Image Enhancement Based on Adaptive Demarcation between Underexposure and Overexposure

Yanfang Wang, Qian Huang
College of Computer and Information
Hohai University
Nanjing 211100, China
yanfang_wang08@hhu.edu.cn

Jing Hu
Department of Computer Science
Chengdu University of Information Technology
Chengdu 610225, China

***Abstract*—Images taken under non-uniform illumination usually suffer from degenerated details because of underexposure and overexposure. In order to improve the visual quality of color images, underexposure needs to be brightened and overexposure should be dimmed accordingly. Hence, an important procedure is discriminating between underexposure and overexposure in color images. Traditional methods utilize a certain discriminating threshold throughout an image. However, illumination variation occurs easily in real life. To cope with this, we propose an adaptive discriminating principle according to local and global luminance. Then, a nonlinear modification is applied to image luminance to light up underexposure and dim overexposure regions. Further, based on the modified luminance and original chromatic information, a natural color image is constructed via an exponential technique. Finally, a local and image-dependent exponential technique is applied to RGB channels to improve image contrast. Experimental results shows that the proposed method produces clear and vivid details for both non-uniform illumination images and images with normal illumination.**

Keywords—image enhancement; non-uniform illumination; underexposure; overexposure;

I. Introduction

In daily life, illumination is usually not uniform, and images taken in these scenes suffer from underexposure and overexposure. Consequently, an image tends to appear extremely bright or dark in some regions. In order to improve corrupted details induced by non-uniform illumination, many image enhancement methods have been published. These algorithms can be roughly categorized as: algorithms based on the Retinex-theory [1], and methods that apply non-linear modification to image luminance[2-6].

In the first category, Retinex-based algorithms try to model the visual perception mechanism of Human visual system (HVS). In general, the common starting point of Retinex-based methods is that the perceived lightness of every object is determined by the relative lightness between it and its neighbors.

In the second category, algorithms focus on the nonlinear modification to image luminance. Tao et al.[2] utilized an inverse sigmoid function to the V channel of color images to increase the luminance of dark areas and decrease the luminance of highly-bright regions. However, the threshold between underexposure and overexposure was not discussed intensively in [2]. Schettini et al. [3] proposed an hypothesis that the expected value of the enhanced luminance is 0.5 (assume that the full dynamic range is [0, 1]). Based on this idea, Schettini et al. devised the parameter setting in the traditional gamma transform via an automatic parameter-tuning technique. Choudhury and Medioni [4] proposed a nonlinear-mapping method based on the logarithmic function. In [4], under and overexposure regions were discriminated according to the proportion of pixels that are smaller than 0.5. Besides, Meylan et al. [5] used Naka-Rushton transformation for nonlinear mapping. Naka-Rushton function increases input intensity, thus performing well on underexposed images. Recently, Shin et al. [6] estimated image luminance using Gaussian smoothing on V channel, modified the luminance through gamma modification. Note that, these algorithms [2-6] modified image luminance according to global luminance, and the demarcation between underexposure and overexposure was designed indirectly according to luminance distribution.

In this work, in order to enhance images with non-uniform illumination, a local adaption approach is developed. In order to separate underexposure from overexposure, a local pixel-wise demarcation technique is designed. Based on this demarcation, local luminance is corrected by SNRF formula [7] to dim highly-bright areas and brighten dark areas. Then, a color image is constructed based on the modified luminance and the input chromatic information. Finally, image contrast is boosted through an exponential technique on RGB channels. Experimental results confirm that our approach brings good details and vivid colors for color images.

Rest of the paper is organized as follows. The proposed approach is detailed in Sec. II. Experimental results and comparisons are given in Sec. III. Finally, conclusions are given in Sec. IV.

II. Proposed Approach

Fig. 1 shows the flowchart of our approach, and a sample image with intermediate results are illustrated as well. Precisely, our method consists of three steps: 1. discriminating between overexposure and underexposure; 2. luminance modification; 3. color image reconstruction; and 4. local contrast improvement.

The project is supported by the funding from the National Natural Science Foundation of China (Grant Nos. 61502145, 61300122, and 61602065), and the Fundamental Research Funds for the Central Universities (Grant No. 2017B42214).

