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Color Constancy Algorithm Using Weighted Multi-scale Correction Coefficients

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Abstract

The degraded images can be improved by image quality enhancement techniques considering color, contrast, and various other parameters related to images. Based on color constancy, the previous image enhancement algorithms, such as white patch assumption (WPA) and gray world assumption (GWA) algorithms, have several limitations. The color correction of resulting image has an antagonistic effect if the local region of an input image is biased by an individual color. Also, the correction result is degraded when the image does not have any white patches. Furthermore, the resulting image has low saturation, which degrades the correction result if images have monotonic color. To improve on these limitations, this paper proposed a color image enhancement algorithm based on the weighted multi-scale compensation coefficients using GWA algorithm. The multi-scale Gaussian filter is used for computing average values of local and global degraded color and calculating correction coefficients for size, pixel, and channel of multi-scale filtered images independently based on the brightness of the image. Then, the weights are determined for weight-sum of multi-scale correction coefficients by analyzing local color distribution of the image. Finally, the degraded color is improved by utilizing correction coefficients, which are integrated in original image, and degraded color saturation is improved using the proposed weights. The experimental results have shown that, compared with previous algorithms, the proposed algorithm improved color and contrast of various degraded image and produced better correction results.

Introduction

In various image processing studies, the color enhancement algorithms have considered characteristics of a human vision. A human visual system is capable of perceiving a scene consistently, regardless of changes in lighting conditions. This phenomenon is known as color constancy [1]. When digital images are captured using a camera, both their color and intensity are influenced by an illuminant. If color change phenomenon on the captured images is regarded as color cast, the computational color constancy methods might be applied to enhance the color of images captured under the illuminant.

During a later stage of these studies on the human visual system, Jobson et al. developed the designator theory into single-scale Retinex (SSR) method and further into multi-scale Retinex (MSR) method [2-4]. As MSR method initially experienced problems which were related to appropriate values for parameters, chromatic unbalance, color distortion, noise, and graying-out, a lot of research has been dedicated to improve these issues. Thus, MSR method with color correction was developed to overcome the graying-out phenomenon in large uniform areas in an image by adopting color correction function to control saturation of the final rendition [5]. To improve color rendition, integrated MSR (IMSR) method was introduced to improve visibility in dark shadow areas of natural color images while preserving a pleasing contrast without banding artifacts [6]. In this case, Gaussian pyramid decomposition is employed to reduce the computation time for generating a large-scale surround, while an integrated surround value for luminance is applied to each channel to preserve color balance in RGB color space. To improve color balance in IMSR method for visibility enhancement, Kyung et al. proposed the enhanced IMSR method in CIELAB color space [7]. To preserve hue values, IMSR method was applied to lightness values for visibility enhancement. Subsequently, the saturation compensation using a gamut extension was performed to enhance saturation in dark areas in the resulting image. However, IMSR method and the enhanced IMSR method cannot correct degraded color images because of their preservation of color balance in input image.

In this paper, the weighted multi-scale compensation coefficients using gray world assumption (GMA) algorithm are proposed to enhance color image with local color cast and low contrast. The multi-scale Gaussian filters are applied for computing both local and global degraded colors, which are based on brightness of an image, are used for calculating correction coefficients for size, pixel, and channel of multi-scale filtered images independently. In this step, the tone reproduction based on IMSR method is applied to luminance of multi-scale filtered images, and the resultant luminance image is used when calculating correction coefficients. Subsequently, the weights are determined for the weighted sum of multi-scale correction coefficients by analyzing local color distribution of an image. It overcomes drawbacks of GWA algorithm, such as graying-out and over-enhancement into the opposite color. Finally, the degraded color is improved by utilizing correction coefficients integrated in the original image and its saturation is improved by the proposed weights.

Conventional image enhancement method

Most color constancy methods assume that the perceptual color is a product of reflectance and illuminant. The reflectance of an object can be calculated from perceptual color by estimating an illuminant. These methods are based on the theory of color image formation. The intensity I measured by a camera sensor at position (x,y) can be modeled as

