

PAPER

A Contrast Enhancement Method for HDR Image Using a Modified Image Formation Model

Byoung-Ju YUN[†], Member, Hee-Dong HONG^{††}, and Ho-Hyoung CHOI^{††a)}, Nonmembers

SUMMARY Poor illumination and viewing conditions have negative influences on the quality of an image, especially the contrast of the dark and bright region. Thus, captured and displayed images usually need contrast enhancement. Histogram-based or gamma correction-based methods are generally utilized for this. However, these methods are global contrast enhancement method, and since the sensitivity of the human eye changes locally according to the position of the object and the illumination in the scene, the global contrast enhancement methods have a limit. The spatial adaptive method is needed to overcome these limitations and it has led to the development of an integrated surround retinex (ISR), and estimation of dominant chromaticity (EDC) methods. However, these methods are based on Gray-World Assumption, and they use a general image formation model, so the color constancy is known to get poor results, shown through graying-out, halo-artifacts (ringing effects), and the dominated color. This paper presents a contrast enhancement method using a modified image formation model in which the image is divided into three components: global illumination, local illumination and reflectance. After applying the power constant value to control the contrast in the resulting image, the output image is obtained from their product to avoid or minimize a color distortion, based on the sRGB color representation. The experimental results show that the proposed method yields better performances than conventional methods.

key words: modified image formation model, global illumination, local illumination, reflectance, JND-based adaptive smoothing method

1. Introduction

The objective of the imaging pipeline is to transform the original real-world scene into a displayed image. A scene in the “real-world” can cover a large absolute luminance range (up to 9log units) between the highlight and shadows, though typical scenes do not span more than 5log units, so the image rendered on a display is hardly a precise physical match to the original scene,

Recently, imaging technology has advanced such that the capture and storage of a broad dynamic range is now possible, but the output abilities of common desktop display and hardcopy print have not necessarily followed the same advances made in image creation.

Researchers and practitioners in several areas encounter problems similar to those faced during a tone-mapping. It is often desirable to increase image contrast

without introducing artifacts in image processing. A full range of enhancement techniques have been proposed over the last forty years [1]. It includes simple methods such as histogram equalization and gamma correction along with fully developed algorithm [2], [3]. These methods modify the contrast in an image to improve the details of the dark and bright regions. Yet, such contrast corrections are limited because the sensitivity of the human eye changes locally according to the position of an object and the illumination in the scene. Therefore a spatial adaptive method is needed to overcome these limitations [4], and it has led to the development of the center/surround retinex model [5], [6], and multi-scale retinex (MSR) [7], [8].

In the MSR algorithm, several images are created with the center/surround retinex algorithm using various scales of Gaussian filter and then these images are weighted and summed to reduce the halo artifacts (ringing effects) and to enhance the local contrast. Meanwhile, a color restoration process is added to reduce the graying-out caused by enhancing the contrast and averaging the image results [6]. In this case, the chromaticity of the original image is added to the resulting image to enhance the saturation, thereby reducing halo artifacts while improving the local contrast and saturation of the resulting image.

However, MSR estimates the local illumination information by averaging the intensity values for a channel-independent logarithm. So, if the chromatic distribution of the image is not uniform and dominated by a certain chromaticity value, then it can then affect the estimated chromaticity of the local illumination, resulting in an undesirable color distortion as the dominated color.

In order to avoid undesirable color distortion by using non-linear logarithmic space, an adaptive scale-gain retinex (ASR) model was proposed to improve the color appearance without non-linear logarithmic space in the single scale retinex (SSR) and MSR methods [9]. In this method, the surround image is generated from only the luminance image and is used for the R, G, and B channels in common, which maintains the color balance. An automatic setting method for weights adapted to the scale gain was also proposed. However, the computation for weight needs the histogram luminance SSRs corresponding to the multiple scales and this takes too much time with the increasing Gaussian kernel sizes.

For this reason, L. Wang proposed that the integrated-surround retinex (ISR) method use the relative luminance Y-value of YIQ representation instead of using the three RGB

Manuscript received June 7, 2011.

Manuscript revised October 5, 2011.

[†]The author is with School of Electrical Engineering and Computer Science, Kyungpook National University, 1370, SanGyeok-dong, Buk-gu, Daegu, 702-701, Korea.

