Joint Visual Sharpness-Contrast-Tone Mapping Model

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Abstract. Center/Surround (C/S) model of human vision has hinted to improve the sharpness, contrast, and color-tones. To recreate a viewer's sensation in realistic scenes, visual Tone Mapping Operators (TMOs) have been actively developed during past decade and now the spatially-variant TMO is the major stream. Retinex is a root of C/S based vision model which restores the reflectance image by removing the spatial non-uniformities of illumination. This paper proposes a joint sharpness-contrast mapping model cooperating with our adaptive scale-gain MSR (Multi-Scale Retinex). The model is based on the common C/S process with small, medium, and large surrounds. "Sharpness" and "contrast" mappings are unified to a single process choosing a small and medium surrounds, and collaborate with "tone mapping" by MSR using all three surrounds. The new model enhances the visual contrast and sharpness as well as tonal color reproduction under the ill-suited illumination.

Keywords: vision-based, center/surround, tone mapping, contrast, sharpness.

1 Introduction

Center/Surround (C/S) response is a first step in human vision. C/S models are applied to improve image sharpness, contrast, and tonal rendition. To recreate a viewer's sensation in real scenes, spatially-variant Tone Mapping Operators (TMOs) have been actively developed during the past decade [1].

Retinex [2] is a root of C/S-based spatially-variant TMO which restores the reflectance image by removing the spatial non-uniformities of illumination.

Sharpness and contrast are often confused and misleading. The sharpness is mainly related to the higher spatial frequency components carrying edge information. As a vision-based edge detector, Gaussian derivative (GD) is recommended by Young [3], Marr & Hildreth [4] and used for pleasant image sharpening by Kotera [5]. GD is also a base of Laplacian operator. While the contrast means how the each object is visually discriminated from the background, in relation to the middle to low spatial frequency components. We reported a spatially-variant visual contrast mapping operator based on Weber's law [6]. Now, to recreate the viewer's sensation, not only sharpness but also contrast and tonal mappings should be simultaneously taken into account.

The proposed model unifies the sharpness and contrast mappings to a single C/S process and collaborates with our adaptive scale-gain MSR [7], which recovers the shadow range for the images taken under ill-suited illumination.

2 Basic Concept

2.1 Three Basic Surrounds

The three scales of representative surrounds, S_L (large), S_M (medium), and S_S (small) are selectively applied to each process. These large, medium, and small surrounds are mainly related to the tone, contrast, and sharpness mapping respectively as illustrated in Fig.1.

Fig. 1. Basic three surrounds for sharpness, contrast, and tone mappings

2.2 Joint Sharpness-Contrast-Tone Mapping Model

Visual Tone Mapping ~ Use All Surrounds (S_S , S_M , and S_L)

All of three scales of surrounds, S_S , S_M , and S_L are used for the adaptive Scale-Gain MSR (Multi-Scale-Retinex) to improve the tonal color reproduction. It's known that at least three scales of SSRs should be combined to construct a minimum MSR. In general, the large surround S_L plays the most important role and is indispensable for visual tone reproduction.

Visual Contrast Mapping ~ Use Medium Surround S_M

A vision-based Weber contrast is defined based on Weber's law, where a medium scale surround S_M , is used for the contrast enhancement. The kernel size of S_M is chosen for reflecting the middle to low spatial frequencies.

Visual Sharpness Mapping ~ Use Small Surround S_S

A small scale surround S_S is used for Laplacian or USM type of sharpness enhancement. S_S is chosen as a representative reflecting high spatial frequencies in the image edges.

Unified Sharpness-Contrast Mapping in Cooperation with Tone Mapping

The proposed model firstly starts from Retinex process. The contrast and sharpness enhancements are unified to a single process and follow on the heels of Retinex collaborating with tone mapping. Fig.2 illustrates an overview of proposed system model. It shows how the three surrounds are related to sharpness, contrast, and tone mapping.

Fig. 2. Overview of proposed joint visual sharpness-contrast-tone mapping model

3 Visual Tone Mapping by Adaptive Scale-Gain Retinex

The insufficient tonal visibility in the shadow range of images taken under a gloomy illumination or dazzling sunlight is improved by applying Retinex. Retinex removes the spatially-variant illumination layer carrying the most of luminance range in HDR scene and reproduces the scene reflectance within the limited range of LDR display.

Here, our previous Adaptive Scale-Gain MSR (Multi-Scale Retinex) is introduced by integrating the three scales of SSR (Single-Scale-Retinex) with small, medium and large surrounds (S_S , S_M , and S_L).

