Research and Implementation of Compression Algorithm for Large-scale Point Cloud Data

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Abstract: *The amount of original point cloud data obtained by 3D scanner is very large and has a lot of redundant information, which is not conducive to the later data processing. Therefore, it is necessary to compress the original point cloud data.In this paper, an improved curvature-graded point cloud compression method based on hierarchical clustering is proposed.First, hierarchical clustering is performed according to Gaussian curvature and included angle,then curvature classification is performed, and finally point cloud compression is performed according to sampling ratio and distance threshold.The experimental results show that the proposed method has advantages.*

Keywords: *Point cloud compression, curvature grading, hierarchical clustering, gaussian curvature*

1. Introduction

Point cloud is a three-dimensional data set that quickly obtains points on the surface of a three-dimensional object by using three-dimensional scanning equipment. Due to the difference of collection equipment, it may also record information such as RGB and depth.Compared with grid representation, point cloud does not contain corresponding topological structure information and is not limited by the requirement of surface continuity. It can represent geometric models of any shape, so the expression of point cloud model is more free and flexible than that of grid model[1].With the continuous development of scanning technology, and constantly improve the precision of the acquisition device and scanning the point cloud data can reach levels hundreds of thousands or even millions, lead to the point cloud data storage, processing, and display will consume large amounts of time and computer resources, therefore, on the premise of preserving important model characteristics, point cloud data compression,Reducing the amount of point cloud data has become one of the main tasks of point cloud data processing[2].

This paper consists of five parts. The first part introduces the background and significance of point cloud data compression; the second part introduces the relevant research work of point cloud data compression from two aspects of clustering and curvature; the third part introduces the specific steps of the method in this paper; the fourth part is experiment and evaluation; and the fifth part is summary.

2. Related Work

People have studied point cloud compression methods from multiple aspects, such as clustering, curvature, color attribute[3], coding[4], neural network[5], etc. In this paper, point cloud compression methods are only introduced from the aspects of clustering and curvature.

He[6] and Wang[7] first adopted the k-means method to calculate the root mean square curvature and average value of all points in the cluster by taking the cluster as the unit.Finally, point cloud compression is completed according to the size relationship between the two.Li[8] first calculates the average curvature. If the curvature of a point is less than the average curvature, the point will be divided into a flat area; otherwise, it will be divided into a steep area,and then different methods are used to complete point cloud compression. Zhang[9] proposed a hierarchical clustering based compression scheme.First, global clustering was performed in luminosity space, and local clustering was performed in geometry space.Finally, the color attributes of the points are mapped to 2D uniform mesh, and image coding is used to achieve effective compression.Li Jintao[10] proposed the idea of

curvature classification.First, octree segmentation is performed.Then the average curvature of the voxels is calculated and graded.Finally, the point cloud data compression is completed according to the sampling ratio.

In reference[8-9], there is no grade division of curvature in point cloud data compression, which will cause serious loss of detailed features in sub-feature regions.Although the curvature is classified by grade in reference[10], the point cloud data belonging to the same detail feature will be divided into different voxels for sampling by using octree for spatial division, which is likely to lead to the loss of detail feature.In reference[6-7], point cloud data compression was carried out by traditional clustering method, which would result in random and uneven clustering results. Aiming at the shortcomings of the methods in the studied reference, this paper proposed an improved curvature hierarchical point cloud data compression method based on Gaussian curvature hierarchical clustering.

3. Method

The steps of the method in this thesis will be introduced successively in the following paragraphs.

3.1. Gaussian Curvature Calculation

The specific calculation steps are as follows:

(1)The original point cloud data is segmented by octree, and then the k nearest neighbor search is conducted for each point. The point p_i including the k nearest neighbor of the point is denoted as $K(p_i)$, and the actual surface of $K(p_i)$ can be fitted with a tangent plane.The tangent plane at the point p_i can be obtained by $K(p_i)$ and the least squares principle, and the projection on the tangent plane is denoted by $N(p_i')$, p_i and p_i' must correspond to one to one.

