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Adaptive Enhancement for non-uniform illumination Images via Pixel-wise Histogram Modification and Color Reconstruction

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Abstract—**Non-uniform illumination images usually suffer from degenerated details and colors due to underexposure or overexposure problems. Traditionally, to improve local details, sophisticated mapping functions have been used to pull up dark intensities and pull down highly-bright regions. Inevitably, proper demarcation between underexposure and overexposure regions is fatal for the enhancing effects. In this work, in luminance channel, a pixel-wise demarcation was designed and cooperates with a nonlinear modification to global histogram. Then a color construction technique with color compensation was proposed to reconstruct color image using the modified luminance and the original chromatic information. Finally, in order to compensate for local contrast, a local comparison-dependent technique is employed to RGB channels. Experiments on several types of images show that our approach brings promising details for both underexposure and overexposure regions. Moreover, comparisons show that the proposed method performs well on globally overexposed images, and has the merit of protecting smooth uniform areas.**

Keywords-non-uniform illumination; globally overexposed; histogram modification; color reconstruction;

I. INTRODUCTION

In real life, surrounding illumination varies often, and therefore images taken by electronic equipments are prone to undergo underexposure and overexposure globally or locally. In order to revive the submerged details in dark and highly-bright regions, many image enhancement algorithms have been developed and can be roughly categorized into three groups: Retinex-based algorithms [1], nonlinear-mapping methods based on luminance channel [2]-[5], and histogram-modification based algorithms [6]-[9].

In the first category, Retinex theory insists on that human perceived lightness of an object is determined by the relative lightness to its neighbors, and that this mechanism works independently for long, middle and short waves [1]. Thus, in RGB channels, for every pixel, mathematical comparisons between the pixel and its neighbors are utilized to renew its intensity. Due to the local comparisons between neighboring pixels, Retinex-based algorithms can push local luminance approaching proper values and improve local contrast effectively. However, treating RGB channels in parallel is prone to induce color distortion, especially for images with a dominant color. In addition, smoothness of uniform areas is apt to be corrupted if local contrast has been enhanced significantly.

In the second category, image luminance is mapped nonlinearly to delight dark regions and dim highly-bright areas, thus compressing global dynamic range. A sigmoid-function based technique was proposed in [2] for the V channel of color images. Another popular mapping method is the gamma correction. Schettini et al. [3] introduced a hypothesis that the expected intensity of global luminance is 0.5. Based on this hypothesis, they designed a sophisticated parameter setting for traditional gamma correction. In addition, Choudhury et al. [4] combined logarithmic function and their symmetric functions for luminance mapping. Recently, Shin et al. [5] utilized an improved gamma correction to enhance the Gaussian smoothed luminance. In these algorithms [2-5], dark luminance was pulled up and highly-bright luminance was pulled down. Note that, the demarcation between dark and bright luminance was devised according to luminance distribution and was consistent throughout an image.

In the third category, image histogram is utilized to remap input intensity. Note that, local relationships between pixels are not utilized, thus avoiding complex computations inside local regions. A classic and popular method is histogram equalization (HE), where the output intensity equals to the cumulated density of the current intensity. However, the spikes (extremely large densities) in image histogram often mislead the result [6], because the output difference between spike-bins and its smaller neighbor is exceptionally large. HE is effective in global contrast enhancement, thus is suitable for low-contrast images. In order to improve local contrast, the contrast-limited adaptive histogram equalization (CLAHE) method [7] was proposed by applying HE independently inside the separate blocks in an image. Thereafter, every pixel intensity is remapped by the weighted average of HE results from nearby blocks around it. Apart from HE, the gray-level grouping (GLG) algorithm [8] was proposed by grouping the histogram into several groups of bins. Recently, Wang et al. [9] proposed the content-adaptive histogram equalization (CAHE) algorithm by integrating local and global HE transformation. In detail, the coefficients for local and global HE were determined by local and global entropies. After content-adaptive HE, image saturation was compensated based on local contrast. For color images, histogram-based algorithms are apt to induce color distortion when treating RGB channel in parallel. Besides, the color construction procedure should be designed carefully if luminance was processed first.

