Multi-Scale Image Sharpening with Background Noise Suppression

Hiroaki Kotera and Wang Hui
Department of Information and Image Sciences, Chiba University, Japan

Abstract

The color image has a various edge profile. In the conventional single kernel filter has the drawbacks of exhausting background noises or insensitivity to the dull edges. In the previous paper[1], we proposed a new image sharpening method adaptive to the edge profiles. In this paper, we present its advanced model, which has both sharpening and smoothing functions. In addition, the paper assesses the edge sharpness factors by introducing the indices, such as ***ES*** (Edge Sharpness), ***FS*** (Spatial Frequency Sharpness), and ***Nf*** (Flat Area Noise). The improved model makes the flat area noises intentionally ***smoothed*** with preserving the enhanced edges. The sharpening filter is applied only to the luminance *Y* image to keep the gray balance. After pre-scanning the *Y* image with sharp ***GD*** filter, the ***edge map*** is generated by classifying the edge types into hard, medium, soft, and flat zones. The multiple ***GD*** operators with different deviations, σ_1, σ_2, and σ_3 are selectively applied to the corresponding edge zones of *Y* image by looking up the ***edge map***. Here the smoothing filters are applied only to the flat zones to reduce the background noises. In simple, the normal Gaussian filter is used as a noise smoother. In comparison with conventional method, the proposed model worked excellent to sharpen the different edge slopes naturally together with dramatically reducing the background noises.

Introduction

The color image has different edge profiles depending on the characteristics of the objects placed in the scene. In the most simple conventional edge enhancement method, a single sharpness filter such as digital Laplacian or unsharp mask operator is applied to the entire image. The non-adaptive single sharpness filter is known to have the following drawbacks such as

[1] random noise in flat area is amplified with edge enhancement.

[2] dull edges are not well sharpened by a single spatial operator with small size

[3] coloring in the gray edges by unbalanced RGB responses.

In the unsharp masking approach, a fraction of the high-pass filtered version of the image is added to the original image. It is simple, but enhances the noise and/or digitization effects resulting in visually unpleasant image. While the noise can be suppressed with low-pass filters associated with the blurring of the edges. Ramponi et al proposed a nonlinear unsharp masking method[2], which combines the features of both high-pass and low-pass filters. Inoue and Tajima reported an adaptive image sharpening method[3], which estimates the edge sharpness by high band-pass filter based on DOG function.

However, these methods don't suppress the flat area noises sufficiently. Also, the conventional Laplacian filters don't create the natural sharpness, because they have local edge responses different from the receptive field in human vision.

In the proposed method, multiple edge enhancement filters are applied to work adaptive to the different edge slopes and to work ***intentionally smoothing*** the background noise in the flat areas avoiding the enhancement. The coloring problem in grayish edges is easily resolved by applying the sharpening filters only to the luminance signal. The enhanced composite luminance signal works to recover the sharpness for component color signals through the inverse matrix.

Edge Sharpening Operator

A variety of simple cell receptive field models for human vision have been considered such as

Gaussian Derivative (=Hermite Polynomial*Gaussian)

Gabor(=Cosine·*Gaussian)

DOG(Difference-Of-Gaussian)

DOOG(Difference-Of-Offset-Gaussian)

DODOG (Difference-Of-Offset-DOGS)

Stork and Wilson[4], Yang[5], and Klein et al[6], disputed which one, Gaussian derivative (***GD***) or Gabor[7] could minimize the joint space-spatial frequency uncertainty $\Delta x \Delta \omega$. Young[8] and others reported the ***GD*** is better than Gabor. DOOG is known to be a good approximation to GD, while DOG is not fit to it. Marr and Hildreth[9] operator using ***GD*** has been applied to detect zero-crossing edges. Here we also applied ***GD***-based operators.

The basic Gaussian distribution function in two dimensions is defined by

$$G(r) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{r^2}{2\sigma^2}\right); \qquad r^2 = x^2 + y^2 \qquad (1)$$

Its second derivative is given by

$$\nabla^2 G(x,y) = \partial^2 G(r)/\partial x^2 + \partial^2 G(r)/\partial y^2$$
$$= \frac{1}{\pi\sigma^4}\left(\frac{r^2}{2\sigma^2} - 1\right) exp\left(-\frac{r^2}{2\sigma^2}\right) \quad (2)$$

Fig.1 shows the 3D shape of ***GD*** spatial filter and its cross sectional view.

