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A Fast Point Cloud Registration Algorithm based on Curvature Key Points

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Abstract

Aiming at the problem of slow registration of 3D point cloud registration and easy to fall into local optimum, this paper proposes a fast and accurate registration method. First, extract the curvature of the detection point, calculate the Euclidean distance and standard deviation of the fitting plane from the detection point to the adjacent point, and construct the curvature key point parameters; secondly, combine the key points to calculate the fast point feature histogram descriptor, and use the sampling consistent initial registration algorithm to complete Coarse registration work; finally, iterative closest point algorithm is used to achieve fine registration. The experimental results show that the key point extraction algorithm increases the calculation speed of the original algorithm by more than 90%, and can be used with a variety of feature descriptor extraction algorithms. It has good universality and has obvious advantages in improving the registration speed.

Keywords

Point cloud registration; Curvature; Key point extraction; Image processing; ICP algorithm.

1. Introduction

With the wide application of 3D laser scanning technology in many fields, how to quickly and accurately pair the point cloud data has become one of the research hotspots. The main work of point cloud alignment is to rotate and pan the point cloud under different coordinate systems, and finally integrate into a complete point cloud, in this process, improve the accuracy of the alignment at the same time, how to overcome the point cloud alignment speed is slow, easy to fall into local optimal solution, vulnerable to noise and other shortcomings, is the main research difficulty.

Point cloud alignment is generally divided into four key stages: feature point extraction, feature point matching, initial alignment, and precise alignment. By improving one or more of these stages, the algorithm's effectiveness can be improved. Daniel F. Huber and other Spin Image features are rationed, and the method can still get better matching results in the case of interference and masking, but it is sensitive to different mesh resolutions and non-uniform sampling of the numberings, and the alignment effect is not good; The point cloud with obvious characteristics has high accuracy, Zhang Zhe and so on put forward the characteristic selection method based on NV key points, and extract the feature points by using the normal vector distribution characteristics, and the algorithm has high anti-jamming characteristics of similar point clouds. Higuchi and other features of the use of curvature to achieve the alignment of the dimensional point cloud, the method for the sphere point cloud has a better alignment effect, Wang Feipeng, such as the use of Gauss curvature filter non-matching points, the results as the point cloud input of the ICP algorithm, the algorithm improves the accuracy and has a better

robustness, but the use of more standardized point cloud data for the alignment, efficiency is not significantly improved.

In this paper, a fast point cloud alignment method based on key point extraction feature description subs is proposed, which focuses on improving the efficiency of point cloud alignment and overcoming the problem of easily getting caught up in local optimal solution. Using curvature and its adjacent features to extract key points, test the effect of key points in a variety of feature matching methods, and complete the point cloud coarse and fine alignment work by SAC-IA algorithm and ICP algorithm respectively.

2. Definition and Selection of Key Points

There is a large number of point sets in the point cloud, and before the alignment can be carried out, a description point that can express the surface feature information of the point dataset needs to be extracted from the point cloud data. In the process of point cloud alignment, we should ensure the key rotation and translation inverseness, thus improving the robustness of the alignment algorithm. The key point extraction method is usually used by a single means, which will lead to incomplete features, redundant calculation and so on. In this paper, a new key definition method is adopted to extract the curvature of the detection point, the European distance of the probe point to the adjacent point, the standard deviation of the distance between the probe point and the neighboring point to the fitted plane, and the key points are constructed together using three kinds of feature information to extract the feature information more accurately.

2.1. Point Cloud Pre-processing

First of all, the source point cloud and the target point cloud are sampled by using the three-dimensional soliger raster filtering method. This method first creates a three-dimensional sophysic grid for the point cloud, using the center of gravity of each point cloud in the enveloping grid (i.e. the soliton) to represent the point in the original enveloping grid, reducing the density of the point cloud while reducing the feature loss and improving the computational efficiency of subsequent point clouds.

2.2. Proximity Point Feature Definition

Using a single feature to describe the features of the detection point can easily cause problems such as the large number of features and the large amount of computation. In order to accurately describe the geometric surface shape, this paper selects the probe point and its neighbor features to combine as a new key point.

