

Sharpness Improvement Adaptive to Edge Strength of Color Image

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Abstract

The color image has different edge profiles depending on the local characteristics of the images. This paper discusses an adaptive image sharpening method depending on edge slopes of color images. First, the edge strengths of color image are measured by Gaussian derivative spatial filter for detecting the differential edge slopes. Secondly, the zone mask pattern is generated to classify the measured edge strengths, such as hard, medium, soft, and gentle or flat. Finally, the color image is processed by switching the plural number of edge sharpening spatial filters according to the mask pattern. The edge sharpening spatial filters worked well without coloring the gray edges when applied to the luminance signal converted from RGB signals by linear matrix. In the gentle or flat areas, all the edge sharpening filters are resumed not to enhance the flat area noises. Here the multiple second derivative filters such as Gaussian or Gabor with different σ are applied to restore the edge sharpness depending on the mask patterns. The proposed method resulted in the dramatic improvements in the reduction of flat areas noises, and the image sharpness is recovered in smooth and in natural adaptive to the edge strengths.

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

- random noise in flat area is amplified with edge enhancement.
- dull edges are not well sharpened by a single spatial operator with small size
- coloring in the gray edges by un-balanced RGB responses

In the unsharp masking approach, a fraction of the high-pass filtered version of the image is added to the original image to enhance the sharpness. 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 1, which combines the features of both high-pass and low-pass filters. Inoue and Tajima reported an adaptive image sharpening method 2 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 not to work in the flat areas avoiding the background noise enhancement. The coloring problem in grayish edges is 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)

Fig.1 shows the 3-D views of typical receptive field models and the cross sectional shapes. Stork and Wilson 3, Yang 4, and Klein et al 5, disputed which is the better function, Gaussian derivative (GD) or Gabor 6 to minimize the joint space-spatial frequency uncertainty $\Delta x \Delta \omega$. Young 7 and others reported the GD is better than Gabor. DOOG is known to be a good approximation to GD, while DOG is not well matched to it. Marr and Hildreth 8 operator using GD is well known and has been applied to detect zero-crossing image edges. Here we used 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

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

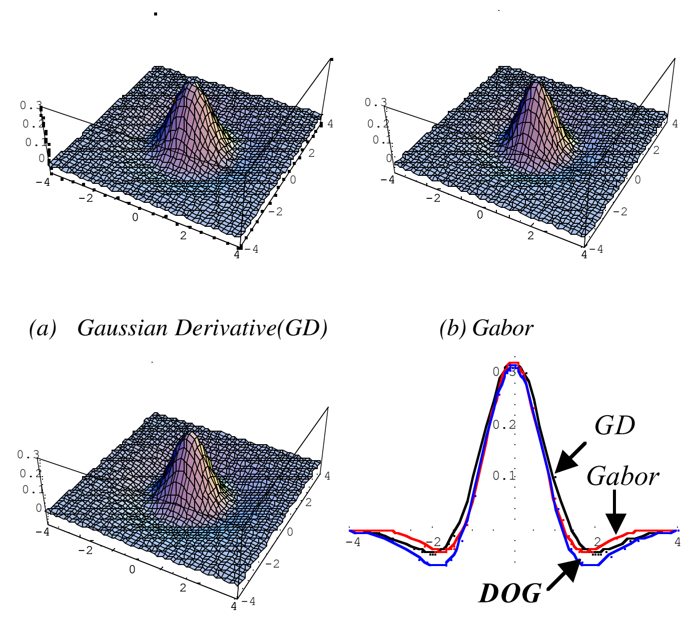
The edge signals are extracted from image f(x, y) by the two-dimensional convolution operation as follows.

$$\delta(x,\ y) = -\nabla^2 G(x,y)\ \text{<*>}\ f(x,\ y) \qquad (3)$$

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

Procedures

Fig.2 illustrates the sharpening process in the proposed system. First, the RGB image is transformed into luminance -chrominance image such as YCrCb, YIQ or HLS. The edge enhancement is applied only to the luminance Y image to keep the gray balance on the edges. In our proposal, the edge strengths are analyzed by the histogram of δ(x, y) and classified into multiple zones reflecting the edge profiles, such as, hard, medium, soft, and gentle or flat. Thus the zone mask M(x, y) is generated to discriminate these edges.



