Color constancy enhancement under poor illumination

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In this Letter, the color constancy and its realization were studied and a novel color constancy image enhancement algorithm under poor illumination was presented. The purpose of this algorithm is to maintain the hue of an image during the processing so that the change of saturation can be minimized. The original image was first multiplied by a scale parameter obtained by the adaptive quadratic function to enhance the luminance, and then the edge details were restored by a shifting parameter. Numerical results of the Simon Fraser University (SFU) image database indicated that the proposed algorithm performed much better in preserving the hue and saturation and avoiding color distortion compared with the existing image enhancement algorithms. © 2011 Optical Society of America

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Color constancy [1] is a very important property of the human vision system. When being implemented in the field of digital image processing, some methods based on color constancy can not only compensate the variation of light conditions, which has a huge impact on the color, but also can correctly restore the natural color of the object itself. In order to maintain color information, traditional gray-scale image enhancement methods are not applicable for color images [2].

Land proposed the Retinex model [3] to study the color constancy. Based on Land's research, Jobson *et al.* developed the single-scale retinex (SSR) [4], the multi-scale retinex (MSR) [5], and the MSR with color restoration (MSRCR) [6], which were successfully applied in image enhancement. Such algorithms can improve the color constancy, compress the dynamic range of images, and improve the contrast. However, they mix the color and illumination, and thus hue, the decider of the kind of color, is changed, resulting in color distortion to some extent [7].

Another category of color constancy algorithms focuses on preserving hue in the color space to avoid the color distortion. The hue-saturation-intensity (HSI) is a commonly used color space that can eliminate the correlation between different color components. The color constancy is achieved by maintaining H and meanwhile adjusting S and I [8]. These algorithms are time consuming and not suitable for the real time processing. Furthermore, we believe that the S component should not be changed since it is also an important attribute of color as hue. But in the results of the above algorithms, the S component is changed. In this Letter, we propose a novel color constancy algorithm that could not only decrease saturation change but also preserve hue.

In the HSI color space, the H and S components are defined as

$$\begin{cases} H = \begin{cases} \arccos(\varphi) & \text{if } G \geq R \\ 2\pi - \arccos(\varphi) & \text{if } G < R \end{cases}, \\ S = 1 - \frac{3\min(R,G,B)}{R+G+B} = 1 - \frac{3X_0}{R+G+B} = \frac{I-X_0}{I}, \end{cases} \tag{1}$$

where R (red), G (green) and B (blue) are the gray values of a pixel of a 24 bit color image,

$$\varphi = \frac{(2B-G-R)/2}{\sqrt{(B-G)^2+(B-R)(G-R)}},$$
$$X_0 = \min(R,G,B),$$

$I = (R+G+B)/3$. Assuming the color vector before processing is $X = (R,G,B)$, the scale parameter is α, and the shifting parameter is β, we can derive the color vector after scale and shift operations as

$$X' = (\alpha R + \beta, \alpha G + \beta, \alpha B + \beta) = \alpha X + \beta. \tag{2}$$

Substituting the X' into Eq. (1), we find that $\varphi' = \varphi$, and so $H' = H$.

In addition, the new S component is

$$S' = \frac{I' - X_0'}{I'} = \frac{\alpha(I - X_0)}{\alpha I + \beta}. \tag{3}$$

In the situation where the shifting parameter $\beta \approx 0$, and then $S' \approx S$, the saturation only varies on a negligible level; i.e., the hue and saturation are all preserved and the color information is fully maintained after being processed.

In order to compute the scale parameter α, we first convert the color image to the luminance image whose mean value reflects the overall feeling of human vision to the image:

$$I = (R+G+B)/3. \tag{4}$$

Then we adopt the adaptive quadratic function to implement the nonlinear transform to the luminance image defined as

$$y^2 = \frac{mv}{127.5^2}(x - 127.5)^2 + (255 - mv), \tag{5}$$

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where mv denotes the mean of the luminance image. Obviously, when x is equal to 0 or 255, y achieves the maximum value of 255. So the processed value will not be over flow. We define the luminance gain at a pixel as

$$l = \begin{cases} 0, & x = 0, \\ \sqrt{\frac{mv}{127.5^2}(x - 127.5)^2 + (255 - mv)/x}, & x > 0, \end{cases} \tag{6}$$

where $X = \max(R, G, B)$ is the maximum gray value of the current pixel. Considering the correlation between R, G, and B, we define the color gain as