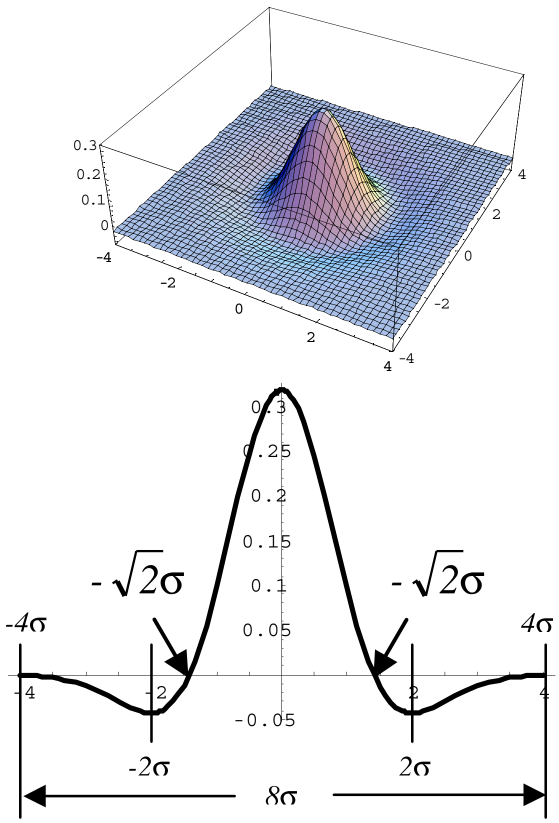


Fig.1 GD operator based on human visual field response

The effective field spreads to $r_2 \cong \pm 4\sigma$ from center. Hence $M \cong 8\sigma + 1$ will be sufficient to reflect the receptive field. For example, $5\times5(\sigma=0.5) \sim 13\times13(\sigma=1.5)$ matrices may be applied to describe the GD filters.

The edge signals are extracted from image f(x, y) by the two-dimensional convolution operation as follows.

$$\delta(x,y) = -\nabla^2 G(x,y) \otimes f(x,y) \quad (3)$$

Where, symbol ⊗ denotes the convolution operation and the edge sharpness is measured by operating the ***pre-scan filter*** $-\nabla^2 G_S$ with appropriate sharp standard deviation σ_S.

Multi-Scale Filtering by Edge Segmentation

Fig.2 illustrates the sharpening process in the proposed system. First, the RGB image is transformed into luminance -chrominance image such as YCrCb or YIQ. The edge enhancement is applied only to the luminance Y image to keep the gray balance on the edges. The edge strengths are analyzed by the histogram of pre-scan edge signal $\delta_S(x, y)$ and classified into multiple zones reflecting the edge profiles, such as, ***hard***, ***medium***, ***soft***, and ***flat***. Thus the ***edge map*** is generated to discriminate these edge types. The multi-scale Gaussian derivative operator $-\nabla^2 G$ with different deviation σ_1, σ_2, and σ_3 is applied to Y image and the hard edge $\delta_1(x, y)$, medium edge $\delta_2(x, y)$, or soft edge $\delta_3(x, y)$ are detected in response to the edge slopes. In addition, a Gaussian smoothing filter $G_F(x, y)$ with σ_F is intentionally applied to the flat area to reduce the background noises.

$$G_F(r) = \frac{1}{2\pi\sigma_F^2} exp\left(-\frac{r^2}{2\sigma_F^2}\right); \quad r^2 = x^2 + y^2 \quad (4)$$

