A Fast Reduction and Denoising Method of Scattered Point Cloud Data Based on Spherical Model

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Abstract. Aiming at the problems of high complexity, long computing time and high hardware requirements of common point cloud reduction and denoising algorithms, a fast point cloud data reduction and denoising method based on ball model is designed. The method of building the sphere model and including the scattered point cloud model of 3D object in the sphere model is introduced. The coding and sorting of the vertebral body region in the sphere and the distribution strategy of each coordinate point is discussed. The different distribution of point clouds in each cone region and the algorithm of data reduction and denoising is studied. A method to transform the scattered point cloud model of 3D object from spherical coordinate to rectangular coordinate is presented. Experimental simulation and analysis show that the method proposed in this paper can simplify and denoise the scattered point cloud at the same time, and the algorithm is simple, with low requirements for the hardware system. This algorithm is more suitable for embedded system operation.

Keywords: scattered point cloud, fast simplification, spherical model

1 Introduction

In reverse engineering, point cloud preprocessing is an important pre work of 3D reconstruction. In the process of target detection, a large amount of point cloud data is usually obtained. Too much point cloud data becomes the burden of data calculation and storage, and not all points are useful for subsequent modeling. Therefore, on the premise of ensuring the accuracy of the data, effectively simplifying the point cloud data is an important content of the point cloud preprocessing, and also the focus of the early steps of reverse engineering. Commonly used point cloud reduction algorithms include clustering method[1], curvature feature method[2], modal decomposition method[3], graph constraint method[4], vector distance method[5], etc. Point cloud filtering technology can be divided into two categories according to the form of point cloud storage. For the ordered point cloud, because of the correlation between points, the filtering algorithm is usually constructed to smooth the point cloud data. Common filtering algorithms include Gaussian filtering, Wiener filtering, Kalman filtering, etc. For scattered point cloud, because there is no topological relationship between points, it is impossible to build filtering algorithm. The
usual method is to establish the topological relationship between point clouds and then filter. At present, for the massive scattered point cloud model, usually simplification and denoising are treated as two different tasks, and the algorithm complexity is high, which requires high hardware system. The technical problem discussed in this paper is to provide a fast and simple de-noising method for scattered point cloud data based on ball model.

2 The establishment of sphere model

First of all, we need to build a sphere model to include the scattered point cloud model of 3D target in the sphere model. The sphere can be regarded as a series of pentahedrons. The vertex of these pentahedrons is the center of the sphere and the bottom is the surface of the sphere. When the bottom is small enough, the pentahedron can be approximated as a pyramid. Each coordinate point is scattered in a cone area. The mathematical definition of the above construction method is as follows: the 3D scattered point cloud model is transformed from the rectangular coordinate form \((x, y, z)\) to the spherical coordinate form \((r, \alpha, \beta)\). The conversion method is shown in formula 1-3:

\[
\begin{align*}
    r &= (x^2 + y^2 + z^2)^{1/2} \\
    \alpha &= \arctan(y/x) \\
    \beta &= \arccos(z/r)
\end{align*}
\]

Taking the origin \((0,0,0)\) of the rectangular coordinate system as the center of the sphere, among the \(R\) values of all points in the 3D target scattered point cloud model, the maximum \(R\) is taken as the radius, the sphere \(Q\) is established. 3D target scattered point cloud model is included in \(Q\). Among them, \(\alpha \in [0^\circ, 360^\circ), \beta \in [-180^\circ, 180^\circ)\). The changes of \(\alpha\) and \(\beta\) divide the sphere into several centrum regions with the center of the sphere as the vertex. For example, when \(\alpha\) and \(\beta\) increase \(\Delta\alpha\) and \(\Delta\beta\) respectively, the enveloped area \(\text{OD}_1\text{D}_2\text{D}_3\text{D}_4\) is shown in Figure 1.

![Figure 1. Construction of sphere model.](image)

In the figure, let \(\Delta\alpha = \Delta\beta = 1^\circ\). The sphere can be divided into \(180 \times 360 = 64800\) regions. Obviously, the target objects in the sphere are also divided into 64800 regions. Reducing the values of \(\Delta\alpha\) and \(\Delta\beta\) can increase the number of regions, improve the discrimination accuracy, but increase the calculation time. Because the scattered point cloud model of 3D object is also in the sphere, it is also segmented accordingly. The coordinate points of the 3D target scattered point cloud model are scattered in a cone area.
3. Coding sequence of vertebral body region

In order to be able to process the data of each vertebra in sequence, it is necessary to code and sort the vertebrae after segmentation. Starting from $\alpha=\alpha_0=0^\circ$ and $\beta=\beta_0=0^\circ$, the values of $\alpha$ and $\beta$ are increased successively, and the steps are $\Delta\alpha$ and $\Delta\beta$. At the same time, the 64800 intervals of the sphere are coded and sorted. Let $\alpha_i=\alpha_{i-1}+\Delta\alpha$, $\beta_i=\beta_{i-1}+\Delta\beta$. Then the coding sorting method is as follows:

$\Phi_1$: from $\alpha_0$, $\beta_0$, to $\alpha_1$, $\beta_1$, i.e. $\Phi_1 \in (0^\circ,0^\circ) \sim (1^\circ,1^\circ)$

$\Phi_2$: from $\alpha_1$, $\beta_0$, to $\alpha_2$, $\beta_1$, i.e. $\Phi_2 \in (1^\circ,0^\circ) \sim (2^\circ,1^\circ)$

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$\Phi_{64800}$: from $\alpha_{359}$, $\beta_{179}$, to $\alpha_0$, $\beta_{179}$, i.e. $\Phi_{64800} \in (359^\circ,179^\circ) \sim (0^\circ,180^\circ)$

By defining the point cloud in each cone region as a point cloud $\Phi$, the scattered point cloud data can be reduced and de-noising can be realized for the point cloud $\Phi$ in each cone region.

