

Noise reduction for mesh smoothing of 3D mesh data

Dae-Hwan, Hyeon

Culture Technology Institute
Kyungwon Univ., Seongnam, Gyeonggi-Do, Korea
ghkseogus@hotmail.com

Taeg-Keun, Whangbo

College of Information Technology
Kyungwon Univ., Seongnam, Gyeonggi-Do, Korea
tkwhangbo@kyungwon.ac.kr

ABSTRACT

In this paper, we propose a mesh smoothing method for mesh models with noise. The proposed method enables not only the removal of noise from the vertexes but the preservation and smoothing of shape recognized as edges and corners. The magnitude ratio of 2D area and 3D volume in mesh data is adopted for the smoothing of noise. Comparing with previous smoothing methods, this method does not need many iteration of the smoothing process and could preserve the shape of original model. Experimental results demonstrate improved performance of the proposed approach in 3D mesh smoothing.

Keywords: Mesh smoothing, Noise smoothing, Shape-preserving filter, Peak noise.

1. INTRODUCTION

Recent tendency of object modeling is to reconstruct 3D data from 2D images. Surface reconstruction of object from multiple 2D images is one of fundamental problem in computer vision. The general methods[1-5] to reconstruct 3D data using geometrical computation are to get 3D points cloud of scene. These studies caused unavoidable errors in each step to reconstruct 3D data – camera calibration, corresponding points searching, fundamental matrix computation, etc. For object modeling from 2D images, these errors appear in peak and Gaussian noise in reconstructed 3D data. When mesh data is generated from these 3D points cloud, non-smooth object surface is made. It is an important requirement to smooth the noise on a surface while preserving geometric features of the surface.

Let us consider the definition of noise on a surface. On a triangle mesh with no additive noise, vertices of each triangle exist at proper positions, especially touching on the mesh surface. If a triangle mesh is added some noise, the vertices are disarranged and their positions separates from the mesh. We define the noise as mesh vertices separating from their proper positions on the mesh surface. Thus, a noise smoothing process is equivalent to the correction of mesh vertex positions. To perform such noise smoothing, concepts based on the differential geometry approaches have been used in previous work [6-9]. However, noise smoothing based on geometrical

approaches usually distorts sharp geometric features.

In image processing, a nonlinear filter usually has a feature-preserving effect. The median filter is one of such nonlinear filters. However, although the median filter can be used to remove peak noise generally, this filter is unable to remove effectively Gaussian noise and meshes of different size in 3D data. Recently, 3D filter[10, 11] using surface normal vector of 3D mesh use to smoothing these noise. These filters cannot remove effectively peak noise that is included during the reconstruction process.

Therefore, to solve the problem, we propose a noise smoothing method for mesh data with noise. The proposed method enables not only the removal of noise from the vertexes but the preservation and smoothing of features recognized as edges and corners. First, 2D area and 3D volume are computed in triangle mesh data. And then, the magnitude ratio of 2D area and 3D volume is adopted for the smoothing of peak noise. As a result, mesh smoothing becomes accomplished by smooth a noise. Compared with previous smoothing methods, the Laplacian smoothing [11], the median filter[6] and adaptive filter[10], our method does not need much iteration of the smoothing operations and could preserve the shape of original model.

This paper is organized as follows. Previous approaches to smooth noise are reviewed in section 2. Section 3 analyzes the noise and describes a method of removing noises according to noise characteristics. In section 4, experimental results are discussed. This paper is concluded in section 5.

This is an excellent paper selected from the papers presented at ICCV 2008.

* Corresponding author: E-mail : 70jazz@hanafos.com

Manuscript received Mar. 24, 2009 ; accepted Sep. 24, 2009

2. PREVIOUS METHODS FOR SMOOTHING

In this section, three conventional methods of polygonal surface smoothing are considered: the Laplacian smoothing flow [5], [11], Taubin's method[7] and the mean curvature method [9]. The Laplacian smoothing is developed from a two-dimensional heat equation, and the mean curvature method is formulated based on concepts of the differential geometry.

