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Image Denoising Based on Surface Design Method and Grid Smoothing

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Abstract

In order to solve the issues like the feature detection algorithm surface design too sensitive to the presence of noise, this thesis proposes the grid processing algorithm. Firstly, the constrained smoothing model is used to smooth the grid, in which the bound terms are the sparse constraint terms of the error term of l_2 *norm and* l_1 *norm. In the process of smoothing, the points of the smooth location move less, while the there is a greater movement of feature points. And then through the anglicizing the movement distances the initial feature points are extracted; finally, after the generating of the initial feature points, the feature points are more complete. Experimental results show that: the proposed algorithm can handle the noise of too sensitive.*

Keywords: *Surface Methodology, Grid Quality, Optimization, Feature Detection*

1. Introduction

With the continuous development of 3D scanners and modeling techniques, the acquisition of three-dimensional model is becoming increasingly easy. Since the triangular grid is the simplest and most effective method to express the three-dimensional model, it is widely used in the field of computer graphics and computer vision, and many applications require maintaining the original features of the model, such as the characteristic grid security de-noising, net simplification, grid segmentation, mesh repair and so on, so the recognizing and extracting the geometry feature of grid have become the necessary steps [1-3].

The existing grid feature detection methods can be divided into the quadratic fit method based on plane or surface, the method based on curvature and the method based on normal vector. In addition, the detection problem of cloud feature is studied. Benk *et. al.*, first fit a plane through the top point of the grid, consider the distance between the peak and the vertex plane, and then take peak whose distance more than threshed as the feature point to realize the dictation of grid features. Since the surface is represented by the discrete, for complex surfaces this method will be affected by the local dimensions of grid and curvature, for example the larger the grid dimensions and curvature, the greater the caused error, which results in feature extraction failure [4-6].

From differential geometry, feature points of surface are mainly in the maxima and minima principal curvatures, so the feature points of the grid are also located at the maximum and minimum principal curvatures. On the basis of this fact, many researchers have proposed a curvature-based grid feature detection algorithm: Baker detects the selected feature by comparing the weighted principal curvature and the suitable threshold value; Vieira et al use the maximum main curvature and the product of average edge of this point to measure the characteristic length of the point. Ohtake *et. al.*, detect the ridges

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and valleys of surface through highly estimate the higher-order partial derivatives of the surface [7-9]; Stylianou et al first detect whether the current point is the local maxima (or minimum) in the direction of the principal curvatures, and then use the regional growth or skeletal features technology to get the final line, which effectively avoids the calculation of partial derivative of curvature [9-11]; Yoshizawa *et. al.*, through the local polynomial fitting estimate the curvature tensor and the partial derivative of curvature, which realizes the feature extraction [12-13]; Kim *et. al.*, firstly use the minimum squares technique to estimate the local differential information of the grid, and then take the zero-crossing point of curvature of the partial derivative as feature point [14-15].

Through the study of the distribution of surface normal results, the local surface norm in a flat surface is continuous, so it will not have a lot of jumping, but in the position surface norm with characteristics there are great jumps, namely the surface norm in the feature point is not continuous. Based on this, Sunil *et. al.*, proposed the feature extraction method based on the surface normal vector, which include analysis of the included angle sharing one edge and two norms and the difference of norms between the current point and the neighbor point with one ring. In addition, some people use the voting method of normal tensor to estimate the curvature on large-scale grid and the noise grid, which achieves the extraction of feature lines. These methods are generally through expanding the neighborhood and putting forward the different weighting factors to improve the performance of the algorithm. Wang et al use the support of the neighborhood features of the feature points to filter false feature points, which realize the extraction of feature points.

In practical applications, feature extraction algorithm of grid-based differential geometric widely exist the following questions: 1) Noise-sensitive. Because the models acquired from different ways have different levels of noise, so the estimated surface with one-order or second-order micro-prone have large deviation, which makes the feature detection algorithm based on micro-component will detects a lot of false feature points and then makes more difficulties to the late working. 2) The second order micro-component of the feature points is difficult to accurately estimate, such as the principal curvatures of the corners. Since the corner is generally the intersection of three or more smooth surfaces, it does not has the determined main direction, which leads to difficulties in accurately estimating the principal curvatures, and finally it may lead to failure of the feature extraction. 3) Transition characteristics are difficult to detect. The feature extraction algorithm based on differential geometry is mainly for the differential amount, such as normal direction and the discontinuities or extreme of curvature. In the transitional characteristics of the surface the micro differential geometry is smooth. As shown in Figure 1, it is a chamfered cube, compared to a normal cube its sides and corners are smooth; the edge is the quarter of the cylindrical surface; corner is quarter of the spherical; the transitional features are appeared in the joint of the plane, the cylindrical and sphere.

