Local Contrast Enhancement Based on Adaptive Multi-Scaled Retinex using Intensity Distribution of Input Image

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Abstract

The limitation of a low dynamic range in a digital still camera causes coarse color reproduction in darker regions of the output images, requiring contrast correction. Recently, local correction techniques are preferred to prevent unintended contrast enhancement from global correction methods. A multi-scaled retinex is a representative method, resulting in high quality output images. However, the sizes of the Gaussian filters and weights are determined empirically, regardless of the image, even though suitable sizes and weights corresponding to the respective image will induce a better quality. Accordingly, this paper proposes an adaptive multi-scaled retinex using a Gaussian filter set relative to the input image. First, the weight of the largest Gaussian filter is determined by the local contrast ratio from the intensity distribution of the input image. The other Gaussian filters and corresponding weights are then determined using a visual contrast measure(VCM) and halo measure. The VCM is obtained based on the local standard deviation and locally averaged luminance for several test images, while the halo measure is obtained based on the average of the maximum color differences for patches in the Macbeth color checker. Through an analysis of the VCM and halo measure, the sizes and weights of the Gaussian filters are then determined. In addition, the chroma is compensated to overcome the graying-out phenomenon due to a multi-scaled retinex. In experiments, the proposed method was found to improve the local contrast and saturation naturally.

Introduction

Human vision is a complicated automatic self-adaptation system that is capable of seeing over five orders of magnitude simultaneously, while also perceiving details in both bright and dark regions[1,2]. In contrast, current color imaging display devices, such as digital cameras, are unable to capture a dynamic range of real scene, resulting in poor scene detail and color reproduction in dark areas, especially in the case of a scene containing both bright and dark areas. Thus, the contrast of an image captured by a digital camera needs to be adjusted to represent the viewer's perception of the natural scene[3-4].

A single-scale retinex(SSR) model, based on the retinex theory as a model of human vision perception, was recently developed[5]. However, this model produces halos artifact and desaturation which is defined as "graying-out" in our paper according to the size of the Gaussian filter, which is varied in relation to the input image. To overcome these problems, a multi-scaled retinex(MSR) algorithm was proposed by Jobson that uses different sizes of Gaussian filter and corresponding weights[6-8], where a small-size Gaussian filter is used for local contrast and details, causing an increase of artifacts, whereas a large-size Gaussian filter is used to smooth and suppress the artifacts. Finally, several images from various single-scaled retinex algorithms with various sizes of Gaussian filter are weighted and summed to reduce the halos and enhance the local contrast. However, there is no method for optimizing the sizes and weights of the Gaussian filters in a multi-scale retinex model, which are currently just determined through subjective evaluation.

Therefore, this paper proposes an adaptive multi-scale retinex that determines the size of the Gaussian filters and corresponding weights according to the intensity distribution of the input image. The weight of the largest Gaussian filter is established as the distribution of the local luminance in the input image. The sizes and weights of the Gaussian filter set for the multi-scale retinex are then determined using a visual contrast measure and halo measure. The visual contrast measure is obtained based on the product of the local standard deviation and locally averaged luminance of the image[6]. Meanwhile, the maximum color differences are used to evaluate any halo artifacts generated in large uniform regions with a high contrast edge, where these values are obtained as an average of the color values for each color patch in the Macbeth color checker. The parameters for the Gaussian filters and weights are then determined considering the visual contrast and halo measures.

Multi-scaled retinex model

An SSR is performed with a Gaussian filter, which is used to estimate the illuminant component. The reflectance is then calculated based on the difference between the original and Gaussian-filtered image as follows:

$$\log I(x,y) = \log R(x,y) + \log L(x,y) \tag{1}$$

where $R(x,y)$ is the reflectance at point (x,y), $L(x,y)$ is the irradiance, i is the RGB channel, and $F(x,y)$ is the Gaussian filter given by

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

where σ is the standard deviation for the Gaussian function.

