Color Preserving Contrast Enhancement for Low Light Level Images based on Retinex

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***Abstract*—In this paper, we propose a novel contrast enhancement algorithm for low light level images, which preserves image details and color constancy based on Retinex. We decompose an input low contrast image into luminance and chrominance components in Lab color space, which reflects the perception characteristics of human visual system well, and enhance the luminance component only. We first estimate illumination using adaptive bilateral filtering, which guarantees the available range of reflectance by considering proper neighboring pixels according to their luminance and color values. Then we enhance the contrast of the estimated illumination image using parabola-based tone mapping function. Finally, the enhanced luminance and the original chrominance are combined together to yield an enhanced color image. Experiment results show that the proposed algorithm enhances image details and edge structures by alleviating halo artifacts, and also preserves naturalness faithfully by avoiding color shifting artifacts.**

I. Introduction

Contrast enhancement is one of the traditional research topics of image processing, which increase the contrast of input degraded images such as low light level images, high dynamic range images, and foggy or hazy images. Retinex theory was first proposed by Land *et al.* [1], and has been widely used for contrast enhancement. In Retinex theory, the perceived image intensity is assumed to be the product of scene reflectance and illumination. Jobson *et al.* proposed single-scale Retinex (SSR) algorithm [2] where the illumination of an input image is estimated as a Gaussian filtered image. However, due to the smoothing nature of Gaussian filtering, resulting enhanced images often yield color shifting artifacts as well as halo artifacts in the vicinity of edges.

To alleviate these artifacts in SSR algorithm, modified Retinex algorithms were proposed [3], [4]. Kimmel *et al.* [5] addressed the color shifting problem by using the HSV color space. Specifically, they enhanced the V channel only and preserved H and S channels. Elad [6] adopted a bilateral filter instead of the Gaussian filter to estimate the illumination to avoid halo artifact. Meylan [7] applied principle component analysis to an input color image, and obtained luminance by taking the first principle component and obtained chrominance by the second and third components, respectively, where only the luminance is processed for enhancement. Choi *et al.* [8] also enhanced V channel for preserving color constancy, and presented a image formation model as the product of global illumination, local illumination, and reflectance. The local illumination is estimated by using JND (just noticeable difference)-based nonlinear low-pass filtering to reduce halo artifact. Shen and Hwang [9] also used HSV color space for color constancy, and developed a smoothing filter by optimizing a cost function to reduce halo artifact.

These Retinex-based algorithms enhance the details of input low contrast images effectively, however, often result in unnatural images, where overall color temperatures are severely changed and/or additional light sources are generated. Chen *el al.* [10] increased the contrast of input images while preserving naturalness of colors. Li *el al.* [11] enhanced the reflectance as well as illumination to preserve natural colors. Wang *et al.* [12] balanced the details and naturalness in resulting images by processing reflectance and illumination together using bright pass filter and bi-log transformation.

In this paper, we enhance the contrast of low light level images while preserving color constancy based on Retinex. We first employ Lab color space to represent an input image by luminance and chrominance components. Then we enhance the low contrast luminance only and preserve the original chrominance. We estimate illumination by applying adaptive bilateral filtering which considers proper neighboring pixels according to their luminance and color values. We also increase the intensity of estimated illumination adaptively using parabola-based tone mapping curve. Finally the enhanced L channel image is combined with the original a and b channel images, which are then transformed to RGB color space. Experimental results demonstrate that the proposed algorithm preserves image details and color constancy faithfully, while improving the contrast of low light level images.

The rest of the paper is organized as follows. Section II briefly reviews the Retinex-based enhancement algorithms. Section III describes the proposed low light level image enhancement algorithm, and Section IV shows experimental results. Section V concludes the paper.

II. Retinex-based Contrast Enhancement

Retinex theory [1] assumes that an image intensity I is represented by the product of scene reflectance R and illumination L, given by

$$I(x, y) = R(x, y) \cdot L(x, y). \tag{1}$$

In SSR algorithm [2], the illumination is estimated by convolving a Gaussian filter with an input image, and the

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resulting scene reflectance R_{SSR} is obtained in log-scale.

$$R_{\mathrm{SSR}}(x,y) = \log I(x,y) - \log\{F(x,y) * I(x,y)\}, \quad (2)$$

where $F(x,y)$ is a normalized Gaussian surround function [2], given by

$$F(x,y) = K \cdot \exp\left(-\frac{x^2+y^2}{c^2}\right). \quad (3)$$

K is a normalization parameter satisfying $\sum_x \sum_y F(x,y) = 1$. When c becomes large, halo artifact becomes severe around high intensity pixels.

To reduce halo artifact of SSR algorithm, multi-scale Retinex (MSR) algorithm [3] was proposed, which yields scene reflectance R_{MSR} as a weighted sum of SSR results at multiple image scales.

$$R_{\mathrm{MSR}}(x,y) = \sum_{n=1}^{N} w_n \cdot R_{\mathrm{SSR},n}(x,y), \quad (4)$$

where N is the number of image scales, and w_n and $R_{\mathrm{SSR},n}$ denote a weighting parameter and the scene reflectance obtained by SSR at the n-th scale, respectively.