In order to eliminate the effects of noise, one way is using the grid smoothing method to pre-treat the grid and then to get a relatively smooth grid. But the following problem is that much weaker feature points are filtered out. Wang *et. al.*, firstly define the significant measure, and through the significant characteristic measure to enhance the weak points, and to ensure filtering out the false feature at the same time, which eliminates the effect of noise and achieve the extraction of the feature. However, because these methods are not only necessary to calculate the first order or second order component of each vertex, but also there are lots of pre-processing and post-processing need to be conducted. This paper presents the sparsity optimization detection algorithm of grid surface features based on sparsity theory. The algorithm can deal with the sharp features characteristics, weak characteristics and transitional characteristics, and computing speed is fast.

This paper mainly makes the extensive and innovative in the following areas:

(1) For the problem of too sensitive to noise existing in the feature detection algorithm in surface design, this thesis propose the grid processing noise algorithms. The algorithm includes three main processes: firstly, the Laplacian energy function with l_1 norm sparsity constraint item and l_2 norm sparsity constraint item is used to smooth the grid, and then the moving distance of the smoothed grid peak is obtained; then according to movement distance of the peak to estract the initial feature point; finally, after the processing of the extracted feature points, it makes the feature point more complete.

(2) In order to further verify the correctness and validity of the proposed grid prosessing noise algorithm, simulation of significant feature detection, feature detection of noise model, feature detection of transition and algorithms comparison is conducted. The simulation results show that: the proposed algorithm can handle the sharp features fuzzy features and transition features of noise model and normal model. The comparison of the testing results and the running time show the high efficient of the proposed algorithm.

2. Grid Smoothing

Given a triangle grid $s = (v, r, y)$, where r, y and v respectively represent the collection of vertice, edge and face of the grid. X represents the matrix vertex coordinates with $n \times 2$, in which each row represents the three-dimensional coordinates of a point; X 'represents the vertices coordinates matrix of the smoothed grid. For the arbitrary point $v_i \in v$, its normal vector and the collection of the neighborhood points with one ring respectively represent n_i and $N(i)$. $d_i = |N(i)|$ represents the number of neighborhood points.

In general, mesh smoothing algorithm is performed offset correction for each vertex of mesh, which eliminates or reduces noise of the vertex, namely the aims of smoothing the mesh is seeking the offset matrix of the vertices.

$$\delta = X' - X \tag{1}$$

Smoothing the offset vertices of the mesh $X' = X + \delta$ as possible.

Laplacian vector (operator) of vertex $v_i \in v$ refers to the vector of the vertex from the center of neighborhood with one ring the vertex.

$$L(v_i) = \frac{1}{|N_i|} \sum_{j \in N_i} v_j - v_i \tag{2}$$

The larger the mode of Laplacian vectors of vertex, the sharper the point; conversely, the more smooth the point. Laplacian smoothing algorithm makes each vertex offset to the vector direction of Laplacian, namely

$$\delta_i = \lambda L(v_i) \tag{3}$$

Wherein, λ is a parameter between [0,1], when the value is greater, this vertex is more tend to the center of the vertex of neighbor with one ring, that the smooth is more. Local Laplacian smoothing algorithm offset all vertices in accordance with the method described above; if the parameter λ is obtained relatively small, then the process is generally carried out by multiple iterations to complete. Visiblely, local Laplacian smoothing algorithm is gradually floating the characteristics of the vertex; after several iterations, the vertex is smooth enough.