(a) Gaussian Derivative(GD) *(b) Gabor*

(c) Difference Of Gaussian(DOG) *(d) 1-D profiles*

Figure 1. Typical field response models for human vision

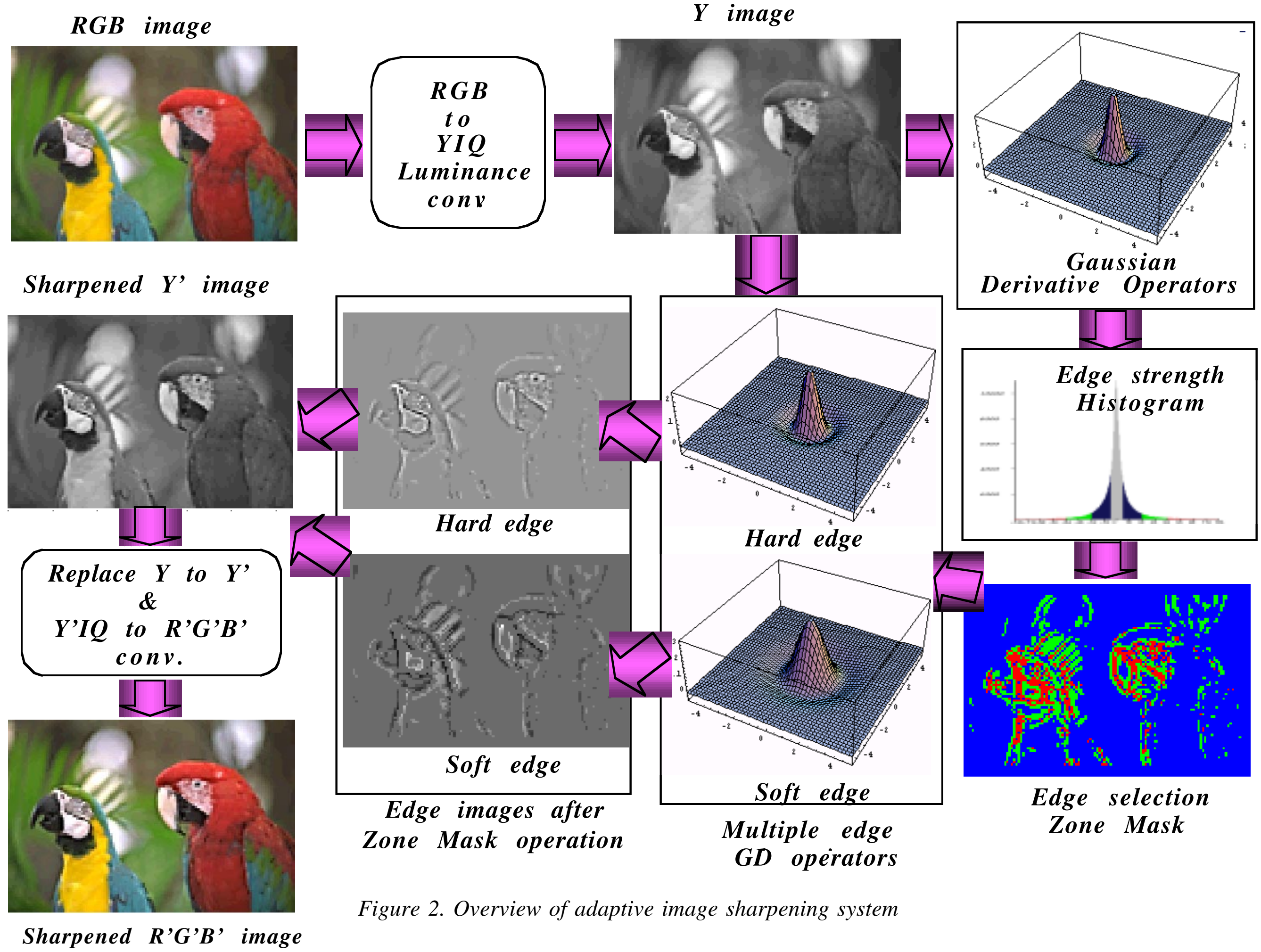


Figure 2. Overview of adaptive image sharpening system

Next, the multiple Gaussian derivative operators -∇2G with different σ_1, σ_2, and σ_3 are applied to Y image and the soft edge $\delta_1(x, y)$, medium edge $\delta_2(x, y)$, or hard edge $\delta_3(x, y)$ are detected in response to the statistical distribution of the edge slopes in the objective image.

These edge signals are selectively activated by looking up the following zone mask $M(x, y)$ according to the edge types and resumed in the gentle or flat areas without edges.

$$M(x,y) = \begin{cases} 0 & \delta(x,y) = 0 \quad \text{for gentle or flat areas} \\ 1 & \delta(x,y) = \delta_1(x,y) \quad \text{for soft edges} \\ 2 & \delta(x,y) = \delta_2(x,y) \quad \text{for medium edges} \\ 3 & \delta(x,y) = \delta_3(x,y) \quad \text{for hard edges} \end{cases} \tag{4}$$

Thirdly, the luminance Y image is sharpened by adding this edge adaptive Gaussian second derivative $\delta(x, y)$ to $f(x, y)$ as follows.

$$f'(x, y)=f(x, y)+ \delta(x, y) \tag{5}$$

Finally, the original Y image is replaced by sharpened luminance image Y' and converted into R'G'B' primary color image from luminance-chrominance image by inverse transform.

