the centers of mass of the two point sets.

$$\text{Let } W = U \begin{bmatrix} \delta_1 & 0 & 0 \\ 0 & \delta_2 & 0 \\ 0 & 0 & \delta_3 \end{bmatrix} V^T \quad (6)$$

Where $U, V \in R^{3 \times 3}$ are unitary, and $\delta_1 \geq \delta_2 \geq \delta_3$ are the singular values of w .
 If $\text{rank}(w)=3$, the optimal solution of $E(R, t)$ is unique and is given by :

$$R=UV^T \tag{7}$$

$$T=u_x-Ru_p \tag{8}$$

The minimal value of error function at (R, t) is:

$$E(R,t)=\sum_{i=1}^{N_p} (\|x'_i\|^2 + \|y'_i\|^2) - 2(\delta_1 + \delta_2 + \delta_3) \tag{9}$$

2.2 Simulation and application of scene simulation

In the combination of the algorithm and the actual application scenario, a lot of simulation is carried out, and the model is shown as follows:

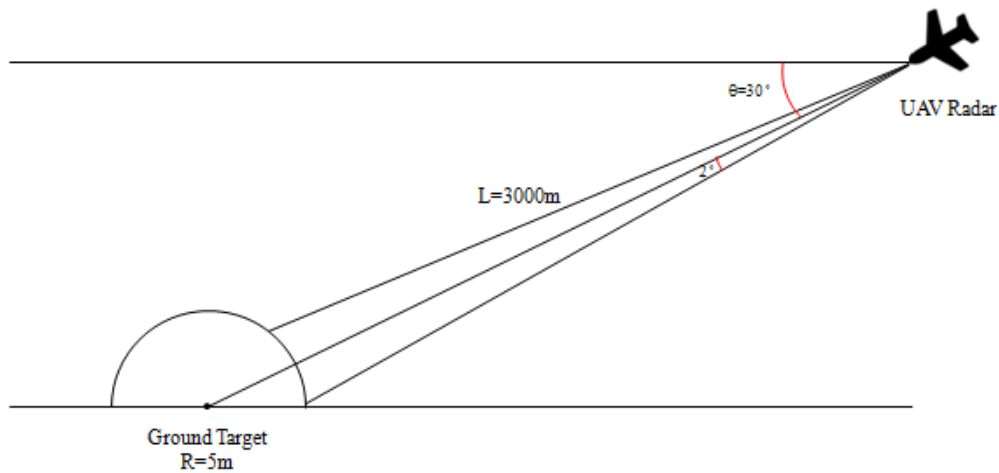


Figure 2. Principle of data acquisition for super-resolution reconstruction of point clouds