$$I(x,y) = E(x,y)\int R(\lambda,x,y)L(\lambda)S(\lambda)d\lambda \qquad (1)$$

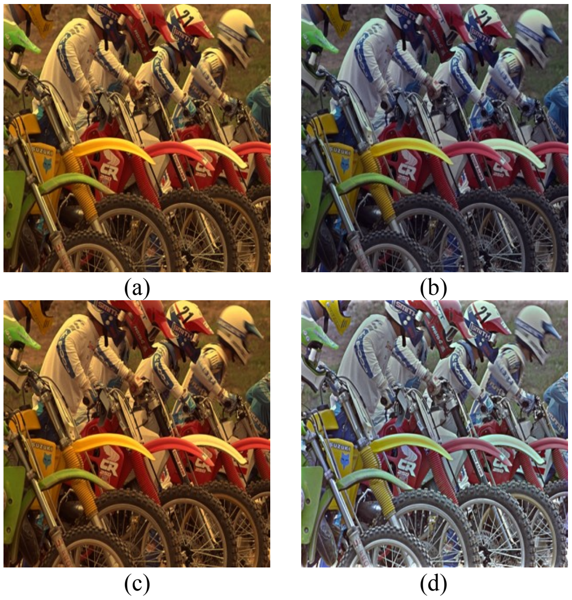


Figure 1. Results of GWA, WPA, and MSR: (a) original image, (b) resulting image by GWA, (c) resulting image by WPA, and (d) resulting image by MSR.

In Eq. (1), $E(x,y)$ is scaling factor resulting from geometry of patch at position (x,y), $R(\lambda,x,y)$ denotes reflectance at position (x,y), $L(\lambda)$ is radiance given off by light source, and $S(\lambda)$ describes sensitivity of sensors [8]. It is assumed that the response functions of the sensors have a very narrow-band, i.e. they can be approximated by a delta function.

Let λ_i with $i \in \{r,g,b\}$ be wavelengths to which sensors respond. Under a nonuniform illuminant, the intensity measured by sensor can be modeled as follows [1].

$$I_i(x,y) = E(x,y)R_i(x,y)L_i(x,y) \tag{2}$$

In Eq. (2), $E(x,y)$ is factor that depends on scene geometry, $R_i(x,y)$ is reflectance for wavelength λ_i, and $L_i(x,y)$ is irradiance at position (x,y) for wavelength λ_i.

Gray world assumption algorithm

A gray world assumption (GWA) algorithm was originally proposed by Buchsbaum [9] and estimated a illuminant by assuming the existence of a certain standard spatial spectral average for total visual field. For an image with size of $M \times N$, $I_R(x,y)$, $I_G(x,y)$, and $I_B(x,y)$ denote red, green, and blue channels of the image, respectively. Then, the average values R_{avg}, G_{avg}, and B_{avg} are calculated as

$$R_{avg} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I_r(x,y) \tag{3}$$

$$G_{avg} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I_g(x,y) \tag{4}$$

$$B_{avg} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I_b(x,y) \tag{5}$$

GWA keeps the green channel unchanged and defines the correction ratio for the red and blue channels as

$$\hat{\alpha} = \frac{G_{avg}}{R_{avg}} \text{ and } \hat{\beta} = \frac{G_{avg}}{B_{avg}} \tag{6}$$

Then, the red and blue pixels can be adjusted by

$$I_{GWA,r}(x,y) = \hat{\alpha} I_r(x,y) \tag{7}$$

$$I_{GWA,b}(x,y) = \hat{\beta} I_b(x,y) \tag{8}$$

Multi-scale Retinex algorithm

To consider the local illumination effect, multi-scale Retinex (MSR) method uses Gaussian filters based on a center/surround model [3,4]. The center/surround models imply the estimates of luminance L around a pixel based on averaging an image I using Gaussian filter F_n. The MSR method composes the integrating multiple SSR_s using different scales and weights, so that the resulting image O for Gaussian filters with various scales is averaged with different weights using the following computation.

$$O_i(x,y) = \sum_{n=1}^{N} w_n \left\{ \log I_i(x,y) - \log\left\{F_n(x,y)\cdot I_i(x,y)\right\}\right\} \tag{9}$$

$$F_n(x,y) = Ke^{-(x^2+y^2)/\sigma_n^2} \quad \text{and} \quad \iint F_n(x,y)dxdy = 1 \tag{10}$$

In Eq. (9), w_n represents weight of the n-th scale. While the result of single Retinex using a small-scale Gaussian filter only includes the detail with graying-out, the result of single Retinex using a large-scale Gaussian filter includes more chromaticity information. Thus, the local contrast and color rendition can be simultaneously obtained based on the weighted summation of these results. Fig. 1 (d) shows the resulting image from MSR method and is corrected with local contrast enhancement. Notwithstanding, MSR method produces a chromatic unbalance.

