DE GRUYTER OPEN

BULGARIAN ACADEMY OF SCIENCES

CYBERNETICS AND INFORMATION TECHNOLOGIES • Volume **16**, No 5
Special Issue on Application of Advanced Computing and Simulation in Information Systems

Sofia • 2016 Print ISSN: 1311-9702; Online ISSN: 1314-4081
DOI: 10.1515/cait-2016-0049

Triangulation Reconstruction for 3D Surface Based on Information Model

Na Li[1,2], *Jiquan Yang*[2], *Aiqing Guo*[2], *Yijian Liu*[2], *Hai Liu*[2]

[1]*Huibei Key Laboratory of Intelligent Vision Based Monitoring for Hydroelectric Engineering, Three Gorges University, Yichang, 443002 China*
[2]*Jiangsu Key Laboratory of 3D Printing Equipment and Manufacturing, Nanjing Normal University, Nanjing, 210042 China*
Email: 63053@njnu.edu.cn

Abstract*: The aim of this paper is to address the surface reconstruction from point cloud in reverser engineering. The data was acquired through a 3D scan device and was processed as point cloud data. The points in cloud were connected to build 3D surface. The points cloud was processed in four steps to get 3D information surface. First, the subtraction scheme was used to get cover boxes ended with the set of convex was found under the convergence rule. Secondly, the points in the box were projected to the directions which were close to the normal direction method. Thirdly the overlap was avoided by using convergence rule and inner subdivision rule. Finally the information model was used to reconstruction. The method was used in landslide monitoring of Three Gorges area for 3D surface reconstruction and monitoring. The reconstruction method obtains high precision and low complexity. It is effective for large scale monitoring.*

Keywords*: Triangulation reconstruction, 3D elastic model, vector projection, point cloud, landslide monitoring.*

1. Introduction

Surface reconstruction from point cloud is a very popular and challenging problem, it is used in reverse engineering for many fields such as model fabrication, production redesign, medical engineering and 3D printing manufacture. The data acquisition is now commercially available. Optical noncontact scanning such as laser scanning is a commercial technology that could be utilized to produce a large cloud data set, but the data are also seen from medical acquisition techniques: MRI, CAT, Serial section microscopy, and confocal microscopy. Point cloud data is used more and more widely with its simple and free formal and discontinuous characteristic. Once a cloud point data set is produced, then it should be processed to extract a digital manufacturing model for 3D printing. There are some methodologies for surface reconstruction. These methods are broadly classified into five categories: Voronoi-based surface reconstruction, Level set based method, volumetric sculpturing method and Algebraic method. Voronoi-based triangulation from point could describe object in any topology which is a virtual method. Voronoi-based Delaunay triangulation is good structure for plane model which has little data redundancy in computation. Delaunay triangulation should be modified for 3D surface constructing, or the 3D surface should project to 2D plane for Delaunay triangulation.

Wu, Liu and Xu [1] gave a multi-resolution reconstruction using iteration method, and realized the multi-resolution description of surface feature. Gao and Pang [2] gave a rapid incremental reconstruction of cloud data using wave front method which produce mesh mode gradually. Guan and Bo [4] gave a eight quadrant projection method to get maximum project plane to ensure high quality of triangulation. Wu [5] gave a subdivision method to get hexagon from triangle using multi-scale technical. Different storage methods are disclosed using octree as storage structure. Habib [6] reviewed the existing 3D surface reconstruction methods and justify the performance using key specifications. Future directions were suggested and also some key problems were present. Bretar and Chehata [7] gave 3D digital model of landform based on aerial map cloud data.

Up to date there is no perfect resolution of 3D triangulation in theory and method [3, 8, 9]. There are four triangulation methods including triangulation growth method, point by point interpolation, merge segmentation method and 3D to 2D projection. The main problems are the high computation cost and low precision.