2.1. Traditional Laplacian method

Let $M=(p,e,f)$ be a triangular mesh. Where p are vertices, e are edges, and f are triangles of M . The Laplacian operator can be linearly approximated at each vertex by the so-called umbrella-operator as follows:

$$D(p) = \frac{1}{n} \sum_{i \in N(p)} (q_i - p)$$

where q_i are the neighbors of the vertex p (Figure 1). Another choice in [7] produces good result.

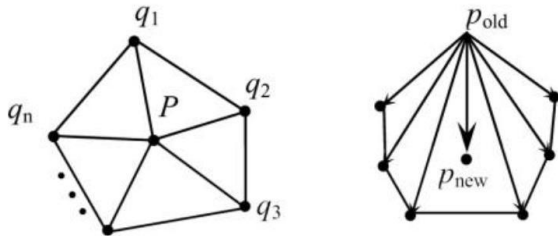


Fig. 1. Umbrella-operator used for Laplacian smoothing

2.2. Taubin's method and bilaplacian method

To avoid the shrinkage of traditional Laplacian smoothing, Taubin proposed to alternate two scale factors of opposite signs with the negative factor of larger magnitude by the Laplacian smoothing method. Such smoothing suppresses high frequencies of the umbrella operator. The two steps of the Taubin's method in one local update rule can be rewritten as follows:

$$p_{new} \leftarrow p_{old} - (\mu - \lambda)U(p_{old}) - \mu\lambda U^2(p_{old})$$

where $\mu > \lambda > 0$, U^2 is the squared umbrella operator.

2.3. Mean curvature method

In [9], an accurate and robust discrete approximation of the mean curvature vector is proposed. Differential geometry definition of the *curvature normal* is used to derive the discrete version as follows:

$$\lim_{diam \lambda \rightarrow 0} \frac{\nabla A}{2A} = H_n$$

where H is the mean curvature and \mathbf{n} is the outer normal vector at vertex p . A is the area of a adjacent region around p , and ∇ is the derivative with respect to p . (Figure 2).

Unlike the umbrella operator, the mean curvature flow is

based on the geometric information instead of the topological information. The discrete curvature normal vector estimated method does not make sense for the vertices on boundaries of mesh [9]. So for non-closed mesh or surface with holes, the mean curvature flow cannot be used for mesh smoothing. Figure 3 gives an example for smoothing a torus model with 10 iterations and 50 iterations respectively. From Figure 3 we can see the application of the mean curvature flow algorithm for faring mesh may result in serious shrinkage and distortion.

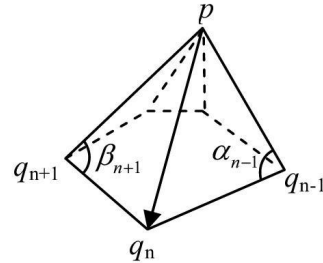


Fig. 2. Vertex and the two angles opposite to the edge pq_n

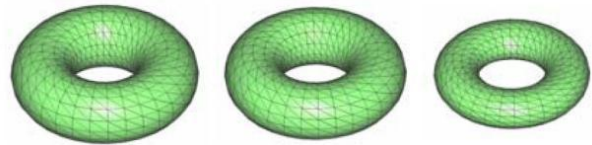


Fig. 3. A torus model smoothed by the mean curvature flow

3. NOISE SMOOTHING BY NOISE ANALYSIS

In this section, we explain the method to smooth peak noise using magnitude ratio of 2D area and 3D volume.

3.1. Analysis of peak noise

3D mesh volume and 2D mesh area are used to detect and smooth peak noise. 3D mesh data made by 3D data reconstructed from laser scanner or 3D reconstruction. It has adjacent meshes to the point P like Fig. 4. First, projected 2D mesh made as follow. In Fig. 4, after compute normal vectors(N_i) of meshes sharing point P, the normal vector(N_p) of point P is computed by average of the normal vectors(N_i) as Eq. (1). So, 2D mesh made by projecting point P with reverse direction of normal vector(N_p).