(2)As the base point, select a point in $N(p_i')$ to make p_j' and p_i' the farthest distance, and connect p_j' and p_i'. Take the straight direction of the two points as the u direction, and the direction perpendicular to the two points as the v direction.

(3)The p_i and p_i' in $N(p_i')$ are successively connected to obtain k line segments, and these line segments are projected in the u direction, denoted as d_i, $1 \le i \le j$.Then sort d_i, denoting the maximum value as, and the minimum value as, then the parameter value of each point pair in $K(p_i)$ can be calculated by the following formula:

$$u_j = \frac{d_j - d_{\min}}{d_{\max} - d_{\min}} \tag{1}$$

(4)Curvature was obtained by quadratic parametric surface approximation method.Use $K(p_i)$ to build a quadratic parametric surface:

$$s(u,v) = \begin{bmatrix} 1 & u & u^2 \end{bmatrix} Q \begin{bmatrix} 1 \\ v \\ v^2 \end{bmatrix} \tag{2}$$

set $W = \left(u^0 v^0, u^0 v^1, u^0 v^2, u^1 v^0, u^1 v^1, u^1 v^2, u^2 v^0, u^2 v^1, u^2 v^2\right)^T$,then the quadric surface can be expressed as:

$$s(u,v) = W^T \bullet Q \tag{3}$$

$$where: Q = \left(M^T M\right)^{-1} M^T Z, M = \begin{bmatrix} W_0^{\ T} \\ W_1^{\ T} \\ \vdots \\ W_k^{\ T} \end{bmatrix}, Z = \left(Z_x, Z_y, Z_z\right) = \begin{bmatrix} x_0 & y_0 & z_0 \\ x_1 & y_1 & z_1 \\ x_2 & y_2 & z_2 \\ \vdots & \vdots & \vdots \\ x_k & y_k & z_k \end{bmatrix}$$

(5)According to reference[11], the Gaussian curvature K can be obtained by the following equation:

$$K = \frac{LN - M^2}{EG - F^2} \qquad (4)$$

where: $L = \dfrac{\partial r}{\partial u^2}, N = \dfrac{\partial r}{\partial v^2}, M = \dfrac{\partial r}{\partial u \cdot \partial v}, E = \dfrac{\partial^2 r}{\partial u^2}, G = \dfrac{\partial^2 r}{\partial v^2}, F = \dfrac{\partial^2 r}{\partial u \cdot \partial v}$

3.2. Hierarchical Clustering

Gaussian curvature is used to cluster point cloud data so that point cloud data with similar characteristics can be divided into the same cluster. The specific methods are as follows:

(1) Calculate the Gaussian curvature of the point;

(2) Divide the point cloud data belonging to the same Gaussian curvature range into the same cluster according to a certain method, and the clustering in this step is rough clustering;

(3) Conduct detailed clustering of the clustering obtained in the previous step according to the angle threshold value set.
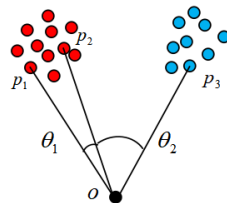

Figure 1: Detailed clustering diagram.

Since point cloud data belonging to the same Gaussian curvature interval may be distributed in different regions, detailed clustering should be carried out.For detailed clustering, the angle between any two points in the same cluster and the center of gravity of the whole point cloud is calculated, and the secondary clustering is conducted according to this angle.If the included Angle is less than or equal to the included Angle threshold, it means that these two points belong to the same local cluster; otherwise, they do not belong to the same local cluster.Detailed clustering schematic diagram is shown in Figure 1.

where, o is the center of gravity of the overall point cloud data, and its coordinate is set as,$\left(x_o, y_o, z_o\right)$ and x_o, y_o, z_o can be calculated by formula (5) .

$$x_0 = \frac{1}{n} \sum_{i=1}^{n} x_i \; ; \; y_o = \frac{1}{n} \sum_{i=1}^{n} y_i \; ; \; z_o = \frac{1}{n} \sum_{i=1}^{n} z_i \qquad (5)$$