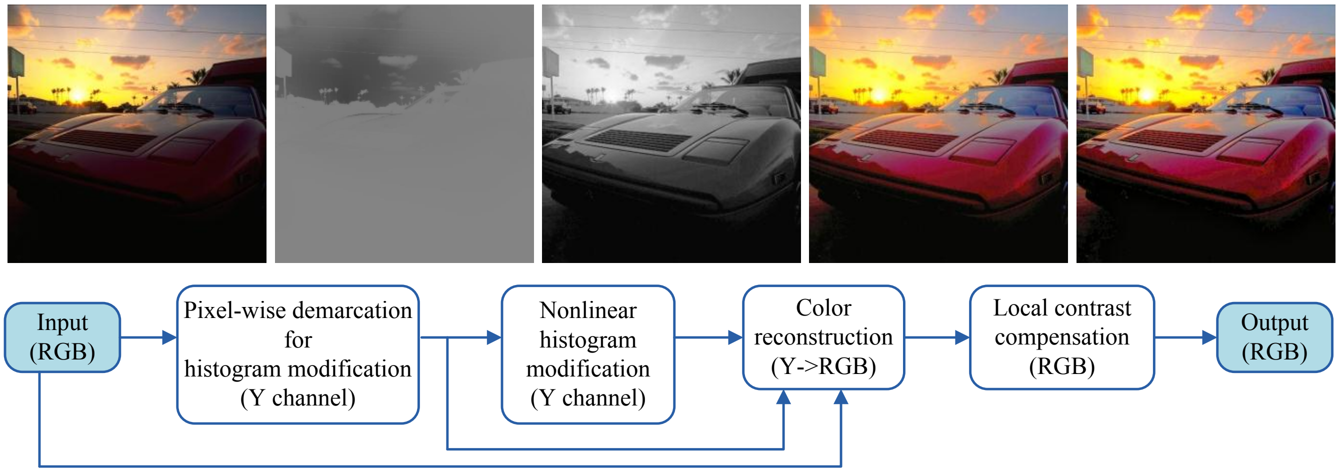


Figure 1. Flowchart of the proposed approach.

In this work, in order to revive non-uniform illumination images, a local image-dependent approach is proposed. First, in luminance channel, nonlinear histogram modification is implemented adaptively based on a pixel-wise demarcation that is determined by local luminance. Then, the modified luminance is integrated with original chromatic information to reconstruct a color image. Finally, to compensate for local contrast, a local-comparison mechanism is utilized to enlarge local disparity for RGB channels. Experimental results show that our approach produces clear details and vivid colors when comparing with recently published algorithms.

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

II. PROPOSED APPROACH

Flowchart of the proposed approach is given in Fig. 1, and a sample image with intermediate results are given as well. In detail, the proposed approach consists of four steps: 1. prepare the pixel-wise demarcation in luminance channel; 2. histogram modification to luminance according to the demarcation; 3. color reconstruction to build up color images using modified luminance and input chromatic information; 4. adjustment for local contrast.

A. Pixel-wise Demarcation

Non-uniform illumination usually induces extremely low or high luminance for color images. Traditional histogram-based algorithms tried to redistribute input gray levels among the whole dynamic range. Considering a image with a quite small overexposed area, such as the left column in Fig. 2, probability densities of the overexposed area are small. Therefore, overexposure may be exaggerated after traditional HE, which is shown in the middle column of Fig. 2. The histogram is almost uniformly distributed among the whole dynamic range. However, the fire area in the middle column suffers from overexposure more seriously.

In order to enhance small areas with overexposure or underexposure, we consider that HE can be implemented roughly based on a localized parameter which is utilized to control the global output. Thus, we proposed a pixel-wise demarcation which is preset as the reference value for average intensity. In order to revive extremely overexposed areas, global histogram can be moved approaching to 0 to pull down overexposure. On the contrary, global histogram can be moved towards 1 to pull up dark regions. Thus, for an image, histogram equalization can be implemented based on local intensity strength. Precisely, the pixel-wise demarcation is expressed as:

$$Y_A(x) = 0.5 + \left[Y_m - BF * Y(x)\right]^3 \tag{1}$$

where Y denotes Y channel, and Y_m is the mean value. The notation BF represents the bilateral filter [10], and * denotes convolution operator. Thus $BF*Y(x)$ approximates the local strength of pixel x. The demarcation defined in (1) varies contrarily with local strength, and will be utilized as the reference value for average intensity in Sec. II.B.