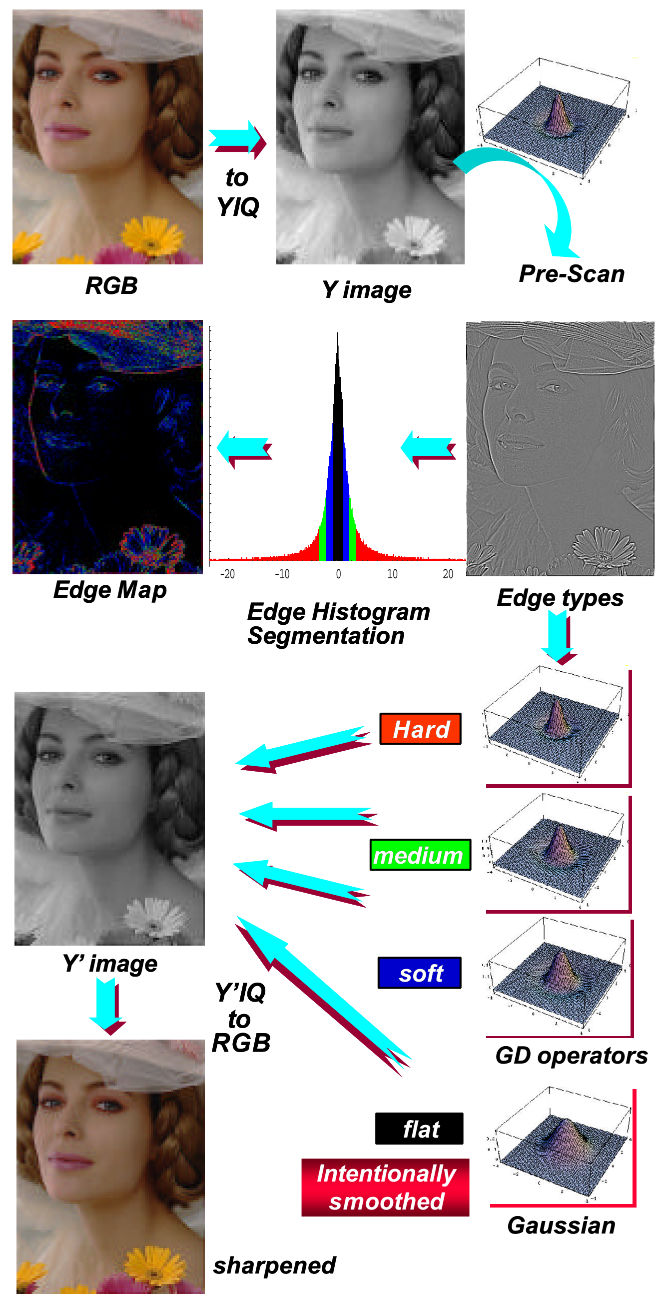


Fig.2 Multi-scale adaptive image sharpening process

These multi-scale edge operators are selectively switched by looking up the ***edge map*** classifying the edge types.
Then, the luminance Y image is sharpened or smoothed according to the edge discriminator $E_{flat}(x, y)$=0 or 1 and edge type indicator E as follows.

$$f`(x,y) = E_{flat}(x,y) G_F(x,y) \otimes f(x,y) + \{1 - E_{flat}(x,y)\} S_E(x,y)$$
$$E_{flat}(x,y) = \begin{cases} 1 & \text{for flat area} \\ 0 & \text{for edge area} \end{cases}$$
$$E = 1 \text{ for hard edge, } = 2 \text{ for medium edge, } = 3 \text{ for soft edge} \tag{5}$$

Here in the flat area, the convolution of the original image with Gaussian filter reduces the background noise
Finally, the original Y image is replaced by sharpened luminance image Y' and converted into $R'G'B'$ primary color image by inverse transform.

GD Kernel Design

In practice, the GD filters are designed in discrete digital form considering the following conditions.
[1] The filter is approximated by $M \times M$ square matrix.
[2] The weights of GD filter should be equivalent to the local integral of continuous GD function in between discrete lattice points.
[3] The sum of GD filter weights is to be equal to zero not to respond to flat signals.

The matrix size M of GD filter depends on the standard deviation σ. As shown in Fig.1, the cross sectional profile of $-\nabla^2 G(x,y)$ in radial direction has the well-known Mexican hat shape with zero cross points at $r_0 = \pm\sqrt{2}\sigma$ and minimum peaks at $r_1 = \pm 2\sigma$.
The two-dimensional GD function $-\nabla^2 G(x,y)$, spreading in radial direction, is approximated by $M \times M$ square matrix $\mathbf{W}=[w_{ij}]$ on discrete lattice points $[i, j]$.
To satisfy the condition [2], we take an odd integer $M=2m+1 (m=1,2,...)$ and the weights $[w_{ij}]$ are calculated by the following local integral between the lattice points $[i, j]$.