$$g = f\left(\frac{x}{\text{sum}}\right) = \log\left(1 + \frac{x}{\text{sum} + 1}c\right), \tag{7}$$

where $x = \max(R, G, B)$, $\text{sum} = R + G + B$, x/sum denotes the color information of the current pixel, $f()$ is a mapping function that can be arbitrarily chosen, and in this Letter we use log function. c is the constant describing color gain. The final scale parameter α of the current pixel can be the multiplication of the luminance gain and color gain:

$$\alpha = lg. \tag{8}$$

It is noticeable that if the RGB value of a pixel is enhanced by multiplying with the same scale parameter, then the enhanced image will be blurred in a certain level. This is because the scaling enhancement not only increases the luminance, but also weakens the gray difference between the adjacent pixels. Since the gray differences can be expressed as the edge details of the image, we can restore such differences between the adjacent pixels by adding these details into the processed image. Since the B3-spline function can fit the edge curves, we convolve the luminance image with the B3-spline kernel and treat the convolution results as the edge details. The 5-by-5 B3-spline kernel is

$$B = \frac{1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}. \tag{9}$$

The shifting parameter β is defined by the edge detail of the current pixel as expressed in Eq. (10):

$$\beta = I - B * I, \tag{10}$$

where $*$ is the convolution operator and I is the luminance image. The final enhanced image is

$$\begin{cases} R' = \alpha R + \beta \\ G' = \alpha G + \beta. \\ B' = \alpha B + \beta \end{cases} \tag{11}$$

As mentioned above, if and only if $\beta \approx 0$, we can believe the saturation is almost unchanged and the color information can be maintained.

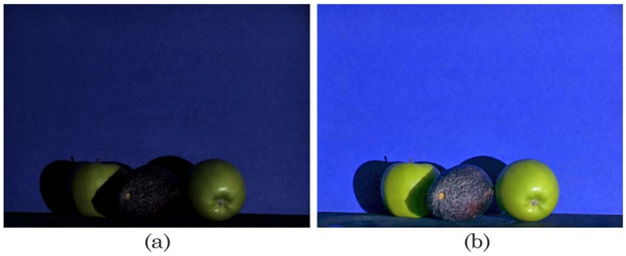

Fig. 1. (Color online) The original and enhanced images: (a) original, (b) enhanced.

Table 1. The Distribution of Edge Details Values

Range	$[-1, 1]$	$[-2, 2]$	$[-3, 3]$	$[-4, 4]$	$[-5, 5]$
Rercent	90.40%	97.23%	98.39%	98.94%	99.19%

An image under poor illumination in the Simon Fraser University (SFU) image database is used to test the enhancement performance. Figure 1 shows the original and final images, and the distribution of values in β is given in Table 1. We can see that the values of more than 90% of pixels are in the range of $[-1, 1]$ and more than 99% are in the range of $[-5, 5]$, indicating that in most pixels, the shifting parameter meets the requirement $\beta \approx 0$. So it is reasonable to treat the edge details as a shifting parameter since it helps to restore the gray differences in the adjacent pixels and maintain the color information.

Actually, in practice, the procedure of computing the scale and shifting parameters is a float operation, while the gray value of an 8 bit output image is an integer between 0 and 255; the precision will decrease during the conversion from float to integer. Hence, although the hue and saturation will not change in the proposed algorithm in theory, there are still some differences in the hue and saturation between the original and enhanced image in practice. However, compared with existing approaches, our method generates fewer differences in hue and saturation, as we show in the following experiments.

We test the proposed and other existing algorithms, i.e., log enhancement and MSRCR, on the SFU image

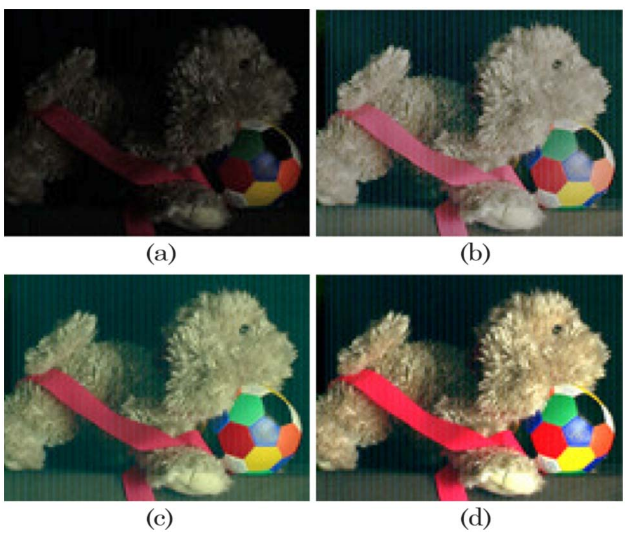

Fig. 2. (Color online) Original and enhanced results. (a) original (b) log (c) MSRCR (d) the proposed algorithm.