^{††}The authors are with Department of Mobile Communication Engineering, Kyungpook National University, 1370, SanGyeok-dong, Buk-gu, Daegu, 702-701, Korea.

a) E-mail: chhman2000@msn.com (Corresponding author)

DOI: 10.1587/transinf.E95.D.1112

channels [2]. As the local contrast of luminance preserving the color balance is enhanced by using the multi-scaled process, the result is stable and has high saturation. Unfortunately, both methods were based on a slow gradient in the integrated surround in the center/surround process and thereby have halo-artifacts. In addition, the chromaticity of illumination could not be removed and the enhanced saturation is unnatural compared with the original image because the single smoothing filter for the Y-luminance channel is used. Further, the local adaptation retinal model (LARM) was also proposed by Wang, and it is based on a retinal model [10]. LARM adopted the bilateral filter to reduce the halo-artifacts in the resulting image, so the local contrast is enhanced without any halo-artifacts compared to the original image. However, LARM is based on a non-linear bilateral filter and a single luminance image to compute the surround image and the local contrast in the dark region could not be enhanced in the resulting image. The detail in the resulting image is hardly perceived by human visual system (HVS). Several tone-mapping methods were also proposed [11], [12].

This paper presents a contrast enhancement method using a modified image formation model in which an image is divided into three components: the global illumination, the local illumination, and the reflectance. This proposed method performs the contrast enhancement by using HSV color representation. The global illumination is the global average of all the light in the field of view. The sensitivity of the human eye changes locally according to the position of an object and the illumination in the scene, and it varies adaptively according to minimum color variation in the highlight region. The local illumination is obtained using the just-noticeable difference (JND)-based adaptive filter [13], [14]. This filter is based on the minimum color variation in the local image and Weber's law. The halo-artifacts occur between highlight region and non-highlight regions and can be reduced by using the proper process between the regions. The reflectance is then estimated by dividing the input image by the estimated global illumination and the local illumination to remove the influence of the illumination effects. After applying the power function to control the contrast, the output image is obtained without a channel-independent logarithm to remove or minimize the color distortion, based on sRGB color representation. This paper is organized as follows: Sect. 2 provides an overview of the integrated-surround retinex, Sect. 3 presents the proposed methods of the contrast enhancement, Sect. 4 illustrates the experimental results and evaluations, and Sect. 5 concludes this paper.

2. Overview of ISR Algorithm

The ISR algorithm proposed by Wang [2] is based on the adaptive scale-gain retinex developed by H. Kotera [9] with certain differences distinguishing them from each other. The ISR algorithm adopts a linear space without a logarithmic conversion to avoid any color distortion. Further, the ISR

algorithm uses the luminance channel to form the surround image, and then applies this result to each color channel to maintain the color balance. As such, the main difference is the use of the integrated multi-scale luminance surround from multi luminance surround images using the Gaussian filters with a different standard deviation.

Preserving the color balance is achieved by applying the integrated surround images $S_{sum}(x, y, \sigma_m)$ to each channel in the ISR algorithm. The ISR algorithm is:

$$SSR_{sum}(x, y, \sigma_m) = A \frac{f_i(x, y)}{S_{sum}(x, y, \sigma_m)}; i \in \{R, G, B\}, \quad (1)$$

where, $f_i(x, y)$ and $SSR_{sum}(x, y, \sigma_m)$ are the input image and the image calculated by the retinex, respectively. A is the gain coefficient.

In Eq. (1), $S_{sum}(x, y, \sigma_m)$ is calculated by integrating the different surround images $S_m(x, y, \sigma_m)$ with different adaptive weights $w(\sigma_m)$, in the following calculations:

$$S_{sum}(x, y, \sigma_m) = \sum_{m=1}^M w(\sigma_m) S_m(x, y, \sigma_m), \quad (2)$$

$$S_m(x, y, \sigma_m) = \langle G_m(x, y) \otimes Y(x, y) \rangle, \quad (3)$$

$$\sum_{m=1}^M w(\sigma_m) = 1. \quad (4)$$

Equation (3) shows the calculation of the surround images performed by convolution between the absolute luminance Y images using Gaussian filter $G_m(x, y)$ with a different standard deviation σ_m .

The optimum gain coefficient A and weight $w(\sigma_m)$ are obtained by the "Trial and Error" method based on human vision [2]. As such, the optimum gain coefficients and weights were used according to Wang [2] to compare to the proposed method. As the local contrast of luminance preserving the color balance is enhanced by using the MSR process, the result is stable and has high saturation. However, as a general image formation model (using a single Gaussian filter) is used, the chromaticity of illumination could not be removed and the enhanced saturation is unnatural when compared with the original image.

