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Feature-preserving mesh denoising based on contextual discontinuities*

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Abstract: Motivated by the conception of Lee *et al*.(2005)'s mesh saliency and Chen (2005)'s contextual discontinuities, a novel adaptive smoothing approach is proposed for noise removal and feature preservation. Mesh saliency is employed as a multiscale measure to detect contextual discontinuity for feature preserving and control of the smoothing speed. The proposed method is similar to the bilateral filter method. Comparative results demonstrate the simplicity and efficiency of the presented method, which makes it an excellent solution for smoothing 3D noisy meshes.

Key words: Mesh denoising, Feature preserving, Contextual discontinuities, Mesh saliency, Bilateral filter
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INTRODUCTION

With the proliferation of 3D scanning tools, interest in removing noise from meshes has increased. An important problem is how to suppress noise while preserving desirable geometric features of the model. In general, smoothing algorithms are roughly classified into two categories: linear and nonlinear smoothing (Gonzalez and Woods, 2002). For linear smoothing, each mesh point is moved to the barycenter of its neighbors. Linear smoothing treats feature (large variations) and noise (small variations) identically, so it is not feature preserving. Nonlinear smoothing updates each mesh point through local weighted averaging of its neighbors. A large weight should be assigned to a point that involves low discontinuities, and vice versa. In nonlinear smoothing, a discontinuity measure critically determines its performance. However, noise corruption can generate discontinuities as well. Therefore, how to measure significant discontinuities is a nontrivial issue. In order to robustly detect salient feature, in this paper mesh saliency is employed as a multiscale measure to detect contextual discontinuity for feature preserving and control of the smoothing speed. Thus, we can update each point within a relatively homogeneous region and can preserve most sharp features.

The remainder of this paper is organized as follows. In Section 2 we review the related works in this field. Section 3 discusses the feature-preserving mesh denoising method based on contextual discontinuities. Section 4 gives some results of our method. We summarize our work in Section 5.

RELATED WORK

Since Taubin (1995a) presented a signal processing approach to fair surface design, there has been a substantial amount of work on surface faring of 3D noisy meshes, resulting in a variety of algorithms such as the Laplacian operator (Taubin, 1995a), anisotropic diffusion (Bajaj and Xu, 2001; Hildebrandt and Polthier, 2004; Desbrun *et al*., 1999; 2000), dif-

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fusion of the normal field (Tasdizen *et al*., 2002; Ohtake *et al*., 2002) and bilateral filtering (Jones *et al*., 2003; Fleishman *et al*., 2003; Choudhury and Tumblin, 2004). Typically, Most mesh denoising methods are based on image denoising approaches.

The bilateral filter introduced by Tomasi and Manduchi (1998) is a nonlinear filter derived from Gaussian blur, with a feature preservation term that decreased the weight of pixels as a function of intensity difference:

$$I'_s = \frac{1}{k(s)} \sum_{p\in\Omega} f(p-s)g(I_p - I_s)I_p, \tag{1}$$

where, $f(\cdot)$ is a spatial weight function, $g(\cdot)$ is an influence weight function, $k(s)$ is the normalization factor

$$k(s) = \sum_{p\in\Omega} f(p-s)g(I_p - I_s). \tag{2}$$

Compared to image, 3D surfaces have an inherent ambiguity: in images, signal is well separated from position in the image; on surfaces, the signal and spatial position are closely intertwined. This makes the definition of the influence weight function challenging. Similar to Eq.(1), in 3D mesh, the influence weight function decreases as a function of discontinuity, so how to measure significant discontinuities is the key feature of the bilateral filter. Chen (2005) proposed an adaptive smoothing method via contextual and local discontinuities. In fact Chen's method is a variation of the bilateral filter. He used local discontinuities to indicate the details of local structures and contextual discontinuities to specify where important features are in a given image. He combines the two discontinuity measures for synergy to preserve nontrivial features. Motivated by Chen's success, we introduces the idea of Lee *et al*.(2005)'s mesh saliency as a measure of important discontinuities for graphics meshes and incorporate it with Chen's adaptive smoothing method to denoise 3D noisy mesh.

