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3D COMPLEX CURVED SURFACE RECONSTRUCTION OF DISCRETE POINT CLOUD BASED ON SURFELS

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ABSTRACT

A Surfels 3D reconstruction method based on improved KD-Tree is put forward, firstly collecting the discrete point cloud data through RGB-D camera, replacing the circular or oval surfel model with hexagonal model for modeling and determining the surfel radius in light of neighborhood distribution of sample points; Moreover, doing inside and outside relations test between one point model and another discrete point model, building KD-Tree for each model, setting the axis with the longest projection length as the separating axis, improving segmentation rules, accelerating the detection of inside and outside and intersecting relations. Experiments show this algorithm has great reconstruction effects on the 3D reconstruction both of heterogeneous sample points and discrete point cloud with different resolution with steady and efficient calculation.

Keywords: *Surfels, Discrete Cloud, 3D Reconstruction, KD-Tree*

1. INTRODUCTION

Surface reconstruction technologies on the object or scene are mainly divided into the following categories: traditional geometric modeling, 3D scanning devices and 3D reconstruction based on stereoscopic vision. The traditional modeling method requires the size of objects which is difficult for irregular curved surface object to be measured, the complex creative process, the modeling staff with high professional knowledge, especially in modeling software including AutoCAD, 3D-Max, Maya, OpenGL etc.. The 3D scanning devices can be divided into contact and non-contact. Although this method is simple to reconstruct object and get accurate 3D model, its devices cost hugely. 3D reconstruction method based on stereoscopic vision uses binocular camera or depth camera to obtain three-dimensional coordinates of the object or scene through triangulation principle and finally have a high-precision reconstruction effect. It is economical and convenient and now widely used around the world.

Surface reconstruction is mainly divided into traditional surface modeling methods and the modeling method based on point model. Traditional surface modeling methods mainly include the following three types: Mesh surface [1-3] uses point, line and plane surface patch to represent geometric model, which can express three-dimensional objects with arbitrary topology and arbitrary shape; Parametric surface reconstruction [4-5], namely explicit surface reconstruction, is always the main method to describe geometric model with simplicity and convenience and ability to determine point location on the curve or curved surface; Implicit surface reconstruction [6-7] is a kind of curve fitting, which is easy to express the geometric model with complex topological structure and has no need to parameterize discrete point cloud. Surface modeling method is not suitable for point cloud modeling, for a polygon mesh contains topology among the sampling points requiring a lot of resource to store the information, and for geometric means of expression based on the point model don't need maintaining a uniform topology.

In 1985, Levoy et al. firstly proposed the thought of surface reconstruction setting point as basic element and using scattered point set intensively sampled from the surface of the object to implicitly represent it, and this model became the point model. Pfister[8] et al. put forward a point model rendering method based on surfels, seeing the point locally as a directive thin wafer and all wafers covering each other to form a closed-up surface. Rusinkiewicz[9] et al. proposed to transform model sequences into linear structure through the Streaming QSplat concept drawn by the hierarchy tree traversal structure. QSplat method uses the opaque square to draw point model with high efficiency but bad graphics aliasing. Botsch[10] et al. chose a point model acceleration method based on Gauss filtering with better rendering effect, but they did not consider the model hierarchy structure. Wu [11] simplified approximately the surface based

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on surface element and resampled the surface to remove the surfels redundancy by the particle mutex method. Schaufler [12] et al. proposed to store surfels in the octree node and graph data by ray tracing algorithm. Botsh[13] et al. expressed point model by mixed data structure which can accelerate rendering and save space. Coconu [14] et al. used hardware acceleration algorithm EWA Splatting, all the sampling points stored in the octree. Adams [15] et al presented a surface element model for Boolean operations, accelerating surface element detection with three-color octree. Zhang long [16] et al. drew multi-resolution LOD for large scale point model using EWA rendering algorithm. Bentley [17] et al. expanded the application of bintree to multidimensional space. Arya [18] et al. proposed to move the divide planar located in the center of the cube box to the nearest point. Stückler [19] et al. proposed to do 3D scene reconstruction using multi-resolution surface element to present depth camera information.

On the foundation of surfels-based 3D point cloud rendering, this paper put forward a kind of improved KD-Tree point cloud data index structure which improved KD-Tree segmentation rules, took bounding box test for surfels, resampled the boundary and finally improved the precision of curved surface modeling.