Proposed weighted multi-scale compensation algorithm

The weighted multi-scale compensation algorithm is proposed to correct degraded color images. The proposed method is composed of three processes, which are color enhancement, tone reproduction, and saturation compensation. In color enhancement process, the multi-scale Gaussian filters are used to estimate partially and completely degraded color. In tone reproduction process, the enhanced luminance image using IMSR method is calculated from luminance images that were obtained from multi-scale filtered images. As the final process, the saturation compensation is performed using a compensation model according to local weights.

Calculation of multi-scale correction coefficients

To correct partially the degraded color, the proposed method uses a multi-scale technique to calculate multi-scale correction coefficients. Moreover, to obtain correction coefficients, the degraded input image with size of $M \times N$ is first blurred using

Gaussian filters. The Gaussian filtered images $g_{i,k}(x,y)$ are calculated by

$$g_{i,k}(x,y) = G_k(x,y) \cdot I_i(x,y) \tag{11}$$

$$G_k(x,y) = Ke^{-(x^2+y^2)/\sigma_k^2} \quad \text{and} \iint G_k(x,y)dxdy = 1 \tag{12}$$

In Eq. (11), k is scale number, i is color channel such as R, G, or B, and σ_k are sizes of Gaussian filters. In the proposed method, the kernel sizes for small and medium filters are 2 and 16, while big filter is replaced by average value of each channel to reduce computational costs.

Then, the point-wise correction coefficients $CR_{i,k}(x,y)$ for each scale k are calculated using

$$CR_{i,k}(x,y) = \frac{L'_k(x,y)}{g_{i,k}(x,y)} \tag{13}$$

In Eq. (13), $L'_k(x,y)$ is enhanced luminance, which is calculated in tone reproduction process. The calculation of coefficients is similar to Eq. (6) in GWA method. To apply correction coefficients to GWA, these coefficients are shown to be integrated by scale using weights. Thus, the integrated correction coefficients $CR_{i,sum}(x,y)$ are as follows.

$$CR_{i,sum}(x,y) = \sum_{k=1}^{3} CR_{i,k}(x,y) \cdot w_k \tag{14}$$

$$\sum_{k=1}^{3} w_k = 1 \tag{15}$$

In Eq. (15), w_k is weight for each scale k. Then, the proposed method adjusts R, G, and B pixels using $CR_{i,sum}(x,y)$. The resulting image $\hat{I}$ is calculated by

$$\hat{I}_i(x,y) = I_i(x,y) \cdot CR_{i,sum}(x,y) \tag{16}$$

Determination of Weights for Weighted Sum of Compensation Coefficients

The proposed method produces various resulting images depending on the combination of weights. The weights of ω_1 were determined according to the number of colors in the local region. The normalized number of colors in local region $nh(x,y)$ can be derived as follows:

$$nh(x,y) = \frac{nh_{nm}(x,y)}{n \times m} \tag{17}$$

In Eq. (17), $n \times m$ is total number of pixels in local region and $nh_{local}(x,y)$ is the number of colors in same region. Note that value of ω_1 was linearly selected according to the normalized number of colors in local regions.

$$w_1(x,y) = 0.7 \cdot nh(x,y) + 0.1 \tag{18}$$

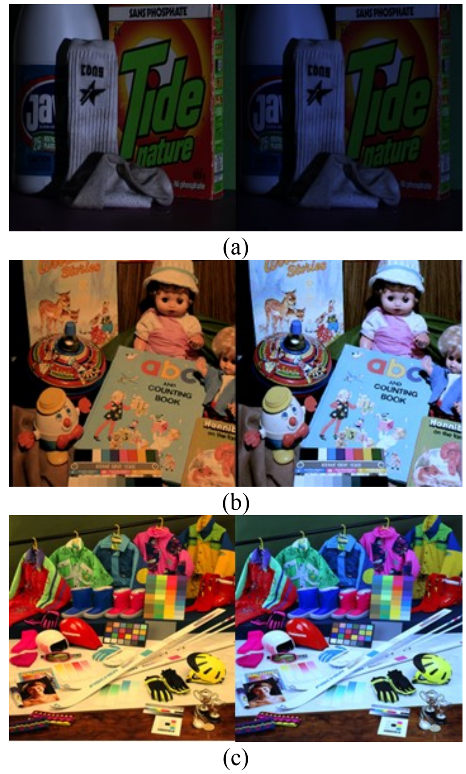


***Figure 2**. Test image pairs for color constancy (4000K and 10000K).*

The degree of local correction was determined by adjusting the value of ω_1 via distribution of colors in image. The overall color balance of the image can be unbalanced because the filter size affects the weight value of ω_2. Therefore, a fixed value of 0.1 on ω_2 is used and the value of ω_3 is determined after the value of ω_1 is determined.

