The New Fast Point Feature Histograms Algorithm Based on Adaptive Selection

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Using Fast Point Feature Histograms feature from point cloud for 3D object recognition or registration, Fast Point Feature Histograms feature descriptor is arbitrarily and inefficiently calculated by subjectively adjusting the neighborhood radius, and the whole process can't be completed automatically. An adaptive neighborhood-selection Fast Point Feature Histograms point cloud feature extraction algorithm has proposed to solve this problem. Firstly, we estimate the point cloud density of many pairs of point clouds. Secondly, compute the neighborhood radius to extract the Fast Point Feature Histograms features for Sample Consensus Initial Alignment registration, and count the radius and the density when the registration performance is optimal, and then the cubic spline interpolation fitting is used to obtain the function expression of the radius and the density. Finally, the Fast Point Feature Histograms feature extraction algorithm has combined with the function to form adaptive neighborhood-selection Fast Point Feature Histograms feature extraction algorithm. The experimental results have shown that the proposed algorithm can adaptively choose the appropriate neighborhood radius according to the density of point cloud, and improve the Fast Point Feature Histograms feature matching performance. At the same time, it is improved the computing speed to a better value, which is of guiding significance.

Keywords: Fast Point Feature Histograms; Sample Consensus Initial Alignment; Point Cloud Density; Neighborhood Radius; Adaptive Selection

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1. Introduction

The 3D object recognition based on point cloud feature descriptors, 3D scene reconstruction, and 3D object position registration are important research contents in the field of computer vision. The existing type of point cloud feature descriptors can be summarized as point cloud global feature descriptors and point cloud local feature descriptors. The literature [1–3] has put forward PFH (Point Feature Histograms) feature descriptor. Then, in order to improve PFH's operation speed, the point cloud local FPFH feature descriptor [4] was introduced which has faster running speed and only 33 dimensions. It saves more computation space and applies more applications in 3D object recognition and registration. The literature [5] had using FPFH feature descriptor with HSV color feature of object recognition of 3D objects. The literature [6] had combined with the CAD model using FPFH descriptor and SVM classifier to complete the detection and recognition of conventional industrial components. The literature [7] had used FPFH feature descriptor of various parts of the human body point cloud extraction and matching. The literature [8] had used FPFH feature descriptor of coarse registration based on the registration of ICP and so on. The application of FPFH based on the characteristics of the existing problems in common [9–18]: the criteria for the selection of neighborhood radius isn't considered in the calculation of FPFH feature descriptor, to automatically select the appropriate radius according to the characteristics of the point cloud, the subjective repeatedly debugging or tried, and has strong subjectivity. On the other hand, several debugging to achieve better method of neighborhood radius is quite inefficient, it doesn't have the actual use effect.

To solve the above issues, we are using FPFH feature adaptive neighborhood selection algorithm based on point cloud density adaptive selection of neighborhood radius are suitable for calculating FPFH feature descriptor. It is improved the performance of FPFH features. The operation has the guiding role to the actual production [19–21, 21]. An adaptive neighborhood-selection FPFH point cloud feature extraction algorithm has proposed to solve this problem. Firstly, we estimate the point cloud density of many pairs of point clouds. Secondly, compute the neighborhood radius to extract the FPFH features for SAC-IA registration, and count the radius and the density when the registration performance is optimal, and then the cubic spline interpolation fitting is used to obtain the function expression of the radius and the density. Finally, the FPFH feature extraction algorithm has combined with the function to form adaptive neighborhood-selection FPFH feature extraction algorithm.

In this paper, we have proposed the improved FPFH Algorithm based on adaptive neighborhood selection method. The algorithm can realize effective results. The total content of paper consists of four parts. The first section is the introduction. In this section, we first analyze the characteristics of existed FPFH algorithm, then describe the advantages and problems of existing algorithms. We draw the second part of research content. The second section is the details of propose algorithm. The third section mainly describes adaptive neighborhood selection FPFH algorithm to present adaptive feature. The fourth section is experimental results and analysis of the paper. The experiment includes experimental setting conditions, extraction of experimental characteristics and experimental results. The fifth section is the conclusion, we are summarizing the content of the paper and explaining the results of the experiment.