3. Proposed Method

In the previous section, we argued that conventional methods have known problems, such as graying-out, halo artifacts, a dominated color, and so on. To overcome these problems, a contrast enhancement method in which the V component image ($f_V(x, y)$) of the HSV system is divided into three components of the global illumination ($\hat{I}_G(x, y)$), the local illumination ($\hat{I}_L(x, y)$), and the reflectance ($\hat{r}(x, y)$), is proposed as follows:

$$f_V(x, y) = \hat{I}_G(x, y) \hat{I}_L(x, y) \hat{r}(x, y). \quad (5)$$

To control the contrast, the output image ($\hat{f}_V(x, y)$) in the proposed method is obtained as follows:

$$\hat{f}_V(x, y) = \hat{I}_G(x, y)^\alpha \hat{I}_L(x, y)^\beta \hat{r}(x, y)^\gamma, \quad (6)$$

where, α , β , and γ are constant values for the power function. The power function is used to control the contrast of the output image. The global illumination ($\hat{I}_G(x, y)$) is estimated by using a Gaussian filter. Thereafter, the local illumination is obtained through the JND-based adaptive smoothing filter. The reflectance is represented by dividing the original image by the estimated global illumination and the local illumination to avoid the influence of the illumination effects. Detailed outlines of the three estimated illumination components are described in the following subsections.

3.1 Color Transformation

There are many color models [1], [15], [16], but the proposed method uses HSV representation. HSV color representation is used because the value V (luminance) and color information (hue and saturation) are decoupled. The HSV color model describes perceptual color relationships more accurately than the RGB color model. The conversion from RGB to HSV is calculated as follows:

$$S = \begin{cases} 0 & \text{if } \max = 0 \\ \frac{\max - \min}{\max} \times 255 & \text{otherwise} \end{cases}, \quad (7)$$

$$V = \max \times 255, \quad (8)$$

$$H = \begin{cases} \text{undefined} & \text{if } \max = \min, \\ 60^\circ \times \frac{g - b}{\max - \min} + 0^\circ & \text{if } \max = r \text{ \& } g \geq b, \\ 60^\circ \times \frac{g - b}{\max - \min} + 360^\circ & \text{if } \max = r \text{ \& } g < b, \\ 60^\circ \times \frac{g - b}{\max - \min} + 120^\circ & \text{if } \max = g, \\ 60^\circ \times \frac{g - b}{\max - \min} + 240^\circ & \text{if } \max = b, \end{cases} \quad (9)$$

where, max and min are the maximum and minimum values of the r , g , and b color vectors, respectively and r , g , and b are the color vectors of R, G, and B. The reverse conversion from HSV to RGB is calculated as follows:

$$(r, g, b) = \begin{cases} (v, t, p) & \text{if } (h_i = 0) \\ (q, v, p) & \text{if } (h_i = 1) \\ (p, v, t) & \text{if } (h_i = 2) \\ (p, q, v) & \text{if } (h_i = 3) \\ (t, p, v) & \text{if } (h_i = 4) \\ (v, p, q) & \text{if } (h_i = 5) \end{cases}, \quad (10)$$

where,

$$\begin{aligned} h_i &= \left\lfloor \frac{H}{60} \right\rfloor \bmod 6, \\ f &= \frac{H}{60} - h_i, \\ p &= v \times (1 - s), \\ q &= v \times (1 - s \times f), \\ t &= v \times (1 - (1 - f) \times s), \end{aligned} \quad (11)$$

where, s , h , and v are the vectors of S , H , and V .

3.2 Global Illumination Estimation

In order to estimate the global illumination, we use the iterative Gaussian pyramid generation [17], which is equivalent to convolving an input image ($f_V^{(0)}$) with a set of $h(m)$ and $h(n)$. The estimated global illumination ($\hat{I}_G(x, y)$) can be calculated as follows:

$$\begin{aligned} \hat{I}_G(x, y) &= f_V^{(k)}(x, y) \\ &= \sum_{m \in W_1} \sum_{n \in W_1} h(m)h(n)f_V^{(k-1)} \\ &\quad \cdot (x + 2^{k-1}(m-1) - 1, y + 2^{k-1}(n-1) - 1), \\ &k = 1, 2, 3, \dots, K_G, \end{aligned} \quad (12)$$

where, $f_V^{(k)}$ is the output image after the k th iteration, both $h(m)$ and $h(n)$ are horizontal and vertical direction linear Gaussian filters, respectively. W_1 is the one-dimensional window and K_G refers to the iteration number.

3.3 Local Illumination and Reflectance Estimation

Generally, the sensitivity of the human eye changes locally according to the position of object and the illumination in the scene, and it varies adaptively according to minimum color variation in the highlight region. In fact, the highlight region needs to be detected. One way to preserve the contrast is to apply a linear mapping to the input image, and linear mappings are popular due to the contrast preservation property [18], [19]. J. Bai proposed a color correction method based on S-CIELAB and gazing information to extract the highlight region [20]. However, this method is an image-independent method for detecting the highlight region.