B. Nonlinear Modification to Histogram

For a pixel x, global histogram of the image can be divided into two parts by global mean luminance Y_m. In order to control the output for pixel x, the output histogram at pixel x needs to be dragged towards the demarcation $Y_A(x)$. Consequently, nonlinear HE can be implemented separately on the two sides of Y_m:

$$F(x) = \begin{cases} Y_A(x)\left(\sum_{j=0}^{255\cdot Y(x)} p_j \cdot w_j\right)/\mathrm{P}_l & Y(x) < Y_m \\ Y_A(x) + \left(1 - Y_A(x)\right)\left(\sum_{j=255\cdot Y_m}^{255\cdot Y(x)} p_j \cdot w_j\right)/\mathrm{P}_h & Y(x) \geq Y_m \end{cases} \tag{2}$$

where p_j denotes the probability density of gray level j, and the notation w_j is the weight for gray level j. Based on the just noticeable difference (JND) theory, the perceived difference by human visual system increases when local intensity deviates away from the middle dynamic range 127. Therefore, in order to enlarge the differences between extreme intensities, the weight w_j is set as

$$w(j) = |j - 127|/255 + 0.7 \tag{3}$$

which has larger value as gray level j deviates away from 127. The denominators in (2) are the weighted sum of probability densities on the two sides of Y_m:

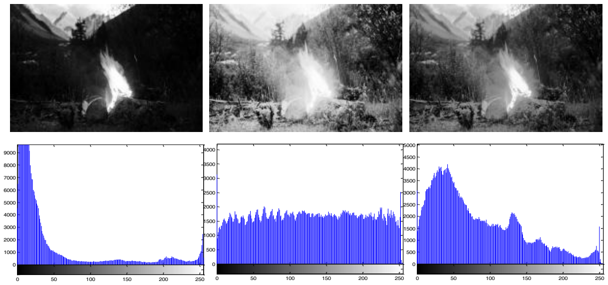


Figure 2. Gray image and its histogram. Left column: input image, middle column: output by HE; right column: result by our method in (2).

$$\begin{cases} P_l = \sum_{j=0}^{255 \cdot Y_m} p_j w_j \\ P_h = \sum_{255 \cdot Y_m}^{255} p_j w_j \end{cases} \quad (4)$$

where Y_m denotes the mean luminance. The right column in Fig.2 shows the output by applying (2) to every pixel of the image in the left column. The bright fire and background snow mountain were protected, and the corresponding histogram illustrates that original highly-bright regions are not compressed exaggeratedly.

C. Color Reconstruction

In previous sections, only the luminance channel was processed. Therefore, input chromatic information needs to be utilized to reconstruct color images. For this purpose, Tao et al. [2] utilized the ratio of the enhanced luminance to input luminance, thus preserving the original ratios between RGB components by:

$$E'_C(x) = I_C(x) \cdot F(x) / Y(x) \quad (5)$$

where index $c \in (r, g, b)$ and I_c represents an arbitrary color channel of the input image. However, the color reconstruction procedure in (5) is apt to exaggerate color for underexposure regions, and gray the color for overexposure regions. For example, for a highly-bright pixel x, $F(x)$ is larger than $Y(x)$, and thus the difference between RGB components will be enlarged according to (5). To cope with this, [3] applied the following method to reconstruct color image:

$$E_C^*(x) = \frac{1}{2} \cdot \left[I_C(x) \frac{F(x)}{Y(x)} + I_C(x) + F(x) - Y(x) \right] \quad (6)$$

which is a tradeoff between the difference and ratio of RGB components. However, the color reconstruction techniques in (5) and (6) always induce faint colors for globally overexposed images. For example, Fig. 3(a) is globally overexposed. Figs. 3(b) and (c) are the color reconstruction outputs using (5) and (6), respectively. In Fig. 3(a), because all the global dynamic range in RGB space are small, differences and ratios between RGB components are quite small as well. Consequently, the reconstructed colors by (5) and (6) are really faint. Therefore, in order to revive overexposed images with low-dynamic range, color saturation needs to be boosted. Precisely, we proposed to add a color-compensation item to (6):

$$E_C(x) = E_C^*(x) + \left(I_C(x) - Y(x) \right) \cdot \left(Y_m / Y_{range} \right) \quad (7)$$