The MSR output g^{MSR} for an input image f is calculated as follows [7].

$$\begin{aligned}
 g_i^{MSR}(x, y) &= \frac{C}{M} \sum_{m=1}^M A(\sigma_m) \left\{ \frac{f_i(x, y)}{S_m(x, y, \sigma_m)} \right\}; i = R, G, B \\
 S_m(x, y, \sigma_m) &= \langle G_m(x, y) \otimes Y(x, y) \rangle; \langle \otimes \rangle = \text{convolution}, \\
 G_m(x, y) &= K \exp\left[-(x^2 + y^2)/2\sigma_m^2\right]; \text{Gaussian function} \\
 \iint G_m(x, y) dx dy &= 1, \quad C = \text{range adjust constant}
 \end{aligned} \tag{1}$$

where, $Y(x, y)$ denotes the luminance image and S_m ($m=1, 2$, and 3) corresponds to the small, medium and large surrounds of S_S , S_M , and S_L respectively.

The weight $A(\sigma_m)$ is given by the ratio of standard deviation of Y_{SSR} (SSR of luminance image Y) for each scale $m=1 \sim M$ ($=3$) vs. total sum for all scales, which reflects the contribution of SSR to MSR as follows.

$$A(\sigma_m) = M \left\{ \frac{\Sigma_Y(\sigma_m)}{\sum_{m=1}^M \Sigma_Y(\sigma_m)} \right\}, \tag{2}$$

$$\Sigma_Y(\sigma_m) = \sqrt{\frac{1}{XY} \sum_{x=1}^X \sum_{y=1}^Y [Y_{SSR}(x, y, \sigma_m) - \overline{Y_{SSR}}(x, y, \sigma_m)]^2}$$

$$Y_{SSR}(x, y, \sigma_m) = Y(x, y) / S_m(x, y, \sigma_m) = SSR \text{ for } Y$$

$$X \times Y = \text{image size}$$
(3)

4 Visual Contrast Mapping Based on Weber's Fraction

The contrast is defined using luminance Y in different manners such as

(A) Simple Contrast: $C_R = Y_{max} / Y_{min}$

(B) Michelson Contrast: $M_{TF} = \frac{(Y_{max} - Y_{min})}{(Y_{max} + Y_{min})}$

(C) Weber Fraction: $W = \Delta Y / Y$

(D) RMS Contrast: root mean square of Weber fraction

Because *Weber fraction* is a vision-based useful measure for contrast, we already applied it to enhance the local visual contrast [8].

Fig.3 shows the schematic illustration of proposed visual contrast mapping model based on Weber's fraction.

Weber fraction= $\Delta Y/Y$ is a well-known measure for JND (Just Noticeable Difference). It's said we can detect the luminance change ΔY in the viewing center surrounded by the background Y when $\Delta Y/Y \geq 0.02$ for wide range of about $1 \sim 10^3$ or more foot-Lambert.

Now, Weber Contrast W_C is defined by the ratio of output Weber fraction W_{out} vs. input *Weber fraction* W_{in} as

$$W_C(x, y) = W_{out} / W_{in} = \frac{dg(x, y)/g(x, y)}{df(x, y)/f(x, y)} \equiv \frac{\Delta g / g_{ave}}{\Delta f / f_{ave}}, \quad (4)$$

Here, $f(x, y)$ is an input image and $g(x, y)$ is the output image after contrast mapping.

In the previous paper, the differential Eq. (4) was solved to get the output $g(x, y)$, while, this time, we use the more simplified notation by substituting the *difference* for the *differential* like as

$$W_{in}(x, y) = \{f(x, y) - f_{ave}(x, y)\} / f_{ave}(x, y)$$

$$W_{out}(x, y) = \{g(x, y) - g_{ave}(x, y)\} / g_{ave}(x, y) \quad (5)$$

Thus the approximated *Weber Contrast* $W_C(x, y)$ is given by

$$W_C(x, y) = W_{out} / W_{in} = \frac{f_{ave}(x, y)}{g_{ave}(x, y)} \cdot \frac{g(x, y) - g_{ave}(x, y)}{f(x, y) - f_{ave}(x, y)} \quad (6)$$

Assuming the system *Tone Reproduction Curve* $TRC(\bullet)$ is calibrated to be linear and the average luminance value after contrast mapping is maintained as same as that of input, namely