3.3. Curvature Classification

In this paper, the Gaussian curvature of point cloud data is graded using the idea of curvature classification. The specific steps are as follows:

(1)The average Gaussian curvature of all points in the cluster is calculated by traversing all clusters, and the maximum h_{max} and minimum h_{min} values of the average Gaussian curvature are obtained;

(2)In order to adapt to different point cloud data, the average Gaussian curvature of the cluster is normalized and mapped to the interval[0,5]. The specific approach is shown in Formula (6) .

$$h' = \frac{5 \cdot h}{h_{max} - h_{min}} \tag{6}$$

(3)In order to reduce the sensitivity of curvature grade to curvature size, the natural logarithm method is adopted to calculate curvature grade. The specific method is shown in Formula (7) .

$$d_i = ceiling\left[2\ln\left(\frac{S \cdot h_i + 1}{S \cdot h_0 + 1}\right)\right] = \begin{cases} 0, & if \quad d_i \leq 0 \\ 9, & if \quad d_i \geq 9 \end{cases} \tag{7}$$

where: $ceiling(\bullet)$ is the upsetting function, S is the compression control factor, h_0 is the average Gaussian curvature value of the extremely flat region, and h_i is the average Gaussian curvature value of the current cluster.

The degree of curvature can be changed by changing the magnitude of S and h_0, so as to control the overall compression rate of point cloud.

3.4. Point Cloud Compression

When the curvature grading is finished, point cloud data compression is performed. In this step, sampling can be performed according to the conditions set by oneself. The specific steps are as follows.

(1) All points belonging to the same cluster are sorted according to the Gaussian curvature value from the largest to the smallest in order to facilitate the following compression work;

(2) On the basis of curvature classification, the sampling ratio of each Gaussian curvature grade is set;

(3) Set the Euclidean distance d threshold ε of adjacent points;

(4) Compression is performed according to the Euclidean distance of adjacent points and the Euclidean distance threshold ε .

In the fourth step, on the basis of sorting, the distance between two adjacent points in the sequence and Euclidean is first calculated. If the distance is less than the distance threshold,the latter is deleted, otherwise no point is deleted.

4. Experiment and Assessment

4.1. Experiment

The experimental data adopts Skull point cloud data, with a total of 20,02 points.The algorithm was programmed in Visual Studio 2017 using PCL 1.6.0, and the comparison experiment was done with MeshLab and Geomagic Studio.

When setting parameters, after experimental analysis, this paper finally uses the interval as shown in Table 1 to divide the Gaussian curvature.The included angle threshold of detailed clustering was set at 27 degrees.The Euclidean distance threshold of adjacent points is set as 0.1mm.

Table 1: Gaussian curvature interval division.

[0.0,0.4)	[0.4,0.8)	[0.8,1.2)	[1.2,1.6)
[1.6,1.9)	[1.9,2.2)	[2.2,2.4)	[2.4,2.5)
[2.5,2.6)	[2.6,2.8)	[2.8,3.1)	[3.1,3.4)
[3.4,3.8)	[3.8,4.2)	[4.2,4.6)	[4.6,5.0]

4.2. Assessment

In this paper, 3D visualization evaluation method and surface area change rate are used to illustrate the advantages of the proposed method.In Figure 3, (a) is the visualization result of the original point