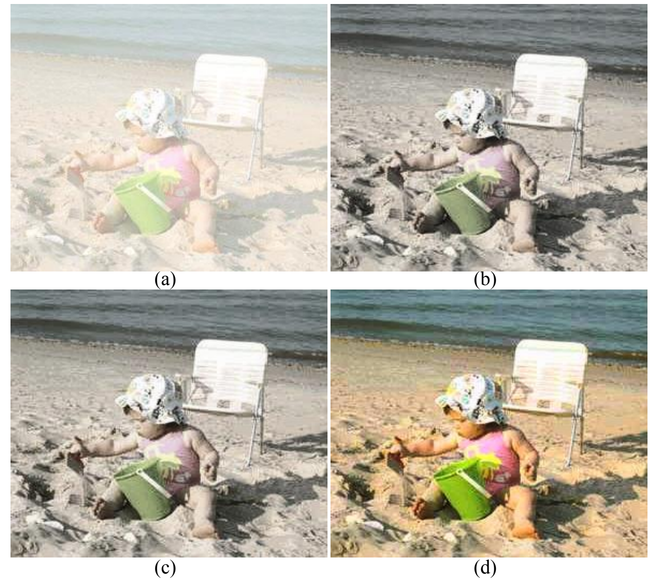


Figure 3. (a) input image, (b) output by (5), (c) output by (6), (d) output by our color-construction method in (7).

where Y_{range} represents the dynamic range of the Y channel in the input color image. The subtraction $I_C(x)$-$Y(x)$ is used to describe the color for pixel x. Fig. 3(d) illustrates the color reconstruction result by our method in (7). It gets rid of overexposure successfully and shows proper color.

D. Local Contrast Compensation

In the histogram modification technique expressed in (2), pixel-wise demarcation varies negatively with local luminance strength. Thus, dark regions were lighted up and highly-bright regions were pulled down. Inevitably, global dynamic range was compressed when the input dynamic range is large. For example, Fig. 4(a) shows a image which has both dark and bright regions, and Fig. 4(b) illustrates the demarcation. Fig. 4(c) gives the enhancing result by (7), and it shows that original dark vines were revealed. However, original bright regions were compressed, such as the sky and cloud. Thus, local contrast will be boosted in this section.

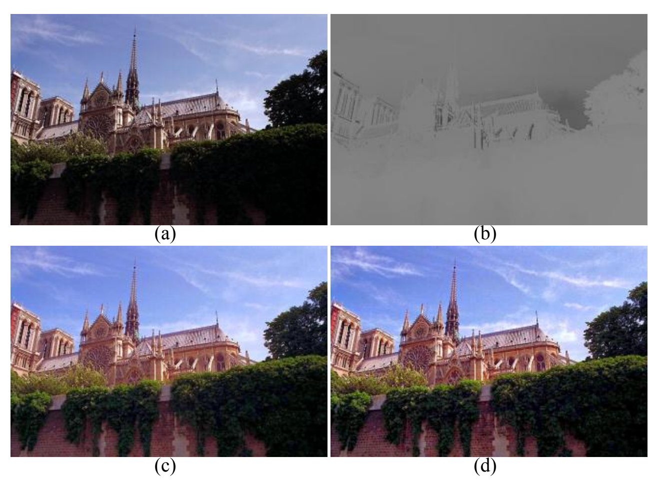


Figure 4. (a) input image, (b) pixel-wise demarcation by (1), (c) output after color construction in (7), (d) output after contrast boosting in (8).