For this reason, we needed to detect the highlight region automatically using image-dependent method. So the proposed method uses a JND-based method to estimate local illumination. The JND-based method is dependent on a linear transformation [12], as follows:

$$JND(x, y) = c_1 \cdot f_V(x, y) + c_2, \quad (13)$$

where, $f_V(x, y)$ is the original V component image, c_1 and c_2 represent arbitrary slope and intercept, respectively.

As shown in Eq. (13), the JND-based method provides a linear transformation and thus can increase the accuracy of color reproduction in imaging applications compared with the conventional methods. The estimated local illumination

is then obtained by using a modified JND-based method, the JND-based adaptive filter, and it is based on the amount of the minimum color variation in the local image and the principles of Weber's law. The key idea of the JND-based adaptive filter is to iteratively convolve the input image with a 3x3 averaging mask whose coefficients reflect the minimum color variation level of the input image. The local illumination ($\hat{l}_L(x, y)$) in Eq. (5) is estimated as the smoothed version of the input image using the JND-based adaptive filter. Then, the local illumination ($\hat{l}_L^{(t+1)}(x, y)$) at the $(t + 1)$ th iteration can be figured as follows:

$$\begin{aligned} \hat{l}_L^{(t+1)}(x, y) &= f_V^{(t+1)}(x, y) \\ &= \frac{1}{N^{(t)}} \sum_{n=-1}^1 \sum_{m=-1}^1 f_V^{(t)}(x+n, y+m) w^{(t)}(x+n, y+m), \end{aligned} \quad (14)$$

where, $f_V^{(0)}(x, y)$ is the original image, $f_V^{(t+1)}(x, y)$ is the output image after $(t + 1)$ th iteration, $N^{(t)}$ and t are the normalization coefficient and iteration number, respectively.

The weight value $w^{(t)}(x, y)$ is given by the following equations:

$$w^{(t)}(x, y) = g(JND^{(t)}(x, y)) = e^{-\frac{JND^{(t)}(x, y)^2}{2k^2}}, \quad (15)$$

where, k represents constant value. If the large k is chosen, all highlight regions disappear, and the result is the same as if Gaussian smoothing was used. If k is chosen to be small, then the entire highlight region is preserved, and no smoothing is performed. According to K. Chen, when the value of k is defined as 7.5, the result shows better performance of contrast enhancement over the value of k [21]. To estimate local illumination the value of k is set as 7.5.

If $JND^{(t)} > 0$, the conduction function $g(\cdot)$ in Eq. (15) is a nonnegative monotonically decreasing function such that $g(0) = 1$ and $g(JND^{(t)}(x, y)) \rightarrow 0$ as $JND^{(t)}(x, y)$ increases, where $JND^{(t)}(x, y)$ represents an amount of the minimum color variation at each pixel (x, y) .

Finally, in order to estimate the reflectance, an assumption that illumination is a constant value has to be made. If the illumination is constant, the influence of the illumination can be removed by computing the first derivative [4]. This works if the two neighboring pixels have the same illumination. Similarly, the reflectance ($\hat{r}(x, y)$) is estimated by dividing the input image ($f_V(x, y)$) by the estimated global illumination ($\hat{l}_G(x, y)$) and the local illumination ($\hat{l}_L(x, y)$) as follows:

$$\hat{r}(x, y) = \frac{f_V(x, y)}{\hat{l}_G(x, y) \hat{l}_L(x, y)}. \quad (16)$$

4. Experimental Results and Evaluations

In order to demonstrate the feasibility of enhancing the contrast, the proposed method is applied to several images. To estimate the global illumination, an iterative low pass filter with coefficients of $h[m] = h[n] = \{0.25, 0.5, 0.25\}$, which is

Table 1 Parameters associated with the viewing condition of the surround.

Viewing condition	Parameters(α, β , and γ)
Average	0.4, 0.3, 0.3
Dim	0.3, 0.2, 0.2
Dark	0.2, 0.3, 0.2

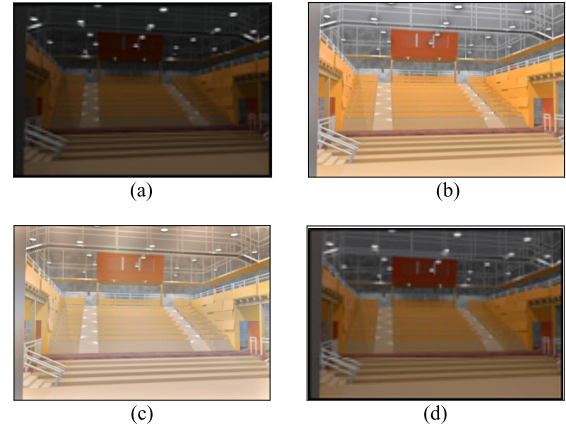


Fig. 1 “Rend03_oB12” image with (a) original image, (b) ISR, (c) EDC, and (d) proposed methods.

approximated to a Gaussian low pass filter, was used. Sixty test images were used to assess the proposed method and to decide the power constant value for the three parameters (α , β , and γ), in Eq. (6). The target images are classified into average, dim, and dark surround images, respectively [22]. There are twenty target images for each surround. Through empirical testing, the three parameters were decided according to the viewing conditions as shown in Table 1.