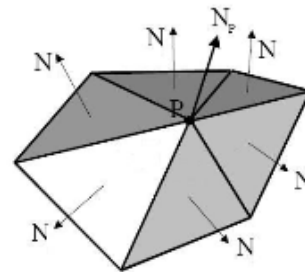


Fig. 4. Point P and its neighboring meshes, N_p is the normal vector of point P, N is the normal vector of mesh adjacent to P.

$$N_p = \frac{1}{n} \sum_{i=1}^n N_i \tag{1}$$

After the above operation processed, 3D triangle mesh and 2D triangle mesh are made as shown in Fig. 5. 2D triangle mesh is projected by $-N_p$ in 3D triangle mesh. The magnitude of 3D mesh data and 2D mesh data is computed from these data to smooth noise.

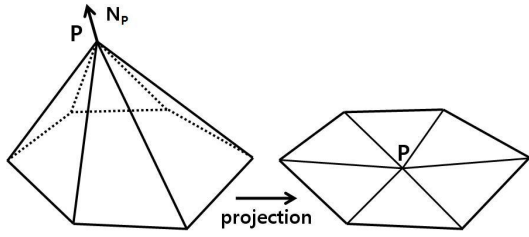


Fig. 5. 3D triangle mesh (left) and the projected 2D triangle mesh (right).

In the 3D mesh data, the elementary calculation unit is a tetrahedron. For each triangle, it connects each of its vertices with the origin and form a tetrahedron, as shown in Figure 6.

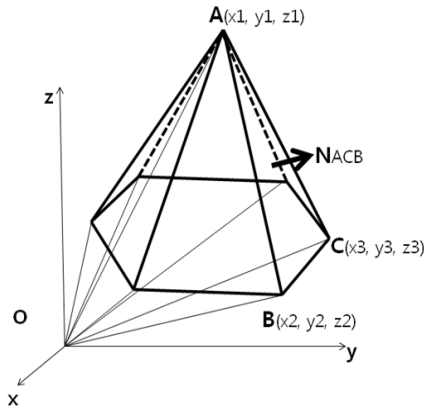


Fig. 6. The calculation of 3D mesh magnitude (volume)

The volume is defined for each elementary tetrahedron as: The magnitude of its value is the volume of the tetrahedron, and the sign of the value is determined by checking if the origin is at the same side as the normal with respect to the triangle. In Figure 6, the volume of tetrahedron $OACB$ is:

$$|V_{OACB}| = \left| \frac{1}{6} (-x_3 y_2 z_1 + x_2 y_3 z_1 + x_3 y_1 z_2 - x_1 y_3 z_2 - x_2 y_1 z_3 - x_1 y_2 z_3) \right| \quad (2)$$

As the origin O is at the opposite side of $NACB$, the sign of this tetrahedron is positive. In real implementation, the volume of tetrahedron is:

$$|V_i| = \left| \frac{1}{6} (-x_{i3} y_{i2} z_{i1} + x_{i2} y_{i3} z_{i1} + x_{i3} y_{i1} z_{i2} - x_{i1} y_{i3} z_{i2} - x_{i2} y_{i1} z_{i3} - x_{i1} y_{i2} z_{i3}) \right|$$

$$V_{total} = \sum_{i=1}^n V_i \quad (3)$$

where i stands for the index of triangles or elementary tetrahedrons. (x_{i1}, y_{i1}, z_{i1}) , (x_{i2}, y_{i2}, z_{i2}) and (x_{i3}, y_{i3}, z_{i3}) are coordinates of the vertices of triangle i . The volume of a 3D mesh model is always positive. The final result can be achieved

by take the absolute value of V_{total} .

A 2D mesh is simply a 2D shape with polygonal contours. As shown in Figure 7, suppose we have a 2D mesh with bold lines representing its edges.

