ICIC Express Letters
Volume **10**, Number **5**, May **2016**

ICIC International ©2016 ISSN 1881-803X
pp. 1187–1192

CLASSIFICATION STRATEGY FRAME FOR THE HOLE OF INCOMPLETE POINT CLOUDS BASED ON SHARP FEATURE

Yanju Liu[1], Xuefeng Dai[2], Honglie Zhang[3] and Yanzhong Liu[3]

[1]Computing Center
[2]Network Information Center
[3]College of Computer and Control Engineering
Qiqihar University
No. 42, Wenhua Street, Jianhua District, Qiqihar 161006, P. R. China
{ 15146692464; daixuefeng203; Zhang_honglie }@163.com; lyzself@tom.com

Received October 2015; accepted January 2016

Abstract. *This paper presents a classification strategy frame for the hole of incomplete point clouds in order to restore the geometrical feature of surface. The frame is constructed in two steps. The first step is to determine the type of the hole by the normal of grid surface, the sharp value and the optimal threshold value. And the second step is to stitch the hole with patch, in which three cases can stitch most part of situations basically. The key ingredient of classification strategy frame is considered to restore the sharp feature of model. Theoretical analysis and experimental results show that the classification strategy frame can fill the hole of denture effectively and recover the shape of original model. In the process of construction, each type of the hole that is cut by threshold can cover 95.4% of the class members.*

Keywords: Incomplete point clouds, Type of the hole, Classification strategy, Sharp feature

1. **Introduction.** Although the precision of laser scanner has been improved continually, the number of point clouds obtained is achieved one hundred thousand, even ten million. It is unavoidable that the data obtained are incomplete because of uncertainty and complexity of object geometrical feature and limitation of scanner measurement. Therefore, the parameters of data are incomplete, the following three-dimensional reconstruction is influenced and the model is distorted.

The research on repairing the incomplete point clouds is still in the early exploration stage. Chehata et al. [1] classified point clouds by K-means of hierarchical clustering according to elevation and slope of adjacent area. Matthew et al. [2] proposed a representation model used for the cascading binary classifier to distinguish point clouds based on three-dimensional shape analysis theory and region growing algorithm. Although the researches above could realize preliminary classification of point clouds, they were mainly used for classification and segmentation among multiple models of point clouds and they were not suitable for classification of incomplete point clouds. Perdan et al. [3] proposed the automatic detection of point clouds surface, and deviation chart analysis method was used to display the deviation between the measured surface and the benchmark teeth surface. Schindler et al. [4] reconstructed the surface by the priori knowledge of topology and geometrical feature, and the relationship between three-dimensional surface area and plane was determined by parametric and classification. Actually, the classification of point clouds involves multi-factors, such as three-dimensional coordination of vertex, curvature variation, gradient and normal. For boundary or ring with the large-area loss, deviation analysis method might produce wrong topological information. The type of the hole cannot be determined by analyzing point clouds. It is necessary to add some priori knowledge to aid cognition. In Figure 1, Casciola and Morigi [5] studied the existing

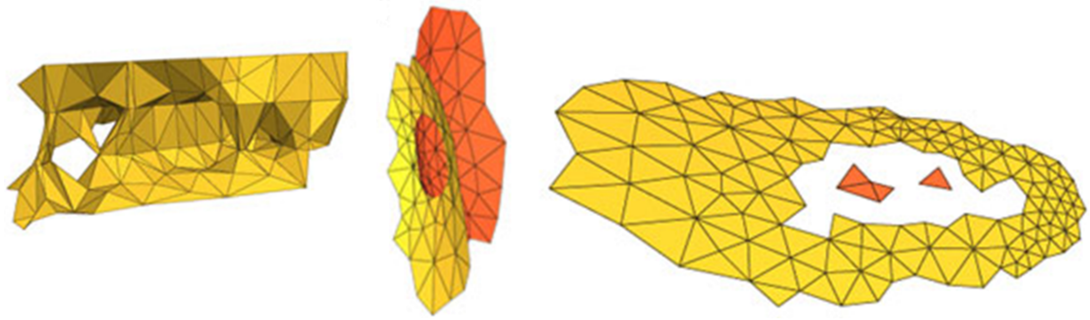


FIGURE 1. Grid topology of incomplete point clouds

three-dimensional reconstruction algorithm for incomplete point clouds and repaired and improved its geometry and topology according to the defect for the different types of grid.

