Adaptive Selection of Weights in Multi-scale Retinex using Illumination and Object Edges

Chan Young Jang[1], Joonho Hyun[1], Suyeong Cho[1], Hi-Seok Kim[2] and Young Hwan Kim[1]
[1]The department of Electrical Engineering , POSTECH, Pohang, Gyeongsangbuk-do, Korea
[1]{jangcytof, lespaul, milkysky, youngk}@postech.ac.kr
[2]The department of Electrical Engineering , Cheongju University, Cheongju, Chungcheongbuk-do, Korea
[2]khs8391@cju.ac.kr

Abstract - *This paper proposes a novel approach to determining the weights in the Multi-scale Retinex (MSR). Existing MSR algorithms commonly used fixed weights regardless of image characteristics, and this sometimes induces serious image artifacts. The proposed algorithm used illumination and object edges to estimate the degree of shade in an image. Then, it determined the optimal weights based on the degree of shade in the image. In experiment, the proposed algorithm accurately distinguished the degree of shade in the image. Thus, the proposed method reduced the image artifacts than the existing methods by controlling the local contrast adaptively depending on the level of image details.*

Keywords: Dynamic range compression; contrast enhancement

1 Introduction

An ultimate goal of most image processing algorithms is satisfaction of the human visual system. Human eyes can see natural world scenes that have a high dynamic range (HDR). Thus, human eyes can concurrently see details in both bright and dark regions. However, many imaging devices cannot perfectly capture HDR scene because imaging devices have a limited dynamic range of about 100:1-500:1, whereas real scenes can have a dynamic range of about 10000:1 [1]. Therefore, to reproduce the captured image in the current display devices, the HDR of the scenes should be compressed appropriately to a low dynamic range (LDR) [2]. To recreate HDR scenes, many effective algorithms have been developed [3-4].

Multi-scale Retinex (MSR) is the basic idea to restore an image using the weighted sum of multiple Single-scale Retinexes (SSRs) [2]. MSR provides good dynamic range compression characteristics. However, MSR result image depends on the quality of the weights it uses. This is because SSRs have different dynamic range compression characteristics according to the scale. As the scale of an SSR decreases, it enhances the local contrast more and provides more dynamic range compression but has several disadvantages including halo artifacts. In contrast, as the scale of an SSR increases, its color constancy characteristics improve. However, it cannot compress the dynamic range of an image well without considering image characteristics [4], because the ratio of reduced dynamic range is differs among images.

The degree of shade is used as the value to restore an image that has reduced dynamic range. This is because the shade in the image can represent saturated regions that have limited dynamic range. Weights in MSR must be determined depending on the degree of shade and the scale of SSR. In this paper, we present a novel algorithm that determines MSR weights appropriate to the image characteristics. The remainder of this paper is organized as follows. In Section 2, we concisely describe SSR and MSR. In Section 3, we explain how to calculate the degree of shade and determine the weights according to it. In Section 4, we show experimental results of the proposed method. In Section 5, we conclude this paper.

2 Background

2.1 Single-scale Retinex

The form of SSR is described as in (1).

$$R(x,y) = \log I(x,y) - \log(F(x,y) * I(x,y)), \qquad (1)$$

where $R(x,y)$ is the Retinex output; $I(x,y)$ is the image intensity; '$*$' represents the convolution operation; $F(x,y)$ is Gaussian function given by

$$F(x,y) = k \cdot e^{-(x^2+y^2)/\sigma^2}, \iint F(x,y)\,dxdy = 1, \qquad (2)$$

where σ is the standard deviation of the Gaussian function that determines the scale of SSR.

2.2 Multi-scale Retinex

The SSR does not provide good tonal rendition [4]. Therefore, the MSR that combines the multiple SSRs with different scales was proposed. It alleviates the defects of the large-scale SSR and the small-scale SSR [4].
The form of MSR is described as in Eq. 3.

$$R'(x,y) = \sum_{n=1}^{N} w_n \cdot R_n(x,y), \tag{3}$$

where $R'(x,y)$ is the MSR output; N means the number of scales; $R_n(x,y)$ is n-th scale SSR image; w_n is the weight for the n-th scale SSR.