Filter 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. Fig.3 shows the cross sectional profile of $-\nabla^2 G(x,y)$ in 1-D radial direction. It has the well-known Mexican hat shape with zero cross points at $r_0 = \pm\sqrt{2}\sigma$ and minimum peaks at $r_1 = \pm 2\sigma$.

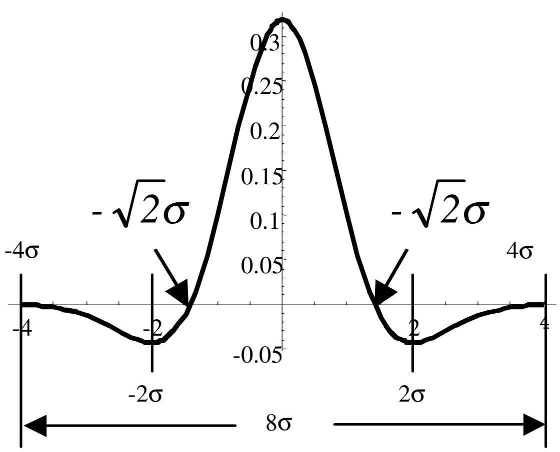


Fig.3 Cross sectional view of GD function

The effective field spreads to $r_2 \cong \pm 4\sigma$ from center. Hence $M \cong 8\sigma$ will be sufficient to reflect the receptive field. For example, 5×5(σ=0.5)~15×15(σ=2.0) matrices may be applied to describe the GD filters. 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 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

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

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.

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

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.

Fig.4 shows a comparison of discrete filter profiles for M=7 with σ=1.0 before vs. after the weights were computed by Eq. (6) and corrected by Eq. (9). In this example, M is a little bit smaller than 8σ, but the positive and negative weights are well adjusted to be zero sum after the correction.