$$w_{ij} = \int_{j-0.5}^{j+0.5}\int_{i-0.5}^{i+0.5} [\nabla^2 G(x,y)] dxdy \tag{6}$$

Finally, the weights $[w_{ij}]$ are adjusted to meet the zero sum condition [3], and corrected to $[w_{ij}']$ as follows.

$$\sum_{i=-m}^{m}\sum_{j=-m}^{m} w_{ij}' = 0 \tag{7}$$

Because the GD function is spreading infinitely in radial direction and approximated by a limited square matrix $\mathbf{W}$, the negative weights outside of matrix are omitted. Then, the sum of positive weights W^+ and the sum of negative weights W^- are not balanced causing the non-zero sum as

$$\Delta W = \sum_{i=-m}^{m}\sum_{j=-m}^{m} w_{ij} = W^+ + W^- > 0$$
$$W^+ = \sum_{i=-m}^{m}\sum_{j=-m}^{m} w_{ij}^+, \quad W^- = \sum_{i=-m}^{m}\sum_{j=-m}^{m} w_{ij}^- \tag{8}$$

Where, w_{ij}^+ and w_{ij}^- denote the weights with positive and negative values. ΔW reflects the lacked negative weights and is compensated by adjusting $[w_{ij}^-]$ as follows.

$$W^+ + kW^- = 0$$
$$w_{ij}^{-\prime} = k w_{ij}^- ; \quad k = 1 - \Delta W / W^- \tag{9}$$

Since ΔW *is* positive and W^- is negative, the corrected negative weights $[w_{ij}^{-\prime}]$ are amplified by the factor of $-(\Delta W/W^-)$ as compared with original $[w_{ij}^-]$.
The matrix $\mathbf{W}$ to satisfy Eq. (7) is given by

$$\mathbf{W} = [w_{ij}'] = [w_{ij}^+] + [w_{ij}^{-\prime}] \tag{10}$$

The design of filter weights based on the condition [2] and [3] helps to make use of smaller size matrix and reduces the computation costs for filtering. In practice, for example, the kernel size $M=9$ was available.

Sharpness Factor

To estimate the sharpening effects, any sharpness index is necessary. Inoue and Tajima introduced the edge sharpness index ***ES*** to measure the strength of edge components after sharpening by

- ***Edge Sharpness: ES***

$$ES = \frac{\iint_E \left| f(x,y) \otimes s_{filt}(x,y) \right| dxdy}{A_E} \tag{11}$$
$$s_{filt} : \text{sharpening filter}, \; A_E : \text{amount of Edge Area}$$

ES is an effective index to measure the enhanced edge components existing in the edge areas.
In addition, we newly introduced the following indices to assess the sharpened image quality taking the other visual factors into consideration.

- ***Frequency Sharpness: FS***

$$FS = \frac{\int \left\{ \left| F_{sharp}(\omega) \right| - \left| F_{org}(\omega) \right| \right\} V(\omega) d\omega}{\int \left| F_{org}(\omega) \right| V(\omega) d\omega} \tag{12}$$

FS means the enhanced Fourier spectra after sharpening measured in 1-D diagonal spatial frequency ω *cycle/deg*.
$\left| F_{org}(\omega) \right|$ and $\left| F_{sharp}(\omega) \right|$ denote the original and sharpened Fourier spectra.

- ***Mean Square Error: MSE***

$$MSE = \iint \left\{ f_{sharp}(x,y) - f_{org}(x,y) \right\}^2 dxdy \tag{13}$$

MSE means well-known mean square error between the original and the sharpened images.

- ***Background Noise in flat area : N_f***

$$N_f = \iint E_{flat}(x,y)\{f_{sharp}(x,y) - f_{org}(x,y)\}^2 dxdy \quad (14)$$

N_f reflects the noise power measured in the flat area except edge areas and signifies very important quality assessment measure.

Experimental Results

Fig.3 shows an example of sharpened images by the proposed multi-scale adaptive method in comparison with non-adaptive single kernel method in the close-up views:
Here, conventional ***single GD*** method used a GD kernel with σ=0.6 designed to response to the sharp edges, while the proposed ***multi GD*** method applied the same GD filter with σ=0.6 for pre-scanning and used three types of GD filters with σ=0.6, 0.7, and 0.8 for hard, medium and soft edges. The normal Gaussian smoothing filter with σ=1.0 was applied to the flat area. As clearly viewed, the flat area noises are enhanced together with the edges in the conventional method, but are dramatically reduced in our method. Watching carefully, the proposed method provides with better background than the original by noise reduction smoothing filter and natural sharpening effects adaptive to the hard, medium, and soft edge slopes in the image.