2. The Details of Proposed Algorithm

According to the point cloud density method to find artificial calculation of multiple neighborhood radius, the FPFH feature extraction algorithm for constructing adaptive neighborhood selection need to estimate the point cloud density. The calculation of cloud point FPFH feature and SAC-IA registration [4], radius and density of cloud point registration performance optimal neighborhood statistics, using three order spline interpolation fitting for the radius and the point cloud density function, called mapping function, mapping the FPFH cloud point extraction algorithm combining the characteristic function and the construction of FPFH feature extraction algorithm of adaptive neighborhood selection. The algorithm does not need to adjust the neighborhood radius artificially, but it can be self-chosen according to the density of the point cloud to achieve the goal of PFFH. The logical block diagram is shown in Fig. 1.

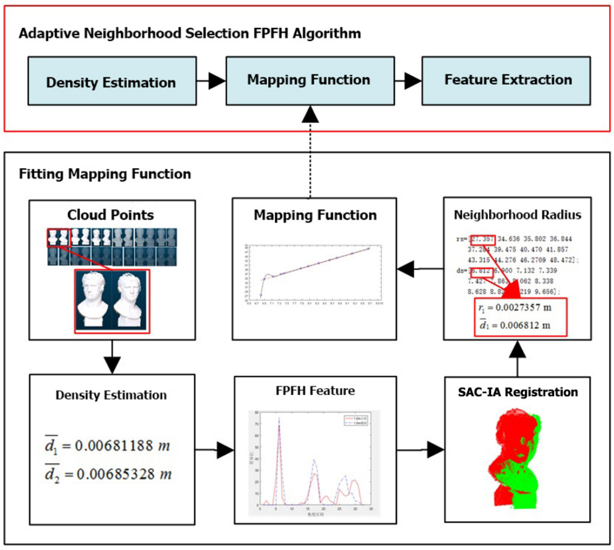


Fig. 1. The Adaptive Neighborhood Selection FPFH Algorithm.

3. Adaptive Neighborhood Selection FPFH Algorithm

3.1. The Estimation of Point Cloud Density

When the acquisition equipment is different, the distance between the equipment and the scene is different, and the density of point cloud will be different. The existing point cloud density estimation method based on distance method and partition method based on the literature [9, 22–24], this paper has used the method of solving the point cloud density that the average distance density based on distance, to estimate the point cloud density distribution by calculating the point cloud points of the average distance, the distance from a point cloud p and q point cloud distance from the point of closest point distance. C is the point cloud and N is the number. The p and q are the points. The distance between point p and point q is expressed as $dis(p, q$, and d_p is used to express the minimum distance between point p and other points, and then there are:

$$d_p = min(dis(p, q), q = 1, 2N, p \neq q \tag{1}$$

The average distance density of the point cloud is given by Eq. 2.

$$\bar{d} = \frac{1}{N} \sum_{p=1}^{N} d_p \tag{2}$$

The average distance $\overline{d}$ is small, the more density from point cloud and the density is large. On the other hand, the larger the $\overline{d}$, the smaller the distribution of the point clouds and the smaller the density. Therefore, it is feasible to estimate the density of the point cloud through the average distance. Fig. 2 is a change in the density of the point clouds at a distance of 1.0 meter from Kinect v2 and 3.2 meter.