The MSR is very efficient at improving the image details and enhancing the contrast of the shaded region in the image [5]. However, the result image cannot be successfully compressed if weights are inappropriately determined in the MSR. To appropriately reproduce the image, the degree of shade can be an important parameter.

For example, if the degree of shade in an image is large, small-scale SSR needs to have higher weight than the large-scale SSR. It means that the local contrast needs to be enhanced in the original image. In contrast, if the degree of shade in an image is small, the small-scale SSR needs to have lower weight than the large-scale SSR. In this case, the original image does not almost need to enhance the local contrast.

Thus, the calculation of the degree of shade in an image is important to determine the proper weights. In the following section, we describe the proposed algorithm that determines adaptive weights according to the degree of shade in an image.

3 Proposed method

3.1 Analysis of the image with reduced dynamic range

To determine appropriate weights, we analyze the characteristics of three images that have the different degree of shade (Fig. 1). In non-shaded images (Fig. 1, right), the local contrast does not need to be enhanced because their dynamic range is almost not constrained by imaging devices.

Fig. 1. Left: dim non-shaded, Center: shaded, right: bright non-shaded

One image (Fig. 1, center) is a shaded image that needs local contrast enhancement. In such image, the objects have lower luminance than the original scene due to the highlights in the background.

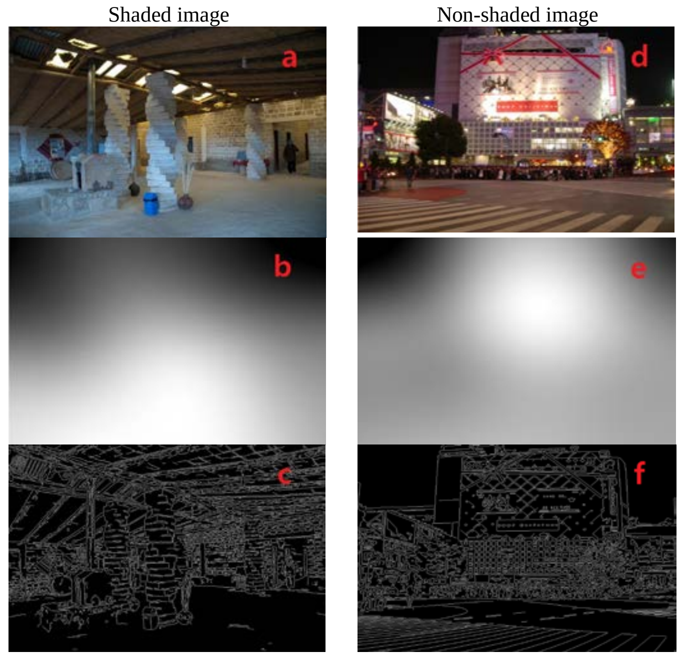

Fig. 2. Comparison between shaded and non-shaded images; a, d: original image; b, e: illumination image; c, f: Edge image

A conventional shaded region has low illumination characteristics due to the limited dynamic range. However, the illuminated image cannot accurately detect the shaded region. Images (Fig. 2. a, d) have similar illumination (Fig. 2. b, e). However, image (Fig. 3. d) is not shaded image. The difference between shaded image and non-shaded image is that the shaded image has most edges in the dark region (Fig. 2. c) compared with image (Fig. 2. f). Therefore, it will be regarded as a shaded region if objects occur in the dark region.

To extract the shaded region of an image, the illumination and edge images are used. Specifically, the illumination is used to classify low luminance region and the edge image is used to find the object in the image.

In this paper, we define the shaded region as low illumination region with many edges. In the following sections, we will present a novel algorithm that chooses appropriate weights by utilizing the degree of shade in an image.