Fig.4 illustrates a comparison in the sharpened edge profiles along a scan line shown in lower butterfly image (a) in Fig.3. The figure shows how the proposed multi-scale GD filters work adaptive to the edge slopes, where the solid black, dotted green, and solid red lines correspond to the profiles of original, sharpened by single GD, and by proposed multi GD method. As shown in these profiles, the proposed method has both the sharpening and smoothing effects. The red line is smoother than the original in the most left side of the scan line, but well responding to the edge slopes in the other parts. On the contrary, the dotted green line causes the unwanted enhancement of background small noises in the flat area.

Fig.5 illustrates another comparison. In this sample, multi-GD filters worked to sharpen the foreground image, while the smoothing filter worked to smooth the background image and dramatically improved its quality by reducing the flat areas noises.

Fig.6 shows different effect from Fig.5. The center house with triangle roof includes many sharp edges while right building has rugged but slow gradient walls. These two buildings are located side by side but the center was sharpened and the wall of right building was smoothed in the proposed method. However the single GD filter enhanced the small ruggedness unnecessarily.

Fig.7 shows the measured edge sharpness factor for typical test images after sharpening. The results by proposed method is compared with the conventional single GD filtering processed by two different σ=0.6 and σ=0.7. The ***ES*** values by these two single kernel methods are larger than our method, because they works to enhance all the edge components in the image uniformly, while the proposed model operate the multiple filters, adaptive to the edge types not to enhance all the edges unnecessarily.

However, as for the frequency sharpness factor ***FS***, the proposed method behaves to lift up the spatial frequency components in the visible range comparative to the single kernel method as shown in Fig. 8.

Fig.9 illustrates a comparison of the flat area noise for typical standard test images. It is clear the noise powers are dramatically reduced in the proposed method.

Discussion and Conclusions

A multi-scale ***adaptive*** image sharpening method with noise smoother is proposed. Multiple Gaussian derivative operators have been applied adaptive to the edge slopes and resulted in natural sharpness improvements with smoothing the background noises.
The classification of edge strengths are based on the histogram of the edge signals and also dependent of the image contents. At present, the segmentation of edge types to make the ***edge map*** is based on the empirical division by referencing the normalized standard deviation σ. The advanced way to generate the better ***edge map*** is under development. Future works on the subjective sharpness quality assessments are under planning based on psychophysical experiments.

References

1. H. Kotera et al, *Proc.8th CIC*, p.149-154 (2000)
2. G. Ramponi et al, *J. E. I.,* **6**(1), pp.353-365(1996)
3. A. Inoue and J. Tajima, *IEICE TTRANS. INF. & SYST.,* E76-D, 10, pp.1174-1180(1993)
4. D. G. Stork and H. R. Wilson, *J. Opt. Soc. Am.* A/**7**, 8, pp.1362-1373(1990)
5. J. Yang, *J. Opt. Soc. Am.* A/**9**, 2, pp.334-336(1992)
6. S. A. Klein and B. Beutter, *J. Opt. Soc. Am.* A/**9**, 2, pp.337-340(1992)
7. D. Gabor, *J. Inst. Elec. Eng.,* **93,** pp.429-457(1946)
8. R. A. Young, *Proc. SPIE,* **1453,** pp.92-123(1991)
9. D. Marr and E. Hildreth: *Proc. R. Soc. Lond.,* **B207,** pp.187-217(1980)
10. R. G. Barten, *J. Opt. Soc. Am.,*A/7, **10**, pp.2024-2031 (1990)