This paper used Octree structure for storage and division of 3D surface. The segmentation and projection method called PCND (Project to Closest Normal Direction) was presented. The points projected to the surface of the box according to inner subdivisions which formed by the lines form center point to the vertexes. Surround boxes were used to cover the points and subdivide the box until the points in one box meet the fractal dimension specification. In division box the cloud points were projected to six planes respectively according to inner box subdivision. After triangulation was done in six planes the triangle meshes were re-projected and the normal vector of triangles was the judgement rule of the result about the triangulation. The elastic object model is for rapid prototyping manufacturing, the reconstruction surface model could be manufactured using 3D printer. One experimental result was given to demonstrate the effectiveness of the method using in landslide monitory.

2. Point cloud division and projection

Point cloud would be divided into many regions before projection. Finding a good project plane is a key factor of reconstruction performance. In this paper the inner box projection method was given which is helpful for surface reconstruction in high precision. First, the cloud data was divided into six regions in one box, where the six regions were formed by the lines from center point to the vertexes, while the 2D planes are the surface of the box. Secondly, the points projected from 3D to 2D plane, the Delaunay triangulation method was used to connect the unorganized points to form surface mesh. Thirdly, the mesh was re-projected to their original place, the overlap should be corrected, and smoothness was processed for regions connection. Overlap of point projection in some direction is a key problem resulting in reconstruction failure. The smoothness of the surface was processed for mesh connection between different boxes. The overlap problem could be avoided and more details would be given to ensure the quality of the object reconstruction. Finally, the elastic property was added to each point in the mesh.

The coverage boxes were stored in octree structure. The subtraction method reduced the boxes with no points in it. It is more effective and quicker than addition method as usual. The first step was to find the outside box to cover the whole points set. Next step to segment the region as follows:

1) Find the longest line in *x*, *y*, and *z* direction as the sideline l of box and draw the box to cover all the points. As seen in Fig. 1a.

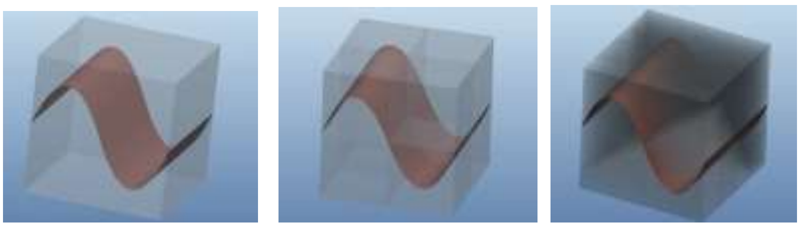
2) Use *l*/2 as new sideline for new box to subdivide the segmentation above, as seen in Fig. 1b.

3) Repeat iteration until the set of segmentation was combined of convex, as seen in Fig. 1c.

4) Delete the empty boxes using the following rule:

a) From the outermost cover boxes, named *i*-layer, empty boxes were deleted.

b) Continue to delete the empty boxes in *i*–1 layer, iterate to the *n* layer which has no empty boxes.



(a) (b) (c)

Fig. 1. Segmentation: Outmost cover box (a); division (b); subdivision (c)

2.1. The overlap region using uneven subdivision

In low density position the overlap projection was less likely to happen. And the inner subdivision rule is in accordance with finding the set of convex. Give the density rule for judging the overlap and find the set of convex. The density function was defined with points set $P=\{p_1, p_2,...,p_n\}$ in d dimension as follows:

(1) $$\hat{f}(p)=\frac{1}{nh^d}\sum_{i=1}^{n}K\left(\frac{p-p_i}{l}\right),$$

where $K(P)$ is Gauss kernel function, h is kernel radius. $K(P)$ is rotation invariant, and

(2) $$K(P)=c\cdot k(\|p\|^2),$$

where $k(p)$ is section function of $K(P)$, c is regularization unit.

The value of threshold density for points in box was given by full box sample with no overlap. This value was predefined by choosing the sample boxes of reconstruction object. The method was not automatic in this step and the thresholds could be defined as several values in different density area of object image. The overlap area should be subdivided until there is no overlap projection was found meet the requirement as

$$d_{\text{box}} < d_{\text{th}}. \tag{3}$$

Iterate the segmentation until the set of convex was found, and there is no overlap in projection. The subdivision result was shown in Fig. 1. After subdivision the projection could be done without overlap.