3.2 Calculation of shaded region

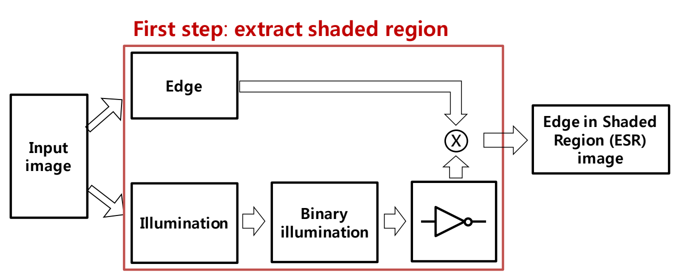

Fig. 3. First step of proposed method

In the method to detect shaded region (Fig. 3), the edge and illumination images are required to extract the shaded region in an image. We use a Gaussian function to obtain the illumination image. Then, to accurately represent the dark region, the illumination image is converted to a binary illumination image. The value of the binary illumination image is 0 if the value of its illumination image is smaller than the threshold and 1 otherwise. Here, the average value of the illumination image was used as the threshold. The edge image is obtained using a canny filter method [9].

The edge in shaded (ESR) image can be determined using its binary illumination and edge images. The ESR image represents the edges in low illumination. Then, the value of ESR image is the same as that of the edge image when the value of binary illumination image is low. Otherwise the value of ESR is 0.

The calculated ESR image can be a measure of shade because it represents the number of the object in the shaded region that needs to be recreated.

3.3 Determination of optimal weight

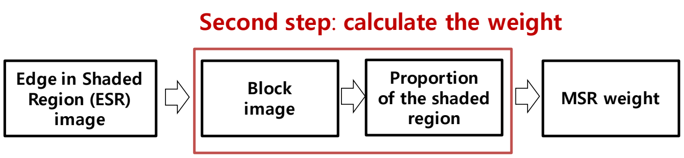

Fig. 4. Second step of proposed method

In this section, we present the method that determines the weights using the ESR image (Fig. 4). Because the ESR ration of input image represents the degree of local contrast to be enhanced, we calculate it in an image to determine the weight of each SSR. The ESR ratio is defined as the sum of the binary values in the ESR image divided by the sum of the binary values in the edge image. Thus, its range is 0-1.

After obtaining the ESR ration of the image, we calculate the weight of each SSR. As mentioned previously, the small-scale SSR increases the local contrast and the middle-scale SSR also improves local contrast slightly. Therefore, the sum of weights of small-scale SSR and middle-scale SSR is equal to the ESR ratio. The rest of weight is given to large-scale SSR and its weight can be expressed as

$$w_l = 1 - ESR\,ratio \quad . \tag{4}$$

To determine appropriate weights for small-scale SSR and middle-scale SSR, we must find the most shaded area in the shaded region. This is because small-scale SSR is superior to middle-scale SSR in the local contrast enhancement. Thus, we must give a larger weight to the small-scale SSR for the most shaded area in the shaded region.

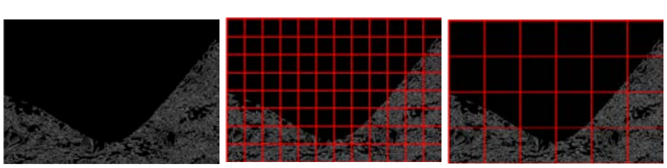
Fig. 5. Example of block image

To find the most shaded area, we divide the ESR image into small and middle blocks (Fig. 5 center, right). The middle size blocks are used to determine proportion of ESR and the shaded middle block can be defined as a block that has ESR ratio greater than the threshold level. The proportion P_m of the shaded middle blocks is represented as in (5).

$$P_m = \frac{a_m}{b_m} \quad , \tag{5}$$

where a_m is the number of shaded middle blocks, and b_m is the total number of middle blocks.

The most shaded region can be determined by the proportion of the shaded small blocks, which are defined as blocks that have ESR ratio greater than the threshold level. The proportion of the shaded small blocks P_s is represented as

$$P_s = \frac{a_s}{b_s} \quad , \tag{6}$$

where a_s is the number of shaded small blocks, and b_s is the total number of small blocks.