The application layer of grid has higher requirements. Therefore, the repairing algorithm is more suitable for the bottom of grid in the given geometry process based on the classification thought, which provides the compatibility model of the hole for the application layer. Hetroy et al. [6] allowed users to identify potential topology errors and area selected, used morphological operators to repair the topology of discrete model, and corrected voxel transformation. In this way, the feature extraction of complex shape object can be restored, which has a large computation. However, it takes too much time to carry on calculation for all kinds of the hole in unknown case. It is necessary to classify point clouds so as to conduct any objects. Liu and Yang [7] analyzed covariance of point clouds by normal and estimated space parameters of each point in local space. Then, echo times of each point and density of local point clouds were combined as input variables of Support Vector Machine (SVM) classifier. The classification of point clouds was realized by SVM based on radial basis function. Kang et al. [8] proposed the multi-source data fusion to fit point clouds obtained by three-dimensional laser scanner and the color image was blended to extract linear information to determine and verify the fitting feature of boundary. Liu and Zhang [9] estimated the normal of incomplete point clouds and fitted the surface of denture model. The methods above can repair the simple hole or island hole, and recover a smooth surface without geometrical feature. Parametric failure may be resulted from the large point error of quadric surface approximation during repairing. In fact, data obtained from the boundary of model are incomplete, and expert information to fuzzy calculation needs to be increased.

To sum up, the smooth area is repaired by implicit surface reconstruction directly. However, there is no effective method to deal with the hole with the complex shape at present, which is caused by two reasons. One reason is that point clouds are discrete three-dimensional set and have no explicit topological structure. Another reason is that uncertain number of the hole formed by incomplete point clouds and uncertain shape of each hole are caused by the complex object. Thus, how to estimate the lost data to fill the hole is an important issue to research. The existing methods are complex and low-efficient, which are suitable for some known models only. There exists a high error rate for unknown complex models, and the precision of three-dimensional reconstruction is affected seriously.

In this paper, a novel classification strategy frame for the hole formed by incomplete point clouds of irregular model is proposed. The sharp value of each vertex is calculated. The hole is classified according to the sharp value by Bayesian classifier, and priori knowledge is added to the optimal threshold value of the classifier. Point clouds are divided into two types: one is with small sharpness and the other is with large sharpness. For the type with large sharpness, fuzzy calculation is used to add the lost data and the mesh mergence method is used to stitch the patch in three cases.

The remainder of the paper is organized as follows. The type of the hole and mesh mergence for incomplete point clouds are presented in Sections 2 and 3, respectively. In Section 4, the simulation experiments are carried out and results are analyzed. Finally, conclusions are given with the importance and the practical value of the classification strategy frame.

2. **The Type of the Hole for Incomplete Point Clouds.** In most cases, there is obvious difference between model repaired and entity model in display effect, which is caused by losing some sharp features of objects after repairing.

A classification strategy frame used to restore the feature of surface is proposed in this paper, which distinguishes whether vertex has sharp feature or not. The boundary vertices of each hole are involved in the three layers of annular area correspondingly. The vertex can be classified into two types: one with small sharp and one with large sharp. The feature of sharp vertex needs to be restored by this algorithm. Otherwise, vertex does not need to be processed further. In this way, the purpose of hole classification is to find out the vertex whose surface feature needs to be restored. The normal of total grid surface is calculated according to the current triangular surface and its surrounding surface. The grid surface of each vertex is calculated sharp value, which is described in detail as follows.

Firstly, normal n of total grid surface is calculated in Equation (1).

$$n = n_f + \sum_{f_j \in N} n_{f_j} \tag{1}$$

where n_f is normal of current triangular surface f, n_{f_j} is normal of surrounding surface f_j, $\{N\}$ is the neighbor set of surrounding surface f in Figure 2, and $N = \{f_j | f_j$ is a neighbor triangular surface of f, j=1,2,...$\}$.

Then, sharp value V_f of surface f is calculated in Equation (2).

$$V_f = \frac{1}{\|N\|} \sum_{f_j \in N} (\varphi_j - \varphi^n)^2 \tag{2}$$

where φ_j is cosine of vectorial angle between n_f and n_{f_j} in Equation (3), $\varphi^n = \varphi(n_f, n)$, and $\|N\|$ is the number in $\{N\}$.

$$\varphi_j = \varphi\left(n_f, n_{f_j}\right) = \cos\left(\angle\left(n_f, n_{f_j}\right)\right) \tag{3}$$

where $\varphi_j \in [0, 1]$. At the edge or corner of grid surface, φ_j becomes larger, and the normal angle of surface has larger sharp value as well.