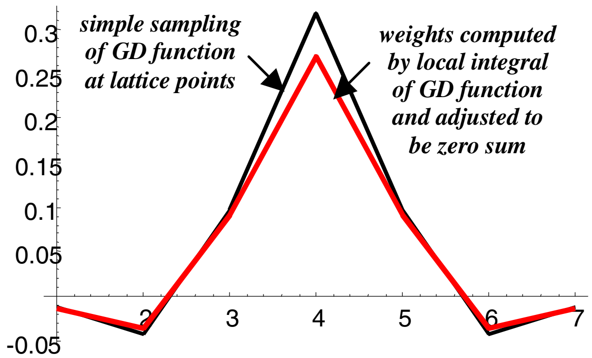


Fig.4 GD filter weights calculated by local integral and adjusted to be zero sum.(M=7 with σ=1.0)

Experimental Results

Fig.5 shows an example of sharpened images by the proposed adaptive method in comparison with non-adaptive method and Fig.6 shows the close-up images :

(a) original
(b) non-adaptive Gaussian derivative
(c) proposed adaptive Gaussian derivative

As clearly viewed in the image (b), the flat area noises are also enhanced together with the edges, but are dramatically reduced in (c), because the enhancement operations are suppressed in the areas with gentle or flat slopes. Moreover, the proposed method provides with smoothed and natural sharpening effects adaptive to the hard, medium, and soft edge slopes in the image.

Fig.7 is the corresponding zone mask image used for switching the three types of edge sharpening filters, and Fig.8 shows the histogram of measured edge strengths. Here, the red, green, and dark blue colors represent the hard, medium, and soft edge zones, respectively. While, the gentle or flat slope areas are shown in white color for the zone mask image in Fig.7 and in gray zone for the histogram in Fig.8.

Fig.9 illustrates a comparison of sharpened image profiles in a typical scan line. In this sample, ***non-adaptive single GD*** method used a single second Gaussian derivative filter with small σ designed to response to the sharp hard edges, while the proposed ***adaptive multiple GDs*** method applied said three types of second Gaussian derivatives adaptively to the selected edge types. The enhanced image profiles in Fig.9 (a) include two different edge zones, that is, (1) mixed edge zone and (2) gentle or flat slope zone. In the proposed method, these different edge slopes are very well sharpened adaptive to the edge strengths without amplifying the background noises, while a single filter method works every where uniformly to enhance all the gradients including unwanted noises. Fig.9 (b) shows how the noises in the flat or gentle slope areas are suppressed in the proposed method.

Discussion and Conclusions

An ***adaptive*** image sharpening method is proposed.

Multiple Gaussian derivative operators have been applied adaptive to the edge strength and resulted in natural sharpness improvements without enhancing the background noises. Here the edge enhancement operators are applied only to the luminance signal. The same process may be applied to RGB tri-color signals simultaneously. However, the edge responses to R, G, and B channel are different one another, then the shears in color for achromatic grayish edges may cause unacceptable artifacts. Because the statistical distributions of edge slopes depend on the image contents, the specifications of pre-scanning GD filter and edge sharpening GD filters should be designed dependent of the given image. The standard deviation σ and the weighting coefficients of GD operators are to be determined by taking the digital matrix sizes into consideration. In our experiments, the sizes of GD filters have been set to 7 x 7 ~ 11 x 11 pixels in practice. The second derivative filter coefficients have been exactly calculated by local integral between the discrete lattice points and adjusted for their sum to be equal to zero.

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 strengths to make the zone mask is based on cut and try or simple division in the min-max range. The automatic generation of optimal zone mask is a future work and is under development. As well, the use of multiple pre-scanning GD filters is now under investigation for the better measurements and classification of edge strengths.