The threshold levels for the shaded small block and the shaded middle block were determined in several experiments.

The weight of large-scale SSR was predetermined and the weights of small-scale SSR and middle-scale SSR were determined by the amount of deeply shaded area in the shaded region. Therefore, appropriate weights of the small-scale SSR and the middle-scale SSR can be determined using P_m and P_s. The weights of small-scale SSR and middle-scale SSR are formulated as in (7) and (8), respectively.

$$w_s = \frac{P_s}{P_s + P_m} \cdot ESR\,ratio \tag{7}$$

$$w_m = \frac{P_m}{P_s + P_m} \cdot ESR\,ratio \tag{8}$$

4 Experiment

4.1 Experimental environment

We performed two experiments to evaluate our proposed method. In the first experiment, we analyzed the weights according to the degree of shade. In the second experiment, we compared the proposed method with the two benchmark methods. Benchmark method1 is a fixed-weight method, and benchmark method2 is an adaptive weight method that uses the standard deviation of an image.

Test image size is 1000 x 669 pixels. The number of test images is about 100. Gaussian filter sizes were fixed to (8, 32, 128). These values were obtained from [2]. The canny filter method was used to extract edge of the image. To preserve the chromaticity of an image, CIE-Lab color space was used instead of RGB color space.

4.2 Experiment results

Fig. 6 shows the change in weights depending on the degree of shade in the image. ω_1, ω_2 and ω_3 are the weights for small-scale SSR, middle-scale SSR and large-scale SSR, respectively. In Fig. 6, the image1 represents the smallest shade in the image and it does not need the local contrast enhancement. Thus, the small-scale SSR and the middle-scale SSR weights can be smaller. In contrast, the image5 needs the local contrast enhancement. Therefore, the weight of large-scale SSR needs to be smaller.

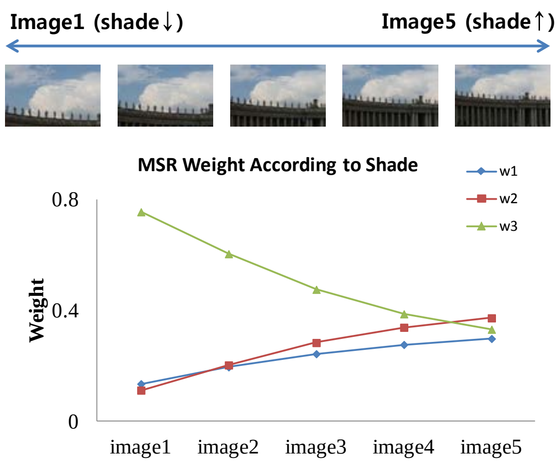

Fig. 6. Weights as a function of the degree of shade

Fig. 7 and Fig. 8 show the original image and the processed images. The benchmark methods 1 and 2 have the artifacts that are caused by the excessive local contrast enhancement and the tonal distortion that is detected in left side of the image. As shown in Fig. 7 and Fig. 8, proposed method appropriately recreates the image details and has fewer defects than benchmark methods.

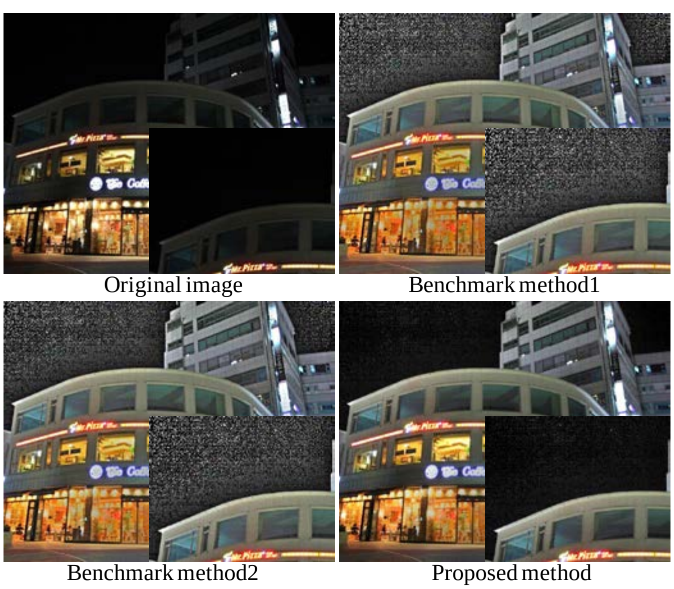

Fig. 7. Original image and the images created by the proposed and two benchmark methods