According to Retinex theory [1], in order to improve local contrast, local disparity between neighboring pixels needs to be enlarged. Consequently, a pixel can be pulled up if its intensity is larger than its neighbors. Contrarily, a pixel should be pulled down. With the reconstructed color image by (7), this principle will be implemented in RGB channels in parallel. Tao et al. [2] employed an exponential formula to enhance local contrast. Based on the exponential function in [2] and its symmetric function, we proposed the following technique to boost local contrast:

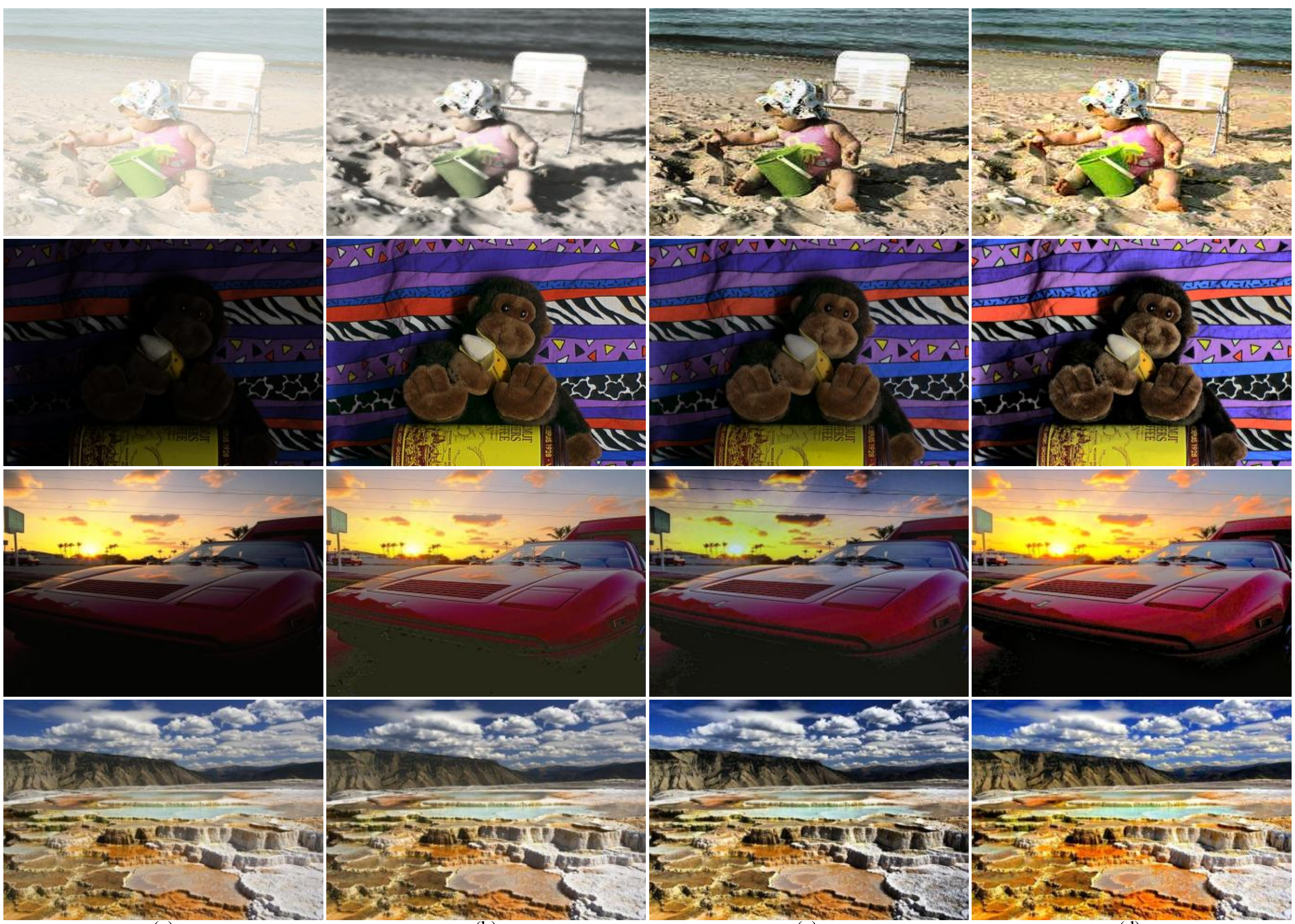
$$T_c(x) = \begin{cases} \left[E_c(x)\right]^{\frac{BF*E_c(x)}{E_c(x)}} & \text{if } E_c(x) \le BF*E_c(x) \\ 1-\left[1-E_c(x)\right]^{\frac{1-BF*E_c(x)}{1-E_c(x)}} & \text{otherwise} \end{cases} \tag{8}$$