Tone reproduction based on MSR algorithm

A tone reproduction is extensively used in the field of image enhancement, especially to provide proper luminance such that captured images provide the same sensation as real scene. In the proposed degraded color correction with a tone reproduction method, the Gaussian filtered images g_k are firstly converted to luminance images L_k using an RGB to YCbCr conversion. Then, the multi-scale luminance images are integrated to produce the integrated blurred images $L_{sum}(x,y)$.

$$L_{sum}(x,y) = \sum_{k=1}^{3} L_k(x,y) \cdot \rho_k \tag{19}$$

In Eq. (19), ρ_k is weight for each k. In the proposed method, ρ_k is determined according to IMSR method [17]. The tone reproduced image is then obtained using the image formation model in Eq. (2). The reproduced luminance image $L'_k(x,y)$ is given by

$$L'(x,y) = \alpha \cdot \frac{L_{in}(x,y)}{L_{sum}(x,y)} \tag{20}$$

In Eq. (20), L_{in} is luminance of input image and α is adaptation parameter which is determined as 0.8 according to IMSR method. Next, to calculate the correction ratio L'_k is obtained using Gaussian filter for each scale k.

$$L'_k(x,y) = G_k(x,y) \cdot L'(x,y) \tag{21}$$

Saturation compensation

The low saturation or grayish color is presented in the resulting images. Consequently, a saturation compensation is required. To enhance the saturation, we performed experiments to determine the amount of saturation. In the experiment, every candidate image for input images is calculated, and then average saturation for each image is calculated. The reducing average saturation model cs is given by

$$cs(x,y) = 0.0023w_1^2(x,y) - 0.1077w_1(x,y) + 1.1087 \tag{22}$$

Then, the compensated saturation $C'(x,y)$ is as follows.

$$C'(x,y) = \frac{C_{in}(x,y)}{cs(x,y)} \tag{23}$$

Experiments and results

To measure the performance of each algorithm to conduct color constancy, the average ΔEa^*b^* distance [10] across all the corresponding pixels is computed between two images of the same size.

$$\Delta Ea^*b^* = \frac{\sum_{p \in \mathrm{Image}} \sqrt{(L_2^*(p) - L_1^*(p)) + (a_2^*(p) - a_1^*(p)) + (b_1^*(p) - b_2^*(p))}}{N \times M} \tag{24}$$

From the mathematical point of view, this measure allows the idealized color constancy. $\Delta Ea^*b^*=0$ indicates a perfect discount of an illuminant and consequently an absolute perception of reflectance of the objects. Such the separation between the illuminant spectral distribution and spectral reflectance objects does not happen in real conditions. The human visual system performs significant, but incomplete adaptation [11]. Thus, the significance of this measure can be observed from the variation of its value after adjustment.

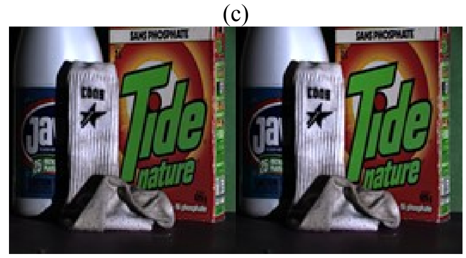
Table 1. ΔEa^*b^* values for color constancy according to test images

	Input image	GWA method	WPA method	MSR method	Proposed method
(a)	14.249	3.174	2.588	5.268	4.266
(b)	49.629	14.826	18.911	17.238	18.940
(c)	45.073	15.282	20.210	7.923	9.218
Average	**40.904**	**13.408**	**18.292**	**9.417**	**9.129**

(a)

(b)

(c)



(d)

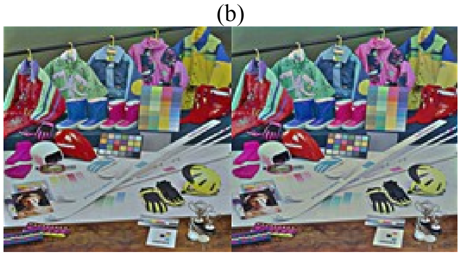
***Figure 3**. Resulting images of test color constancy for Fig. 2(a): (a) GWA, (b) WPA, (c) MSR, and (d) proposed method.*

Fig. 2 shows the images used for experiments to compare color differences. The test images from Fig. 2 (a) to (c) are acquired by capturing the same scenes with different illumination and transforming the color temperature (4000K and 10000K) using the von Kries model.