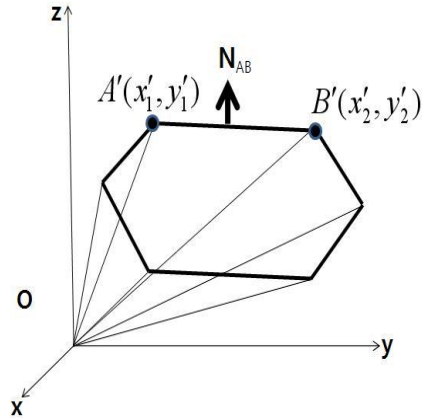


Fig. 7. The calculation of a 2D mesh magnitude

Each edge and the origin form an elementary triangle. We define the signed magnitude for each elementary triangle as below: The magnitude of this value is the magnitude of the triangle, while the sign of the value is determined by checking the position of the origin with respect to the edge and the direction of the normal. Take the triangle OAB in Fig. 7. The magnitude of OAB is:

$$|S_{OAB}| = \left| \frac{1}{2} (-x_2 y_1 + x_1 y_2) \right| \quad (4)$$

In real implementation, the magnitude of triangle is;

$$|S_i| = \left| \frac{1}{2} (-x_{i2} y_{i1} + x_{i1} y_{i2}) \right|, \quad S_{total} = \sum_{i=1}^n S_i \quad (5)$$

where i stands for the index of all the edges or elementary triangles. (x_{i1}, y_{i1}) , (x_{i2}, y_{i2}) are coordinates of the starting point and the end point of edge i . According to the final sign of the result S_{total} , we may know whether we are looping along the right direction, and the final result can be simply achieved by taking the magnitude of S_{total} .

Using the above result, in each vertex of mesh data, magnitude ratio of 3D mesh and projected 2D mesh, $|V_{total}|/|S_{total}|$, is evaluated. The average of magnitude ratio of mesh data is and computed as Eq. (6).

$$\bar{m} = \frac{1}{n} \sum_{i=1}^n \left(\frac{|V_i|}{|S_i|} \right) \quad (6)$$

If obtained magnitude ratio in each vertex is bigger than the sum of magnitude ratio average and standard deviation, $(\bar{m} + \sigma)$ in Eq. (7), the vertex is recognized as a peak noise.

$$Peak_noise: \frac{|V_i|}{|S_i|} > (\bar{m} + \sigma) \quad (7)$$

3.2. Smoothing of peak noise

The points that detected peak noise have information about the sum of magnitude of 3D mesh data and area of 2D mesh data. So, as seen in Fig. 8, translation distance between point that detected peak noise, Pold, and new point that removed noise, Pnew, is computed by Eq. (8).

$$D = Min [|V_i| - |S_i| (\bar{m} + \sigma)] \quad (8)$$

The point (Pnew) in 3D that will be updated newly is placed on the minus direction of normal vector of the point P in Fig. 8. The peak noise can be removed effectively as updating the noise point Pold by Eq. (9).

$$P_{new} = D \cdot P_{old} \quad (9)$$

$$\begin{bmatrix} x_{new} \\ y_{new} \\ z_{new} \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & D_x \\ 0 & 1 & 0 & D_y \\ 0 & 0 & 1 & D_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{old} \\ y_{old} \\ z_{old} \\ 1 \end{bmatrix}$$

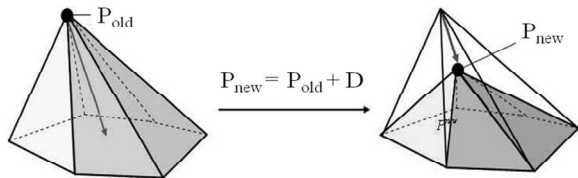


Fig. 8. Peak noise point(Pold) in triangle mesh is translated on new point(Pnew)by distance D from Eq. (8). (left) The triangle mesh included noise, (right) The triangle mesh removed noise

4. EXPERIMENTS

To test the performance of algorithm proposed in this method, it executes experiments with 3D data obtained in various ways. This study has executed a test by adding peak noise to images obtained from the laser scanner (Minolta vivid 700), composite images by computer and images from photograph. The magnitude of meshes close to peak noise presents much bigger surface magnitude than other meshes forming objects. With these characteristics of peak noise, it detects the peak noise like Fig. 9(a) by using ratio of magnitude of meshes in adjacent 3D to all 3D data and magnitude of projected images. If the limitation to reduce surface magnitude of adjacent meshes to peak noise is applied adaptively in accordance with magnitude

ratio, the peak noise will be equalized effectively like Fig. 9(b). Fig. 9 is the test result of applying peak noise filter only proposed in this method.