Local Laplacian vector of each vertex can be written in matrix form as the following:

$$X' = LX \tag{4}$$

Wherein, L is the Laplacian matrix of the grid.

$$(L)_{ij} = \begin{cases} 1, i = j \\ -1/d_i, (i, j) \in E \\ 0, otherwise \end{cases} \quad (5)$$

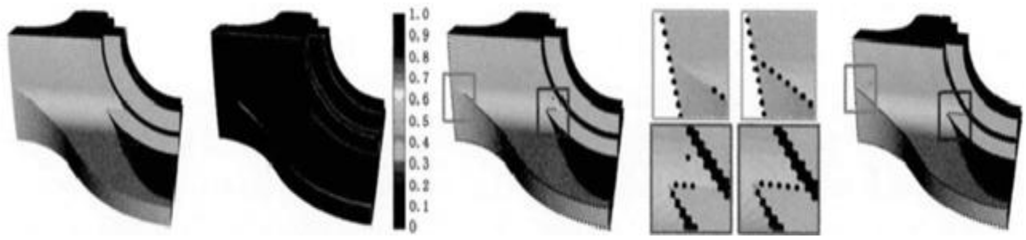
Nealen *et. al.*, proposed overall smoothing algorithm based on mesh Laplacian.

$$\min_{\delta} \| L(X + \delta) \|_F^2 + \beta \| \delta \|_2^2 \quad (6)$$

Wherein, β is a parameter. Intuitively, the global Laplacian smoothing algorithm is making the whole mesh smooth enough under the circumstance of a little vertex offset. Global Laplacian smoothing algorithm smoothes the grid by optimizing the overall, which avoids sufficient of the iterations required by the local Laplacian smoothing algorithm (it is related to the vertices order of the iteration).

3. Grid Processing Noise Algorithm

In fact, the sharp features on the mesh surface are sparse, that is the proportion of the sharp features to all point vertices is smaller. Based on this observation, this thesis proposes a new feature grid extraction algorithm based on sparse optimization. As shown in Figure 1, the position with the largest degree of grid smoothing is the position with the feature points. As shown in Figure 1b, the color bar from black to white indicate the distance from small to large; all the distance maps are using the same color bar, so by anglicizing the movement distance of the grid vertices, the feature points can be extracted (as shown in Figure 1c). However, the usual grid smoothing algorithm will make the flat position of the grid deformation, so the extracted feature points will contain a lot of false feature points. To overcome this problem, the proposed algorithm introduces the sparsity constraint item of l_1 norm, which makes the flat position in the grid move slightly or not move, so it is easy to separate the feature points and non-feature points. This method avoids the calculation of the second-order differential geometry, which greatly enhance the computing speed.



(a) Initial Network (b) Distance map and color bar (c) Initial feature point (d) Partial enlarged view (e) Results of after-treatment

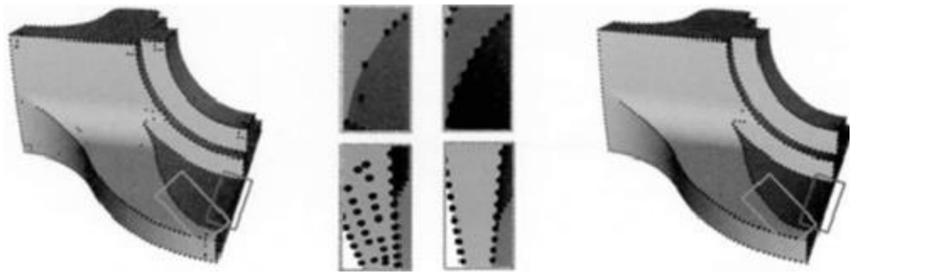
Figure 1. Algorithm Flow

A. Smoothing Model of Grid Characteristics

Through experiments, in Laplacian smoothing algorithm, the comparatively smooth point will not occur large offset after the mesh smoothing; while generally the distance between the feature points and the center point of the neighborhood with one ring is relatively large, so the feature points will have large offset after the smoothing. Based on this observation, if the point with large offset after smoothing is detected, the feature points in the grid can be detected.

However, if the offset vector is directly obtained by global Laplacian smoothing algorithm to extract the features, the extracted characteristic feature points will contain a lot of false feature. Because such methods is just try to ensure the minimum energy of Laplacian in the case of ensuring close to the original model, but there is no constraints on the type of mobile vertex (for example, the point is trying not to move in flat position). So when the quality of the grid is relatively poor, a lot of points in the flat position will move largely. Figure 3b shows enlarged figure of the corresponding rectangular block in Figure 3a, 3c; a number of points in the flat lower left position are extracted as the feature points. Since the distribution of the position of the point is irregular, the distance from the center point is relatively large, so in the process of smoothing there is great move.