978-1-5386-1978-0/17/$31.00 ©2017 IEEE

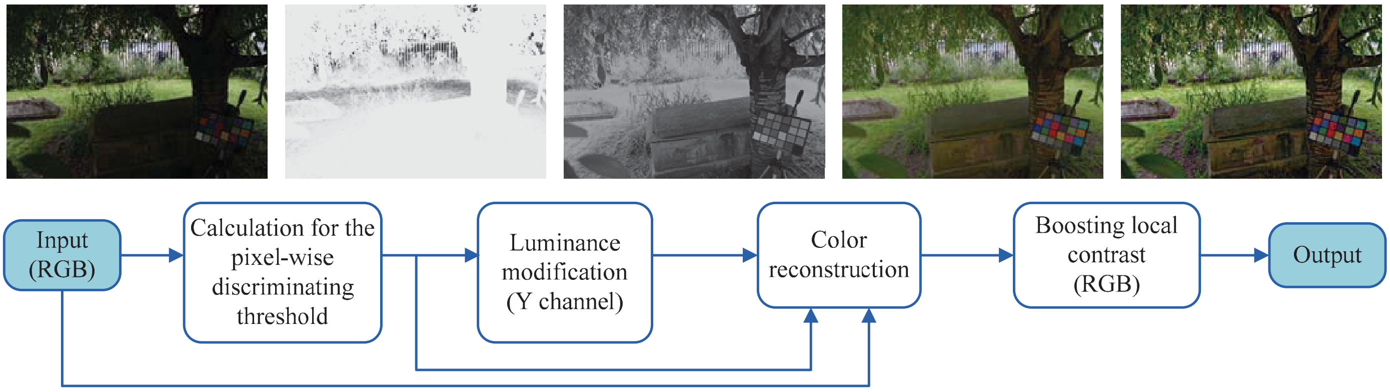

Fig. 1. Flowchart of the proposed approach.

A. Pixel-wise Discriminating

For non-uniform illumination images, dark regions need more substantial increments to the luminance, and therefore should be identified as underexposed. Accordingly, for dark regions, the discriminating threshold should be large, and thus the luminance of dark regions will be smaller than the corresponding threshold. On the other hand, for highly-bright regions, the discriminating threshold needs to be small, which guarantees that these regions will be discriminated as overexposed. Based on the above analysis, the discriminating threshold is set to change inversely with local luminance.

In addition, for globally dark images, the whole image should be determined as underexposed. On the contrary, for globally bright images, the image needs to be identified as overexposure. Therefore, the discriminating threshold is set to vary contrarily to global luminance to light up globally dark images and depress globally bright images. Precisely, the discriminating principle is defined as:

$$T(i,j) = (1-Y_m)\left\{1-\left[BF*Y(i,j)\right]^2\right\} \tag{1}$$

where (i, j) denotes a two-dimensional pixel location, and Y is the luminance channel. Global luminance is approximated by Y_m which is the median value of the luminance channel. The item BF is the bilateral filter [8] which implements smoothing while preserving distinct edges, and the asterisk * denotes convolution operation. Fig. 2(b) illustrates the pixel-wise discriminating threshold for the image Fig. 2(a). It is demonstrated that darker areas in the color image correspond to larger T values, and this compels original dark regions to be identified as underexposure. In Fig. 2(c), black regions are the underexposed regions that are discriminated by Fig. 2(b).

(a) (b) (c)

Fig. 2. (a) example color image, (b) the T image, and (c) demarcation result.

B. Luminance Modification

In order to revive details in color images, intensities in underexposed regions need to be pulled up, whereas overexposed areas should be pulled down. For this purpose, Wang and Luo [7] proposed the symmetric Naka-Rushton formula (SNRF) to modify image luminance, as follows

$$Y'(i,j) = \begin{cases} \dfrac{Y(i,j)}{Y(i,j)+H}(T+H) & 0 < Y \le T \\ 1-\dfrac{1-Y(i,j)}{1-Y(i,j)+H}\left[(1-T)+H\right] & T < Y \le 1 \end{cases} \tag{2}$$