An MSR was then introduced to prevent the halo artifacts produced by an SSR[5]. The MSR model adopts Gaussian filters with various scales and corresponding weights using the following computations[6-8]:

$$O_i(x,y) = \sum_{n=1}^{N} w_n \{\log I_i(x,y) - \log\{F_n(x,y) * I_i(x,y)\}\} \tag{3}$$

$$F_n(x,y) = Ke^{-(x^2+y^2)/\sigma_n^2} \quad \text{and} \quad \iint F_n(x,y)\,dxdy = 1 \tag{4}$$

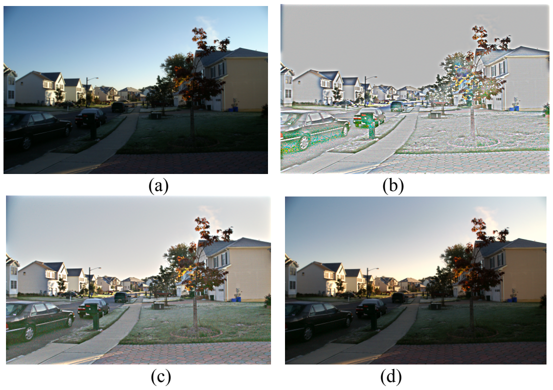

Figure 1*. Resulting images by SSR and MSR. (a) input image, (b) SSR with σ = 5, (c) SSR with σ = 240, and (d) MSR*

where w_n represents the weight for the n-th scale. Fig.1 compares the resulting images when using an SSR with different sizes of Gaussian filter and an MSR. In Fig. 1(b), the use of an SSR with a small-scale Gaussian filter results in details and halo artifacts with graying out. In Fig. 1(c), the effect of using a large-scale Gaussian filter results in more chromaticity information.

In Fig. 1(d), the MSR is very efficient in improving the detail and local contrast of the shadow. However, there is no established method for selecting the appropriate Gaussian filter set and corresponding weights. Thus, halo artifacts can be caused by the combination of the filters and corresponding weights. In addition, the weighted sum of the SSR images can cause graying-out in the resulting image.

Visual contrast measure

The sizes and weights of the Gaussian filters used for an MSR are usually determined empirically, resulting in a different quality according to the image. Therefore, this study adopts two measures: the visual contrast measure (VCM) and halo artifact measure.

The general idea behind the VCM is that a good visual representation usually combines a high regional visual lightness and contrast[6]. First, the input image is blocked based on the 2˚ viewing angle of the viewing angle of the fovea [9], as the regional scale is sufficiently granular to capture the visual sense of the regional brightness and contrast. The VCM is then computed by taking the mean of the regional standard deviations, thereby providing a gross measure of the regional contrast variations as follows:

$$V = \frac{1}{N}\sum_{k=1}^{N} m_k s_k \tag{5}$$

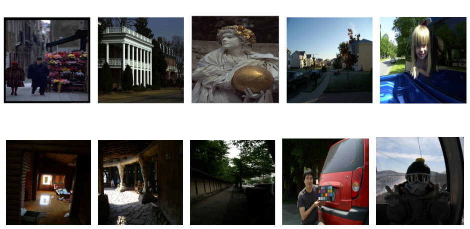

Figure 2*. Test images for VCM and halo measure.*

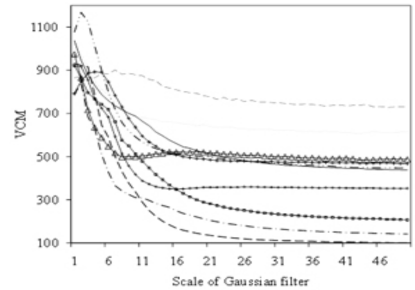

Figure 3*. VCM from SSR with various size of Gaussian filters*

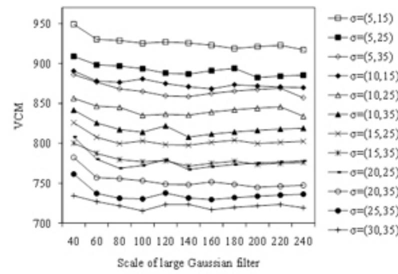

Figure 4*. VCM according to the size of the large Gaussian filter in MSR*

where k is the index of the blocks, N is the number of blocks, m_k is the mean of the k' th block, and s_k is the standard deviation of the k' th block.