The proposed algorithm by adding sparsity constraints of l_1 norm can solve this problem (as shown in Figure 3c); Similarly, many feature points in the feature line of the upper left graph in Figure 3b are loosed, while the points in the feature line of the upper right are basically detected.



(a) Global Laplacian (b) Partial enlarged view (c) Proposed algorithm

Figure 2. Initial Feature Point

In the mesh surface, usually the sharp features are sparse, that is, the proportion of the sharp points in grid vertexes is small. Based on this observation, this thesis proposes a new optimized model, which minimize the l_1 norm on offset vectors ξ with global Laplacian smoothing energy, namely

$$\min_{\delta} \| L(X+\delta) \|_F^2 + \beta \| \delta \|_2^2 + \alpha \| \delta \|_1 \tag{7}$$

Wherein, ∂ and β are parameters. By the compressed sensing theory it can be shown that the minimization of ζ's l_1 norm will sparse the elements as possible, that is, the nonzero elements of ξ is as little as possible. Therefore, the above optimization will make the apex sharp features making more offset; the relatively smooth apex will smooth the grid surface without offset as possible, which is to ensure less moving points in flat position and the distance of the points in feature place is greater.

The third item of the proposed optimization model is the sparsity constraint item of l_1 norm. However, this improvement is non-trivial, by the l_1 norm, the optimization results can constraint the number of moving points in the smoothing process. By adding the sparsity constraint of l_1 norm, moving points in the smoothing process can be constrained, which minimize the total number of the moving points. Because the distance feature point to the center-point is usually greater than the points in flat position, under the constraint of l_1 norm, the point moving in flat position will be very small, while the feature points will occurs larger movement, thus can guarantee the initial feature points extracted by the proposed algorithm containing little pseudo-feature points (as shown in

Figure 2c). The simultaneous effect of l_1 norm and l_2 norm can make the flat position smoothed by grid has a little deformation, while the feature points occur great movement, which is more conducive to the separation of the non-feature points and feature points by moving distance.

Since there is constraint item of l_1 norm in the proposed model, it is difficult to directly solve the problem; the model can be transformed into the following form:

$$\min_{\delta} \| L(X+\delta) \|_F^2 + \beta \| \delta \|_2^2 + \alpha \| \delta' \delta \|_1 \quad (8)$$

B. Feature Point Extraction

After obtaining displacement matrix δ of vertex, according to offset distance of the vertex the feature points of the mesh surface are extracted. One of the most direct ways is by measure the size of the vertex's model of the offset vector to detect. However, since some of grids are non-uniform, there are many tangential movements occurred inevitably in the flat place during smoothing, and these points may be mistaken for the feature points. To solve this problem, firstly, the offset vector of each point is projected onto the normal vector of the point, *i.e.,* the normal offset of this point is calculated, and even if the points on the plane occurs movement, the projection in the normal direction will be small. Projection distance is defined as

$$d_i = \delta_i \bullet n_i' \quad (9)$$

Wherein, n_i is the normal vector of the grid's vertex v_i after smoothing. As shown in Figure 4, the distance of the left figure is the Euclidean distance corresponding to the two points of smoothing. The distance of right figure is the result calculated by the formula (1). The black represents that the distance is small, and the opposite of white. As can be seen, after normal projection, the difference between the feature points and non-feature points becomes clearer.

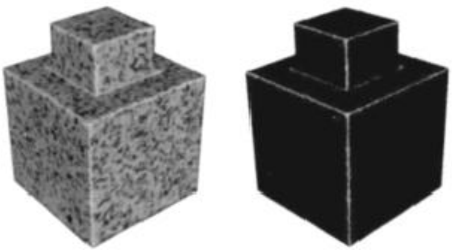
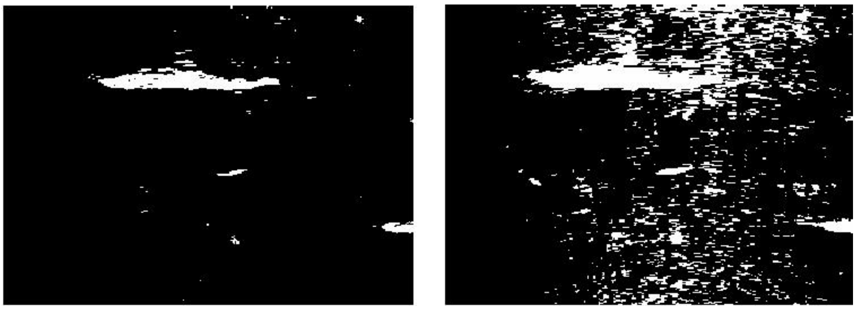