1) Detect the curvature of the point

Curvature is one of the most commonly used feature point descriptions, curvature can intuitively describe the bump of the geometry, this paper uses the average curvature to describe the curvature of the detection point, calculates the maximum and minimum main curvature of any search point Pi in point cloud P, and calculates the formula for the average curvature H (1):

$$H=\frac{1}{2}\left(\mathrm{k}_1+k_2\right) \tag{1}$$

In the formula, k1 is the maximum main curvature, k2 is the minimum main curvature, by which the calculation can represent the bump situation of the surface, when H is positive, local concave surface, when H is negative, local convex surface.

2) The European distance from the detection point to the adjacent point to fit the plane

In the point cloud, how to extract key points according to the characteristics of neighbors is one of the difficulties of key detection. In order to solve this problem, this paper adds the European distance from the neighboring point to the fitted plane in the detection of the key point, as one of the parameters of the key extraction. As shown in Figure 1, Pi1', Pi2', Pi3'... Pi6' is a projection of Pi's neighbors on the fitted plane, and Figure 1 (a) mid-point Pi is farther from the fitted plane than Figure 1 (b) mid-point Pi is farther from the fitted plane, with a higher probability as the key point.

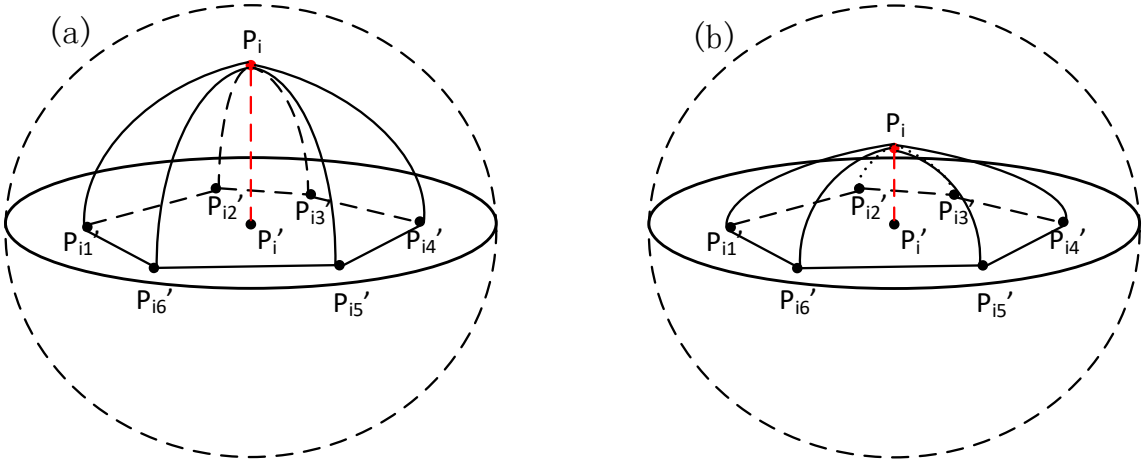

Figure 1. The probe point fits the plan with the adjacent point

The distance between the probe point and the adjacent point to the fitted plane is shown in Figure 2 (a) (b), in Figure 1 (a) the Pi-plane distance is greater than its adjacent point-to-fit plane distance, and in Figure 1 (b), the Pi6-plane distance di6 > di, so similar probe points in Figure 2 (b) are not taken into account when extracting key points.

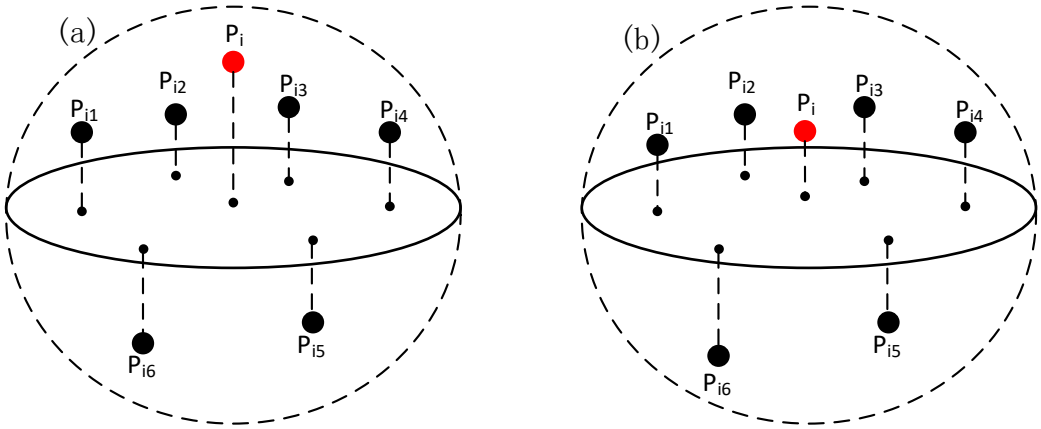

Figure 2. Probe points fit the floor plan from the adjacent point to the adjacent point