Figure 1 shows the resulting images. Figure 1(a) is the original image, which is available at the High Dynamic Range Imaging homepage at (<http://www.anywhere.com/gward/hdrenc/pages/originals.html>). Figure 1(b) is obtained based on ISR. We implemented the ISR using Visual C++ source codes according to Wang [2].

The parameter is fixed based on the value suggested in the research paper as $A = 0.2$ and $w_n = \{0.3, 0.1, 0.6\}$ with $\sigma_n = \{2, 16, 128\}$. The resulting image is much improved and without color change. However, the ISR method is based on a slow gradient in the integrated surround in the center/surround process and creates halo-artifacts near the electronic lamps as shown in Fig. 1(b). Figure 1(c) is the resulting image based on the EDC color correction method [23]. We also implemented the EDC method using Visual C++ source codes according to the research paper. The parameter is fixed based on the value suggested in research paper. If the chromatic distribution of the image is not uniform and dominated by a certain chromaticity value in the MSR method, then it can affect the estimated chromaticity of the local illumination, which resulting in an undesirable color distortion as the dominated color.

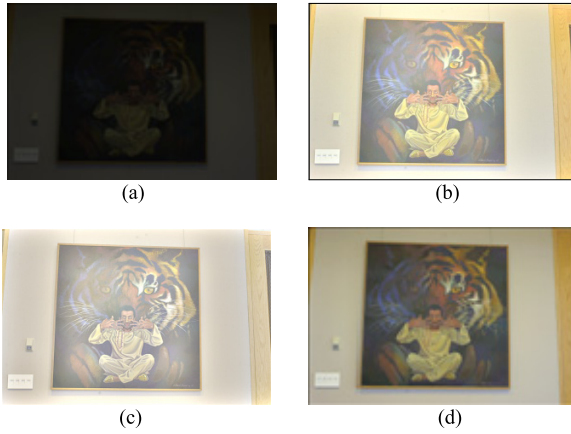


Fig. 2 “Tiger painting” image with (a) original image, (b) ISR, (c) EDC, and (d) proposed.

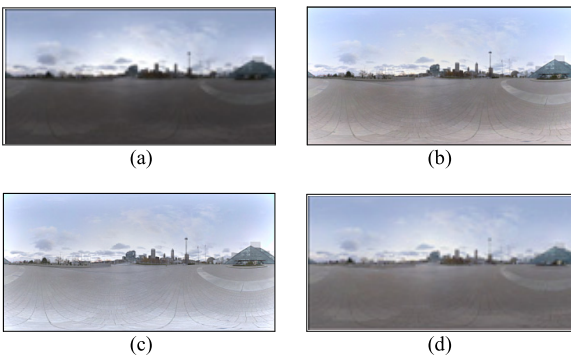


Fig. 3 “A rock-hall” image with (a) original image, (b) ISR, (c) EDC, and (d) proposed.

In order to overcome the dominated problem in the MSR, the EDC method uses the dominant chromaticity information to balance and stabilize the color. The local contrast is enhanced well compared to the original image and MSR method. The EDC method is also based on independent-logarithmic space, and Gray World Assumption like MSR. By using non-linear logarithmic space, the color balance is changed in the resultant image. That is, the resultant image has the dominated color problem throughout the entire image. In addition, the Gray World Assumption yields poor color constancy results, and the resulting image has halo-artifacts near the electronic lamps. On the contrary, the proposed method uses the linear tone-mapping method without the non-linear logarithmic space of the MSR and EDC methods, and the color constancy processing corrects the mismatch between the illumination chromaticity calibrated by the imagine system and the actual illumination of the scene. Additionally, the image is smoothed in the identical spectrum of reasonable range using an adaptive filter in the proposed method. Thus, the dominated color is reduced by using a linear tone-mapping method, and the halo-artifacts are reduced using the JND-based adaptive filter compared to the conventional methods such as ISR, and EDC, as shown in Fig. 1 (d). In addition, the reference colors of the image are

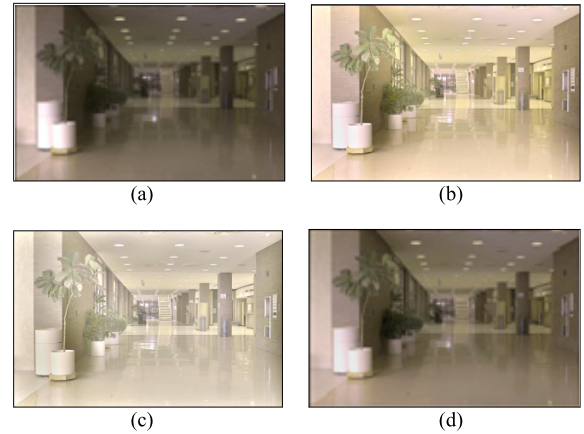


Fig. 4 “A new long hall-way” image with (a) original image, (b) ISR, (c) EDC, and (d) proposed.