Suppose that sharp feature of surface are normal, and Bayesian classifier is adopted. Set u_1 and u_2 to be two types of sharp value, respectively. θ_1 and θ_2 are standard deviation

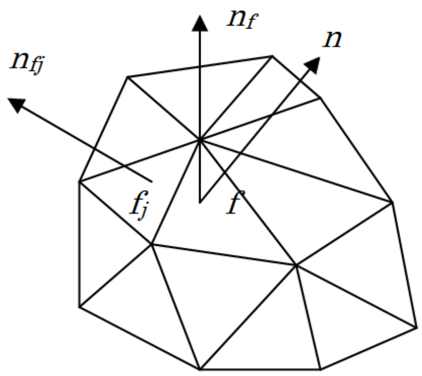


Figure 2. Neighbors of surface f

correspondingly. Equation (4) can distinguish optimal threshold between two types of the vertex.

$$\begin{cases} h_1(x) = \ln p(x|w_1) + \ln P(w_1) \\ h_2(x) = \ln p(x|w_2) + \ln P(w_2) \end{cases} \tag{4}$$

where $h_1(x)$ and $h_2(x)$ are classifier functions. w_1 and w_2 belong to different types. When x is equal to optimal threshold value k, then $h_1(k) = h_2(k)$. Therefore, the standard is used to classify the vertex.

$$\begin{cases} p(x|w_1) = \frac{1}{\sqrt{2\pi}\theta_1} e^{-\frac{1}{2}\left(\frac{x-u_1}{\theta_1}\right)^2} \\ p(x|w_2) = \frac{1}{\sqrt{2\pi}\theta_2} e^{-\frac{1}{2}\left(\frac{x-u_2}{\theta_2}\right)^2} \end{cases} \tag{5}$$

The optimal threshold value k is obtained in Equation (6).

$$k = \frac{\left(\theta_2^2 u_1 - \theta_1^2 u_2\right) - \sqrt{\left(\theta_2^2 u_1 - \theta_1^2 u_2\right)^2 - \left(\theta_2^2 - \theta_1^2\right)\left(\theta_2^2 u_1^2 - \theta_1^2 u_2^2 - 2\theta_1^2\theta_2^2\right)}}{\left(\theta_2^2 - \theta_1^2\right)} \tag{6}$$

To satisfy the condition that $|u_1 - k|/\theta_1 \geq 2$ and $|u_2 - k|/\theta_2 \geq 2$, each type is separated by k, which covers 95.4% of the class members and only 4.6% of other class members. In a word, the type of the hole can be included in the class separated by k.

3. **Mesh Mergence for Incomplete Point Clouds.** In this section, the surface generated by the hole is merged to the mesh around the hole. The objective of mergence is to determine the corresponding relationship between the boundary vertices generated by the hole and the border vertices of surface mesh model. And then, the corresponding vertices are merged and each border vertex in hole mesh is connected to the boundary vertices around mesh. Set b_i and b_{i+1} to be boundary vertices of the original mesh adjacent. p_k is the boundary vertices of the repaired hole surface mesh. There are three conditions in the processing of connecting mesh [11] in Figure 3.

(a) If b_i and b_{i+1} correspond to p_k at the same time, then the three vertices are merged into one vertex.

(b) If b_i and b_{i+1} correspond to p_k and p_{k+1} respectively, and p_k and p_{k+1} are adjacent vertices, then b_i and p_k are merged while b_{i+1} and p_{k+1} are merged as well.

(c) If b_i and b_{i+1} correspond to p_k and p_{k+n} respectively, and the vertex p_j between p_k and p_{k+n} is merged with p_k or p_{k+n}. If $|p_j p_k| < |p_j p_{k+n}|$, then p_j is merged with p_k; else p_j is merged with p_{k+n}. The process is not halted until there are only two vertices. And then b_i and p_k are merged, and b_{i+1} and p_{k+n} are merged as well.