where $Y(i, j)$ and $Y'(i, j)$ denote the input luminance at the pixel location (i, j), respectively. Reference [7] has shown that the parameter H controls the enhancing degree of SNRF, and it can be set to possess different values for underexposure and overexposure regions. In general, when H gets larger, the enhancement degree get larger as well. The notation T represents the demarcation threshold between underexposure and overexposure regions, and it also affects the enhancement degree. For example, larger value of T produces globally larger output of Y' through Eq. (2). Here, we utilize the pixel-wise demarcation that is computed by Eq. (1) to replace the parameter T in Eq. (2). Then, Eq. (2) can be employed to increase underexposure and decrease overexposure for non-uniform illumination images. For example, Fig. 3 shows the effect of luminance-adaption using Eq.(2). Fig. 3(a) shows a color image with underexposure in the vine regions, and Fig. 3(b) illustrates the luminance channel of 3(a). In detail, we use Eq. (1) to calculate the pixel-wise demarcation, as shown in Fig. 3(c), between underexposure and overexposure. Then, we employ Eq. (2) to modify the luminance, and we can get Fig. 3(d) where the underexposed vines has been revived.

C. Color Image Reconstruction

With the adapted luminance by Eq. (2), the original input chroma information is then utilized to reconstruct a enhanced color image. For this purpose, in [2] and [3], the authors have used various methods for color reconstruction. Here, we employed the method in [3] to RGB channels, and obtained the transformed values by

$$\begin{cases} R^* = \dfrac{1}{2}\left[\dfrac{Y'}{Y}R + (R + Y' - Y)\right] \\ G^* = \dfrac{1}{2}\left[\dfrac{Y'}{Y}G + (G + Y' - Y)\right] \\ B^* = \dfrac{1}{2}\left[\dfrac{Y'}{Y}B + (B + Y' - Y)\right] \end{cases} \tag{3}$$

where (R^*, G^*, B^*) are the reconstructed color image. According to Eq. (3), the input color image in Fig. 3(a) and the modified luminance in Fig. 3(d) are used to compute the color image illustrated in Fig. 3(e).

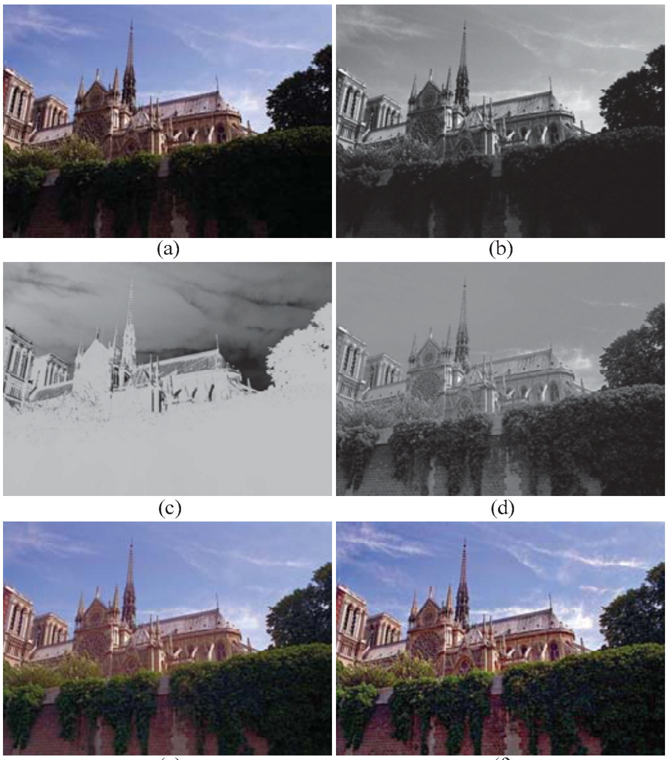

Fig. 3. (a) a color image, (b) luminance channel, (c) pixel-wise demarcation between underexposure and overexposure, (d) modified luminance, (e) reconstructed color image, (f) result of the proposed approach.

D. Local Contrast Boosting

Due to the luminance adaption technique in Eq. (2), small intensities were lighted up and large intensities were pulled down. Consequently, global luminance dynamic range was compressed. For example, observing the reconstructed color image in Fig. 3(e), green vines were revealed successfully. However, regions that are with original normal luminance, such as the sky and the building, were corrupted in local contrast. Therefore, in this section, local contrast will be boosted to get more vivid colors.