Fig. 10 is a graph presenting the magnitude ratio of all 3D data from proposed peak noise detection algorithm.

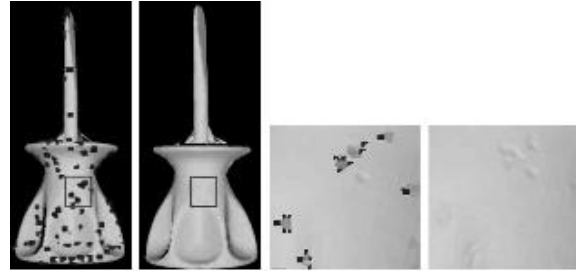


Fig. 9. Detection of peak noise and result image after filtering process, (a) peak noise detection, (b) peak noise smoothing, (c) the enlarged image of (a), (d) the enlarged image of (b)

Threshold value of peak noise has a magnitude ratio of 1.73258. The total numbers of 3D data are 10764, and the numbers of data detected as peak noise among these data are 113. It has detected most of the 107 peak noises added to ideal data and resulted in equalization. Table 1 displays the changes of whole magnitude and tolerance of average distance for this test result in a quantitative numerical value. The proposed method deems to be approved to remove noises effectively.

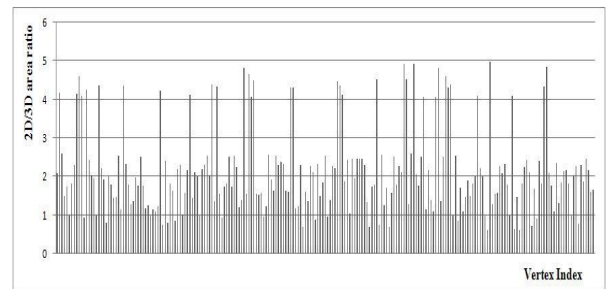


Fig. 10. Magnitude ratio of adjacent mesh on 2D and 3D space (peak noise > 2.33258)

Table 1. After applying peak noise filter, the change of surface magnitude and average distance error

	Surface magnitude	Average distance error(pixel)
ideal data	8085.29779 (100.00%)	
Adding noise	8622.98630 (106.65%)	0.326997
Noise reduction filter	8238.51752 (101.89%)	0.108264

Next, like Fig 8(top left), 3D objects have been produced by using 3D Max. As appeared in Fig. 8(top left), after making like (top right) by adding noise randomly to input images having clear edges and boundaries, it tests by applying filter of average value and proposed method.

The next experiment used the 3D hat data which is synthesized with computer. The figure 11(top) is the original hat data and the data that noise is added, respectively. As you see the noise added data, A distortion occurred in top and brim parts of the hat.

Laplacian smoothing still remained noise in the parts where the distortion occurred. Median filtering removed noise in many parts, but the noise in the brim of hat data was not totally removed. However, proposed method effectively removed noise in the distortion parts. Figure 12 is the graph for the position variation of vertex that considered as noise in accordance with the number of smoothing iteration.