cloud data, and (b), (c) and (d) are the visualization results of compression of the original point cloud data into the original 64.36% by using the traditional clustering method, the method in reference[12] and the method in this paper, respectively.
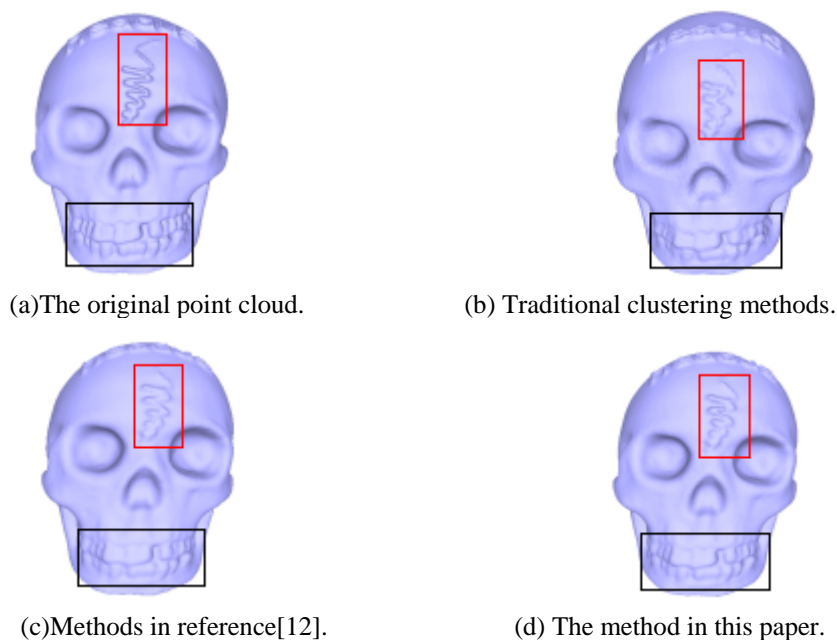

(a)The original point cloud.   (b) Traditional clustering methods.

(c)Methods in reference[12].   (d) The method in this paper.

Figure 2: Comparison diagram of the same compression rate.

When the compression ratio is both 64.36%, the comparison of 3D visualization effects in the black box and the red box in Figure 3 shows that both the method in this paper and the method in reference[12] can well retain the detail features, and the detail features in the sub-feature area can also be well preserved. However, the traditional clustering method loses the detail features seriously.From the comparison of the visualization results in the red box, it can be seen that the effect presented by the method in this paper is a little better than that presented by the method in reference[12].

The surface area calculation was carried out in Geomagic Studio software. The changes of model surface area before and after compression by different algorithms are shown in Table 3.The smaller the area change rate is, the better the compression effect is.

Table 2: Change table of model surface area () before and after compression by different compression algorithms.

Compression method	Compression ratio	Before compression	After compression	Difference	Rate of change
Traditional clustering	52.43%	103936.05	103805.09	130.96	0.126%
	64.36%	103936.05	103778.07	157.98	0.152%
	72.23%	103936.05	103731.30	204.75	0.197%
	81.38%	103936.05	103661.66	274.39	0.264%
Reference [12]	52.43%	103936.05	103871.61	64.44	0.062%
	64.36%	103936.05	103848.74	87.31	0.084%
	72.23%	103936.05	10.813.41	122.64	0.118%
	81.68%	103936.05	103765.59	170.46	0.164%
This thesis	52.43%	103936.05	103878.89	57.16	0.055%
	64.23%	103936.05	103866.41	69.64	0.067%
	72.23%	103936.05	103878.74	87.31	0.084%
	81.68%	103936.05	103817.56	118.49	0.114%

According to the data in Table 2, when the compression rate is equal, the traditional clustering method has the largest surface area change rate, while the proposed method has the smallest surface area change rate,and the method in reference[12] has the middle surface area change rate.This indicates that the traditional clustering method has the worst compression correlation, and the compression effect of the proposed method is a little better than that of the reference[12].

5. Conclusions

A point cloud compression algorithm based on Gaussian curvature clustering is proposed in this paper.Firstly, the Gaussian curvature values of the point cloud data are calculated and normalized, and the Gaussian curvature values are mapped to the interval of[0,5], which can enhance the adaptability of the method in this paper to the data of different point clouds.Then, the Gaussian curvature range is divided in a non-uniform way with large interval length at both ends and small interval length in the middle. According to the divided interval, initial clustering of Skull point cloud data is conducted.Then detailed clustering was carried out according to the included Angle threshold.Finally, point cloud data is compressed according to the set sampling ratio and the Euclidean distance threshold of adjacent points.It can also be seen from the experimental results that the proposed method is superior to the traditional clustering method and the method in reference[12].

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