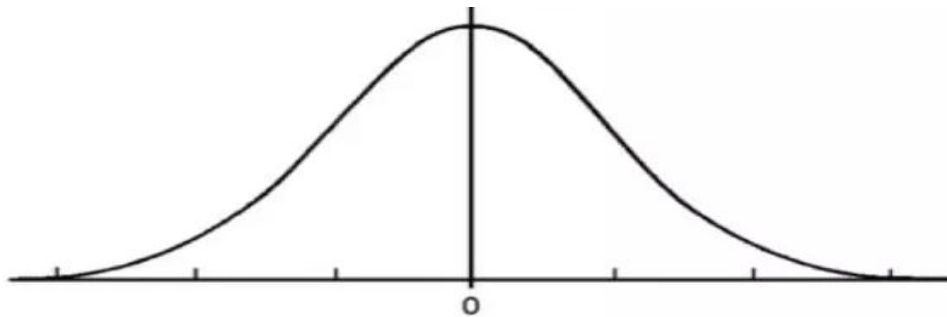


Figure 3. Standard Gauss Random Error Distribution

Figure 2 shows the principle diagram of point cloud super-resolution reconstruction data acquisition. At present, under the technical level of domestic area array radar, assuming that the radar resolution is 64×64 , the radar angle is $2^\circ \times 2^\circ$, the radar shooting frequency is 10 hz, the flight speed of UAV is 300 m/s, and the radius of ground target is 5 m, according to the speed information of UAV and the shooting frequency of radar system, the ground target will be photographed once every 30 m area array radar, and its point cloud image will be obtained. Every time we pick a point at intervals of 30 meters for ground targets. As shown in the figure above, the UAV's flight direction is 30 degrees from the horizontal plane. Considering the measurement error, we add the standard Gauss random error ($f(x)=1/2 \pi \cdot e^{-x^2/2}$) which is not greater than 1 degree as shown in the figure. The UAV starts shooting when it is 3000m away from the target. Similarly, we add the ranging random error which is not more than 0.1m. According to the information of distance, angle and radar resolution, I add the ranging random error which is less than 0.1m. The intersection

coordinates of the laser line emitted by the radar and the sphere (including deviations, with the spherical center as the coordinate origin, the horizontal direction as the Y axis, and the vertical direction as the Z axis) are calculated as follows:

Spherical equation

$$x^2 + y^2 + z^2 = 25 \quad (10)$$

Vertex coordinates:

$$(L \cos \theta, 0, L \sin \theta) \quad (11)$$

General formula of ground point coordinates:

$$[(L \tan \theta / 64) * (\sqrt{6} / 4) * (2k_1 + 1), (L \tan \theta / 64) * (\sqrt{2} / 2) * 2k_2 + 1, - (L \tan \theta / 64) * (\sqrt{2} / 4) * (2k_1 - 1)],$$

$-32 < k_1 < 32$

The general formula of all the lines emitted by the radar can be obtained by using the two-point general formula, and the intersection point of the laser emitted by the area array radar and the ground target can be simulated by using MATLAB with the two functions. Experiments show that the sequence of point cloud images obtained at L is almost unchanged when the distance continues to decrease. It shows that when L = 400 m, the radar can receive all the returned points. After obtaining all the point cloud image sequences, we register all the point cloud image sequences according to the way mentioned above, and reconstruct the dense point cloud image by point cloud matching, we can get three final point cloud images (different registration order).

3. Data acquisition of point cloud super-resolution reconstruction

In the following figure, three point cloud images (only 6 images in space) captured by 0-3000m UAV lidar at 30m intervals are obtained by MATLAB simulation.