As has been explained in [2], in order to enhance local contrast, a pixel intensity needs to be increased if its value is larger than the averaged value of its neighbors. On the contrary, a pixel intensity will be decreased. Based on this idea, Tao et al. [2] enhanced local contrast of the luminance via an exponential technique:

$$Y^+(i,j) = \left[Y(i,j)\right]^{\frac{G*Y(i,j)}{Y(i,j)}} \tag{4}$$

where G is the Gaussian filter, and the asterisk * denotes convolution operation. Consequently, $G*Y(i, j)$ represents the local luminance around the pixel (i, j). Note that the dynamic range is [0, 1], and thus a pixel intensity $Y(i, j)$ will be decreased when the local luminance $G*Y(i, j)$ is larger than it. Motivated by the idea in Eq. (4), we proposed to boost local contrast of RGB channels by

$$O(i,j) = \begin{cases} \left[I(i,j)\right]^{\frac{BF*I(i,j)}{I(i,j)}} & \text{if } I \le BF*I \\ 1 - \left[1 - I(i,j)\right]^{\frac{1-BF*I(i,j)}{1-I(i,j)}} & \text{otherwise} \end{cases} \tag{5}$$

where $I(i, j)$ denotes an arbitrary channel in RGB space, i.e. $I \in \{R, G, B\}$. The notation BF denotes the bilateral filter [8], and thus $BF*I(i, j)$ is used to approximate the local intensity level around the pixel (i, j).

III. Experimental Results

The proposed enhancement algorithm has been tested on images that are affected by underexposure, overexposure and both problems. Moreover, in order to confirm the effectiveness of the proposed algorithm, experimental results have been compared with several popular algorithms. Typical experimental results are listed below.

Fig. 4(a) shows a underexposed image with a bright sunset. Fig. 4(b) gives the result of [5] which concentrates on improving the luminance of underexposed regions. Consequently, the output image in Fig. 4(b) was washed out at the sunset region. Figs. 4(c) and (d) are the output results by the methods in [4] and [6]. Global luminance in Figs. 4(c) and (d) are moderate, but local contrast still need to be improved. For example, contrast of the lid of the car was degenerated in Figs. 4(c) and (d). Fig. 4(e) illustrates the result of [7], and suffers from color distortion, because the algorithm in [7] modified RGB channels in parallel via a mapping technique. Result of the proposed approach is given in Fig. 4(f). Compared with other result images in Fig. 4, Fig. 4(f) has better local contrast, especially in the sunset region. In addition, because we firstly processed the luminance channel and reconstructed the color image carefully by Eq. (3), Fig. 4(f) avoids color distortion successfully.

Fig. 5(a) illustrates an overexposed image. Fig. 5(b) is the processed result of [5], but is rather overexposed. Figs. 5(c) and 5(d) are the output images of [9] and [6], respectively. These two images have moderate luminance, but suffer from dim colors. For example, the green leaves tends to be black in both 5(c) and 5(d). The processed result by [7] is shown in Fig. 5(e) where local contrast still needs to be improved. For instance, the black pods are not distinctive from other parts, such as green leaves and blue sky. The proposed result is given in Fig. 5(f) which shows good contrast and vivid color. In Fig. 5(f), tree trunks and flowers are striking.