2. MODELS AND ALGORITHMS

2.1 Surfels-based Point Model

2.1.1 Point model radius

The definition of point model proposed by Levoy is (x,y,z,r,g,b,a) of which each value is a property exclusive of normal vector and radius. Point cloud is a sampling collection on unknown surfaces, namely $Q=\{q_i \in R^3\}$, and the definition of normal vector is:

$$N=\{n_i \in R^3, \|n_i\|=1\}\text{, where } i \in \{1,\cdot,m\} \quad (1)$$

Due to the large cavity on the boundary in 3D reconstruction based on circular or oval surfels, we utilize hexagon surfel point model to smoother surface, as shown in figure 1.

Estimation formula of the radius of surfel point model is :

$$r_i = \varepsilon * \max(d(q_i q_j)), i \in \{1,\cdot,m\},\ j \in \{1,\cdot,m\} \quad (2)$$

Where ε is initial radius coefficient, $d(q_i q_j)$ is the distance between q_i and q_j .This sampling method is suitable for heterogeneous sample points which can make surfels cover the entire model surface by increasing the radius of surfels on the surface with sparse sample points and decreasing that with intensive sample points, and at the same time reduce overlapping phenomenon.

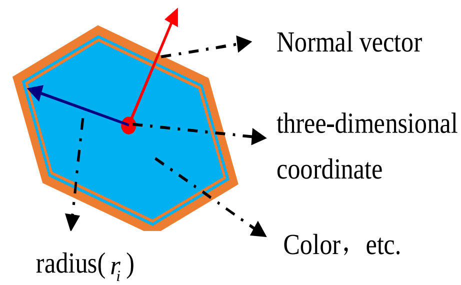

Figure 1: Surface Element

2.1.2 Normal vector of point model

The surface profile around the discrete point q is determined by the neighborhood points of the point. Normal vector to a tangent plane of the surface on point q is the normal vector of point q . Through least square method, we calculated the tangent plane to point q , $V(x)$: $n^T q = n^T s_i$, $\|n\|=1$ when $(n^T(q-s_i))^2$ is the minimum, s_i is the k-order least proximal point of point q or the point weighted by local compactly support function δ :

$$\min_{\|n\|=1} \sum_i (n^T(q-s_i))^2 \delta(\|s_i - q\|) \quad (3)$$

Because of the constraint $\|n\|=1$, above expression can be simplified to:

$$\sum_i (q-s_i)(s_i-q)^T = Ediag(\sigma_0,\sigma_1,...,\sigma_m)E^T \quad (4)$$

$$\min(n) = n^T Ediag(\sigma_0,\sigma_1,...,\sigma_m)E^T n \quad (5)$$

where E is orthogonal matrix composed of the eigenvectors corresponding to $\sigma_0,\sigma_1,...,\sigma_m$.

When $n^T E = (1,0,0,...,0)^T$, $\min(n)$ reaches to the least so as to get the normal of the tangent plane to point q .

2.2 Improved KD-Tree

Point model doesn't record the topological relations between points determined by spatial position. Before the complicated surface 3D reconstruction, discrete point cloud data is organized according to spatial data structure, such as octree, KD-Tree etc.

KD-Tree is a kind of binary tree, each non-leaf node of which can be split into two subspaces by segmentation plane. According to different segmentation planes, usually hyperplanes, the mode of construction of KD-Tree includes: balanced KD-

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Tree, middle-point segmented KD-Tree and KD-Tree with sliding midpoint. Segmentation plane of balanced KD-Tree gets through one point of the node-containing points, the points on both sides of plane substantially equal. Segmentation plane of midpoint segmented KD-Tree locates in the center of subspace, of which adjacent layers have characteristic of shared location between nodes. Sliding midpoint KD-Tree moves segmentation plane in the center of the subspace to the nearest point, and then goes segmentation on KD-Tree.

Firstly, we determine the local coordinate system and the bounding box size of discrete point cloud $Q=\{q_i \in R^3\}$ during spatial segmentation, to make q_o the average position of Q:

$$q_o=\frac{1}{m}\sum_{i=1}^{m} q_i \tag{6}$$

Then the third order covariance matrix is:

$$L=\frac{1}{n}\sum_{i=1}^{m}(q_i-q_o)(q_i-q_o)^T \tag{7}$$

L is symmetric positive semi-definite matrix with eigenvectors orthogonal to each other, then its eigenvalues are:

$$L-\lambda_i\beta_i=0, i\in\{1,2,3\} \tag{8}$$

where λ_i as the eigenvalue, β_i as the eigenvector. We suppose ϕ_1, ϕ_2 and ϕ_3 are three eigenvectors for discrete cloud points along three coordinate axes, then:

$$\phi_1=\frac{1}{2}(\min\{\underset{1\le i\le m}{q_i}.\beta_1\}+\max\{\underset{1\le i\le m}{q_i}.\beta_1\})$$

$$\phi_2=\frac{1}{2}(\min\{\underset{1\le i\le m}{q_i}.\beta_2\}+\max\{\underset{1\le i\le m}{q_i}.\beta_2\})$$

$$\phi_3=\frac{1}{2}(\min\{\underset{1\le i\le m}{q_i}.\beta_3\}+\max\{\underset{1\le i\le m}{q_i}.\beta_3\}) \tag{9}$$

The bounding box center is:

$$\psi_o=\phi_1\beta_1+\phi_2\beta_2+\phi_3\beta_3 \tag{10}$$

It is determined the segmentation plane is to divide current point cloud space along one axis. This paper projects coordinate of the node into each coordinate axis in KD-Tree segmentation, setting the axis with the longest projection length as the separating axis, also the direction of normal vector of segmentation plane. Suppose node subspace $q_i(x_i,y_i,z_i)$, where x_i is the projected length on the x-axis of knot subspace. y_i is the projected length on the y-axis of knot subspace. z_i is the projected length on the z-axis of knot subspace.

If $Max(x_i,y_i,z_i)=z_i$, then select the plane parallel to z-axis for segmentation. According to these segmentation rules KD-Tree has the same space size and the same segmentation direction, and can produce the same segmentation sequence without saving segmentation information. After the production of KD-Tree, same segmentation rules can be followed to access knot subspace.

3. BOOLEAN OPERATIONS ON SURFELS-BASED POINT MODEL

There are three relations between a surfel model and another model: internal relation, external relation and intersecting relation.

Framework of the algorithm is as follows:

1) Establishing the surfel model of each point, and improved KD-Tree data index based on point cloud quantity accelerating the neighborhood search.

2) Calculating surfel radius of sample point which is required to cover just the sample point surface according to the neighborhood of each sample point.

3) Doing "internal, external, intersecting" relationship test on the surface between each of the surfel model and another point model.

Suppose α and β are surfels sets of curved surface model, S_α and S_β are the point model surfaces covered by α and β, V_α, V_β are 3D spatial entities surrounded by S_α and S_β, and ψ is surfel for a discrete point. Boolean operations on the complex curved surface model are performed as:

$$\alpha\cup\beta=\langle\psi|\psi\in\alpha\&\&\beta_{out}\&\&\psi\in\beta\&\&\alpha_{out}\rangle$$

$$\alpha\cap\beta=\langle\psi|\psi\in\alpha\&\&\beta_{in}\&\&\psi\in\beta\&\&\alpha_{in}\rangle$$

$$\beta-\alpha=\langle\psi|\psi\in\beta\&\&\alpha_{out}\&\&\psi\in\alpha\&\&\beta_{in}\rangle$$

$$\alpha-\beta=\langle\psi|\psi\in\alpha\&\&\beta_{out}\&\&\psi\in\beta\&\&\alpha_{in}\rangle \tag{11}$$

Among them, α_{in}, α_{out}, β_{in}, β_{out} point ψ is inside and outside of the model S_α and S_β, respectively.`

4) For intersecting surfels, firstly working out the confidence neighborhood, then calculating the nearest surfel boundary on the point model, and resampling the surfel in the confidence neighborhood.

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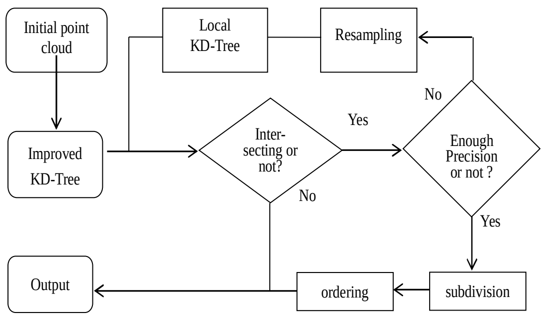

Figure 2: Boolean Operation Flowchart Of Point Model

4. EXPERIMENT RESULTS

In order to verify the validity of the algorithm, we used the Kinect to collect 3D point cloud data: test data is from indoor complex scenes with the data size up to 149821 points. The server we used for operation is the CPU I73610QM, 4G RAM, graphics card GeForce GTX 675M, and operation rate is 30 frame / sec.