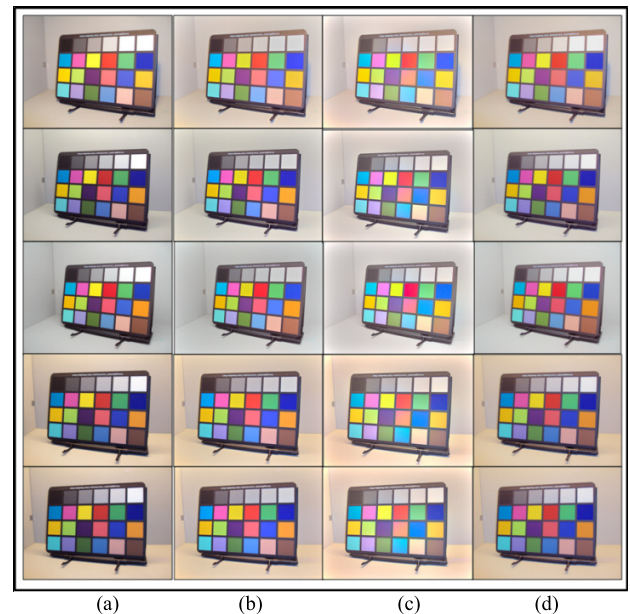


Fig. 5 “Five difference illumination” image with (a) Original image, (b) ISR, (c) EDC, and (d) proposed.

preserved in the resultant image.

Figure 2 shows the resulting images after correcting the color. Figure 2 (a) is the original image. Figure 2 (b) is the resulting image from using ISR. Figure 2 (c) is obtained using the EDC method. To avoid the color change problem (or graying-out) from the MSR and ISR method, this method attempts to do contrast enhancement in the linear space. The color change is improved by using the linear space in the ISR method. However, both ISR method and the EDC methods are based on the Gray-World Assumption, so they still yield poor color constancy result. The resulting image looks washed out and is saturated throughout the entire image. On the contrary, in the case of the proposed method (d), the saturation is greatly enhanced compared with ISR and EDC methods. Figure 3 and 4 show the resulting image. Each (a) is an original image with no processing; each (b) is pro-

Table 2 Comparison of color difference according to illumination.

Illumination	A	CWF	D	TL84	UV
ISR	0.0017	0.0018	0.0009	0.0028	0.0029
EDC	0.0061	0.0032	0.0029	0.0093	0.0078
Proposed	0.0011	0.0017	0.0008	0.0022	0.0024

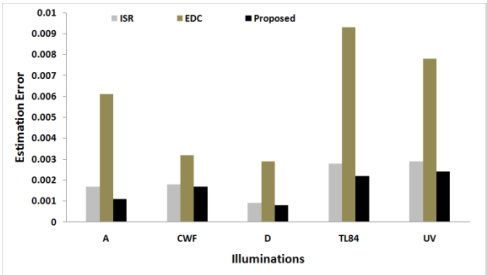


Fig. 6 Comparison of color difference according to illumination.



Fig. 7 Test images for psychophysical experiment.

cessed based on the ISR method, each (c) is processed with the EDC method, and each (d) is processed with the proposed method. The images have similar result as shown in Fig. 1 and Fig. 2.

To evaluate the color preservation performance of the proposed method, we took five images with different standard illuminations (D, CWF, TL84, A, and UV), as shown in Fig. 5, and then stored them using a TIFF image format. Figure 5 (a) is the original image. The resulting images are (b) based on ISR, (c) based on the EDC, and (d) based on the proposed method. Table 2 and Fig. 6 show the estimation error [23], [24] and it is apparent that the proposed method has less estimation error than the conventional methods.