2.2. The encoder of the division box

The octree structure was used to store the boxes of subdivision, and the sequence was $z \to x \to y$, which was in accordance with 3D printing manufacturing. The points were allocated with position information. As to point, $P_i(x_i, y_i, z_i)$, $(i = 1, 2, ..., n)$, the hush function was used to encode the position number of the box position:

$$\begin{aligned} \text{box} - \text{index}(p_i) &= (\text{int})(z_i / e_0) + (\text{int})(x_i / e_0) \times \text{number}\_z + \\ &+ (\text{int})(y_i / e_0) \times \text{number}\_z \times \text{number}\_x + 1. \end{aligned} \tag{4}$$

As to the coordinate of the point P_i, the $\text{box} - \text{index}(p_i)$ was the position of the division segmentation.

2.3. The Delaunay triangulation based on projection

The Delaunay triangulation was designed for 2D surface and it should be modified for 3D applications. The usual methods are dimensionality reduction, α – shape, partition and extension propagation. The division method in this paper was different than the usual methods using subtraction instead of addition. The complexity of the method reduced largely as using empty box deleted. After division and subdivision points was projected to six planes and the triangulation was constructed on six planes separately.

The invalid triangles were produced because of projection from 3D to 2D. They were seen during re-projection from 2D to 3D. The invalid triangle triangles were defined in several cases as follows:

1) The Euclid space of two points was large than *k*-order neighbor.

2) The triangles crossed.

3) The normal vector direction was not in the curvature scope of subdivision.

The invalid triangles should be deleted and points left searched the triangles to be added in *k*-order neighbor.

Consider the sidelong of the box was *m*, the size of box the next iteration was *m/*2, *k* was fractal dimension as follows:

(5) $$k = \frac{m}{n},$$

where m is the number of boxes and n is the number of facets. If $\Delta k \approx 0$ when iterate, which means result convergence. As seen in Fig. 2, the mesh was constructed when the method convergences.

In subdivision region curvature was fit using difference of normal vectors. The facets were connected using uneven shifting method.

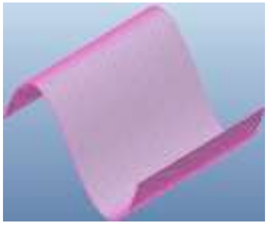


Fig. 2. Mesh generation after division projection

3. Functional elastic surface manufacturing model

Functional elastic object means that the structure of the object was designed for bending, shifting circumstance such as the skin of arms and face of the humanoid robot. Material's elasticity couldn't meet the requirements completely. The functional elastic object was generated adding elastic performance in model.

3.1. Surface reconstruction from cloud point

Generating accurate 3D models using videogrammetry requires a specific system designed and calibrated. The system included elements are as follows:

1) A constant speed rotating support that allows the complete recording of the object by generating a sequence of more than 1000 images in a reduce time frame.

2) A platform system to obtain the geometry of the camera-support and scale the 3D model generated.

3) The system has a single coordinate system centered in the central of the bottom platform, the image co-ordinate system (x, y, f) and object co-ordinate system (x, y, z) results approximately parallel.

The point cloud data was got and segmented as in Section 2, projected and reconstructed as in Fig. 2.

4. Reconstruction surface used in landslide monitoring

Slid often occurs in massif, river land form, reservoir dam, as in Fig. 3a. The aerial vehicle is used to take aerial photography to supervise the area. The photography is used with GPS, ground displacement and macroscopic inspection professional data to give transformation rule of the space-time in landslip take considerate of rain and wind factors.

In Three Gorges of China the surface was supervised and reconstructed from a point cloud picture used the method above. In elastic range the movement of the monitoring area was in normal motion. The landslide occurs when reconstruction surface changes out of the range, as in Fig. 3b.

(a) (b)

Fig. 3. Landslide in Three Gorges area: Supervision area (a); landslide monitoring (b)

5. Conclusion

The traditional approach of reconstruction surface for reverse engineer ignores the function information of object. The elastic performance is an important function for many applications. The paper gave an effective projection reconstruction method and model of elastic object. The outermost cover box was used and the final cover boxes were gotten by subtraction method. The complexity of the method is $O(n)$. The set of convex and concave is good for avoiding the overlap projection and the subdivision inner box is designed for single projection deleting overlap projection. The complexity of method in [11, 12] is $O(n^2)$, $O(n)$ in [13]. It is more accurate because the elastic mode was used. Although the sensitiveness is lower, the accuracy is higher than others.