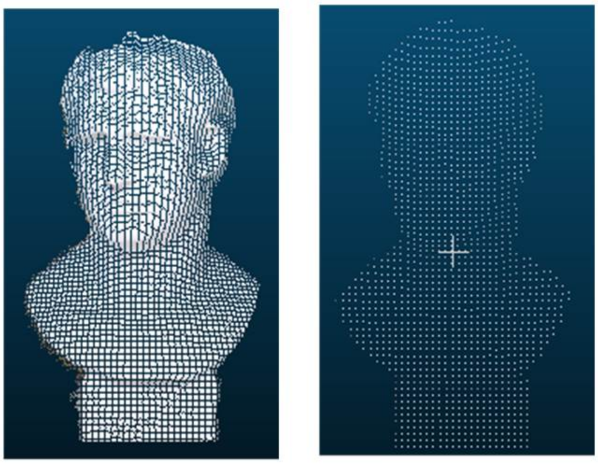


Fig. 2. Point Cloud Distribution at Different Distances from Kinect v2.

3.2. The Mapping Function

3.2.1. *Point Cloud FPFH Feature Descriptor*

The features of histogram PFH [1–3, 24] is geometric characteristics with high dimensional histogram depicts the way point cloud, cloud point formed by statistical histogram of all points in the K- neighborhood of relative to normal, the calculation process of the influence area as shown in Fig. 3. p_q is a query point shown in red. It is located in the center of radius r, p_q and p_q neighborhood point distance is less than r. The neighborhood of all points is connected to 22. The calculation of PFH feature histogram is based on such point pairs.

The calculation of cloud point feature histogram PFH any point of the p surface normal local coordinate system and point cloud based on the calculation steps are as follows: (1) to find the point at a given radius r ball inside the K-neighborhood; (2) in the K-neighborhood of any point on the p_i and p_j (i and j are not equal the corresponding normal), respectively n_i and n_j in p_i (p_i is normal in two and two points of connection to the smaller angle) defined on the local coordinate system of uvw, as shown in Fig. 4.

$$u = n_i \tag{3}$$

$$v = \frac{p_j - p_i}{\left\| p_j - p_i \right\|} * u \tag{4}$$

$$w = uxv \tag{5}$$

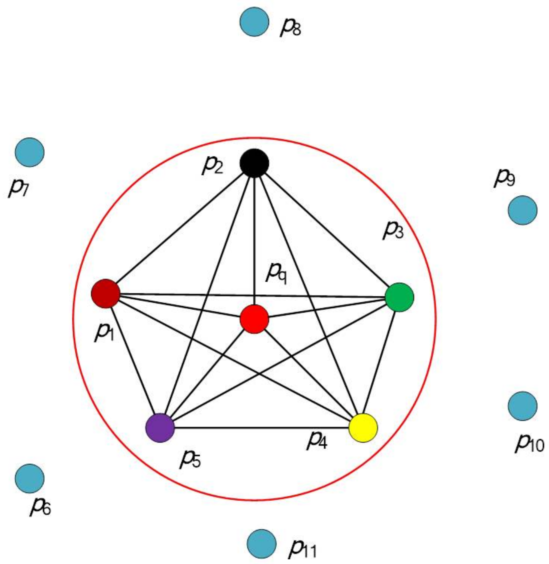


Fig. 3. The Influence Region for Point Feature Histogram.

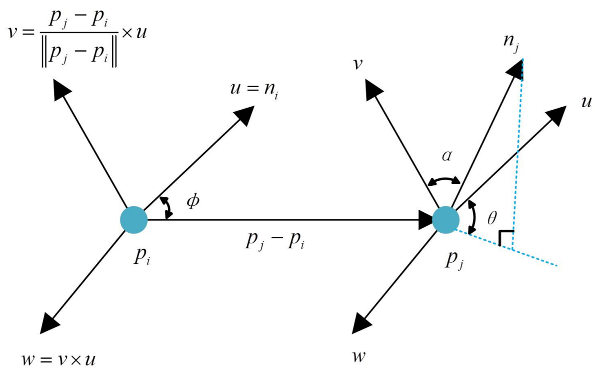


Fig. 4. The local coordinate system.