Fig. 3. Schematic illustration of proposed Weber Contrast Mapping model

$$g_{ave}(x, y) = TRC\{f_{ave}(x, y)\} \cong f_{ave}(x, y), \quad (7)$$

Using the medium surround as $f_{ave} \approx S_M$ under the Eq. (7), the output $g^{Cont} = g(x, y)$ to keep the Weber Contrast $W_c \cong \alpha$ (constant) is derived from Eq. (6) as

$$\begin{aligned} g^{Cont}(x, y) &= \alpha f(x, y) - (\alpha - 1)S_M(x, y), \\ S_M(x, y) &= \langle G_M(x, y) \otimes f(x, y) \rangle, \\ G_M &= \text{Gaussian func. with standard deviation } \sigma_M \end{aligned} \quad (8)$$

Eq. (8) is a simplified contrast enhancement solution that keeps the Weber Contrast $W_c \cong \alpha > 1$ to be constant everywhere in the coordinate (x, y) .

5 Visual Sharpness Mapping Based on Diffusion Model

Image blurring is modeled by a partial differential equation as an analogy to thermal diffusion like as

$$\begin{aligned} \partial f / \partial t &= k \nabla^2 f = k(\partial^2 f / \partial x^2 + \partial^2 f / \partial y^2) \\ \text{where, } k &= \text{diffusion constant} \end{aligned} \quad (9)$$

Letting the original image be $f(0)$ at time $t=0$, the blurred image $f(\Delta t)$ after passing time $t=\Delta t$ by thermal diffusion is given by Taylor expansion as

$$f(\Delta t) = f(0) + (\partial f / \partial t) \Delta t + \frac{1}{2} (\partial^2 f / \partial t^2) \Delta t^2 + \dots \quad (10)$$

Neglecting the higher terms than 2nd order and setting the blurring constant to be $k\Delta t = \beta - 1$, we can recover the original sharp image $\mathbf{g}^{sharp} = \mathbf{f}(0)$ from the blurred image $\mathbf{f}(x, y) = \mathbf{f}(\Delta t)$ as

$$\mathbf{g}^{sharp}(x, y) \cong \mathbf{f}(x, y) - (\beta - 1)\nabla^2 \mathbf{f}(x, y). \quad (11)$$

Eq.(11) is just equal to the well-known image sharpening process by USM (Unsharp Mask) or Laplacian operators.

Now, the second derivative $\nabla^2 \mathbf{f}$ (Laplacian) can be replaced by the second-order difference as

$$\nabla^2 \mathbf{f}(x, y) \approx \mathbf{f}(x, y) - \mathbf{f}_{ave}(x, y), \quad (12)$$

Using the small surround as $\mathbf{f}_{ave} \approx \mathbf{S}_S$, finally Eq. (11) is simply described as

$$\begin{aligned} \mathbf{g}^{sharp}(x, y) &= \beta \mathbf{f}(x, y) - (\beta - 1)\mathbf{S}_S(x, y) \\ \mathbf{S}_S(x, y) &= \langle \mathbf{G}_S(x, y) \otimes \mathbf{f}(x, y) \rangle \\ \mathbf{G}_S(x, y) &= \text{Gaussian func. with standard deviation } \sigma_S \end{aligned} \quad (13)$$

Eq. (13) is a simplified sharpness mapping solution that gives the enhancement effect when $\beta > 1$.

It's notable that Eq. (8) and Eq.(13) are described by the same format, only different in their sizes of surround. Sharpness is just equivalent to the contrast when its medium surround $\mathbf{S}_M$ is replaced by the small $\mathbf{S}_S$ and the coefficient α by β . Hence, the sharpness and contrast mapping are considered to be the families each other, so that both are unified to a single simple model.

6 Joint Sharpness-Contrast-Tone Mapping

In practice, think about the sequential mappings of contrast and sharpness for the luminance image $\mathbf{gMSR}$ after tone mapping process by MSR.