***Acknowledgements*:** This work was financially supported by Natural Science Foundation of China (No 61273243, 61304227), Open fund of Hubei Key Laboratory of Intelligent Vision Based Monitoring for Hydroelectri c Engineering (2014KLA12), and Jiangsu Science and technology key project of infrastructure (No BM2013006), and Nature science Foundation of Jiangsu Higher Education Institution of Jiangsu (No 15KJB510018).

References

1. Wu, H., C. Liu, Z. Xu. Surface Reconstruction and Multi-Resolution Express from Terrestrial Laser Scanning Data Based on Stratified Contours. – Journal of Tongji University (Natural Science), Vol. **43**, 2015, No 2, pp. 319-324.
2. Gao, X., M. Pang. Incremental Mesh Reconstruction from Unorganized Points. – Journal of Chinese Computer Systems, Vol. **32**, 2011, No 10, pp. 2096-2100.

3. Z h a n g, Y. D., S. H. W a n g, P. P h i l l i p s et al. Binary PSO With Mutation Operator for Feature Selection Using Decision Tree Applied to Spam Detection. – Knowledge Based Systems, Vol. **64**, 2014, pp. 22-31.
4. G u a n, M., Z. B o. Eight Quadrants Triangulation Algorithm about Space Closed Point Cloud. – Journal of Harbin University of Science and Technology, Vol. **14**, 2009, No 3, pp. 20-24.
5. W u, R. Based on Hexagonal Grid Geometry Processing Method. Doctoral Dissertation of JI Lin University, Ji Lin China, 2007.
6. F a t h i, H., F. D a i, M. L o u r a k i s. Automated As-Built 3D Reconstruction of Civil Infrastructure Using Computer Vision: Achievements, Opportunities, and Challenges. – Advanced Engineering Informatics, Vol. **29**, 2015, pp. 149-161.
7. B r e t a r, F., N. C h e h a t a. Terrain Modeling from Lidar Range Data in Natural Landscapes: A Predictive and Bayesian Framework. – IEEE Transaction on Geoscience and Remote Sensing, Vol. **48**, 2010, No 3, pp. 1568-1578.
8. L i a n g, X., Y. W a n g, A. J a a k k o l a et al. Forest Data Collection Using Terrestrial Image-Based Point Clouds from a Handheld Camera Compared to Terrestrial and Personal Laser Scanning. – IEEE Transactions on Geoscience and Remote Sensing, Vol. **53**, 2015, No 9, pp. 5117-5132.
9. Z h a n g, Y. D., S. H. W a n g, Z. C. D o n g. Classification of Alzheimer Disease Based on Structural Magnetic Resonance Imaging by Kernel Support Vector Machine Decision Tree. – Progress in Electromagnetics Research-Pier, Vol. **144**, 2014, pp. 171-184**.**
10. V o L i n h, A n h-V u, T r u o n g-H o n g, D. F. L a e f e r, M. B e r t o l o t t o. Octree-Based Region Growing for Point Cloud Segmentation. – ISPRS Journal of Photogrammetry and Remote Sensing, Vol. **104**, 2015, pp. 88-100.
11. A g a r w a l, S., N. S n a v e l y, S. S e i t z, R. S z e l i s k i. Bundle Adjustment in the Large. – In: Proc. of European Conference on Computer Vision, Spring Berlin Heidelberg, Vol. **6312**, 2010, No 1, pp. 29-42.
12. B y r o d, M., K. A s t r o m. Conjugate Gradient Bundle Adjustment. – In: Proc. of European Conference on Computer Vision, Spring, Berlin, Heidelberg, Vol. **6312**, 2010, No 1, pp. 114-127.
13. A g a r w a l, S., N. S n a v e l y, I. S i m o n, S. S e i t z, R. S z e l i s k i. Building Rome in a Day. – IEEE International Conference on Computer Vision, Vol. **54**, 2009, No 10, pp. 2-79.