To conduct a subjective evaluation, psychophysical experiments were performed. Fourteen observers with normal color vision participated in the test, and twenty test images were used to assess the contrast enhancement algorithms. Figure 7 shows some of the test images. A pair comparison method was used, where the ISR, EDC, and the proposed method were compared. Since the HVS has a veiling glare limit at the white background in a light room, the psychophysical experiment was conducted in the darkroom. The parameters used for each algorithm were fixed based on the values suggested in the research papers. Each observer

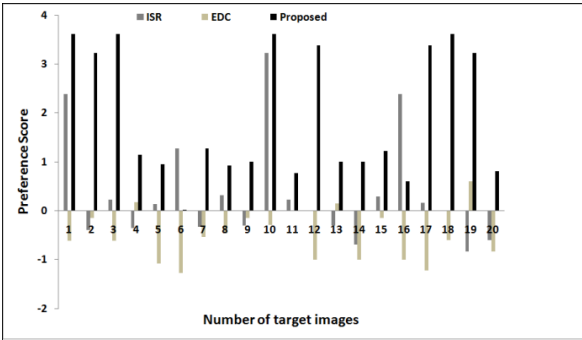


Fig. 8 Preference score for 20 test image samples.

Table 3 Preference score for 20 test image samples.

No.	ISR	EDC	Proposed
1	2.38673	-0.61326	3.61326
2	-0.3933	-0.14447	3.21995
3	0.21995	-0.61326	3.61326
4	-0.35845	0.17922	1.1411
5	0.13694	-1.08031	0.94337
6	1.27805	-1.27435	0.0037
7	-0.33098	-5.40E-01	1.27805
8	0.31502	-0.45592	0.91712
9	-0.31061	-0.14447	0.99936
10	3.21995	-0.29544	3.61326
11	0.22716	0	0.77219
12	0	-0.99936	3.38609
13	-0.31061	0.14447	0.99936
14	-0.68874	-0.99936	0.99936
15	0.29544	-0.14447	1.22652
16	2.38673	-0.99936	0.60605
17	0.16614	-1.22652	3.38609
18	0	-0.60605	3.61326
19	-0.83322	0.60605	3.21995
20	-0.60605	-0.83322	0.80745
average	0.34000	-0.50200	1.91793

Table 4 Comparison of the computation time between conventional methods and proposed method (Unit: sec, image size: 1000 × 656).

Method	ISR	EDC	Proposed
Time	5.429	20.132	1.669

judged a pair of images and assigned a 1 to the selected image and a 0 to the rejected image. In case of a tie, a 0.5 was assigned to each image. The scores were then added and converted into preference scores [25]. Figure 8 and Table 3 show the preference scores of each algorithm for the twenty images. The average preference score for images processed with the proposed method is much higher than those processed by the conventional methods.

Table 4 shows the comparison of the computation time

of conventional methods and the proposed method. To calculate the computation time, we used a CPU with 3.0 GHz clock speed. The size of the target image is 1000×656 pixels. The proposed method remarkably reduced the computation time compared to the conventional methods.

5. Conclusions

In the conventional methods like ISR, and EDC, the resulting image has several problems, such as halo artifact, graying-out, and dominated color. The halo-artifacts are caused by a single Gaussian filter, and graying-out and dominated-color occur by using non-linear space for the channel-independent logarithm in the MSR algorithm.

Therefore, the proposed method uses a contrast enhancement method for HDR images using a modified image formation model. By using the JND-based adaptive filter, halo-artifacts are remarkably reduced compared to the conventional method. Additionally, the proposed method uses a linear process (as product of the global illumination, the local illumination and the reflectance components) without a channel-independent logarithm to avoid or minimize a color distortion in the form of graying out and dominated color. As result, the local contrast and image detail are greatly improved without any color distortion, and the saturation is restored. The proposed method also remarkably reduced the computation time; it went down to 87.4% when compared to the EDC method. In addition, the proposed method has less estimation error than conventional methods. The proposed method showed a higher preference score in the psychophysical experiment as well. Future studies in this area of research will investigate a method for improving global and local contrast based on the lightness and the chroma adaptations of the HVS.