First, the output image $\mathbf{g}^{MSR \bullet Cont}$ after contrast mapping for the MSR image $\mathbf{g}^{MSR}$ is described by applying Eq. (8) as

$$\begin{aligned} \mathbf{g}^{MSR \bullet Cont}(x, y) &= \alpha \mathbf{g}^{MSR}(x, y) - (\alpha - 1)\mathbf{S}_M^{MSR}(x, y) \\ \text{where, } \mathbf{S}_M^{MSR}(x, y) &= \langle \mathbf{G}_M(x, y) \otimes \mathbf{g}^{MSR}(x, y) \rangle \end{aligned} \quad (14)$$

Next, performing the sharpness mapping according to Eq. (13) in succession,

$$\begin{aligned} \mathbf{g}^{MSR \bullet Cont \bullet Sharp}(x, y) &= \beta \mathbf{g}^{MSR \bullet Cont}(x, y) - (\beta - 1)\mathbf{S}_S^{MSR \bullet Cont}(x, y) \\ \text{where, } \mathbf{S}_S^{MSR \bullet Cont}(x, y) &= \langle \mathbf{G}_S(x, y) \otimes \mathbf{g}^{MSR \bullet Cont}(x, y) \rangle \end{aligned} \quad (15)$$

Substituting Eq. (14) for Eq. (15) and rearranging the final output for the tone mapped input $\mathbf{g}^{MSR}$,

$$\begin{aligned} \mathbf{g}^{MSR \bullet Cont \bullet Sharp}(x, y) = & \alpha \beta \mathbf{g}^{MSR}(x, y) - \alpha(\beta - 1) \langle \mathbf{G}_S(x, y) \otimes \mathbf{g}^{MSR}(x, y) \rangle \\ & - (\alpha - 1) \beta \langle \mathbf{G}_M(x, y) \otimes \mathbf{g}^{MSR}(x, y) \rangle \\ & + (\alpha - 1)(\beta - 1) \langle \mathbf{G}_S(x, y) \otimes \langle \mathbf{G}_M(x, y) \otimes \mathbf{g}^{MSR}(x, y) \rangle \rangle \end{aligned} \quad (16)$$

Here, the last term in Eq. (16) needs a troublesome double Gaussian convolution.

However, since this double convolution means to carry out a small Gaussian blurring for the medium surround of $\mathbf{g}^{MSR}$, considering $M \gg S$, it's reduced to

$$\langle \mathbf{G}_S(x, y) \otimes \langle \mathbf{G}_M(x, y) \otimes \mathbf{g}^{MSR}(x, y) \rangle \rangle \approx \langle \mathbf{G}_M(x, y) \otimes \mathbf{g}^{MSR}(x, y) \rangle, \quad (17)$$

Thus finally, we get the much simplified solution as follows.

$$\mathbf{g}^{MSR \bullet Cont \bullet Sharp}(x, y) \approx \alpha \beta \mathbf{g}^{MSR}(x, y) - \alpha(\beta - 1) \mathbf{S}_S^{MSR}(x, y) - (\alpha - 1) \mathbf{S}_M^{MSR}(x, y) \quad (18)$$

Where, $\mathbf{S}_S^{MSR}(x, y)$ and $\mathbf{S}_M^{MSR}(x, y)$ denote the small and medium surround for the $\mathbf{g}^{MSR}$ respectively by

$$\begin{aligned} \mathbf{S}_S^{MSR}(x, y) &= \langle \mathbf{G}_S(x, y) \otimes \mathbf{g}^{MSR}(x, y) \rangle \\ \mathbf{S}_M^{MSR}(x, y) &= \langle \mathbf{G}_M(x, y) \otimes \mathbf{g}^{MSR}(x, y) \rangle \end{aligned} \quad (19)$$

The above mentioned contrast and sharpness mappings are performed only to the luminance image $\mathbf{g}^{MSR}$ of Y channel through YIQ luminance-chrominance transform.. Lastly, Y is combined with IQ channels and converted to color image through $YIQ \rightarrow RGB$ transform.

7 Parameters for Optimal SQF Based on MTF Analysis

MTF (Modulation Transfer Function) is a most popular metrics for testing the spatial frequency response of imaging devices. While, CSF (Contrast Sensitive Function) denotes the corresponding human visual performance limited by the eye's optics, cones, and neural system. Both functions are related to measure the image quality.

Granger & Cupery (1972) introduced SQF (Subjective Quality Factor) which correlates with perceived image quality defined by *log-frequency* integration as

$$\begin{aligned} SQF &= K \int_{f_1}^{f_2} CSF(f) MTF(f) d(\log f) = K \int_{f_1}^{f_2} CSF(f) MTF(f) / f df \\ CSF(f) &= 1.0 \text{ for } 3 \leq f \leq 12 \text{ cycles/deg, otherwise } CSF(f) = 0.0 \end{aligned} \quad (20)$$

In practice, CSF is simplified to a rectangular function in the most sensitive frequency range in $f_1=3 \sim f_2=12$ cpd (cycles/deg) for human vision [9]. SQF (or Acutance) has been used for measuring the photographic print quality as an optimal merit function.