Table 1 shows the calculation of the resulting image with different algorithms for each test image pair and shows the color difference between test images and resulting images using Eq. (24). As has been mentioned previously, this result can determine the enhancement of images that humans perceive with given input images. According to Table 1, the results show that the color difference in image pairs of WPA method is mostly higher than other methods, while the proposed method has the lowest average error compared to other methods. The results shown in Fig. 3 indicate the lowest color difference using GWA method, but visibility decreases with low contrast. Note that MSR shows the lowest color difference on all the test images. However, understanding whether the color has been enhanced is difficult because images tend to be grayish, as shown in Fig. 4. As a result, on the proposed method, the performance of aspects of color

(a)

(b)



(c)

(d)

***Figure 4**. Resulting images of test color constancy for Fig. 2(c): (a) GWA, (b) WPA, (c) MSR, and (d) proposed method.*

constancy can be satisfied with results similar to different aspects of the identical scene.

Conclusion

The weighted multi-scale correction coefficient based on gray world assumption (GWA) algorithm that enhances color in both completely and partially degraded images is proposed. To enhance the degraded colors of a local region, the multi-scale correction coefficients are calculated using Gaussian filtered images, which are based on GWA algorithm. Then, the weights are determined using the number of hues in the local region. The proposed method overcomes the drawback of various algorithms using GWA. Furthermore, a tone reproduction method is applied to enhance the visibility of a degraded image based on IMSR method. Next, the weighted sum of multi-scale correction coefficients is determined using calculated weights for each pixel. To compare the performance between previous and the proposed method, quantitative evaluations for color constancy were conducted. The proposed method produced low color difference using various degraded images. Thus, the proposed method produced color enhancement for various degraded images with low contrast.

References

[1] G. Wyszecki and W.S. Stiles, *Color Science:* Concepts and Methods, Quantitative Data and Formulas, J. Wiley & Sons, New York, 1982.

[2] E. H. Land, "Recent advances in Retinex theory and some implications for cortical computations: Color vision and the natural image," Proceedings of the National Academy of Sciences of the United States of America, vol. 80, no. 16, pp. 5163–5169, 1983.

[3] Z. Rahman, "Properties of a center/surround Retinex: Part 1: Signal processing design," NASA Contractor Report 198194, pp. 13, 1995.

[4] D. J. Jobson and G. A. Woodell, "Properties of a center/surround Retinex: Part 2: Surround design," NASA Technical Memorandum 110188, pp. 15, 1995.

[5] Z. Rahman, D. J. Jobson, and G. A. Woodell, "Multiscale Retinex for color rendition and dynamic range compression," Proc. SPIE 2847, pp. 183, 1996.

[6] L. Wang, T. Horiuchi, and H. Kotera, "High dynamic range image compression by fast integrated surround Retinex model," Journal of Image Science and Technology, vol. 51, no. 1, pp. 34-43, Jan.-Feb. 2007.

[7] W. J. Kyung, T. H. Lee, C. H. Lee, and Y. H. Ha, "Hue preservation using enhanced integrated multi-scale Retinex for improved color correction," Journal of Imaging Science and Technology, vol. 55, no. 1, pp. 010504-1 - 010504-10, Jan./Feb. 2011.

[8] O. S. Kwon, Y. H. Cho, Y. T. Kim, and Y. H. Ha, "Illumination estimation based on valid pixel selection from CCD camera response," Journal of Imaging Science and Technology, vol. 49, pp. 308-316, 2005.

[9] Buchsbaum G, "A spatial processor model for object colour perception," Journal of the Franklin Institute, vol. 310, no. 1, pp. 337-350, 1980.

[10] J. Morovic, Color Gamut Mapping, Published in Association with the Society for IS&T, 2008.

[11] J.J. McCann, S.P. McKee, and T.H. Taylor, "Quantitative studies in Retinex theory—a comparison between theoretical predictions and observer responses to the color mondrian experiments," Vis. Res., vol. 16, pp. 445–458. 1976.

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