Figure 3. Distance Map

After calculating the moving distance of each vertex in the direction of normal vector, the point corresponding to the k_{-th} largest distance is taken as the initial feature point to make subsequent processing.

C. After Treatment

Since the extracted initial feature points often comprises a number of false feature points and the deletion of some feature points, the feature points need to be treated and the final feature points need to be improved. After treatment methods take the Neighbor Supporting method as reference, and the level of feature points are defined as the number of feature points in the neighborhood with one ring. As shown in Figure 5a, there are 6 feature points in the Figure in total (four black points, a gray point and a white point), in which the degree of the gray feature point is 3 and the degree of the white feature point is 2.



(a) Definition of degree (b) Feature points of different degree

Figure 4. The Degrees of Feature Points

Processing steps are as follows:

Step 1 removing the feature point with degree as 0 (such as the leftmost point in Figure 5b)

Step 2 for the feature points with degree as one, if the degree of the feature points in neighborhood are also as 1 (such as the gray points in Figure 4b), these two points are deleted; if the degree of the points in neighborhood are 2, these two points are used to conduct the direction ad then stretches until the new feature points exist. By giving a new threshold the number of new extended points can be controlled. If the degree of the points in neighborhood is greater than or equal to 3 (such as the first black point of the left of the white point in Figure 4b), the current point is deleted (such as the second black point of the left point of white point in Figure 4b);

Step 3 for the feature points with degree as three, if the included angle conducted by the two feature points and the current feature points, which is close to 180°, then the third point is deleted (such as the first black point of the left of the white point in Figure 4b); if the three included angle conducted by the three feature points and the current feature points, which is close to 90 °, then these points are kept.

D. Extraction of Feature Line

By the processing Section 3.2 and 3.3, the set F of the feature points has been obtained. The extracted feature points are lined to the feature line, as shown in Figure 5.

Figure 5. Extraction of Feature Line

4. Experimental Simulation and Analysis

A. Experimental Environment and Setting

The proposed algorithm involves a total of k, α and β 3 parameters. Since ∂ and β are not sensitive to the different models, so they are separately set as α = 0.6 and β = 0.2; threshold k is more crucial for the algorithm. As shown in Figure 7, the black curve is the distance curve; taking a point in the relatively flat position closer to the x-axis, and the abscissa of the point is the value of k, such as the abscissa of the intersection.