MESH DENOISING BASED ON CONTEXTUAL DISCONTINUITIES

In this section, we first discuss Chen (2005)'s adaptive smoothing method, then modify Lee *et al*.(2005)'s mesh saliency to capture important discontinuities of 3D mesh. At last, we incorporate mesh saliency with Chen (2005)'s adaptive smoothing method to denoise 3D noisy mesh.

Adaptive smoothing by combining discontinuity measures for image

Chen (2005) first defined inhomogeneity $H_{(x,y)}$ as a robust multiscale measure computed by an ensemble of coupled pixels. Inhomogeneity tends to reveal the intrinsic disconnectedness or incoherence between a pixel and its surrounding by means of a scale-based or image-dependent property. Then an adaptive smoothing scheme is proposed by combining both inhomogeneity and spatial gradient:

$$I^{(t+1)}_{(x,y)} = I^t_{(x,y)} + \alpha_{(x,y)} \frac{\sum\limits_{(i,j)\in B_{(x,y)}(1)} \alpha_{(i,j)}\beta^t_{(i,j)}(I^t_{(i,j)} - I^t_{(x,y)})}{\sum\limits_{(i,j)\in B_{(x,y)}(1)} \alpha_{(i,j)}\beta^t_{(i,j)}}, \tag{3}$$

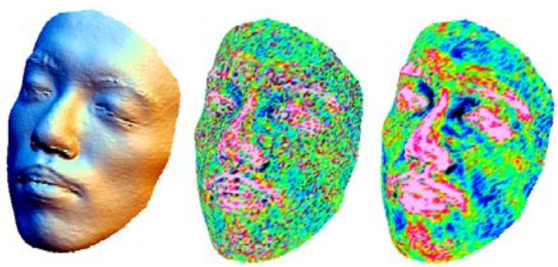
where, $B_{(x,y)}(1)$ is the 1-neighborhood of pixel (x,y), $I^t_{(x,y)}$ is the intensity of pixel (x,y) at iteration t, α and β are weight functions and defined as

$$\alpha_{(x,y)} = g(H_{(x,y)}, h);\ \beta^t_{(x,y)} = g(|\nabla I^t_{(x,y)}|, S), \tag{4}$$

here, $g(\cdot)$ is a nonnegative monotonically decreasing function. h and S are two parameters. The α term encodes the effect of intrinsic contextual discontinuities while the β term encodes the instantaneous effect of local discontinuities during smoothing. In fact, Eq.(3) is similar to Eq.(1).

Mesh saliency

Mesh saliency method (Lee *et al*., 2005) merges perceptual criteria inspired by low-level human visual system cues with geometric properties based on discrete differential geometry for 3D mesh, so it can successfully capture salient regions in meshes. For 3D objects, we feel that a sphere is a canonical zero-saliency feature. The invariant property of a sphere is the curvature. So as a robust multi-scale measure defined by the curvatures, the mesh saliency $\varphi(p)$ can capture the interesting features at all perceptually meaningful scales and reveal the difference between the vertex and its surrounding context. That is, the value of $\varphi(p)$ would be high if the point is a perceptually salient feature point. Otherwise, the value tends to be low (Fig.1). In this section we modify Lee *et al.*(2005)'s method to compute mesh saliency as shown below.



(a) (b) (c)

Fig.1 Saliency computed by an ensemble of the boundary region vertices specifies where important features are in a given mesh. (a) Original model; (b) Visualize the principal curvature of each mesh vertex with color; (c) Visualize the saliency value of each mesh vertex with color

First, we define the boundary region of a neighborhood of each mesh point p by

$$B(p,K)=N(p,K)-N(p,K-1),$$

where $N(p,K)$ denotes the K-neighborhood of vertex p. For convenience in notation, we stipulate that $B(p,0)$ is the vertex itself and $B(p,1)$ is the 1-neighborhood of the vertex p.