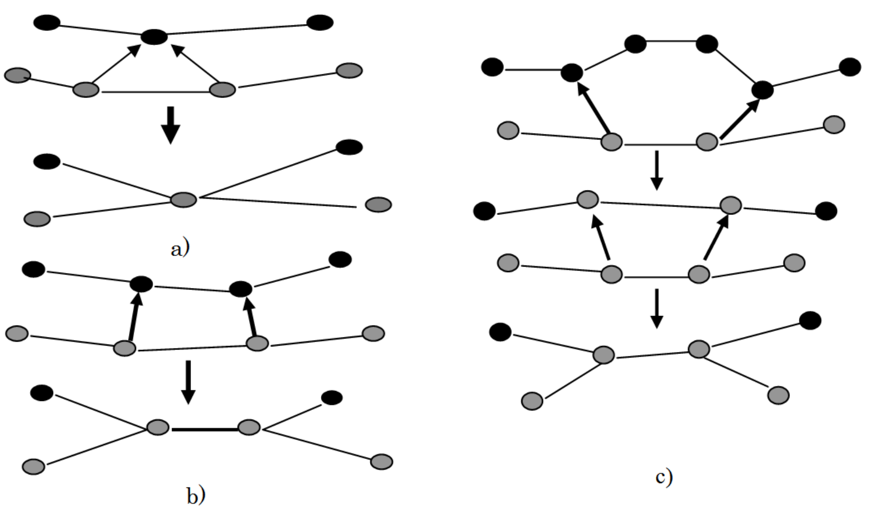
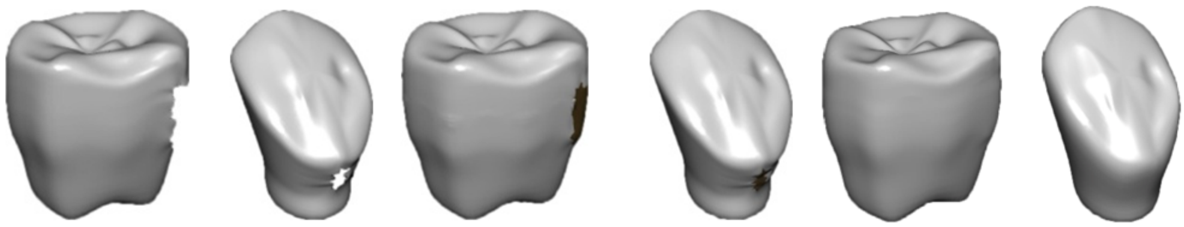


Figure 3. Three cases of mesh stitching

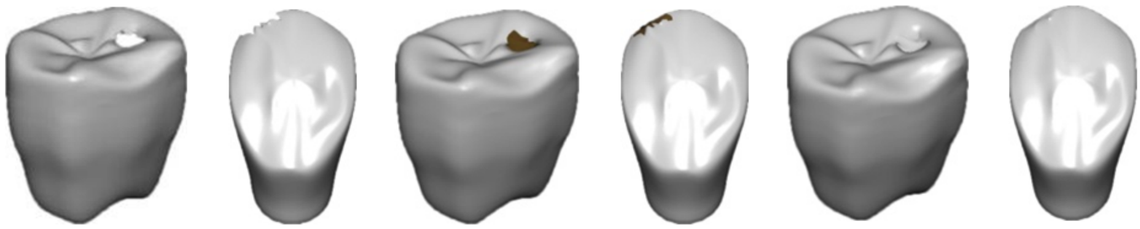
4. **Simulation.** The purpose of the simulation is to evaluate the performance of this proposed classification strategy by incomplete point clouds of molar and canine. The experiments are implemented on a PC equipped with an Intel Core 2 processor, 2.93GHz and 2GB main memory. And point clouds are from 3D laser scanner, PICZA LPX-250. The numbers of the scanned models are 129,870 and 81,875, respectively.

Among existing methods of the hole-filling, the algorithm proposed by Casciola can repair unknown irregular models well by polar coordinates, relatively. Therefore, our algorithm is compared with it. Figure 4(a) is the model with lost point clouds. Figure 4(b) is the result of the hole-filling by Casciola's algorithm [10]. Figure 4(c) is the result of the hole-filling by our algorithm. The hole-filling results are shown in Figures 5(a)-(c) by Casciola's algorithm and the proposed algorithm in this paper. Notice that this novel algorithm can preserve more detailed feature than Casciola's algorithm. Point clouds of the model are divided into two types by computing sharp value of vertex on the mesh of the hole in this algorithm. One type with small sharp is confirmed by implicit surface directly in Figure 4(c), and the other with large sharp is used by the algorithm proposed



(a) Hole models (b) Model filled by Casciola's algorithm (c) Model filled by ours