3) The standard deviation between the detection point and the adjacent point to the fitted plane

In order to accurately filter feature points, this paper adds the distance between the probe point and the adjacent point to the fitted plane as one of the reference conditions. First, select the point with the high curvature of the probe, and as the alternative feature point, calculate the standard deviation between the k adjacent points of the alternative feature point (Pi) and the fitted plane, which is expressed as formula (2):

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$$\sigma=\sqrt{\frac{1}{k}\sum_{i=1}^{k}(d_i-\mu)} \tag{2}$$

In the formula, μ is the average of the distance between the neighboring point and the fitted plane, and by calculating the standard deviation, the degree of discreteness of the neighboring point is determined, and when the σ value is too small, the adjacent points are evenly distributed, the average around the alternative feature point is smoother, generally non-featured area; σ one of the key factors when selecting key points, reflecting the important information of the proximity point.

At the same time, the European distance d between the probe point Pi and the fitted plane is calculated, and the difference between μ d and the Δ d. When Δd is positive, the probe point is retained and Δd is negative, indicating that the alternative feature point, interwoven with the neighboring point, cannot be defined as a feature point, so it is rejected.

2.3. The Construction of Curvature Key Parameters

First of all, the parameters calculated by using formula (3) are normalized (delete 0, 1 point), the curvature of the normalized probe point (H), the standard deviation of the detection point and the distance from the neighboring point to the fitted plane (σ), and the curvature key parameters β 4) are defined by Δd.

$$X_{\text{norm}}=\frac{X-X_{\min}}{X_{\max}-X_{\min}} \tag{3}$$

$$\beta=\sigma\cdot H\cdot\Delta\text{d} \tag{4}$$

In (4), the greater the H, the more obvious the curvature feature, the greater the discrete σ proximity point, the greater the chance that the nearby area will be the feature area, define the point's non-feature point when Δd is less than 0, and when the Δd is greater than 0, the greater the value means that the greater the distance between the probe point and the neighbor, the more obvious the feature.

3. Point Cloud Alignment based on Curvature Keys

The key to point cloud alignment is to calculate the rotating translation matrix, unify the source point cloud with different attitudes and the target point cloud under the same coordinate system, so that the two sets of point cloud match to the maximum extent, that is, to achieve the goal of point cloud alignment.

3.1. Point Cloud Characteristics Describe the Subcalculation Process

First of all, the source point cloud P and the target point Q cloud in the NaN point, the source point cloud and the target point cloud respectively for downsampling processing, the pre-processed point cloud, using the curvature key extraction method proposed in this paper, the key point extraction. Using the Quick Point Feature Histogram (FPFH) to calculate the spatial difference between the extracted key points and their proximity to the key points and to calculate the feature histogram, the descriptor can more accurately describe the changes around the key points, and the specific process of feature extraction is shown in Figure 3.