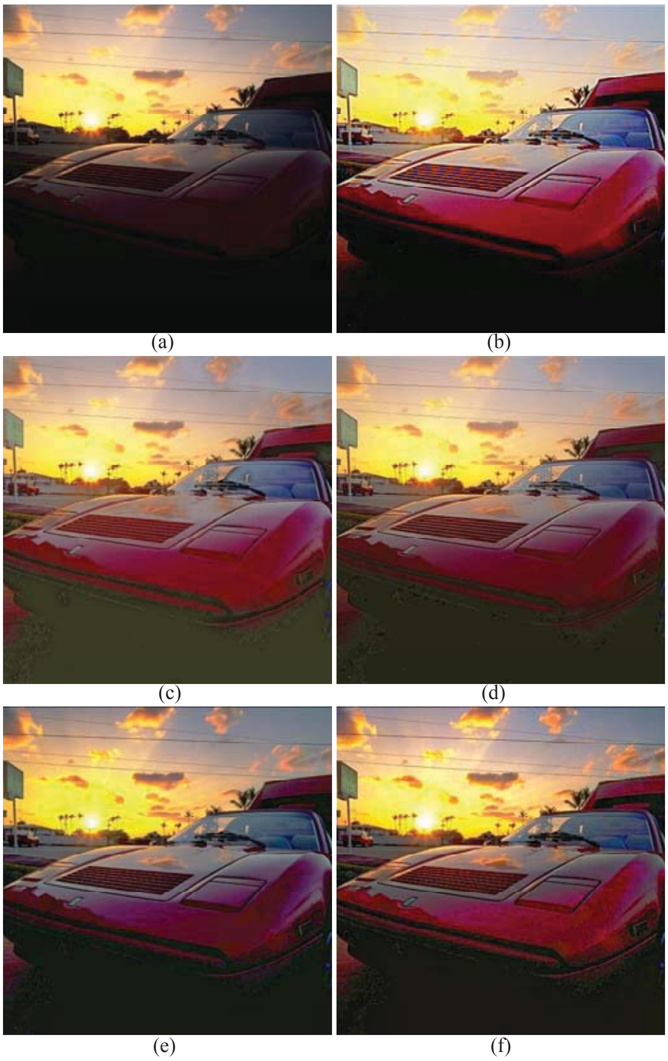

Fig. 4. (a) original image, and processed results by (b) Meylan et al. [5], (c) Choudhury et al. [4], (d) Shin et al. [6], (e) Wang et al. [7], (f) the proposed approach.

IV. Conclusion

In this work, an algorithm was proposed to enhance images which are under non-uniform illumination. In order to protect the original chroma information, the luminance channel is modified first. Specially, considering the underexposure and overexposure problems induced by non-uniform illumination, we tried to design an adaptive demarcating principle. Different from the globally demarcation values used in [2] and [4], the proposed demarcation changes as local luminance varies, thus is suitable for manipulating complicated illumination. Then, based on this adaptive demarcation, image luminance is modified to light up underexposed regions and dim overexposed regions. Finally, after reconstructing a color image using the original chroma information and the modified luminance, we tried to boost image color and local contrast by adjusting RGB channels in parallel. Experimental results of the proposed approach were compared with several recently published algorithms. Comparisons confirm that the proposed approach produces promising details and vivid colors.

Fig. 5. (a) original image, and processed results by (b) Meylan et al. [5], (c) Li et al. [9], (d) Shin et al. [6], (e) Wang et al. [7], (f) the proposed approach.

References

[1] E. Land and J. McCann, "Lightness and retinex theory," Journal of the Optical Society of America, vol. 61, pp. 1-11, January 1971.

[2] L. Tao, R. Tompkins, and V. K. Asari, "An illuminance-reflectance model for nonlinear enhancement of color image," in *Proc. IEEE International Conf. on Computer Vision and Pattern Recognition*, pp. 159-167, 2005.

[3] R. Schettini et al., "Contrast image correction method," Journal of Electronic Imaging, vol. 19, pp. 023005-023005-11, April 2010.

[4] A. Choudhury and G. Medioni, "Color contrast enhancement for visually impaired people," in *Proc. IEEE International Conf. on Computer Vision and Pattern Recognition*, pp. 33-40, 2010.

[5] L. Meylan, D. Alleysson, and S. Susstrunk, "Model of retinal local adaption for the tone mapping of color filter array images," Journal of the Optical Society of America A, vol. 24, pp. 2807-2816, September 2007.

[6] Y. Shin, S. Jeong, and S. Lee, "Efficient naturalness restoration for non-uniform illumination images," IET Image Processing, vol. 9, pp. 662-671, August 2015.

[7] Y. Wang and Y. Luo, "Balanced color contrast enhancement for digital images," Optical Engineering, vol. 51, pp. 107001-107001-11, October 2012.

[8] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in Proc. IEEE International Conference on Computer Vision, pp. 839-846, 1998.

[9] Y.C. Li et al., "Saliency guided naturalness enhancement in color images," Optik - International Journal for Light and Electron Optics, vol. 127, pp. 1326-1334, March 2016.