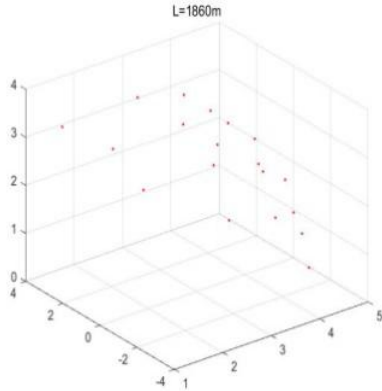


Figure 4. Point Cloud of 1860m Distance Target

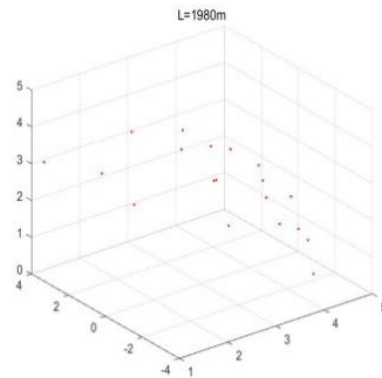


Figure 5. Point Cloud of 1980m Distance Target

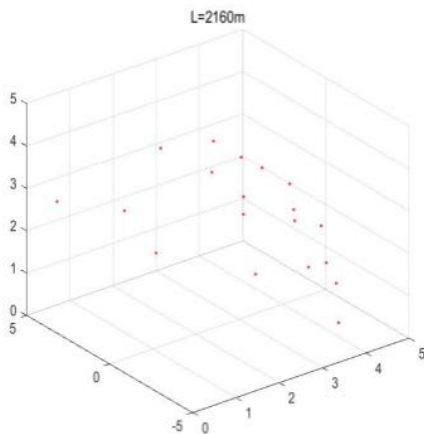


Figure 6. Point Cloud of 2160m Distance Target

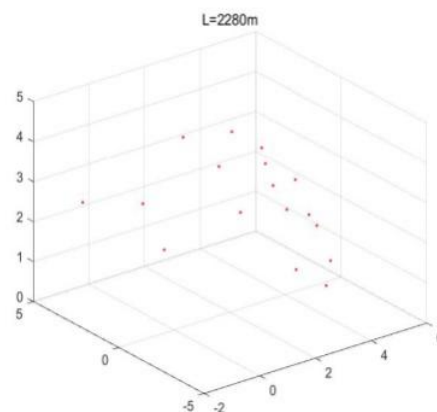


Figure 7. Point Cloud of 2280m Distance Target

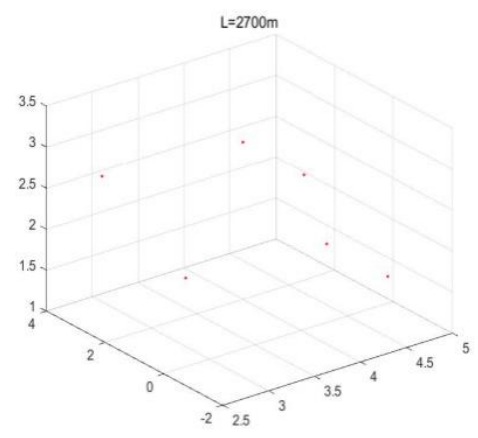
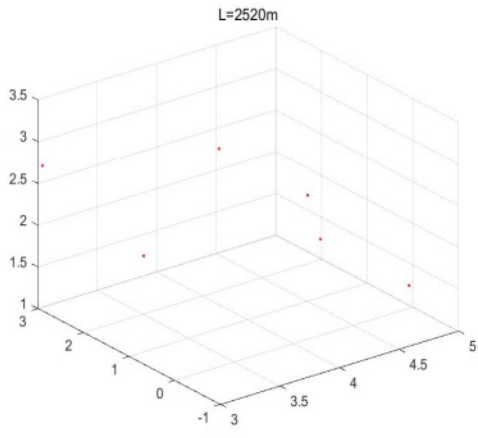


Figure 8. Point Cloud of 2520m Distance Target Figure 9. Point Cloud of 2700m Distance Target

As can be seen from the above image, as the detector is farther and farther away from the detection target, the number of point clouds is getting smaller and smaller, and the resolution is getting lower and lower, which is consistent with the actual situation. After calculation, when the detector is about 300 meters away from the target and the distance keeps close, the point cloud images obtained are almost the same. After obtaining a sequence of 300-3000m single point cloud images, we iterate the obtained point cloud images through ICP algorithm, and the SVD algorithm is used to calculate the registration. The final registration point cloud images are as follows:

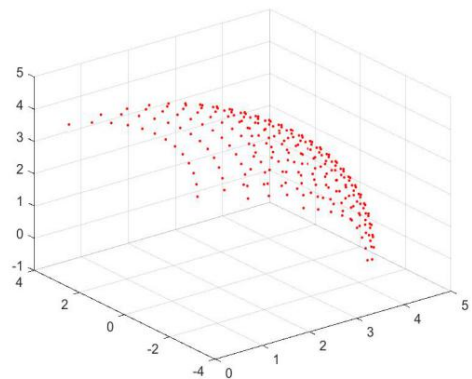
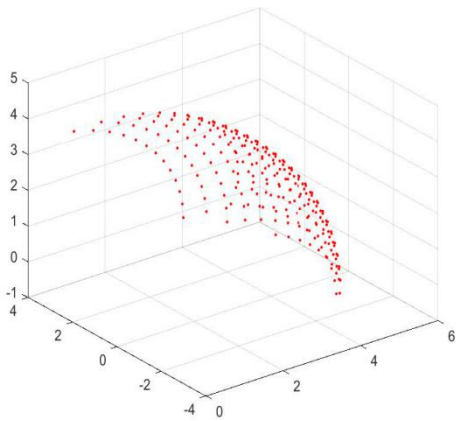