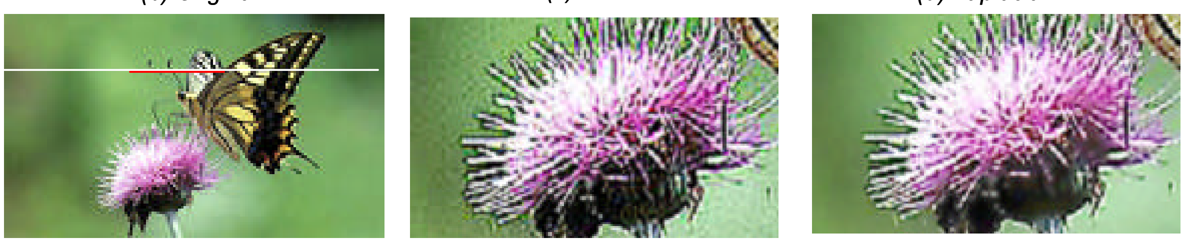
Biography

Hiroaki Kotera received his B.S degree from Nagoya Institute of Technology and Doctorate from University of Tokyo. He joined Matsushita Electric Industrial Co in 1963. Since 1973, he has been working in digital color image processing at Matsushita Research Institute Tokyo, Inc. In 1996, he moved to Chiba University. He is a professor at Dept of Information and Image Sciences. He received Johann Gutenberg prize from SID in 1995 and journal awards from IS&T in 1993, from IIEEJ in 1990 and 2000.

(b) Original (c) USM (d) Laplacian

(a) Original (e) Single GD (f) Multi GD (proposed)

(b) Original (c) USM (d) Laplacian



(a) Original (e) Single GD (f) Multi GD (proposed)

Fig 3. Comparison in sharpening effects

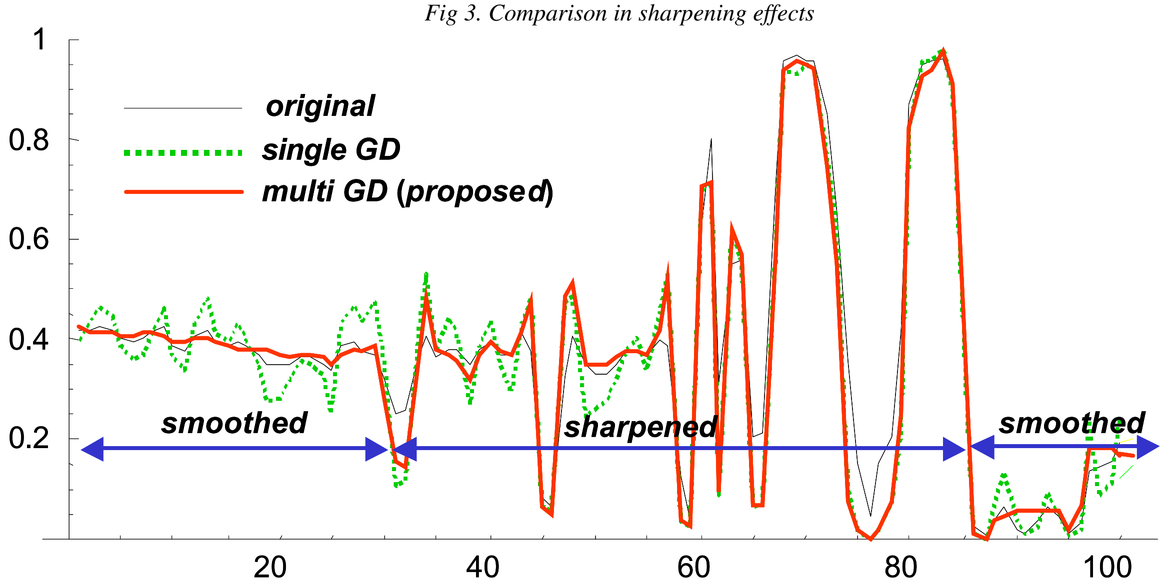
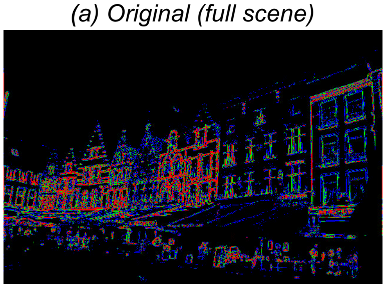


Fig. 4 Comparison of edge profiles along a scan line

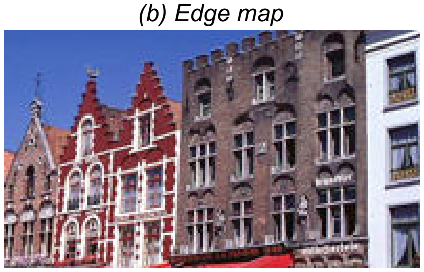
(a) original (b) background close up (c) single GD (d) Multi GD (proposed)