While in the proposed joint model, the contrast and sharpness are enhanced for $\alpha > 1$ and $\beta > 1$, while they are kept unchanged when $\alpha = 1$ and $\beta = 1$. On the contrary, in case of $\alpha < 1$ and $\beta < 1$, the surrounds play a role of smoothing filter resulting in noise suppression. Table 1 summarizes the typical sharpness and contrast enhancement effects for the set of parameters (α, β) .

The image enhancement effect with the parameter (α , β) is simulated by using Log frequency MTF test chart as shown in Fig. 4. Each horizontal line in chart is composed of sinusoidal grating in log-scaled cpd and its contrast is modulated vertically corresponding to MTF=0.0 ~ 1.0 from the bottom to top.

Table 1. Enhancement effects for the parameters of (α , β)

α	β	effects
<1	<1	Contrast, Sharpness, both down
<1	=1	Contrast down, Sharpness unchanged
<1	>1	Contrast down, Sharpness up
=1	<1	Contrast unchanged, Sharpness down
=1	=1	Contrast, Sharpness, both unchanged
=1	>1	Contrast unchanged, Sharpness up
>1	<1	Contrast up, Sharpness down
>1	=1	Contrast up, Sharpness unchanged
>1	>1	Contrast, Sharpness , both up

Fig. 4. Improvement in MTF resulting in the better SQF by proposed model

The right half in Fig.4 shows the response profile to the top line with $MTF=1.0$. (b) is a blurred example by camera and (c) ~ (e) show how the MTF is improved by the proposed model. Although the contrast is over enhanced in (d), a quasi-optimal solution with $SQF \approx 1.0$ is obtained by the joint sharpness-contrast process as shown in (e).

8 Experimental Results

In short, the proposed model works to improve the image “contrast”, “sharpness”, and “color-tone” reproduction simultaneously by a collaboration of the joint sharpness-contrast enhancement algorithm with the adaptive scale-gain MSR.

Fig.5 shows a tonal mapping result for the input image “Star Trek Voyager” by our adaptive scale-gain MSR using three scales of surrounds. The weight $A(\sigma_m)$ is automatically calculated for the scales of $\sigma_1=2$, $\sigma_2=8$, $\sigma_3=32$ as illustrated. The Retinex effect dramatically improves the shadow visibility but the sharpness and contrast are still insufficient. It’s shown that the image visibility after MSR is further improved by the synergy effect with the proposed joint sharpness-contrast mapping model.

Fig.6 shows the samples taken by a low-end commercial compact digital camera, The close-up of “clock tower” clearly shows how the sharpness and contrast mappings work to enhance the high and middle spatial frequency components separately and both of them by the joint collaboration.

Fig. 5. Typical appearance improvement by proposed model

Fig. 6. Results for image by a low-end digital camera

Fig. 7. Results for image "Taj Mahal" by a high-end digital camera

Fig.7 is a result applied to the photo taken by a high-end digital camera. In this sample, the adaptive scale-gain MSR works only to improve the shadow visibility in the right side tree. While the delicate textural patterns in marble mausoleum and dome of “Taj Mahal” are better enhanced both in sharpness and contrast as shown in the middle and top close-up views.

The proposed model is highly simplified but has the most striking features in the contrast enhancement process based on vision-based Weber’s law and also in the synergy effect by the collaboration with Retinex. Though a variety of contrast enhancement algorithms have been proposed, most of them are designed independent of vision model, such as generalized histogram equalization [10], histogram warping [11], improved USM [12], correction on screen contrast [13] and so on.

Fig. 8. Comparison with other methods for visual contrast mapping

While the sub-band enhancement algorithm-**A** [14] uses Wavelet and HSV space considering color appearance, but unfortunately doesn't reflect the visual contrast. On the contrary, the vision-based evaluation algorithm-**B** [15] also uses Wavelet, which is an advanced model based on CSF.

Fig.8 shows a comparison between the proposed model and the above two algorithms **A** and **B**. All the test images are picked up from the literatures.

In Fig.8, the enhancement parameters with the proposed model are set to $\alpha > 1.0$ and $\beta = 1.0$ in order to compare the contrast effect only. In a comparison for the image "Mt. Fuji", the proposed model looks to be better than **A** in the details of front city view and in the blue sky color. For the image "Palace", the proposed model is clearly superior to **B** in the visual contrast. The image "Night scene" seems to be much the same at a glance, but looking carefully, the local contrast and detailed visibility are better for the proposed model than **B**.