Figure 4. Repairing the crown of molar and smooth area of canine



(a) Hole models (b) Model filled by Casciola's algorithm (c) Model filled by ours

Figure 5. Repairing occlusal surface of molar and tip or edge of canine

Table 1. Running time of hole-filling algorithm in main parts

Model	Number of vertices	Number of triangles	Casciola's algorithm time (s)	Restore sharp feature time (s)	Our algorithm time (s)
crown of molar	129,870	129,774	0.6097	0	0.2364
occlusal of molar	126,745	126,721	0.4813	0.2145	0.2453
canine surface	81,875	80,942	0.5038	0	0.1737
edge of canine	79,971	79,843	0.7146	0.3371	0.2392

in this paper based on implicit surface in Figure 5(c). The function of the proposed algorithm is to recover the geometrical feature of surface, which allows the sharp feature to be extended to the surface patch inside the hole and the parameter of sharp is adjusted according to the local occlusion area of teeth in Figure 5(c). Complex holes in the model are successfully filled by applying the proposed algorithm.

The final results of four different models are shown in Table 1. The execution time of our classification strategy is compared with Casciola's. Also, the proposed algorithm is only a matter of second even in the case of complex hole without any user intervention.

5. **Conclusions.** For simple hole and island hole, smooth surface can be calculated to repair incomplete point clouds. However, the geometrical feature of point clouds is incomplete, because quadric error is too large and causes the failure of parametric approximation in the process of repairing. The type of the hole is classified based on sharp feature in this paper. Bayesian classifier is used to distinguish whether the vertex with sharp or not. And three emergence cases are presented. The classification strategy frame of the paper can fill the hole of denture effectively and recover the shape of original model, which improves the accuracy of surface reconstruction to a certain extent. In the future, the research should be related to irregular model. According to uncertainty of the model of the hole, the information of fuzzy inference should be added.

Acknowledgment. This work was jointly supported by the National Natural Science Foundation of China (Grant No. 61403222), Natural Science Foundation of Heilongjiang Province (Grant Nos. F201331, F201439, F201440).

REFERENCES

[1] N. Chehata, N. David and F. Bretar, LiDAR data classification using hierarchical k-means clustering, *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol.37, no.3, pp.325-330.

[2] C. Matthew, G. Peiran, C. George et al., Classifying urban landscape in aerial LiDAR using 3D shape analysis, *IEEE International Conference on Image Processing*, Cairo, pp.1701-1704, 2009.

[3] B. Perdan, D. Bracun and J. Diaci, Automated detection of surface defects on power transmission belts, *The International Journal of Advanced Manufacturing Technology*, vol.53, nos.1-4, pp.267-273, 2011.

[4] F. Schindler, W. Worstner and J. M. Frahm, Classification and reconstruction of surfaces from point clouds of man-made objects, *Computer Vision Workshops (ICCV Workshops)*, Barcelona, pp.257-263, 2011.

[5] G. Gasciola and S. Morigi, Polygon mesh repairing: An application perspective, *ACM Computing Surveys (CSUR)*, vol.45, no.2, pp.542-548, 2013.

[6] F. Hetroy, S. Rey, C. Andujar et al., Mesh repair with user-friendly topology control, *Computer Aided Design*, vol.43, no.1, pp.101-113, 2011.

[7] F. Liu and Z. G. Yang, A multi-feature image classification method based on SVM, *Science of Surveying and Mapping*, vol.2, no.3, pp.93-96, 2010.

[8] Z. Z. Kang, W. W. Wang and Z. Li, An integrative method of 3D point clouds feature segmentation and fitting fusing multiple data sources, *Geomatics and Information Science of Wuhan University*, vol.38, no.11, pp.1317-1321, 2013.

[9] Y. J. Liu and Y. D. Zhang, A novel normal estimation based on fuzzy inference for mass point clouds of deture in the three-dimensional reconstruction, *ICIC Express Letters, Part B: Applications*, vol.3, no.4, pp.931-937, 2012.

[10] G. Casciola, D. Lazzaro, L. B. Montefusco and S. Morigi, Fast surface reconstruction and hole filling using positive definite radial basis functions, *Numerical Algorithms*, vol.39, no.3, pp.289-305, 2005.

[11] C. Y. Chen and K. Y. Cheng, A sharpness-dependent filter for recovering sharp features in repaired 3D mesh models, *IEEE Trans. Visualization and Computer Graphics*, vol.14, no.1, pp.200-212, 2008.