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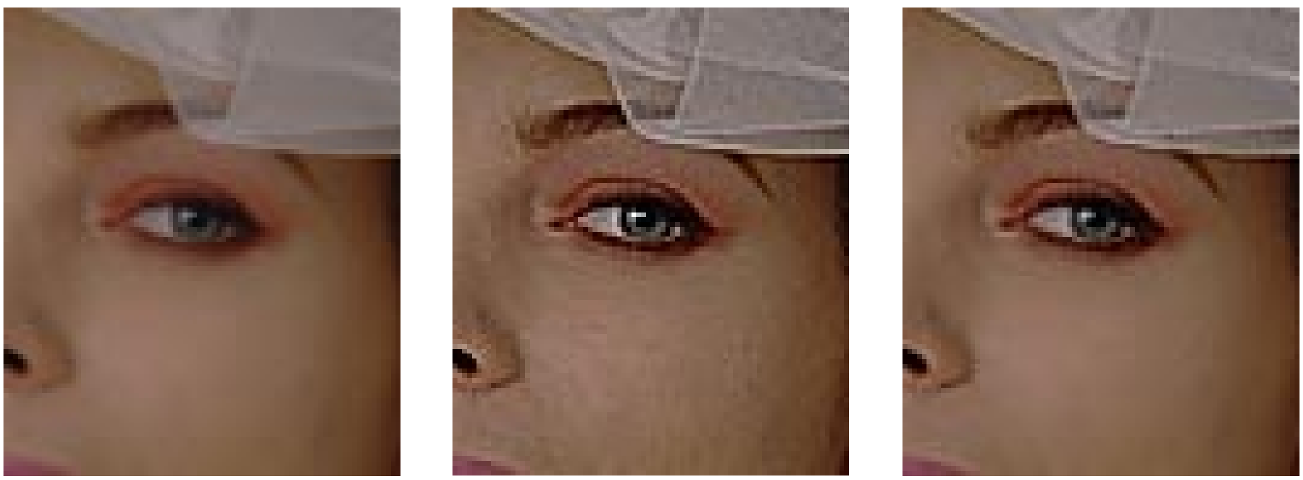
Biography

Hiroaki Kotera received his B.S degree from Nagoya Institute of Technology in 1963 and Doctorate from University of Tokyo in 1987. In 1963, he joined Matsushita Electric Industrial Co. 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.

(a) original image *(b) conventional non-adaptive* ***GD*** *(c) proposed adaptive* ***GD***

Fig.5 Comparison of sharpened images



(a) original image *(b) conventional non-adaptive* ***GD*** *(c) proposed adaptive* ***GD***