Second, we should compute surface curvatures. There are many excellent approaches to estimate surface curvatures accurately (Taubin, 1995b; Hameiri and Shimshoni, 2003). Let $k(p)$ denote the largest absolute value of the principal curvatures:

$$k(p)=\max(|k_{\max}(p)|,|k_{\min}(p)|).$$

Third, an ensemble of surrounding vertices is computed by the center-surround mechanism (Itti *et al.*, 1998). Let $G(k(p),K)$ denote the Gaussian-weighted average of $k(x)$, computed as shown below:

$$G(k(p),K)=\frac{\sum_{x\in B(p,K)} k(x)\exp[-|x-p|^2/(2\sigma^2)]}{\sum_{x\in B(p,K)} \exp[-|x-p|^2/(2\sigma^2)]}. \quad (5)$$

Define $G(k(p),0)=k(p)$. Assume that the average length of edges of the mesh is $\bar{e}$, we set $\sigma=\lambda\bar{e}$. Here, λ=1 is a good selection in our algorithm.

At last, we compute the saliency $\varphi_K(p)$ as the absolute difference between the Gaussian-weighted averages computed at the two neighboring boundaries:

$$\varphi_K(p)=|G(k(p),K+1)-G(k(p),K)|. \quad (6)$$

In order to capture the saliency at multiple scales, we calculate an average value $\varphi(p)$ as:

$$\varphi(p)=\frac{1}{n+1}\sum_{K=0}^{n}\varphi_K(p). \quad (7)$$

Adaptive mesh denoising based on contextual discontinuities

From Section 3.2 we know that the mesh saliency $\varphi(p)$ can capture the important features at all perceptually meaningful scales and reveal the difference between the vertex and its surrounding context. Denote $Saliency_{\max}$ is the maximal saliency value and $Saliency_{\min}$ is the minimal saliency value in the mesh. To facilitate the use of saliency for adaptive mesh smoothing, we normalize $\varphi(p)$ as

$$\varphi(p)=\frac{\varphi(p)-Saliency_{\min}}{Saliency_{\max}-Saliency_{\min}}. \quad (8)$$

Similar to Eq.(3), we get:

$$p'=p+\alpha_p\frac{\sum_{q\in B(p,1)}\alpha_q\beta_q(q-p)}{\sum_{q\in B(p,1)}\alpha_q\beta_q}. \quad (9)$$

α and β are weight functions defined as

$$\alpha_q=\exp\left(-\frac{\varphi(q)^2}{2\sigma_\alpha^2}\right),\ \alpha_p=\exp\left(-\frac{\varphi(p)^2}{2\sigma_\alpha^2}\right).$$
$$\beta_q=\exp\left(-\frac{|q-p|^2}{2\sigma_\beta^2}\right), \quad (10)$$

where, σ_α and σ_β determine the smoothing scales. In order to enhance the $\varphi(p)$ value, we introduce a nonlinear sine transformation (Chen, 2005) (Fig.2).

$$\varphi(p)=\sin\left(\frac{\pi}{2}\varphi(p)\right),\ 0\le\varphi(p)\le 1. \qquad (11)$$

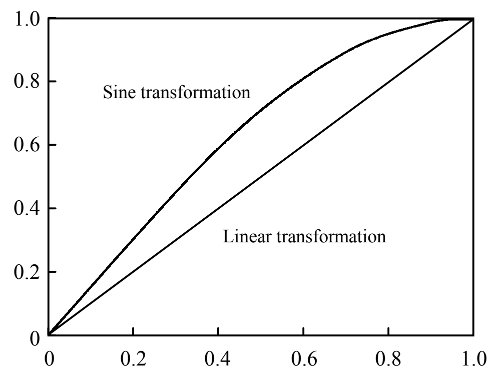


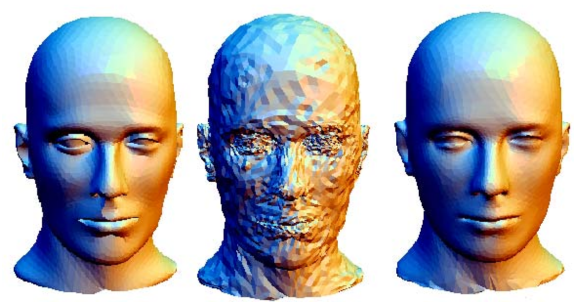
Fig.2 Enhance the $\varphi(p)$ value by nonlinear sine transformation