In the coordinate system of Fig. 4, the PFH features are calculated by calculating following values between p_i and p_j. They are normal n_i and n_j:

$$\alpha = v * n_j \tag{6}$$

$$d = \left\| p_j - p_i \right\| \tag{7}$$

$$\phi = u * \frac{p_j - p_i}{d} \tag{8}$$

$$\theta = arctan(w * n_i * u * n_j \tag{9}$$

In the Eq. 7, $d = \left\| p_j - p_i \right\|$ is the Euclidean Distance between two points. The relative position relation of the point pair is expressed by calculating four sets of values

$(\alpha, \phi, \theta, d)$ of all points in the K-neighborhood. But the effect of d on PFH features is very small, which is usually omitted, only to calculate the three sets of values (α, ϕ, θ). Each value uses five intervals for statistics, thus generating a 5_3-dimensional PFH eigenvector.

As shown in Fig. 3, the computational complexity of PFH is (nk^2) (n is the total point number of the point cloud), and the computing speed is slow. Therefore, the literature [4] had proposed the FPFH feature extraction algorithm, improved the PFH, reduced the computational complexity to (nk), and improved computing speed. The computation process is divided into three steps: 1) for query point p_q, it only calculates the PFH between the point and the point in its K-neighborhood, called SPFH; 2) for every point in p_q neighborhood, it also calculates SPFH in K- neighborhood; 3) uses Eq. 10 to calculate FPFH(p_q):

$$FPFH(p_q) = SPFH(p_q) + \frac{1}{k}\sum_{i=1}^{k}\frac{1}{w_i}SPFH(p_i) \qquad (10)$$

In the Eq. 10, w_i is the Euclidean Distance between point p_q and its neighborhood point p_i, as the weight of the calculation. The computing impact area of the FPFH feature is shown in Fig. 5.

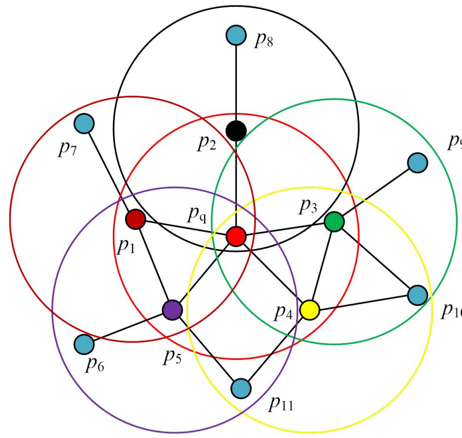


Fig. 5. The Influence Region for Fast Point Feature Histogram.

In Fig. 5, we can see that when the neighborhood radius is fixed, the density of point cloud will affect the number of points in the neighborhood, which will affect the operation complexity and speed. When the point cloud density is fixed, the improper neighborhood radius will slow down the computation speed and the operation time will increase exponentially. The FPFH features at the same point in the neighborhood radius and the point cloud at the distance of Kinect v2 1.0m or 3.2m are shown in Fig. 6. The difference in the distance between the acquisition equipment and the scene determines the difference of the density of the point cloud directly. Fig. 6 has illustrated the difference between the FPFH features that lead to the same density and the difference in density.

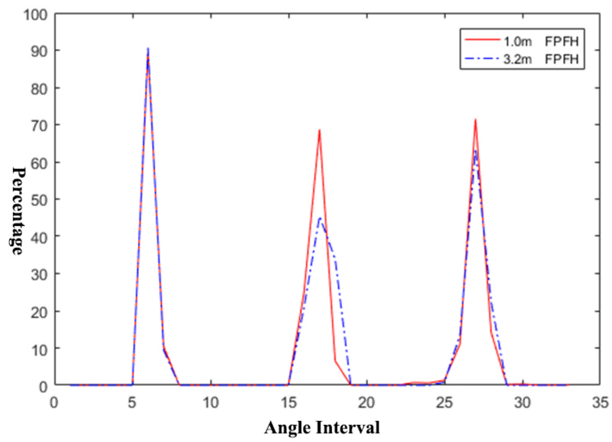


Fig. 6. The FPFH features of 1.0m and 3.2m.