Fig. 2 shows the standard test images used to evaluate local contrast enhancement algorithms. Fig. 3 shows the VCM evaluation of the test images after using an SSR with various sizes of Gaussian filter. Whereas the VCM changed sharply when using a Gaussian filter under σ=50[pixel], it converged to a certain value when using a Gaussian filter over σ=100[pixel], indicating that the small Gaussian filter needed to be under σ=50[pixel] to enhance the contrast.

Meanwhile, the variation of the VCM according to the size of the large Gaussian filter is shown in Figure 4. For several combinations with a small- or middle-size Gaussian filter, the variation of the VCM according to the size of the large Gaussian filter was only slight, indicating that instead of contrast enhancement, the focus for selecting the large Gaussian filter needs to be on reducing the halo artifacts and stabilizing the resulting image.

Halo artifacts measure

Depending on the size and weight of the smaller Gaussian filter, halo artifacts occur between the center of a uniform area and the edge of the area. Thus, since the Macbeth color checker[9] consists of uniform patches between black-bold edges, it was used to evaluate the halo artifacts based on the maximum color difference between each pixel and the averaged color in a patch in CIELAB standard color space as follows[10]:

$$h_k = \max\left(\sqrt{(L^*_{m,k} - L^*_k(x,y))^2 + (a^*_{m,k} - a^*_k(x,y))^2 + (b^*_{m,k} - b^*_k(x,y))^2}\right) \tag{6}$$

where k is the index of the patch, $L_{m,k}$, $a_{m,k}$ and $b_{m,k}$ represent the mean of the CIELab color in the k'th patch, and

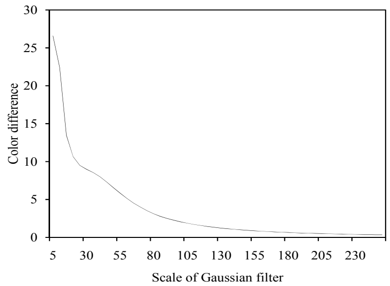

***Figure 5**. Averaged maximum color differences with various Gaussian filters*

$L_k(x,y)$, $a_k(x,y)$, and $b_k(x,y)$ represent the color at the (x,y) position of the k'th patch. Finally, the overall halo artifact measure was obtained as the averaged-maximum color differences:

$$H = \frac{1}{N}\sum_{k=1}^{N} h_k \tag{7}$$

where N is the number of patches. As human vision usually don't perceive a color difference under 3 in CIELAB color space for displays, only Gaussian filter and weight sets with an averaged maximum color difference under 3 were considered [10].

Figure 5 shows the averaged maximum color differences for the test images after using an SSR with various sizes of Gaussian filter. In the case of a Gaussian filter under 80, the color difference was more than 3, resulting in halo artifacts.

Adaptive multi-scaled retinex considering intensity distribution of input image

When using an MSR, the local contrast should be controlled based on the input image to reduce unnecessary contrast. Thus, to judge the condition of the input image, a normalized standard deviation of the local luminance is used as follows:

$$P = 1 - \frac{1}{m_a}\sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(m_k - m_a\right)^2} \tag{8}$$

where k is the index of the divided images, m_k represents the average luminance of the k'th sub-image, N is the number of sub-

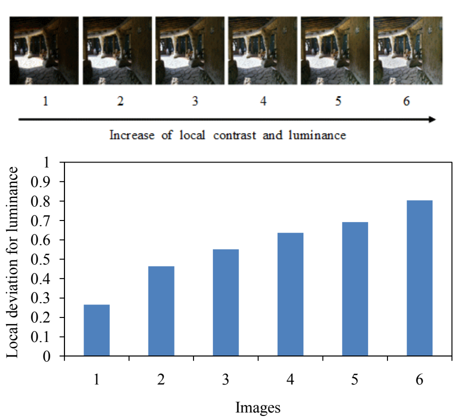

***Figure 6**. Variation of P according to image contrast and luminance.*

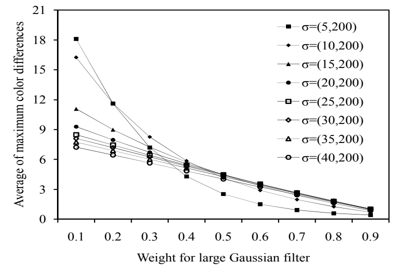

***Figure 7**. Average of maximum color difference.*

images, and m_a indicates the average luminance of the input image. In the case of a low luminance and high difference for the local luminance, P is close to 0 and vice versa in the opposite case.