Table 1 : Surface Reconstruction Complexity Of Three Complex Scenes

Scene	Reconstruction points number	Surfel reconstruction	Reconstruction time
1	75564	52340	0. 021
2	149821	117780	0.031
3	84730	70919	0. 025
4	69857	58818	0.022

As show in table 1, we test the algorithm in 4 indoor scene using Nvidia Geforce GTX 675m. The discrete points was sent to GPU accelerated, has to meet the real time requirements.

The discrete point's data is quite big in the 4 indoor scene. By the Surfels and KD-Tree algorithm for 3D reconstruction can effectively remove the useless point cloud data, and effectively carry out the data compression.

As shown in the below figure is robot plane surface reconstruction. Through two different resolution three-dimensional reconstruction based on this algorithm, it takes the good experimental effect.

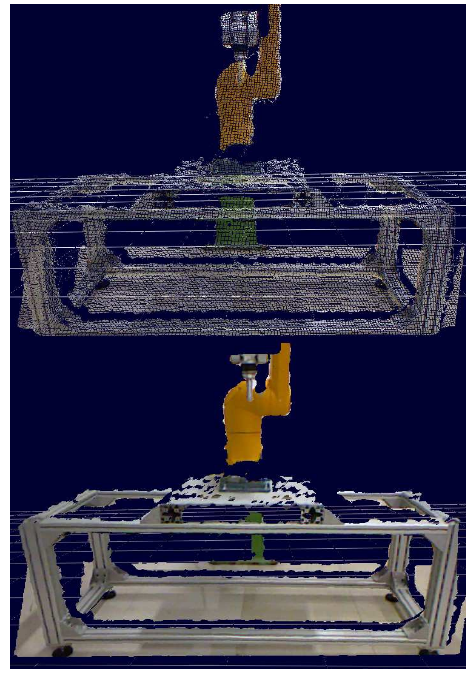
Figure 3: The 3D Reconstruction Of A Large-Scale Landscape

Up of Figure 3 used the pure point cloud for 3D reconstruction, and the below was the surfels model of reconstruction. In the 3D reconstruction of pure point cloud, apparent voids or continuous cavity appeared, and 3D reconstruction effect was not good. 3D reconstruction based on the surfels model has no cavity with continuous surface and good 3D reconstruction effect.

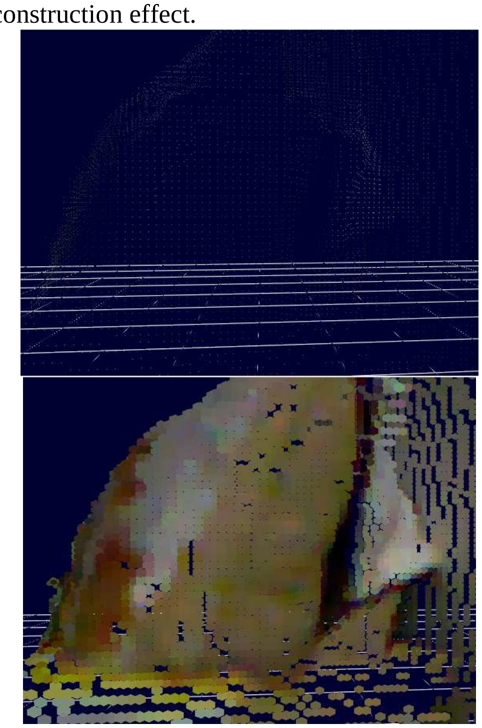
Figure 4: Detailed Hierarchical Control

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As shown up in Figure 4, when modeling target is far away from us, under the condition of lower resolution, we can only get the less details of the scene after amplifying many multiples. As shown below in Figure 4, after processing by our algorithm, 3D modeling based on the surfels model can get the high resolution details and obtained more continuous curved surface model.

5. CONCLUSION

This paper made adjustment of the shape of surfels point model, determined the surfels radius according to the neighborhood distribution of sample points, and put forward a segmentation rule of KD-Tree. The detection of inside and outside and intersection relations could be accelerated by testing the surfels point model inside and outside. Great reconstruction effects were demonstrated for the 3D reconstruction both of heterogeneous sample points and discrete point cloud with different resolution. However, improved KD-Tree segmentation rules are helpless to the segmentation of two-dimension points. Therefore, further research will be conducted on processing technology of point cloud data.

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