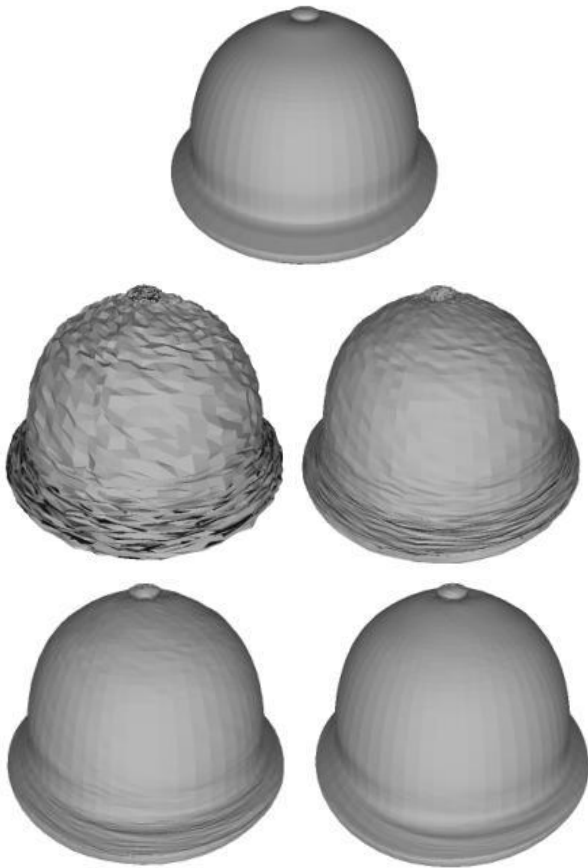


Fig. 11. The hat data that is synthesized with computer, Input data(top), Adding noise(middle left), Laplacian filtering method[11] (middle right), median filtering[6] (bottom left), Proposed filtering method(bottom right).

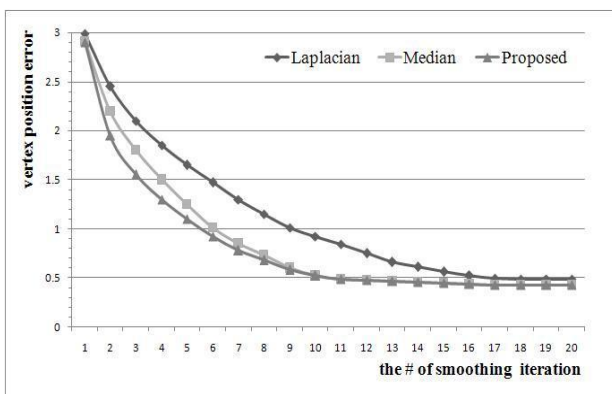


Fig. 12. The comparison of vertex's position variation of hat data

2D multiple images by the analysis of geometrical features. Fig. 13 presents the noise smoothing results of previous and proposed method using the reconstructed house data. In Fig. 13 (bottom left) and (bottom center), previous methods smoothed noise in the part of wall and roof so much. Therefore, original feature disappeared. However, applying the proposed method to this data, the noise in roof, wall and other parts effectively removed in Fig 13 (bottom right). Figure 14 is the graph about the position variation of noise vertex.



Fig. 13. Reconstructed 3D mesh data from multiple images, (top) Original Image, (top right) 3D reconstructed data, (bottom left) The result using laplacian method[11], (bottom center) the result using median filtering[6], (bottom right) the result by proposed method.

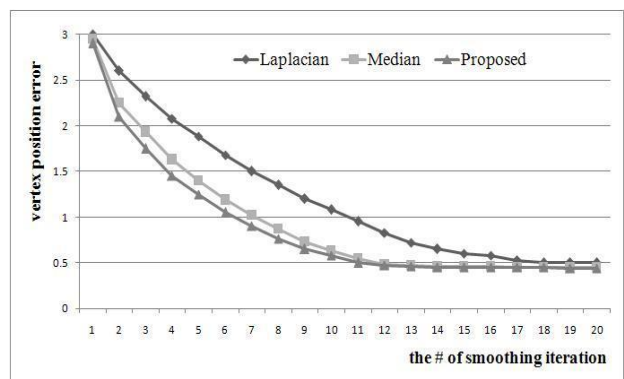


Fig. 14. The comparison of vertex position variation of house mesh data

The third experimental data is a reconstructed 3D data from

5. CONCLUSION

A mesh smoothing method for mesh model with noise was presented in this paper. The proposed method enabled not only the removal of noise from the vertexes but the preservation and smoothing of features recognized as edges and corners.