Fig.6 Comparison of close-up images

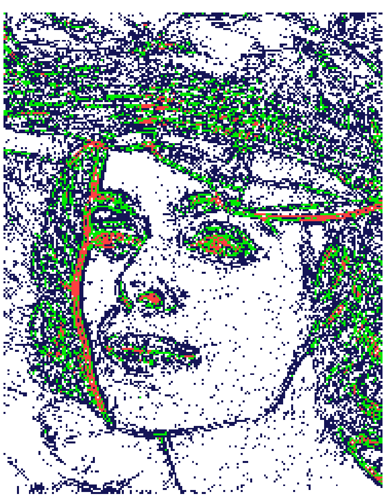


Fig.7 Edge selection zone Mask pattern

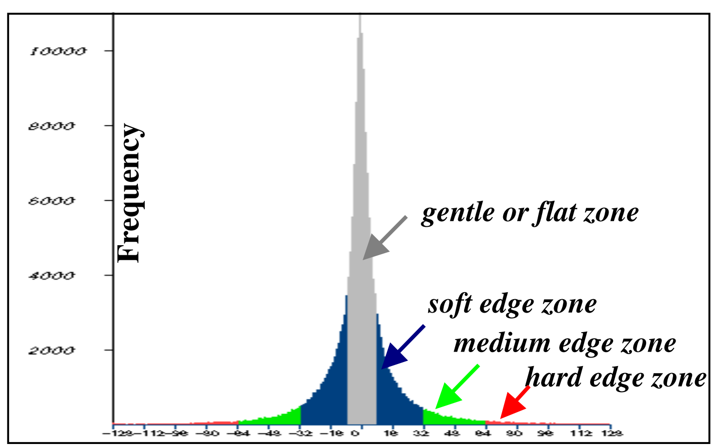
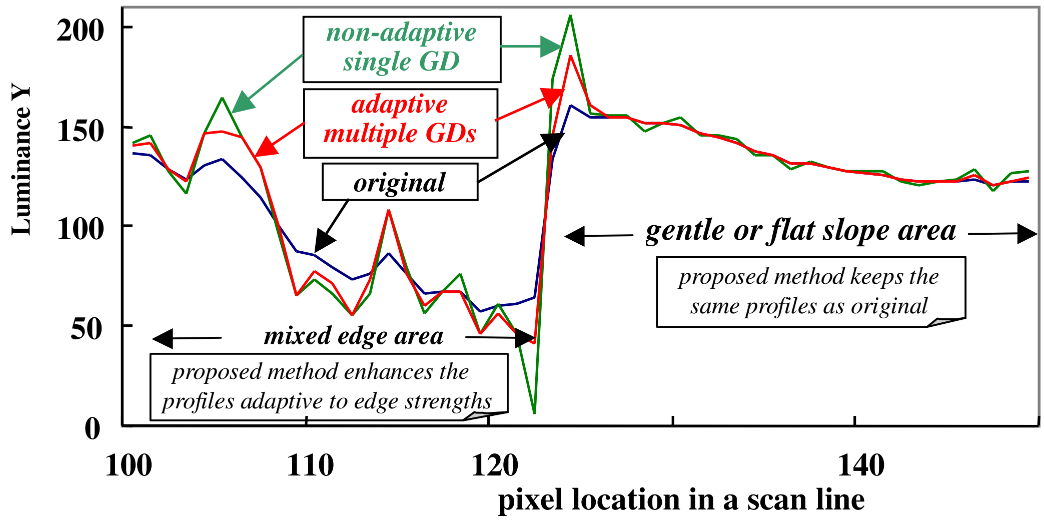
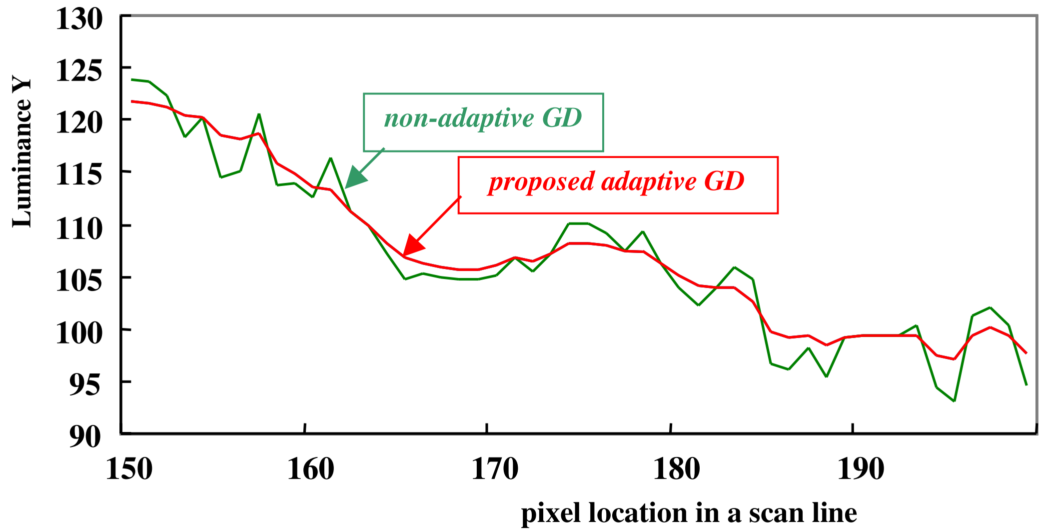


Fig.8 Histgram of edge strength



(a) Comparisons in edge sharpening effect



(b) Comparisons of noises in gentle or flat slope area

Figure 9. Sharpened image profiles in a scan line