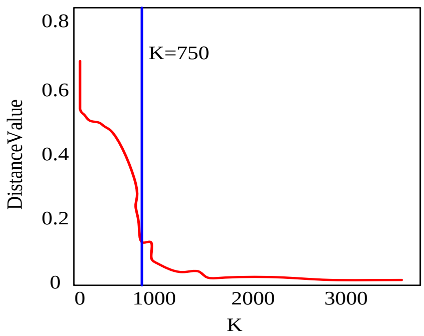


Figure 6. Distance Curve

B. Result Analysis

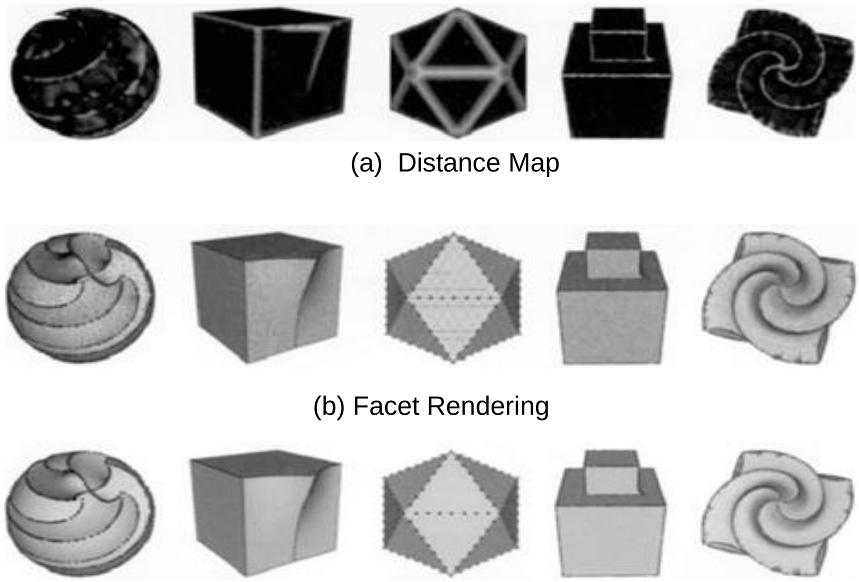
Table 1 shows the values of s taken from different models in the proposed experiments

Table 1. The Values of k Taken from Different Models

Model Name	s	Model Name	s
Smooth Feature	450	Reylinder	240
Sharp Sphere	760	Pin-CAD	1243
Lcosabe-dron222	224	Noise Fandisk	760
Box	1061	Fandisk	903
Twirl	552	Round cube	1180

Remarkable feature detection

Figure 8 shows he test results of the salient features with the proposed algorithm. In Figure 8a, black represent that the distance is small and white is the contrast; the other coolers represent the distance between the black and white. It can be seem that there is a big change occurred in the feature positions during smoothing, so after smoothing the distance of the feature points is larger than the non-feature points. The black points in Figure 8b, 8c are the extracted feature points. It can be seen, the proposed algorithm has the significant feature model, which can give a perfect result.



(a) Distance Map

(b) Facet Rendering

(c) Smooth Rendering

Figure 6. Test Results of the Sharp Features with the Proposed Algorithm

The Noise Model Feature Detection

The proposed algorithm is also applicable to the model with small amount of noise. The black points in Figure 8c and 8d indicate the extracted feature points. It can be clearly seen from Figure 8b, although Fandisk model is with noise, the distance of feature points is still large after smoothing, which ensures that the proposed algorithm can better extract feature points, as shown in Figure 8d.

(a) Fandisk model with Gauss noise (b) Distance map (c) Grid forms (d) Surface forms

Figure 7. Test Results of the Noise Model with the Proposed Algorithm

Detection of Transition Feature

Figure 10 shows the result of the detected transition characteristics with the proposed algorithm. Transition feature is located in the joint of the two smooth surfaces, as shown the features of the third raw in Figure 10, which is formed with flat, cylindrical and spherical. So the characteristics are very weak, while it is hard to detect relatively good results with the methods based on curvature and normal vector, so curvature and normal vector in the transition are smooth. After smoothing of the surface stitching place, the moving distance of this point is larger than the ones in the flat position. The proposed algorithm can detect these transition characteristics.

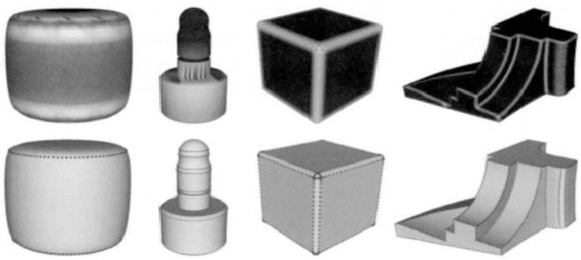


Figure 8. Test Results of the Transition Characteristics with the Proposed Algorithm

C. Comparison of Algorithms

This paper are mainly compared with the literature [16-18, 19-21]; there are different dealing situation of kinds of algorithms as shown in Figure 11. As can be seen, due to the influence of noise, the literature [16-18, 19-21] algorithm basically can not extract the good characteristic line, and the algorithm is robust to noise, which can extract more complete characteristic line.