Figure 6 shows P for six input images. With a higher local contrast, P also increased. Thus, the value of P can be used as the weight for the large Gaussian filter to control the contrast enhancement with an MSR.

Next, when considering the halo artifacts, Fig. 7 shows the halo measure for the first image in Fig. 6 when varying the weight of the large Gaussian filter and keeping the other filters fixed. The results show that the weight of the large Gaussian filter needs to be higher than that of the small Gaussian filters. However, when using a multi-scale retinex model with n Gaussian filters, the halo artifacts were reduced by limiting the weight of the large Gaussian filter to the value of P, ranging from 0.5 to 1, as follows:

$$w_L = \frac{(n-1)P+1}{n} \tag{10}$$

where n indicates the number of Gaussian filters included in the MSR. From the results of the halo measure, the size of the large Gaussian filter needs to be more than 200 to reduce the halo artifacts. In addition, the weight of the large Gaussian filter is determined using the local luminance distribution of the input image.

Meanwhile, the sizes and weights of the other Gaussian filters are determined based on the VCM and halo artifact measure using an iterative process. The number of Gaussian filters is pre-determined by computing the VCM. In Figure 8, the VCM was used to evaluate ten test images with several combinations of Gaussian filters and weights, where the weight for the large Gaussian filter was more than the sum of the other weights. As a result, the VCM was found to be higher when using three Gaussian filters, than when varying or using more than four filters. Therefore, three filters are used for the proposed method.

To check the halo artifacts, the color difference is computed using the Macbeth color checker with various sizes and weights of filter. First, the weight was sampled using a 0.1 step. The large size filter was limited to 0.3 to reduce the halo artifacts, while the weights for the small and middle size filters were never the same. As a result, nine weight combinations were considered: W1=(0.33, 0.33, 0.33) [6], W2=(0.1, 0.4, 0.5), W3=(0.4, 0.1, 0.5), W4=(0.2, 0.3, 0.5), W5=(0.3, 0.2, 0.5), W6=(0.1, 0.3, 0.6), W7=(0.3, 0.1, 0.6), W8=(0.1, 0.2, 0.7), and W9=(0.2, 0.1, 0.7). Fig. 9 shows the averaged maximum color difference for each weight combination. The combinations with a color difference under 3 were initially