Therefore, point cloud density and neighborhood radius are very important for the computation of FPFH. When the density is constant, the proper neighborhood radius can not only improve the performance of FPFH, but also improve the computing speed under the premise of guaranteeing performance.

3.2.2. Sampling Conformance Registration Algorithm

For each pair of point clouds, we can calculate multiple neighborhood radii based on the point cloud density $\overline{d}$, calculate the FPFH characteristics, and complete the SAC-IA registration [4]. The neighborhood radius and point cloud density of the best registration performance are counted out. The SAC-IA registration algorithm, namely the sampling consistency registration algorithm, which comprises the following steps: (1) in the source point cloud P, sample s sample points between the distance is greater than the threshold d_{min}, d_{min} based on point cloud density selection; (2) at the target point cloud in Q, and 1) to find out the same s or close to the FPFH feature of the sampling point of a point or more points, corresponding points choose one point as P in Q; (3) calculating the corresponding points of the rigid transform matrix and solving the registration error score. The registration error score is generally represented by the Huber penalty function $L_h(e_i)$.

$$L_h(e_i = \begin{cases} \frac{1}{2}e_i^2 & \|e_i\| \le t_e \\ \frac{1}{2}t_e(2\|e_i\| - t_e) & \|e_i\| > t_e \end{cases} \qquad (11)$$

In the Eq. 11, t_e is the preset threshold, and e_i is the distance error for registration of group I corresponding points. The above three steps are repeated, and the transformation matrix with the smallest error score is used in the subsequent registration. As a result, the error score is regarded as a basis of performance evaluation. The smaller the score, and the smaller the error. Fig. 7 is the diagram of relationship between the registration score and the point cloud density multiplier.

3.2.3. Fitting Mapping Function

In order to be able to according to the point cloud density $\bar{d}$ adaptive selection of neighborhood radius r, and need to find the function relationship between the neighborhood radius r and the density of $\bar{d}$, known as the radius of the neighborhood density mapping function, referred to as the mapping function, denoted as $f(\bar{d})$, the paper has used three splines interpolation fitting method for mapping function. The three splines interpolation [10] is a smooth curve through a series of data points. The method is numerically stable and has good convergence. It is applied to many fields such as automotive manufacturing and aerospace instruments. In mathematics, the curve function group is obtained by solving the three moments equation group. Let $[a, b]$ have an interpolating node $a = x_1 < x_2 < \ < x_n = b$, and the corresponding function value is $y_1, y_2, \ , y_n$. If the function $f(x)$ satisfies $f(x_j) = y_j, (j = 1, 2, \ , n)$, $f(x)$ is a polynomial that is not more than three times on the $[x_j, x_{j+1}](j = 1, 2, \ , n-1)$. When $f(x)$ is in $[a, b]$ has the two-order continuous derivative, which is called the $f(x)$ as the three splines interpolation function. $f(x)$ is the three orders polynomial on each subinterval $[x_j, x_{j+1}]$.

$$f_j(x) = a_j x^3 + b_j x^2 + c_j x + d_j, \ (j = 1, 2, ..., n-1) \quad (12)$$

In the Eq. 12, a_j, b_j, c_j, d_j are coefficients. Three cubic spline interpolations are used to fit the functional expressions of each section of $f(\bar{d})$ and form a complete mapping function. The mapping function figure that is fitted through a part of the point is shown in Fig. 8. In engineering, the line can be approximated, as shown in the red dotted line. In the diagram, the transverse coordinates are 1000 times after the point cloud density magnified, and the longitudinal coordinates are 1000 times larger than the FPFH neighborhood radius.