References

- [1] R.C. Gonzalez and R.E. Wood, Digital Image Processing, Prentice Hall, Englewood Cliff, NJ, 2002.
- [2] L. Wang, T. Horiuchi, and H. Kotera, "High dynamic range image compression by fast integrated retinex method," Journal of Imaging Science and Technology, vol.51, pp.34–43, 2007.
- [3] T. Watanabe, Y. Kuwahara, A. Kojima, and T. Kurosawa, "Improvement of color quality with modified linear multi-scale retinex," Proc. SPIE 5008, pp.59–69, 2003.
- [4] M. Ebner, Color constancy, Wiley, London, 2007.
- [5] D.J. Jobson, Z. Rahman, and G.A. Woodell, "Properties and performance of a center/surround retinex," IEEE Trans. Image Process., vol.6, no.3, pp.451–462, 1997.
- [6] B. Funt, F. Ciurea, and J. McCann, "Retinex in MATLABTH," J. Electronic Imaging, vol.13, pp.48–57, 2004.
- [7] Z. Rahman, D.J. Jobson, and G.A. Woodell, "Retinex processing for automatic image enhancement," J. Electronic Imaging, vol.13, pp.100–110, 2004.
- [8] G.A. Woodell, D.J. Jobson, and Z. Rahman, "Method of improving a digital image having white zones," US Patent Application 2003/0, 026, 494 AI, 2004.
- [9] H. Kotera and M. Fujita, "Appearance Improvement of color image by adaptive scale-gain retinex," Proc. 10th Color Imaging Conference, pp.166–171, 2002.
- [10] L. Wang, T. Horiuchi, H. Kotera, and S. Tominaga, "HDR image compression and evaluation based on local adaptation using a retinal model," J. SID, vol.15, no.9, pp.731–739, 2007.
- [11] M. Ashikhmin, "A tone mapping algorithm for high Contrast images," Eurographics Workshop on Rendering, pp.1–11, 2005.
- [12] G. Ward, High Dynamic Range Imaging, ELSVIER, 2005.
- [13] J.J. McCann, "Local/global mechanisms for color constancy," Die Farbe, vol.34, pp.275–283, 1987.
- [14] B.W. Keelan, Handbook of Image Quality Characterization and Prediction, New York, Basel, 2002.
- [15] M.D. Fairchild, Color Appearance Models, Second Edition, John Wiley & Sons, 2005.
- [16] H.R. Kang, Computational Color Technology, SPIE, 2006.
- [17] P.J. Burt and E.H. Adelson, "The Laplacian pyramid as a compact image code," IEEE Trans. Commun., vol.COM-31, no.4, pp.532–540, 1983.
- [18] K. Barnard and B. Funt, "Investigations into multi-scale retinex," Colour Imaging Vision and Technology, pp.9–17, 1999.
- [19] G. Ward, A contrast-based scaled factor for luminance display, In Paul Heckbert, editor, Graphics Gems IV, Academic Press, Boston, 1994.
- [20] J. Bai, T. Nakaguchi, N. Tsumura, and Y. Miyake, "Evaluation of image corrected by retinex method based on S-CIELAB and gazing information," IEICE Trans. Fundamentals, vol.E89-A, no.11, pp.2955–2961, Nov. 2006.
- [21] K. Chen, "Adaptive smoothing via contextual and local discontinuities," IEEE Trans. Pattern Anal. Mach. Intell., vol.27, no.10, pp.1552–1567, 2005.
- [22] R.W.G. Hunt, The Reproduction of Color, 6th ed., John Wiley & Sons, 2004.
- [23] I.-S. Jang, K.-H. Park, and Y.-H. Ha, "Color correction by estimation of dominant chromaticity in multi-scaled retinex," J. Imaging Science and Technology, vol.53, no.5, pp.050502-1–050502-11, 2009.
- [24] O.-S. Kwon, Y.-H. Cho, Y.-T. Kim, and Y.-H. Ha, "Illumination Estimation Based on Valid Pixel Selection from CCD Camera Response," J. Imaging Science and Technology, vol.49, no.3, pp.308–316, 2005.
- [25] J. Morovic, Color Gamut Mapping, Wiley, London 2008.



Byoung-Ju Yun received a B.S. degree in Electronics Engineering from Kyungpook National University, Daegu, Korea, in 1993 and M.S. and Ph.D. degrees in Electrical Engineering and Computer Science from Korea Advanced Institute of Science and Technology, Daejeon, Korea, 1996 and 2002, respectively. From 1996 to May 2003, he worked at Hynix Semiconductor Inc., where he was a senior engineer. Since June 2003, he has been with the School of Electrical Engineering and Computer Science, Kyungpook National University, where he is a professor. His current research interests include image processing, MPEG-4, H.264, Color correction, computer vision, SVC, HCI, and multimedia communication systems.



Hee-Dong Hong received his B.S. in Industrial Engineering from Korea Advanced Institute of Science and Technology, Daejeon, Korea, and his M.S. degree in Industrial and Mechanical Engineering from POSTECH, Korea, in 1996 and 1998, respectively. Now, he is working toward his Ph.D. degree at the Mobile Communication Engineering, Kyungpook National University, Korea. His research work focuses on smart learning, image processing, color constancy, computer vision, and multimedia com-

munication system.



Ho-Hyoung Choi received his B.S. degree in Computer and Electronics Engineering from Gyeongju University and his M.S. degree in Computer and Electronics Engineering from Gyeongju University, Korea, in 1997 and 2003, respectively. Now, he is working toward his Ph.D. at the Mobile Communication Engineering, Kyungpook National University, Korea. His research work focuses on color correction algorithms, color constancy, image processing, machine vision, and computer vision.