Through the tested images in Fig.6~Fig.8, the model almost worked well but the parameters (α , β) with the scales (σ_M , σ_S) of surrounds are tuned empirically, because the MTF for the image capture device is unknown. If the degraded MTF for each image is obtained beforehand by any estimation method, the parameters (α , β) may be possible to optimize to maintain $SQF \geq 0.9$ which gives A-class photographic image quality. However, the parameters (β , σ_S) for sharpness and (α , σ_M) for contrast are related to the overlapped spatial frequency ranges in MTF as shown in Fig. 4.

As mentioned in 1. Introduction, the sharpness and contrast are often confused and misleading. It's hard to separate both effects clearly in MTF and also in visual perception. The optimal combination of (β , σ_S) and (α , σ_M) to give the MTF correction to keep $SQF \geq 0.9$ is not unique but many possible solutions may be found. The development in estimation method for image MTF and an image-dependent optimization algorithm is left behind as a future work.

9 Conclusions

The visual effects in the sharpness and contrast are hard to discuss strictly separate. The popular Laplacian or USM operator improves the sharpness by enhancing the higher spatial frequency components carrying the edge information, but enhances the edge contrast at the same time. The C/S based contrast model will be useful for discriminating the object in attention from the background. The sharpness is mainly related to the edges carrying the higher spatial frequency components, while the contrast corresponds to the rather lower to middle spatial frequency components.

The paper proposed a very simple but effective joint sharpness-contrast enhance algorithm based on visual tone mapping by collaboration with adaptive scale-gain MSR. The model is basically grounded on the common C/S concept with small, medium, and large surrounds. The "sharpness" and "contrast" mappings are simply unified to a single algorithm choosing the small and medium surrounds, and connected to the "tone mapping" by MSR with the integration of all three surrounds.

References

1. Reinhard, E., et al.: High Dynamic Range Imaging. Morgan Kaufmann Publisher (2006)
2. McCann, J.J.: Retnex at 40. *Jour. Elect. Imaging* 13(1), 6–145 (2004)
3. Young, R.A.: Oh say can you see? The physiology of vision. In: *Proc. SPIE*, vol. 1453, pp. 92–123 (1991)
4. Marr, D., Hildreth, E.: Theory of edge detection. *Proc. R. Soc. London B* 207, 187–217 (1980)
5. Kotera, H., Wang, H.: Multiscale image sharpening adaptive to edge profile. *Jour. Elect. Imaging* 14(1), 1–17 (2005)
6. Yamashita, H., et al.: Contrast-Gain-Based Visual Tone mapping for Digital Photo Prints. *Jour. IS&T*, 458–468 (2006)
7. Kotera, H., Fujita, M.: Appearance Improvement of Color Image by Adaptive Scale-Gain Retinex Model. In: *Proc. 10th CIC*, pp. 166–171 (2002)
8. Kotera, H., et al.: Visual Contrast Mapping Based on Weber's Fraction. In: *Proc. CIC* 14, pp. 257–262 (2006)
9. Barten, P.G.J.: Contrast Sensitivity of the Human Eye and Its Effect on Image Quality. SPIE Optical Engineering Press (1999)
10. Stark, J.A.: Adaptive Image Contrast Enhancement Using Generalizations of Histogram Equalization. *IEEE Trans. Image. Processing* 9(5), 886–896 (2000)
11. Grundland, M., Dodgson, N.A.: Automatic Contrast Enhancement by Histogram Warping. In: *Proc. Intl. Conf. Computer Vision and Graphics, Warsaw*, pp. 22–24 (2004)
12. Luft, T., et al.: Image Enhancement by Unsharp Masking the Depth Buffer. In: *SIGGRAPH* 2006, pp. 1206–1213 (2006)
13. Lebedev, D.S., et al.: Local Contrast Enhancement for Improving Screen Images Exposed to Intensive External Light. In: *Proc. Graphicon Se7/62* (2009)
14. Xiao, D., Ohya, J.: Contrast Enhancement of Color Images Based on Wavelet Transform and Human Visual System. In: *Proc. IASTED Graphics and Visualization in Eng.*, pp. 58–63 (2007)
15. Huang, K.Q., et al.: Natural color image enhancement and evaluation algorithm based on human visual system. *Computer Vision and Image Understanding* 103(1), 52–63 (2006)