Usually high saliency values correspond to the sharp features. The higher its $\varphi(p)$ value is, the better are sharp features preserved during smoothing. So we amplify the saliency values using a threshold β and an amplification factor λ:

$$A(\varphi(p),\beta,\lambda)=\begin{cases}\lambda\varphi(p), & \text{if } \varphi(p)\ge\beta;\\ \varphi(p), & \text{if } \varphi(\mathrm{p})<\beta.\end{cases} \qquad (12)$$

RESULTS

We have implemented our adaptive smoothing algorithm as described in the previous sections and compared our results to Lapalacian smoothing, bilaplacian and bilateral filtering algorithm. The comparison demonstrated that our method can preserve most detailed features during smoothing of a noisy mesh. In order to give a visual comparison, we corrupted some model by Gaussian noise with $\sigma(n)=k\cdot average(S)$ in some tests, where k=0.15 and $average(S)$ is the mean edge length of the surface S. Fig.3 shows a 3D mesh data of a man's head. We give the origin model, the noisy model with $\sigma(n)$=0.15 of the mean edge length and the smoothed model by our method. We present this comparison to demonstrate the effectiveness of our approach. Fig.4 gives a comparison to bilateral filtering algorithm. In our method we set λ=2.0, β=80th percentile saliency value. Fig.5 gives a comparison to classical Laplacian smoothing algorithm. After 2 iterations, the image in Fig.5b is blurred and our algorithm (2 iterations, λ=2.0, β=80th percentile saliency value.) still preserves most sharp features (Fig.5c). Notice the details such as the eyes and stomach. Usually high saliency values correspond to the sharp features. In order to preserve the sharp features effectively, we amplify the saliency values using a threshold β and an amplification factor λ. Fig.6 gives some results for different λ. The higher its λ value is, the better are the sharp features preserved. Notice the details such as the letter on the stomach. Usually we set β=60th~80th percentile saliency value and $1\le\lambda\le3$. The big λ can preserve the sharp features during denoising of 3D noisy model, but if we arbitrarily amplify λ, it will make the result worse. Fig.7 compares our method with bilaplacian method. After 2 iterations, the surface smoothness in the flat area in our method (Fig.7c) is better than the smoothness in bilaplacian methods (Fig.7d).



(a) (b) (c)

Fig.3 Denoising a man head model. (a) The initial model; (b) The noisy model; (c) The smoothed model by our method (2 iteration)

(a) (b) (c)

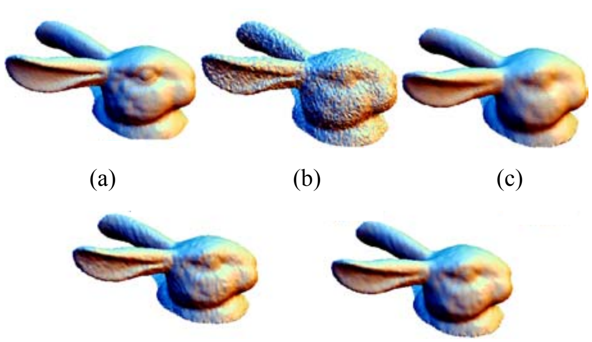
Fig.4 Comparison with Jones *et al.*(2003)'s method. (a) The noisy model; (b) The smoothed model by our method (1 iteration); (c) The smoothed model by Jones *et al.*(2003)'s method (1 iteration)

(a) (b) (c)

Fig.5 Comparison with Laplacian operator. (a) The noisy model; (b) The smoothed model by Laplacian operator (2 iteration); (c) The smoothed model by our method (2 iteration)

(a) (b) (c) (d) (e)

Fig.6 Noisy model smoothed by our method with different λ. (a) Initial model; (b) Noisy model; (c)~(e) Smoothed model by our method with λ=1.0, λ=2.0, λ=3.0 respectively (All with 3 iterations and the same β=80th percentile saliency value)



(a) (b) (c)

(d) (e)

Fig.7 Comparison with bilaplacian method. (a) Initial model; (b) Noisy model; (c) Smoothed model by our method (2 iterations); (d) Smoothed model by bilaplacian method (2 iterations); (e) Smoothed model by bilaplacian method (5 iterations)

CONCLUSION AND FUTURE WORK

Motivated by the concept of Lee *et al*.(2005)'s mesh saliency and Chen (2005)'s contextual discontinuities, a novel adaptive smoothing approach is proposed for noise removal and feature preservation. A good saliency map can capture the interesting sharp features effectively. So a number of tasks in graphics can benefit from the computational model of mesh saliency. In this paper mesh saliency is employed as a multiscale measure to detect contextual discontinuity for feature preserving and control of the smoothing speed. The proposed method is similar to the bilateral filter method. Comparative results demonstrate the simplicity and efficiency of the presented method, which makes it an excellent solution for smoothing 3D noisy meshes.