Figure 10. Final point cloud for global registration Figure 11. Final point cloud for positive registration

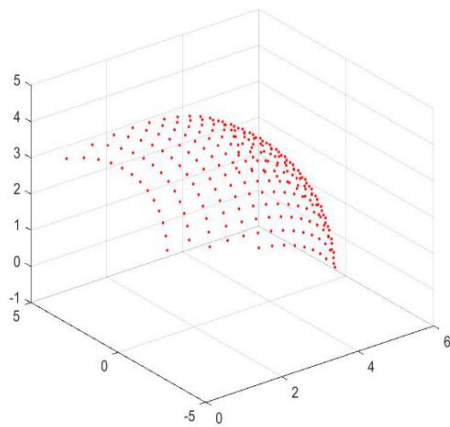


Figure 12. Final point cloud for inverse registration

4. Data Processing Analysis of Simulation Experiments

In order to further illustrate that the method described in this paper can improve the resolution of laser scanning radar and compare the effect of point cloud images obtained in different registration order, and get the best registration order, it is necessary to analyze the point cloud of single point cloud image and the point cloud image after registration mathematically, in order to judge whether the method can meet the requirements of improving radar resolution. In this paper, the average error (average distance of point cloud from sphere) is used to calculate the degree of deviation from sphere of three-dimensional point cloud coordinates in original point cloud images and the degree of deviation from sphere of point cloud coordinates in registered point cloud images.

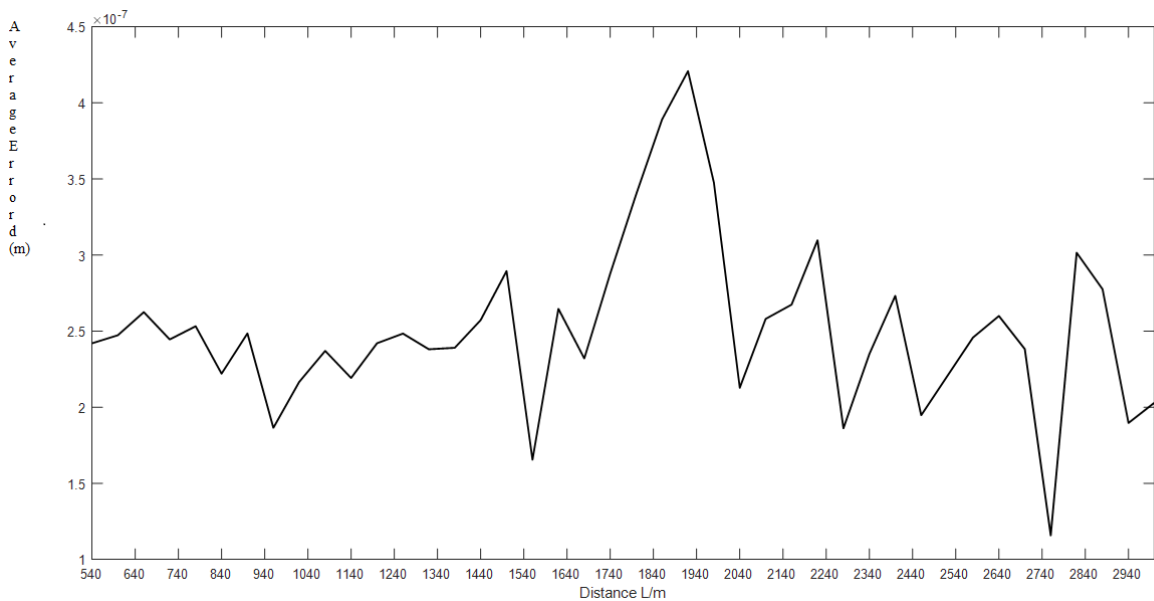


Figure 13. Average Error Graph under Different L

As shown in Figure 11 above, the error data in the case of larger L is eliminated, and the whole broken line diagram is basically consistent with the Gauss standard error diagram added in the experiment, which shows that the method of obtaining the experimental data is basically correct. In order to evaluate the effect of the method used in this paper on improving radar resolution, it is necessary to compare the average distance between the point clouds of three registered point clouds and the sphere as well as the average distance of a single point cloud sequence. The average distance of a single point cloud sequence is taken as a part of the comparison, as shown in Table 1 (Fig. 14):