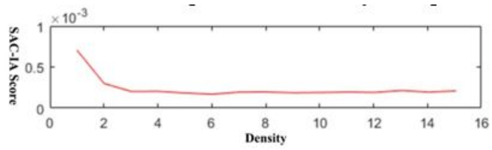
3.3. The Proposed Algorithm Based on Adaptive Neighborhood Selection

The mapping function $f(\bar{d})$ combined with the construction of PFFH feature extraction algorithm with adaptive neighborhood selection algorithm of FPFH feature extraction, FPFH feature in the calculation, estimate the point cloud density $\bar{d}$, according to the mapping function of $f(\bar{d})$ calculation of neighborhood radius r, finally FPFH feature extraction for object recognition or registration, the calculation process of eliminating inefficient, people participate in the adjustment of the FPFH complex, according to the characteristics of the neighborhood radius of cloud properties density selection and point cloud matching calculation itself.

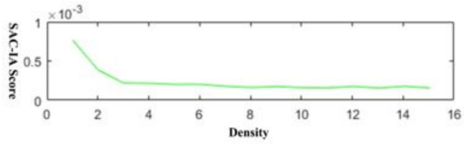
4. The experimental results and analysis

In order to verify the effectiveness of the proposed algorithm in this paper, with Windows 10 professional edition system, CPU Intel (R) Core (TM) i5-3470@3.2GHz, 8G PC memory, using VS 2017 database based on the development of experimental program cloud 1.80 version of the PCL, test data for the Stanford University Bunny point cloud, a huge number of point cloud the use of pigment after filtering, manual selection of neighborhood radius and the algorithm calculated FPFH feature point cloud registration, SAC-IA. Fig. 9 shows the relationship between error registration score and neighborhood radius, the radius of every 4 mm manual value is 20. Fig. 10 is the registration effect diagram (a) for point cloud the original location, (b) - (e) and P1 in Fig. 9, P2, P4, P5 (d) for the corresponding to the proposed algorithm and registration effect; Table 1 and P1, P2, P4, P5, the algorithm of figure 10 star mark points are experimental results corresponding to the parameters.

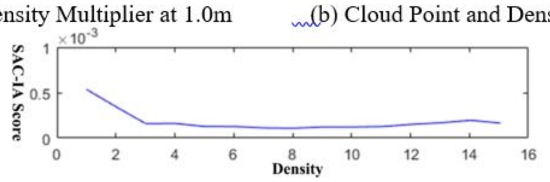
From Fig. 9, we can see that (b) the overall registration effect is not ideal. (e) the registration is poor in the ears and legs. (c), (d) and the algorithm registration effect is ideal, (c), (d) registration score is almost the same as the algorithm score. Fig. 11 compares the subgraphs of (c), (d) and (f) three. We can see that (c) and (d) ears do not completely coincide. Table 1 from the data analysis for further evidence, numerical method of artificial selection of neighborhood radius is hard to give a suitable neighborhood radius is too large, will make the FPFH feature extraction time is too long, such as P5, FPFH and the characteristics of poor performance; small neighborhood radius can accelerate the speed of feature extraction of FPFH, but the properties decrease sharply. Such as P1. Adaptive neighborhood selection FPFH proposed feature extraction algorithm to calculate the registration error in the SAC-IA score reached 2.19205e-05, and the operation speed is faster, the total time of only 15.146 seconds, compared with the method of subjective field radius adjustment, guarantee the performance characteristics of FPFH on the one hand, and has high operation speed and overcome the blind and the subjective participation value selection inefficient and cumbersome, has a certain practical significance.



(a) Cloud Point and Density Multiplier at 1.0m



(b) Cloud Point and Density Multiplier at 2.0m



(c) Cloud Point and Density Multiplier at 3.0m

Fig. 7. The Relationship of Registration Score and Point Cloud Density Multiple.

Table 1. The Experimental Result.