In Fig. 7, the benchmark methods have the artifacts because these methods excessively enhance the local contrast of the region that has no object. This is because these methods do not consider the details of object to be recreated. In contrast, the proposed method shows the image appropriate to the degree of shade of the object in it.

In Fig. 8, the benchmark methods have significant distortions in the bottom of the left region. However, the proposed method has smaller artifacts than the benchmark methods.

Fig. 8. Original image and the images created by the proposed and two benchmark methods

5 Discussion

Existing MSR weight select methods cannot calculate the shaded details of the image. Processed image can have significant artifact if inappropriate weights are selected. In the experimental results, the degree of shade is calculated. It shows the change in weights depending on the degree of shade in the image. In the small shade of the image, it does not need the local contrast enhancement. Thus, the small-scale SSR and the middle-scale SSR weights should be reduced. In contrast, in the large shade of the image, it needs the local contrast enhancement. Therefore, the weight of large-scale SSR should be reduced.

6 Conclusions

In this paper, we proposed an adaptive weights algorithm for MSR that determines the proper weights according to the degree of shade in the image. When compared with the existing methods using fixed weights and standard deviation of an image, the proposed method minimizes significant artifacts.

7 Acknowledgement(s)

This research was supported by Basic Science Research Program through the National Research Foundation of

Korea(NRF) funded by the Ministry of Education, Science and Technology(20100023428), and by the IT Consilience Creative Program of MKE and NIPA (C1515-1121-0003), Korea.

8 Reference

[1] Marius Herscovitz and Orly Yadid-pecht. “A modified Multi Scale Retinex algorithm with an improved global impression of brightness for wide dynamic range pictures”; Machine Vision and Applications, 15, 220-228, 2004.

[2] Lijie Wang, Takahiko Horiuchi and Hiroaki Kotera. “High Dynamic Range Image Compression by Fast Integrated Surround Retinex Model”; Journal of Imaging Science and Technology, 51(1), 34-43, 2007.

[3] Firdaus Zakaria, M., Ibrahim, H. and Azmin Suandi, S. “ A Review: Image compensation technique ”. Computer Engineering and Technology (ICCET), 2010.

[4] Zia-ur Rahman, Daniel J. Jobson and Glenn A. Woodell. “ Multi-scale retinex for color image enhancement ”. International Conference on Image Processing, 1996.

[5] In-Su Jang, Ho-Gun Ha, Tae-Hyoung Lee and Yeong-Ho Ha. “ Computer Adaptive Color Enhancement Based on Multi-Scaled Retinex Using Local Contrast of the Input Image ”. International Symposium on Optomechatronic Technologies (ISOT), 2010.

[6] E. Land. “An alternative technique for the computation of the designator in the retinex theory of color vision”; Proc. Nat. Acad. Sci., 83, 3078-3080, 1986.

[7] Tae-Hyoung Lee, Wang-jun Kyung, In-Su Jang and Yeong-Ho Ha. “Local Contrast Enhancement Based on Adaptive Multi-Scaled Retinex using Intensity Distribution of Input Image”; Journal of Imaging Science and Technology, 55, 4, 2011.

[8] B. Funt, F. Ciurea, and J. McCann. “Retinex in MATLABTM”; journal of Electronic Imaging, 13, 1, 48-57, 2004.

[9] John Canny. “ A computational approach to edge detection. Pattern Analysis and Machine Intelligence ”; IEEE Transactions on, 8, 6, 679-698, Nov., 1986.