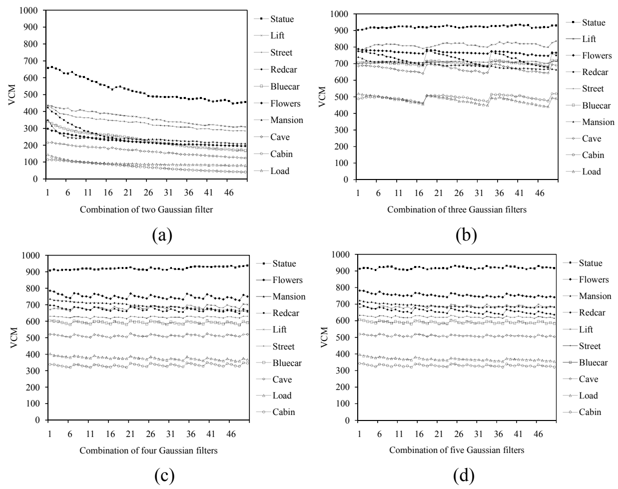

***Figure 8**. VCM with different number of Gaussian filters. (a) two, (b) three, (c) four, and (d) five.*

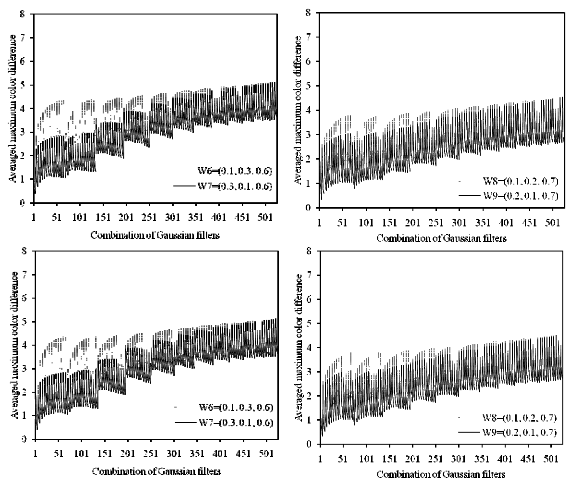

***Figure 9**. Averaged maximum color difference for each weight combination*

selected to reduce halo artifacts. The Gaussian filter sets with the maximum VCM were then determined, as presented in Table 1. Consequently, the Gaussian filter set was determined as 2, 4, and 240 based on the results in Table 1. While the weights of the large Gaussian filter were determined by the local luminance distribution of the input image, the weights of the small and middle Gaussian filters were compared with the normalized VCM values in figure 10. As shown in figure 18, the weight combinations with the highest VCM and 3 lowest maximum color differences were selected as (0.3, 0.2, 0.5), (0.3, 0.1, 0.6), and (0.2, 0.1, 0.7). These combinations are then used in the proposed method.

Chroma compensation

As previously mentioned, an MSR induces graying out when the images are merged. Thus, to overcome this problem, the chroma ratio between the current chroma and the maximum chroma in CIELab color space is preserved according to the lightness variation in the MSR in Fig. 11 as follows:

$$C'_o(x,y) = \frac{C_{L_o,\max}(x,y)}{C_{L_i,\max}(x,y)} \times C_i(x,y) \tag{11}$$

Table 1: Gaussian filter set with maximum VCM

Images	Parameters	Gaussian filter			Maximum VCM
		Small	Middle	Large	
Flowers	Weights	0.2	0.1	0.7	788
	Scales	2	3	240	
Mansion	Weights	0.3	0.2	0.5	739
	Scales	2	3	238	
Statue	Weights	0.3	0.2	0.5	945
	Scales	4	28	227	
Street	Weights	0.333	0.333	0.333	701
	Scales	2	4	212	
Blue car	Weights	0.333	0.333	0.333	709
	Scales	2	4	234	
Cabin	Weights	0.333	0.333	0.333	492
	Scales	2	4	237	
Cave	Weights	0.333	0.333	0.333	688
	Scales	2	4	241	
Lift	Weights	0.333	0.333	0.333	780
	Scales	2	4	212	
Load	Weights	0.333	0.333	0.333	518
	Scales	2	3	234	
Red car	Weights	0.333	0.333	0.333	774
	Scales	2	3	218	

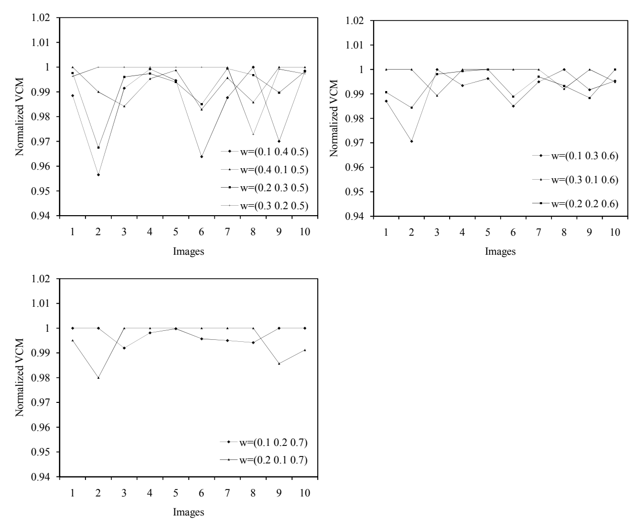

***Figure 10**. Normalized VCM with different set of filters.*

where $C_{Lo,max}$ is the maximum chroma value corresponding to the lightness, L_o, and $C_{Li,max}$ is the maximum chroma value corresponding to the lightness, L_i.