where index $c\in(r, g, b)$, and E_c denotes a certain color channel of the reconstructed image by (7). The symbol BF represents bilateral filter [10], and $BF*E_c(x)$ approximates the local intensity level around pixel x. Fig. 4(d) exhibits the contrast enhancing result for Fig. 4(c) by (8). It is shown that contrast between sky and cloud was enhanced properly.

III. EXPERIMENTAL RESULTS

Experiments were done on several types of images which are downloaded from Internet, and comparison was made with recently published algorithms, including a gamma-correction based algorithm [5] and CAHE algorithm [9].

In the first row of Fig. 5, column (a) shows a globally overexposed image. As shown in column (c) and (d), CAHE [9] and the proposed approach get rid of overexposure successfully. However, the reconstructed color seems faint by [9] in column (c). In the second row, column (a) illustrates a globally underexposed image. In columns (b)-(d), it is shown that underexposure has all been eliminated well. Moreover, the proposed approach, given in column (d), brings better contrast. In the third row, column (a) exhibits a image which has both underexposure and overexposure. Column (b) shows the output of [5], and it has low local contrast, such as the car area. As shown in column (c), output of [9] exhibits good contrast, but suffers from color distortion. For instance, the red car appears blue in column (c). In addition, [9] implements HE inside every local area, and therefore highly-bright areas, such as the sunset, has been pulled down excessively. In the fourth row, column (a) shows a low-contrast image. In columns (c) and (d), CAHE and the proposed method produce improved contrast. Besides, compared with CAHE, the proposed approach brings vivid color and protects highly-bright areas, such as the white rock in the lower right corner.



(a) (b) (c) (d)

Figure 5. (a) input image, (b) output of [5], (c) output of CAHE algorithm [9], (d) output of the proposed approach.

(a) (b) (c) (d)

Figure 6. (a) input image, (b) output of [5], (c) output of CAHE algorithm [9], (d) output of the proposed approach.

Moreover, when dealing with consistent regions, the proposed approach also has the merit of protecting smoothness. Fig. 6(a) shows an image with slight overexposure. The T-shirts of the children are smooth uniform regions, and thus are zoomed in specially under every image. Comparison between Figs. 6(b)-(d) shows that the proposed method produces better contrast and vivid color than [5] and [9], such as the cloud and mountain. In Fig. 6(c), T-shirts have been corrupted because CAHE algorithm utilizes HE inside local areas. On the contrary, the proposed approach utilized global histogram at every pixel, thus avoiding over-enhanced contrast at local areas. Fig. 6(d) shows that the T-shirts are protected successfully.

IV. CONCLUSIONS

In this work, a local image-based approach was proposed to enhance non-uniform illumination images. First, image luminance is modified via a nonlinear HE method. Different from traditional HE, the "nonlinear" characteristic relies on two aspects: (1) a pixel-wise demarcation parameter was devised to control the output using local luminance strength. Thus, a HE-based histogram modification is implemented at every pixel using the global histogram of the input image. (2) based on the JND theory, corresponding weights were assigned to different bins to calculate a weighted accumulation of density probabilities. This nonlinear histogram modification runs fast since the same global histogram is used at each pixel. On the other hand, this modification is effective for small dark and highly-bright regions, because the pixel-wise demarcation is utilized to control the mapping degree during histogram modification. After luminance adaption, image color is reconstructed using original chromatic information and luminance. Note that, the proposed color reconstruction method takes global dynamic range into consideration, thus is also effective for globally overexposed images. Finally, to revive image details, local contrast was boosted via comparison between neighbors.

Experiments were done on globally underexposed, globally overexposed, and partially illuminated images. Comparisons with recently published algorithms show that the proposed approach produces vivid color and proper contrast. In addition, our method has the advantage of protecting smooth uniform areas.

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