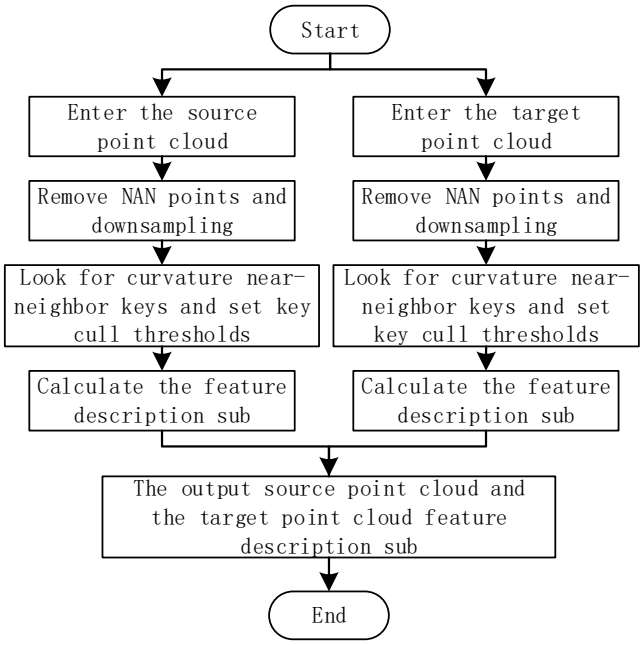

Figure 3. Feature extraction flowchart

Kp and Kq are calculated according to the construction method of curvature key parameters proposed in 2.3. Using the quick point feature histogram, query Kp and Kq for all adjacent points within their k neighborhoods, as shown in Figure 4:

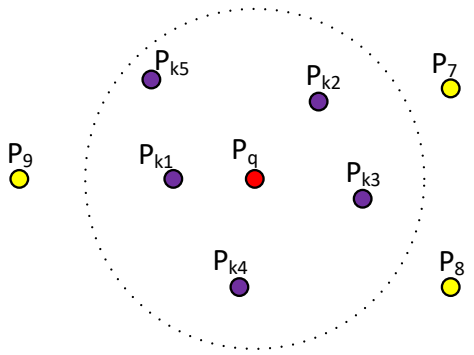

Figure 4. k domain inside and outside point diagram

The dotted line in the figure is the k neighborhood proximity point (Pk1, Pk2,... P k6)

Define a three-dimensional coordinate system UVW to calculate the deviation between each pair of points in point P neighborhood k and their estimated legal lines, and the calculation formula for the coordinate system UVW (5):

$$\begin{cases} u = n_s \\ v = u \cdot \dfrac{(p_t - p_s)}{\|p_t - p_s\|} \\ w = u \times v \end{cases} \tag{5}$$

Using formula (6) to calculate alpha beta crucifs to represent the deviation between two estimated common lines, alpha beta tyrance is called SPFH;

$$\begin{cases} \alpha = v \cdot \vec{n}_t \\ \beta = u \cdot \dfrac{(p_t - p_s)}{\|p_t - p_s\|} \\ \theta = \arctan\left(\omega \cdot \vec{n}_s, u \cdot \vec{n}_t\right) \end{cases} \tag{6}$$

Using formula (7) to calculate the FPFH value, the formula is defined as:

$$FPFH(P_q) = SPFH(P_q) + \frac{1}{K}\sum_{i=1}^{k}\frac{1}{w_k} \cdot SPFH(P_q) \tag{7}$$

3.2. Point Cloud Alignment Process

Point cloud alignment process is usually divided into two stages of coarse and fine alignment, the purpose of fine alignment is to minimize the spatial location difference between point clouds on the basis of coarse alignment. In this paper, the SAC-IA algorithm based on feature matching is used for coarse alignment, and on this basis, the ICP algorithm is used for fine alignment, the specific process is shown in Figure 5:

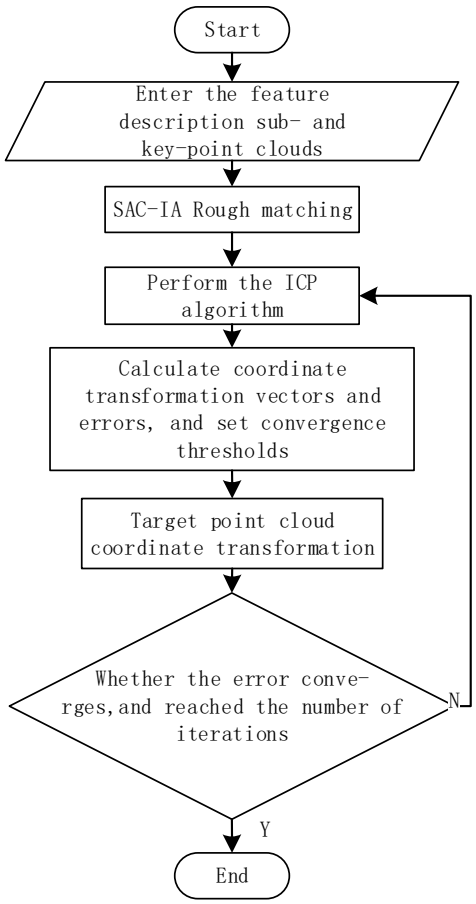

Figure 5. Point Cloud Weight Alignment Flowchart

4. Experimental Results and Analysis

4.1. Key Extraction Experiments

In order to verify the feasibility and robustness of key point extraction, two types of point clouds were used for experiments, one for point clouds scanned through different perspectives,

and the point cloud density was high, the experiment used Bunny, Dragon point cloud in The Stanford 3D point cloud database, the number of point clouds is about 40000; The results of the key extraction experiment are shown in Figure 6:

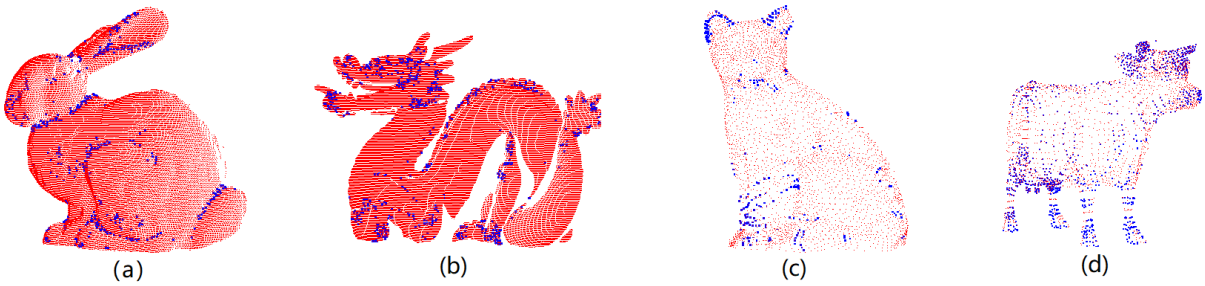

Figure 6. Key points extract experimental results (a) Bunny key points; (c) Cat key;

The red in the figure is the input point cloud, and the blue dot is the key point extracted according to the algorithm in the text. The experimental results show that the key point extraction method used in this paper is less affected by point cloud density and the extraction effect is accurate.

Table 1. Keys extract data

Point cloud model	Enter the number of points	The number of sample points dropped	The number of key points	Processing time (s)
Bunny	41841	7155	633	0.140625
Dragon	40256	7133	432	0.125
Cat	4538	4513	258	0.09375
Cow	2903	2825	1103	0.0625

4.2. Use Point Cloud Alignment Experiments for Key Points

In this section, the four-to-point cloud data sampling consistency algorithm (SAC-IA) and iterative nearest point algorithm (ICP) are used respectively, and the coarse and complete alignment experiments are carried out. Using the key point data calculated by 4.1 as input with the original data, comparing experiments, the matching situation of the four-to-point cloud model is shown in Figure 8, as shown in figure 8, it can be seen from the figure that in the use of FPFH-SAC algorithm for coarse punctuality, the Dragon model in the middle, Cat model back, Cow model mouth have some point cloud alignment degree is poor, combined with key points when using FPFH-SAC algorithm, the accuracy of the matching is significantly improved; Since the Cat model and the Cow model are complete point cloud models, both models can obtain very accurate alignment results, and the Bunny model and Dragon model are ideal when using the SAC-ICP algorithm in combination with key points. Combined with Figure 7, it can be seen that after using key points (key), the calculation time of the algorithm is greatly improved, and the calculation time of combined with table 2 is reduced by 91.96% and 94.29%, respectively.