Experiment and evaluations

Figs. 12 and 13 show the original and resulting images when using a conventional MSR, the MSR developed in our previous work[9], and the proposed MSR with chroma compensation. As shown in Fig. 12(d), the proposed method prevented the color changes and graying out for the sky that resulted from the conventional MSR method, and enhanced the details in the shadow areas.

In Fig. 13, the conventional method distorted the color of the cabin with cyan and reduced the saturation. However, in Fig 13(c),

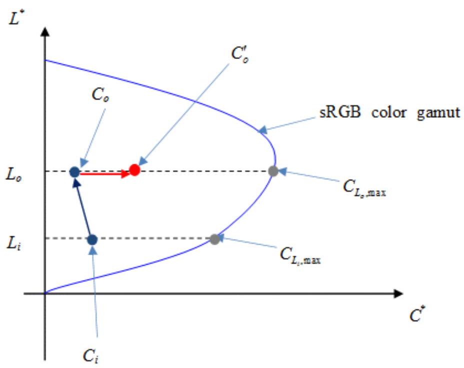

Figure 11. *Chroma compensation according to variation of lightness.*

the cabin is brown. Thus, the proposed method reproduced high quality images without any halo artifacts.

Conclusions

This paper proposed an adaptive multi-scaled retinex that uses Gaussian filters selected according to the intensity distribution of the input image. The proposed method solves the unstable output of an MSR according to the luminance distribution of the input image, causing over-enhancement of the contrast and an unnatural saturation. Two measure factors are adopted: the visual contrast measure and maximum color difference. Also, the standard deviation of the local luminance in the input image is used for the weight of the large Gaussian filter. Considering the impact of the color difference on the generation of halo artifacts, the sizes and weights of the Gaussian filters producing a higher visual contrast measure are determined using test images. Furthermore, the chroma is compensated by preserving the chroma ratio of the input image based on the maximum chroma values of standard sRGB color space in the lightness-chroma plane.

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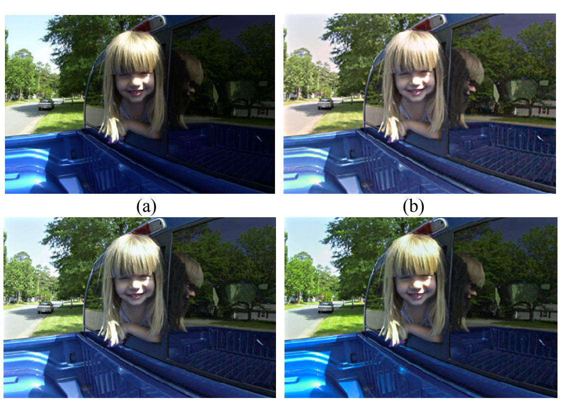
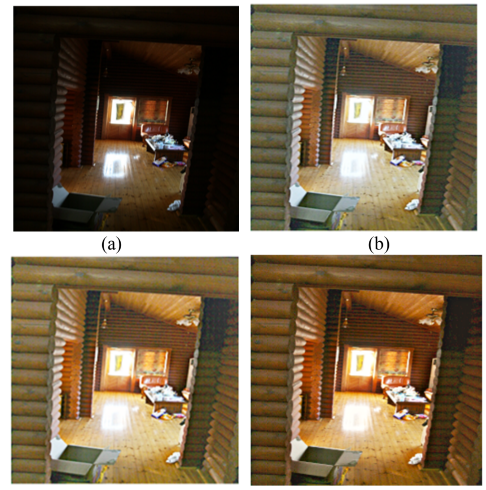


(a) (b)

(a) (b)

Figure 12*. Resulting images. (a) input image, (b) conventional MSR, (c) proposed MSR, and (d) proposed MSR with chroma compensation.*



(a) (b)

(c) (d)

Figure 13*. Resulting images. (a) input image, (b) conventional MSR, (c) proposed MSR, and (d) proposed MSR with chroma compensation.*

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