References

Bajaj, C., Xu, G., 2001. Anisotropic Diffusion of Noisy Surfaces and Noisy Functions on Surfaces. TICAM Report, p.1-7.

Chen, K., 2005. Adaptive smoothing via contextual and local discontinuities. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, **27**(10):1552-1567. [doi:10.1109/TPAMI.2005.190]

Choudhury, P., Tumblin, J., 2004. The Trilateral Filter for High Contrast Images and Meshes. Proc. of the Eurographics Symposium on Rendering, Leuven, Belgium, p.186-196.

Desbrun, M., Meyer, M., Schröder, P., Barr, A.H., 1999. Implicit Fairing of Irregular Meshes Using Diffusion and Curvature Flow. Proceedings of SIGGRAPH'99, p.317-324.

Desbrun, M., Meyer, M., Schröder, P., Barr, A.H., 2000. Anisotropic Feature-preserving Denoising of Height Fields and Bivariate Data. Proceedings of Graphics Interface 2000, Montreal, Quebec, Canada, p.145-152.

Fleishman, S., Drori, I., Cohen-Or, D., 2003. Bilateral mesh denoising. *ACM Trans. on Graphics*, **22**(3):950-953. [doi:10.1145/882262.882368]

Gonzalez, R.C., Woods, R.E., 2002. Digital Image Processing, 2 Ed. Publishing House of Electronics Industry, Beijing, p.175-220 (in Chinese).

Hameiri, E., Shimshoni, H., 2003. Estimating the principal curvatures and the darboux frame from real 3D range data. *IEEE Trans. on Systems Man and Cybernetics Part B (Cybernetics)*, **33**(4):626-637. [doi:10.1109/TSMCB.2003.814304]

Hildebrandt, K., Polthier, K., 2003. Anisotropic Filtering of Non-linear Surface Features. Proc. of EUROGRAPHICS, Zuse Institute, Berlin, p.4-25.

Itti, L., Koch, C., Niebur, E., 1998. A model of saliency based visual attention for rapid scene analysis. *IEEE Trans. on*

Pattern Analysis and Machine Intelligence, **20**(11):1254-1259. [doi:10.1109/34.730558]

Jones, T.R., Durand, F., Desbrun, M., 2003. Non-iterative, feature-preserving mesh smoothing. *ACM Trans. on Graphics*, **22**(3):943-949. [doi:10.1145/882262.882367]

Lee, C.H., Varshney, A., Jacobs, D.W., 2005. Mesh saliency. *ACM Trans. on Graphics*, **24**(3):659-666. [doi:10.1145/1073204.1073244]

Ohtake, Y., Belyaev, A., Seidel, H.P., 2002. Mesh Smoothing by Adaptive and Anisotropic Gaussian Filter Applied to Mesh Normal. Proceedings of Vision, Modeling, and Visualization (VMV) 2002, Erlangen, Germany, p.203-210.

Tasdizen, T., Whitaker, R., Burchard, P., Asher, S., 2002. Geometric Surface Smoothing via Anisotropic Diffusion of the Normals. Proc. IEEE Visualization'02, p.125-132.

Taubin, G., 1995a. A Signal Processing Approach to Fair Surface Design. Proceedings of SIGGRAPH'95. New York, USA, p.351-358.

Taubin, G. 1995b. Estimating the Tensor of Curvature of a Surface from a Polyhedral Approximation. Proceedings of IEEE International Conference on Computer Vision ICCV-95, p.902-907. [doi:10.1109/ICCV.1995.466840]

Tomasi, C., Manduchi, R., 1998. Bilateral Filtering for Gray and Color Images. Proc. IEEE Int. Conf. on Computer Vision, p.836-846.