Fig. 5 Smoothed rendition in background scene

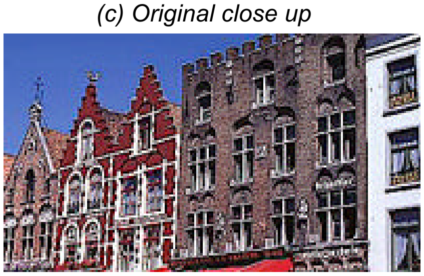
(a) Original (full scene)



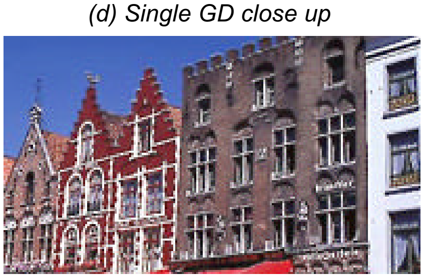
(b) Edge map



(c) Original close up



(d) Single GD close up



(d) Multi GD close up

Fig.6 Comparison of edge sharpness factors

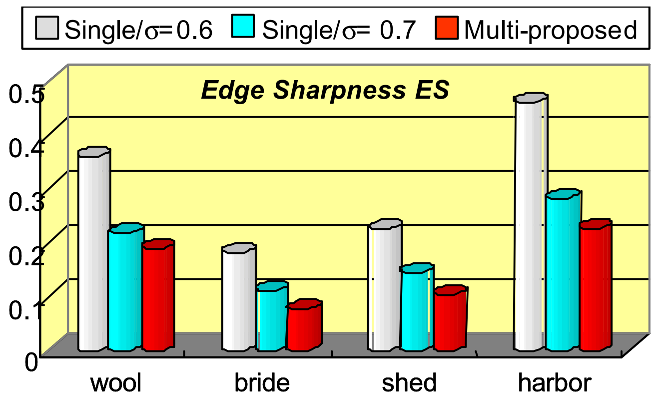


Fig.7 Comparison of edge sharpness factor ES

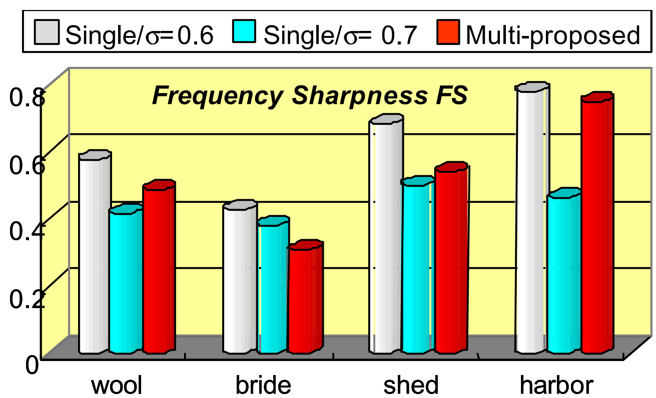


Fig.8 Comparison of frequency sharpness factor FS

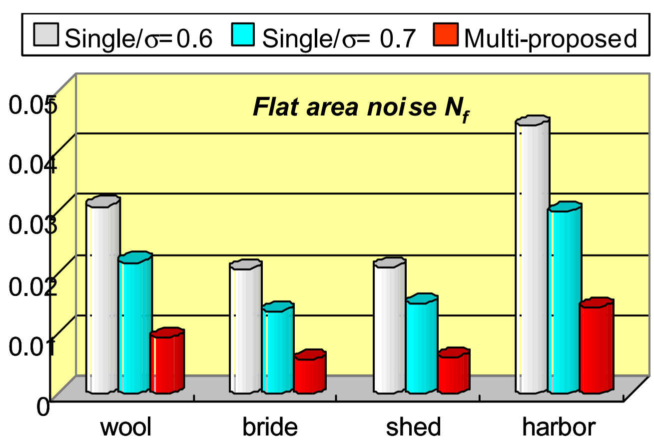


Fig.9 Comparison of flat area noises