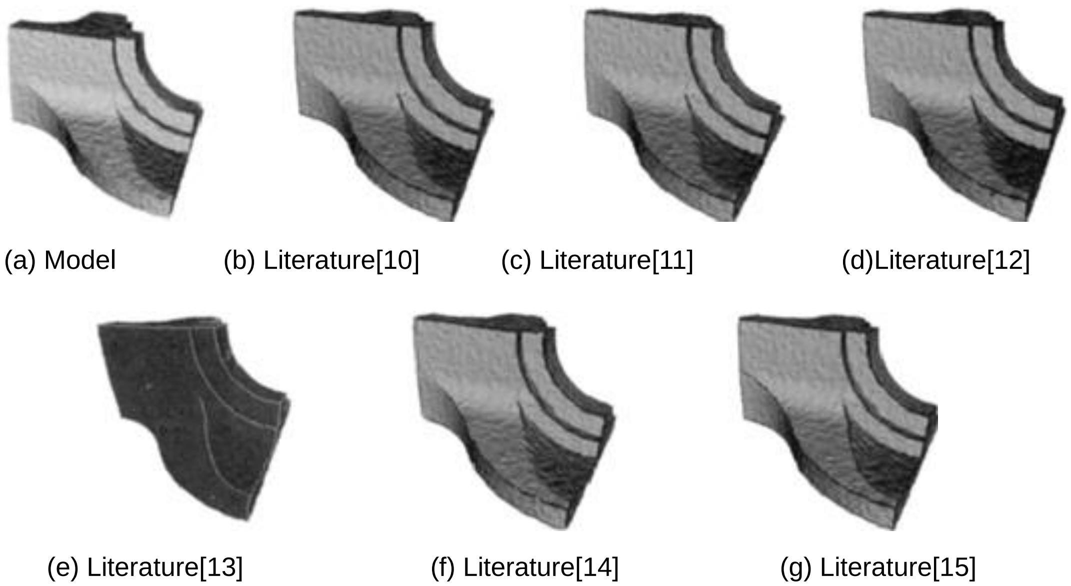


Figure 9. Test Results Comparison of Noise Model Feature Line with 6 Algorithms

Figure 12 shows the comparison of transition characterized by Round cube model testing; it can see that, the comparing algorithm or the extraction feature line is incorrect or vague; literature [10] algorithm can not find the location of transition characteristics; while the proposed algorithm can accurately extract a complete transition characteristics.

(a) Model (b) Literature[10] (c) Literature[11] (d) Literature[12]

Figure 10. Test Results Comparison of the Transition Characteristic Line

Table 2 shows the running time comparison of Fandisk, Noise Fandisk, Pin-CAD and Round cube model with the six algorithms; these data are detected on a Intel Core Duo 3.4GHz CPU and 8GB memory machine. Among them, the proposed algorithm gives the global optimization running time and overall running time. It can be seen that the efficiency of the proposed algorithm is high.

Table 2. Comparison of the Running Time

Model	Literature[10]	Literature[11]	Literature[12]	Text algorithm	
				Global Optimization	Overall operation
Pin-CAD	1.864	0.943	1.232	0.223	0.371
Fandisk	1.864	0.945	1.561	0.451	0.673
Round cube	1.195	0.601	0.961	0.180	0.300
Noise Fandisk	1.712	0.803	1.312	0.203	0.285

The table shows the computing time of the proposed algorithm to Fandisk model with different sizes; it can be seen that, the time complexity of the algorithm is linearly with the number of vertices of the model. Because the proposed optimization model need to enter the matrix L of the Laplacian and the matrix X of the initial vertex coordinate, at the beginning of the calculation these two matrices need to be stored, but in the process of calculation there not introduce a particularly large matrix, so the overall space complexity is as O (n).

Table 3. Time Comparison of the Fandisk Model with Different Sizes

Number of vertices	Running time
6000	0.370
25642	0.853
100982	3.482
450036	13.982

5. Conclusion

This paper presents a grid processing noise algorithm. Firstly, the constrained Laplacian smoothing model is used to make mesh smoothing, in which the constraint items are the error term of l_2 norm and the sparsity constraint item with l_1 norm. In the smoothing process, the points in flat position move less, while the feature points have a greater movement. Then through the analysis of the moving distance of the vertices after smoothing to extract the initial feature points; finally, the initial feature points are processed to make the feature points more complete. The experimental results shows that the proposed algorithm can deal with sharp features of noise model and normal model, and also the fuzzy features and transition features can ne handled. The comparison of the testing results and the running time shows the high efficient of the proposed algorithm.

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