Method	Neighborhood radius	Score	$T_{FPFH} + T_{SAC-IA}(s)$
Artificial adjustment	0.0041	$8.15853e^{-05}$	0.345+11.017
	0.0202	$2.33304e^{-05}$	2.242+11.338
	0.0643	$2.34060e^{-05}$	17.049+11.275
	0.0804	$4.73696e^{-05}$	23.927+11.234
The Proposed	Adaptive selection	$2.19205e^{-05}$	4.134+11.012

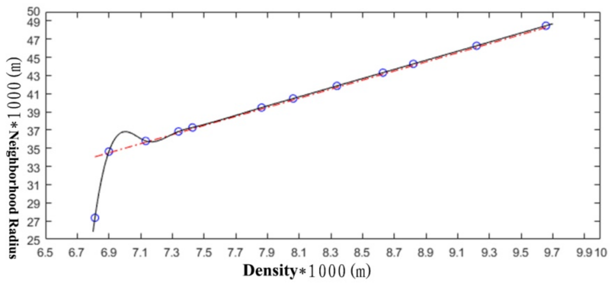


Fig. 8. Mapping Function Curve.

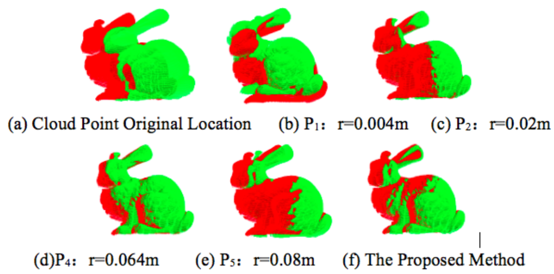


Fig. 10. The registration effect comparison.

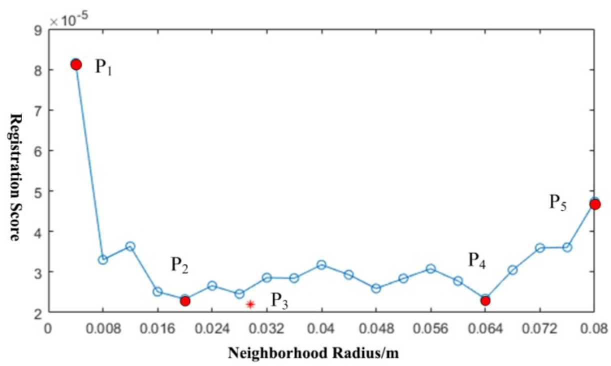


Fig. 9. The relationship between Error Score and Neighborhood Radius.

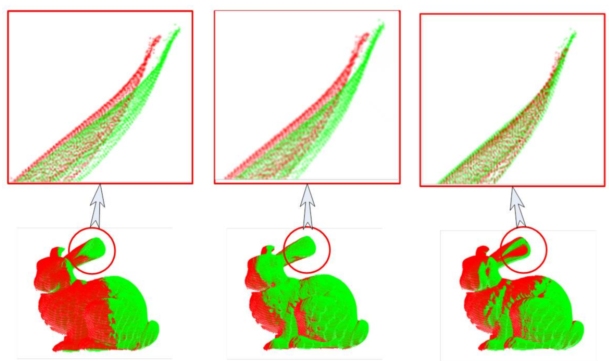


Fig. 11. The comparison for (c), (d), (f) from Figure 10.

5. Conclusions

In the FPFH feature descriptor using the 3D point cloud scene recognition or registration process, adjust FPFH characteristic calculation of neighborhood radius, we can't guarantee the performance of the FPFH feature extraction, and can't guarantee the FPFH operation has the advantages of high speed, with a certain blindness, low efficiency and complicated. To solve the above problems, this paper proposes adaptive neighborhood selection FPFH feature extraction algorithm, the mapping function solve the radius and the density of point cloud, can adaptively select the neighborhood radius in the calculation of FPFH features, the one hand makes the FPFH feature extraction has good performance, and the extraction time is short and fast. The experiment shows that the algorithm is feasible and has a strong practical prospect. However, it can be seen that this algorithm speed is not fast, did not meet the real-time requirements, in the days after the study, will continue to be improved at the same time, researchers in all aspects can be improved, making it faster, and meet the real-time requirement, strengthen its practical performance.

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