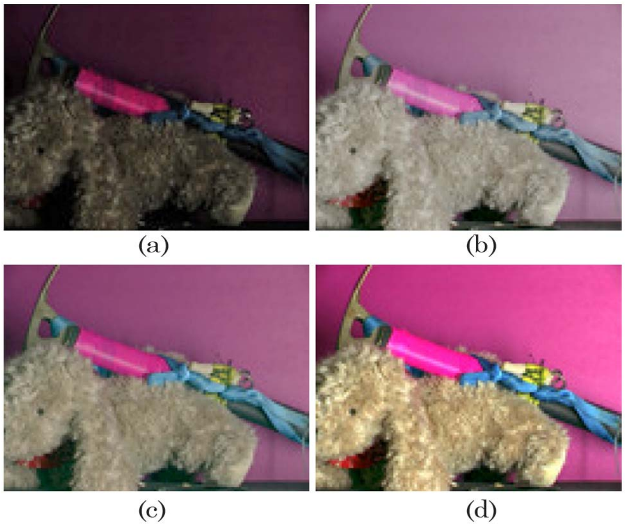

Fig. 3. (Color online) Original and enhanced results. (a) original (b) log (c) MSRCR (d) the proposed algorithm.

database, which consists of four categories, 529 poor illumination images with different illuminations, low contrast, and local details. We choose two images, and the results are shown in Figs. 2 and 3. From the results, we can find that some color distortions are obvious in the results of log and MSRCR algorithms. However, the results of our algorithm show more vivid color, richer details, and better visual effects.

The evaluation indices that Jobson proposed in [9] are based on the mean and local variation of the image, i.e., contrast (C) and luminance (L) changes; they are used to assess the quality of enhanced images objectively. In addition, in order to measure the amount of change in hue and saturation, we follow Jobson's indices and propose the following hue (H) and saturation (S) deviation indices:

$$H = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{|H_{\mathrm{Ori}}(i,j) - H_{\mathrm{Re}}(i,j)|}{H_{\mathrm{Ori}}(i,j)}, \tag{12}$$

$$S = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{|S_{\mathrm{Ori}}(i,j) - S_{\mathrm{Re}}(i,j)|}{S_{\mathrm{Ori}}(i,j)}, \tag{13}$$

where M and N are the width and height of images, H_{Ori} and H_{Re} denote the hue of the original and enhanced images, and S_{Ori} and S_{Re} are the saturation of the original and enhanced images, respectively. The evaluation results are shown in Tables 2 and 3.

From Tables 2 and 3, it is evident that the C and L of the proposed algorithm are greater than those of log and MSRCR algorithms, suggesting that our algorithm is more effective in improving the contrast and luminance. In Table 2, the H and S of our algorithm are only 16.17% and 27.21% of that of log, and 3.16% and 53.16% of that of MSRCR. And in Table 3, the H and S of the proposed algorithm are only 13.56% and 8.42% of that of log, and 7.38% and 12.41% of that of MSRCR. These results indicate that our algorithm is superior in maintaining color information; however, the log enhancement and MSRCR suffer more serious color distortion.

Table 2. The Evaluation Results of Fig. 2

	C	L	H	S
Log	8.2805	7.9282	0.0402	0.3859
MSRCR	7.4820	9.4451	0.2058	0.1975
Proposed	9.8577	9.8886	0.0065	0.1050

Table 3. The Evaluation Results of Fig. 3

	C	L	H	S
Log	2.1715	4.9460	0.0295	0.6197
MSRCR	1.6481	4.2532	0.0542	0.4207
Proposed	3.2294	5.1197	0.0040	0.0522

In conclusion, the color constancy would be achieved if the hue and saturation are preserved in image enhancement, and the proposed algorithm proves to be effective to reach the goal of color constancy.

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