4. Design of reduction and denoising method

For each vertebral body, the idea of fast and simplified denoising algorithm is as follows: If the R values of all points in the cone region are similar, the surface of the object in the cone region is considered to be a smooth plane. By setting a feature point to replace all the original points in the cone area, the point cloud $\Phi$ can be reduced. If the R values of the points in the cone area are not similar, the points with the largest and the smallest R values in the cone area are removed. Then compare them. If the remaining points R are similar, it means that there is noise in the two removed points. The set of the remaining points is treated as a smooth plane, and a feature point is set to replace all the original points in the cone region, so as to realize the simplification of the point cloud $\Phi$. If the R value of the remaining points is not similar, it means that there is a slope angle on the surface of the object corresponding to the cone area, all the spot should be kept. The slope angle means that the surface of an object is a slope or has a large curvature.

The implementation of the above algorithm includes the following two steps:

Step 1: Based on the results of coding and sorting of vertebrae, N points on the target object in the $i$th region are defined as point clouds $\Phi_i$: $\{D_{ij}, (j=0,1\ldots N-1)\}$. Among them, $D_{ij}, (j=0,1\ldots N-1)$ is the N points in $\Phi_i$. Note that the r values of these N points are $r_{i,1},r_{i,2}\ldots r_{i,N-1}$. Sort N points by r value from large to small. Note that the maximum value is $r_{i,\text{max}}$, and the minimum value is $r_{i,\text{min}}$. Let the range $R_{i,1}=r_{i,\text{max}} - r_{i,\text{min}}$. Remember that the median is $R_{i,0}$. As shown in Figure 2.

Step 2: Set threshold $\delta=10^{-3} R_{i,0}$. Adjust $\delta$ value to adjust noise tolerance. The smaller $\delta$ is, the smaller tolerance is. On this basis, judge the size of $R_{i,1}$. As shown in Figure 3, if $R_{i,1}<=\delta$, the set of points in $\Phi_i$ is a smooth surface of the original object. In this case, define feature point $S_i$ to replace all the original points in the region, and use this feature point to represent the surface of the object in this region. The coordinates $l_i$, $\theta_i$ and $\varphi_i$ of the feature point $S_i$ are defined as follows:

$$l_i=(r_{i,1}+r_{i,2}+\ldots +r_{i,N-1})/N \quad (4)$$

$$\theta_i=\alpha+\Delta\alpha/2 \quad (5)$$

$$\varphi_i=\beta+\Delta\beta/2 \quad (6)$$
If $R_1 > 10^{-3} R_0$, it means that there is noise in this area or there is a slope angle on the surface of the object composed of points in this area. The judgment method is as follows:

Delete a point with the largest r value and a point with the smallest r value among N points in $\Phi_i$. Then we can find the range $R_{i,2}$ of the remaining points.

If $R_{i,2} \leq \delta$, then the set of points in $\Phi_i$ is a smooth surface of the original object. One or two of the two deleted points are noisy. The presence of noise is shown in Figure 4. In this case, the feature point $S_i$ is defined to replace all the original points in the region, and it is used to represent the surface of the object in this region. The coordinates $l_i$, $\theta_i$, and $\phi_i$ of the feature point $S_i$ are defined as shown in equations 4 to 6.

If $R_{i,2} > \delta$ at this time, there is a slope angle on the surface of the object composed of points in this area, and all points are reserved. The slope angle is shown in Figure 5.

After all the vertebral body regions are processed, the scattered point cloud model of 3D target is transformed from spherical coordinate to rectangular coordinate. The formula of transforming the scattered point cloud model of 3D object from spherical coordinate to rectangular coordinate is as follows:

$$x = r \cos \alpha$$

$$y = r \sin \beta \cos \alpha$$

$$z = r \cos \beta$$

5 Experiment and analysis

In this paper, strawberry point cloud model is used to verify the simplification and denoising effect of the algorithm. In this algorithm, the reduction degree can be adjusted by
changing the $\Delta \alpha$ and $\Delta \beta$ of spherical coordinates. In this paper, $1^\circ$, $2^\circ$, $5^\circ$ are selected. The simplified effect is shown in Figure 6.

![Figure 6. Effect of reduction algorithm.](image)

In this paper, we use different denoising algorithms to denoise the existing point cloud model, and analyze and compare the experimental results to verify the effectiveness of the algorithm. In Figure 7, from left to right, there are the added noise model, the denoising effect of Laplace algorithm and the denoising effect of this algorithm. Table 1 shows the time taken by different algorithms.

![Figure 7. Effect of Denoising algorithm.](image)

**Table 1. Time comparison of different denoising algorithms.**

<table>
<thead>
<tr>
<th>Point cloud denoising algorithm</th>
<th>Algorithm in this paper</th>
<th>clustering method</th>
<th>curvature feature method</th>
<th>vector distance method</th>
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<tbody>
<tr>
<td>Time to denoise</td>
<td>1.73</td>
<td>2.74</td>
<td>4.52</td>
<td>5.61</td>
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</tbody>
</table>

**6 Conclusion**

Scattered point cloud processing is an important work in reverse engineering. At present, the common simplification and de-noising algorithms are usually complex in pursuit of accuracy. Based on the spherical coordinate system, this paper proposes a fast denoising and simplification algorithm for scattered point cloud. The algorithm has low computational complexity and fast operation speed, and can be used in machining occasions with low hardware configuration and low precision requirements.

This work was supported by Natural Science Foundation of Universities in Jiangsu Province (Grant No.: 16KJA460001), Creation Foundation Project of Nanjing Institute of Technology (Grant No.: ZKJ201611).

**References**