The general approaches to reconstruct 3D data from multiple images caused unavoidable errors in each step to reconstruct 3D data, camera calibration, corresponding points searching, fundamental matrix computation, etc. These errors appeared in peak noise in reconstructed 3D data. When mesh data is generated from the reconstructed 3D data, non-smooth object surface is made.

In this paper, the 2D/3D magnitude ratio of mesh data is adopted for the smoothing of peak noise. If a reconstructed 3D data includes peak noise, the previous smoothing methods were effectively smooth noise. As mentioned in the experiment section, the proposed approaches smoothed peak noise and preserved features recognized as edges and corners. Also, this method doesn't need many repetition of the smoothing process. The results of this study can utilize in many applications such as computer graphics, 3D animation, virtual reality, augmented reality and computer games

ACKNOWLEDGMENT

This research is supported by Ministry of Culture, Sports and Tourism(MCST) and Korea Culture Content Agency(KOCCA) in the Culture Technology(CT) Research & Development Program 2009

REFERENCES

- [1] Marc Pollefeys, "Tutorial on 3D modeling from images," Dublin, Ireland In conjunction with ECCV, Lecture Notes, CH. 6, 26 June 2000.
- [2] Zhengyou ZHANG, "A Robust Technique for Matching Two Uncalibrated Images Through the Recovery of the Unknown Epipolar Geometry," Technical Report, May, 1994.
- [3] Zhengyou ZHANG, "A Robust Technique for Matching Two Uncalibrated Images Through the Recovery of the Unknown Epipolar Geometry," Technical Report, May, 1994.
- [4] A. Heyden, K. Astrom, "Euclidean Reconstruction from Constant Intrinsic Parameters," *Proc. 13th International Conference on Pattern Recognition, IEEE Computer Soc. Press*, pp. 339-343, 1996.
- [5] Richard N. Ellson, Joseph H. Nurre, "A new approach for modeling and smoothing of scattered 3D data," *Proc. SPIE, Three-Dimensional Image Capture and Applications, Vol. 3313*, pp. 168-177, 1998.
- [6] Hirokazu Yagou, Alexander Belyaevy, Daming Weiz, "Mesh Median Filter for Smoothing 3-D Polygonal Surfaces", *Proceedings of the First International Symposium on Cyber Worlds*, 2002.
- [7] G. Arce and J. Paredes. "Image enhancement and analysis with weighted medians," *Nonlinear Image Processing*. Academic Press, 2001.
- [8] L. Kobbelt, S. Campagna, J. Vorsatz, and H.-P. Seidel, "Interactive multi resolution modeling on arbitrary meshes," *In Computer Graphics (SIGGRAPH 98 Proceedings)*, pp. 105-114, 1998.

- [9] G. Taubin, "Linear anisotropic mesh filtering," *IBM Research Report*, October 2001.
- [10] Yutaka Ohtake, Alexander Belyaev, Ilia Bogaevski, "Mesh regularization and adaptive smoothing," *Computer-Aided Design*, Vol. 33, pp. 789-800, 2001.
- [11] Yuanfeng Zhou, Caiming Zhang, Shanshan Gao, "A Quasi-Laplacian Smoothing Approach on Arbitrary Triangular Meshes," *IEEE International Conference on Computer-Aided Design and Computer Graphics*, 2007.



Dae-Hwan, Hyeon

He received the B.S. in electronic engineering from HanYang University, the M.S in image engineering from ChungAng University, Korea in 1996, 2000 respectively. His main research interests include computer vision, image retrieval and computer graphics.



Taeg-Keun, Hwangbo

He received the B.S. in physical metallurgy engineering from Korea University, Korea in 1983, the M.S in computer science from City University of New York, USA in 1987 respectively and also received Ph.D. in computer science from Stevens Institute of Technology, USA in 1987. His main research interests include image processing, pattern recognition, computer graphics and 3D searching engine.