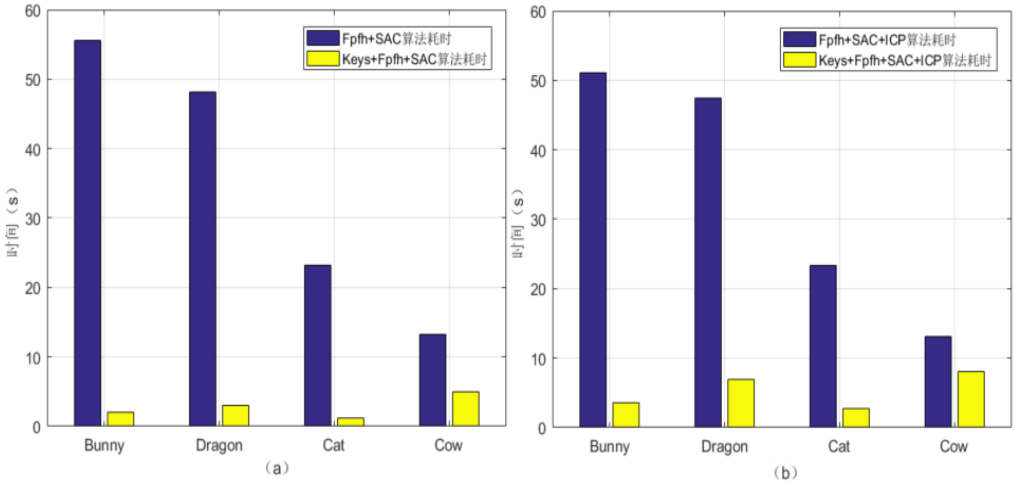

Figure 7. Compares the time used for the experiment (a) with the coarse alignment time for the use of key points (b) Rough alignment and coarse alignment time for the use of key points

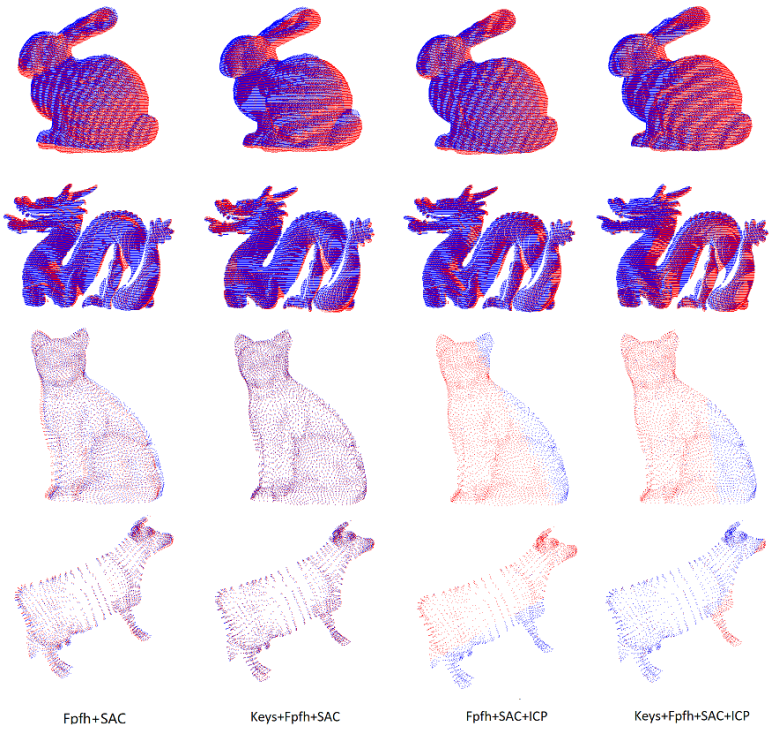

Figure 8. Fast point cloud alignment results based on curvature keys

Table 2. Comparing the time used for the experiment

	FPFH+SAC (s)	Keys+FPFH+SAC (s)		FPFH +SAC+ICP (s)	Keys+ FPFH +SAC+ICP (s)	
		key	FPFH +SAC		key	FPFH +SAC+ICP
Bunny	55.5938	0.125	1.8594	51.1562	0.125	3.4375
Dragon	48.2031	0.125	2.9219	47.5	0.125	6.7813
Cat	23.2656	0.0938	1.125	23.3281	0.0938	2.6562
Cow	13.2969	0.0625	4.96875	13.0938	0.0625	7.9375

5. Conclusion

In view of the problem of slow three-dimensional cloud alignment and low robustness, a fast alignment method based on curvature key points is proposed. The experimental results above show that the point cloud alignment effect based on curvature key points proposed in this paper

has universality for point cloud alignment for different feature extraction methods, and the alignment efficiency is obviously improved. According to the experiment, it can be seen that the algorithm is fast and effective at key points, and is suitable for various types of point cloud data. Combined with different characteristics to describe the use of sub-show a strong universality. Figure 8 shows that there are still deficiencies in the use of 3dsc and the results need to be corrected by fine-ration. Therefore, the next step is to ensure the efficiency of key extraction methods while improving accuracy.

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