Table 1. Average Error Comparison Table

	Primitive point nephogram	Positive-order registration point nephogram	Inverse registration point nephogram	Global registration point nephogram
Average Error d	2.2895866e-07	1.8282077e-07	1.3306247e-07	1.6914882e-07

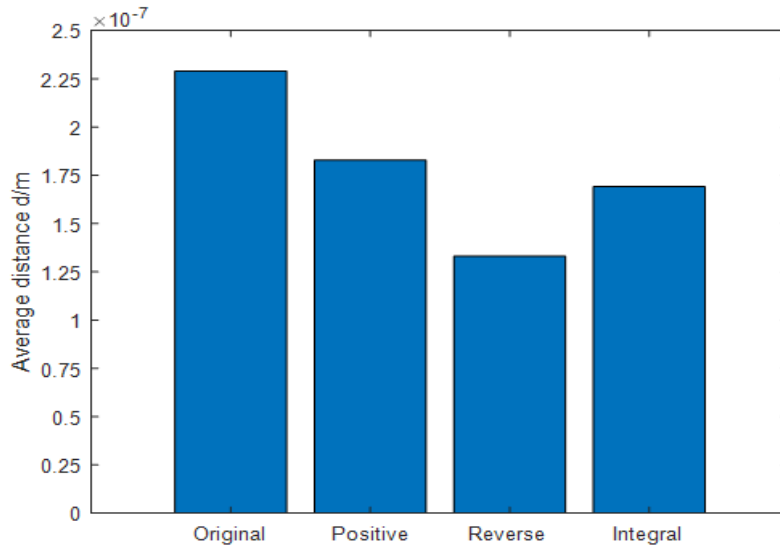


Figure 14. Average Error Contrast Chart

As shown in the table above, the registration used in this paper can indeed reduce the average distance between the point cloud and the sphere in the point cloud image, that is to say, increase the fitting degree of the point cloud. By comparing the point cloud images with different registration sequences, it is shown that the inverse registration can achieve better results than the positive registration and the whole registration, that is, the first registration of dense point clouds can achieve better results. After comparing the average error between the original point cloud and the registered point cloud image, in order to analyze the deviation degree of the point cloud image itself, the mean square error of the three registered point cloud images is calculated, as shown in Table 2 (Fig. 15):

Table 2. Contrast Table of Mean Square Errors

	Primitive point nephogram	Positive-order registration point nephogram	Inverse registration point nephogram	Global registration point nephogram
MeanSquare Error (MSE)	2.4201916e-14	2.1518414e-14	2.1174151e-14	2.1418100e-14

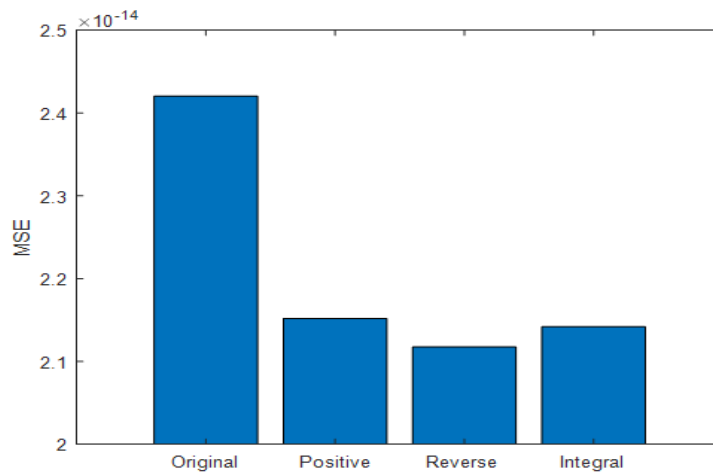


Figure 15. Mean Square Error Contrast Diagram

As shown in the table above, the point cloud sequence with smaller mean square error can be obtained by inverse registration.

5. Conclusion

Through the visual analysis of the original point cloud image and the registered point cloud image, as well as the analysis of the average error and mean square error of measuring the degree of deviation in mathematics, it can be found that the inverse registration of the three-dimensional point cloud image described in this paper can indeed increase the density and fitting degree of the point cloud, which indirectly proves that the method described in this paper can improve the three-dimensional laser scanning. The resolution of tracing radar is of great significance to the following three-dimensional reconstruction and target recognition.

References

- [1] Dong Anguo Fast Maximum Cross-correlation Algorithms for Image Matching Volume 18, No. 4, Zhejiang Wanli University Journal, August 2005
- [2] Zhou Peng, Tan Yong, Xu Punctuality. A New Algorithms for Corner Detection Image Registration Volume 32, No. 4, University of Science and Technology of China, August 2002
- [3] Meltzer, J. Soatto, S.Edge descriptors for robust wide-baseline correspond- dence 2008 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2008
- [4] Li Chenxi, Zhang Jun, Jin Xinyu, et al. Research progress of lidar SLAM technology and its application in unmanned vehicles [J], Journal of Beijing Union University, 2017, 31
- [5] Sun Boya, SLAM Technology of Mobile Robot [J]. Electronic Technology and Software Engineering, 2018
- [6] Dai Jinglan, Chen Zhiyang, Ye Xiuzi. Application of ICP algorithm in point cloud registration [J]. Chinese Journal of Image Graphics, 2007, 12
- [7] Pei Bo, Liu Donghui, Qian Jiuchao. Overview of indoor positioning technology and application [J]. Navigation, positioning and timing, 2017, 4
- [8] Zou Wanhong, Research on Geometric Modeling Technology of Large Scale Point Cloud Model: [Master's Degree Thesis], Hangzhou: Zhejiang University, 2007
- [9] Xue Yaohong, Zhao Jianping, Jiang Zhenggang and others. Point cloud data registration and surface subdivision technology. Beijing: National Defense Industry Press, 2011
- [10] Huang Yanqun, Tian Ailing, Grating Projection Triangle Method for Measuring Three-Dimensional Contour of Objects, Journal of Xi'an Institute of Technology, 2004
- [11] Yang J, Li H, Campbell D, et al. Go-ICP: a globally optimal solution to 3D ICP point set registration [J]. IEEE Transactions on Pattern Analysis and Machine intelligence, 2016, 38(11): 2241-2254.
- [12] Ghang J, Singh S. Enabling aggressive motion estimation at low-drift and accurate mapping in real-time[C]//2017 IEEE international Conference on Robotics and Automation (ICRA), IEEE, 2017: 5051-5058.
- [13] Rusu R B, Cousins S. 3D is here; Point cloud library (PCL)[C]//2011 IEEE international Conference on Robotics and Automation (ICRA). Shanghai. IEEE, 2011: 1-4.
- [14] Application of Dai Jinglan, Chen Zhiyang and Ye Xiuzi. ICP algorithm in point cloud registration [J]. Chinese Journal of Image Graphics, 2007, 12(3): 517-521.
- [15] Huang Xingsen. Research on registration technology of three-dimensional point cloud data [I]. Dalian: Dalian Maritime University, 2010.
- [16] Samet H. K-nearest neighbor finding using MaxNcat-cstDist [J]. IEEE Transactions on Pattern Analysis & Machine intelligence, 2008, 30(2): 243.

- [17] Zhao Fuqun, Zhou Mingquan. Improved scale iteration nearest point registration algorithm [J]. Computer Engineering and Design, 2018, 39 (1): 146-150.
- [18] Pomcrleau F, Colas F, Siegwart R, et al. Comparing ICP variants on real-world data sets [J]. Autonomous Robots, 2013, 31(3): 133-148.
- [19] Li Chenxi, Zhang Jun, Jin Xinyu, et al. Research progress of lidar SLAM technology and its application in unmanned vehicles [J]. Journal of Beijing Union University, 2017, 31 (4): 61-69.