Moreover, to alleviate color shifting artifact of MSR algorithm, MSR color restoration (MSRCR) algorithm [4] was also proposed. The output reflectance R_{MSRCR} is obtained by performing color restoration function to the resulting reflectance of MSR, given by

$$R_{\mathrm{MSRCR}}(x,y) = H(x,y) \cdot R_{\mathrm{MSR}}(x,y) \quad (5)$$

where $H(x,y)$ is a color restoration function.

III. PROPOSED ALGORITHM

A. Lab Color Space

The conventional Retinex-based image enhancement algorithms convert RGB colors into other space such as HSV or YCbCr, and process the luminance channel using Retinex. However, in HSV and YCbCr color spaces, when the luminance is changed, the related chrominance values are also changed accordingly. Moreover, the amount of color difference is not exactly same to that of perceived difference by human visual system (HVS). In contrary, Lab color space changes the luminance and chrominance values independently and reflects HVS more faithfully [13]. Therefore, we employ Lab color space and perform Retinex-based enhancement to the luminance channel only. We also preserve the original color information in chrominance channels to avoid color shifting artifacts.

B. Illumination Estimation

According to the Retinex theory [1], we also represent the observed intensity of L channel luminance image as the product of the related reflectance and illumination.

$$I_{\mathrm{lum}}(x,y) = R_{\mathrm{lum}}(x,y) \cdot L_{\mathrm{lum}}(x,y) \quad (6)$$

where $I_{\mathrm{lum}}(x,y)$, $R_{\mathrm{lum}}(x,y)$, and $L_{\mathrm{lum}}(x,y)$ denote the intensity, reflectance, and illumination, respectively, at the pixel position (x,y) in L channel image. Note that, since the reflectance is normalized into $[0,1]$, $I_{\mathrm{lum}}(x,y) \le L_{\mathrm{lum}}(x,y)$.

The conventional Retinex-based algorithms estimate the illumination by performing convolution on an input image with smoothing filters, such as the Gaussian [4], [8] and bilateral filters [6], and guided filters [14]. The Gaussian filter computes an average pixel value, and thus often causes halo artifacts. In contrary, bilateral filter [15] can preserve the edges in an input image, and alleviate halo artifacts efficiently.

Note that, the conventional bilateral filtering assigns a higher weight to a neighboring pixel, which is geometrically closer and has a more similar pixel value to a given target pixel. However, at some target pixels, estimated illumination values can be even smaller than the observed intensity values due to the smoothing nature of bilateral filter, which results in invalid reflectance values larger than 1. In such cases, it is additional required to normalize or clip the range of reflectance values, which may yield smoothed pixel values in enhanced images.

Therefore, we employ the bilateral filtering adaptively in order to guarantee the available range of reflectance. To be specific, among the neighboring pixels to a given target pixel, we only consider the pixels which have similar colors to the target pixel and larger luminance values than the target pixel. Let $\mathcal{P}(x,y)$ denote the set of neighboring pixels to the pixel (x,y). We obtain the set of pixels, $\mathcal{S}(x,y)$, by selecting the pixels (u,v)'s from $\mathcal{P}(x,y)$ which have similar colors to the pixel (x,y) and larger luminance values than the pixel (x,y).

$$\begin{aligned}\mathcal{S}(x,y) \;&= \{(u,v) | (u,v) \in \mathcal{P}(x,y),\ I_{\mathrm{lum}}(u,v) > I_{\mathrm{lum}}(x,y),\\ &\qquad d_{(x,y)}(u,v) < \tau\}\end{aligned} \quad (7)$$

where the chrominance distance $d_{(x,y)}(u,v)$ between (x,y) and (u,v) is computed as

$$d_{(x,y)}(u,v) = \sqrt{(I_a(x,y) - I_a(u,v))^2 + (I_b(x,y) - I_b(u,v))^2} \quad (8)$$

where I_a and I_b are a and b channel images in Lab color space, and τ is a given threshold which is empirically set as $\tau = 10$.

Then we estimate the illumination value at the pixel (x,y) as

$$\hat{L}_{\mathrm{lum}}(x,y) = \frac{\sum_{(u,v)\in\mathcal{S}(x,y)} F_{\mathrm{geo}}(u,v) \cdot F_{\mathrm{int}}(u,v) \cdot I_{\mathrm{lum}}(u,v)}{\sum_{(u,v)\in\mathcal{S}(x,y)} F_{\mathrm{geo}}(u,v) \cdot F_{\mathrm{int}}(u,v)}, \quad (9)$$

where $F_{\mathrm{geo}}(u,v)$ and $F_{\mathrm{int}}(u,v)$ reflect the geometric similarity and intensity similarity in bilateral filtering.

$$\begin{aligned}F_{\mathrm{geo}}(u,v) &= \frac{1}{2\pi\sigma_1^2} \exp\left(-\frac{(x-u)^2+(y-v)^2}{2\sigma_1^2}\right),\\ F_{\mathrm{int}}(u,v) &= \frac{1}{2\pi\sigma_2^2} \exp\left(-\frac{(I_{\mathrm{lum}}(x,y) - I_{\mathrm{lum}}(u,v))^2}{2\sigma_2^2}\right), \end{aligned} \quad (10)$$

where we set $\sigma_1 = 3$ and $\sigma_2 = 5$, respectively.

Note that the original bilateral filtering is implemented by replacing $\mathcal{S}(x,y)$ with $\mathcal{P}(x,y)$ in the above equation (9). Since we only consider the neighboring pixels which have larger luminance values than a target pixel, we can guarantee that the

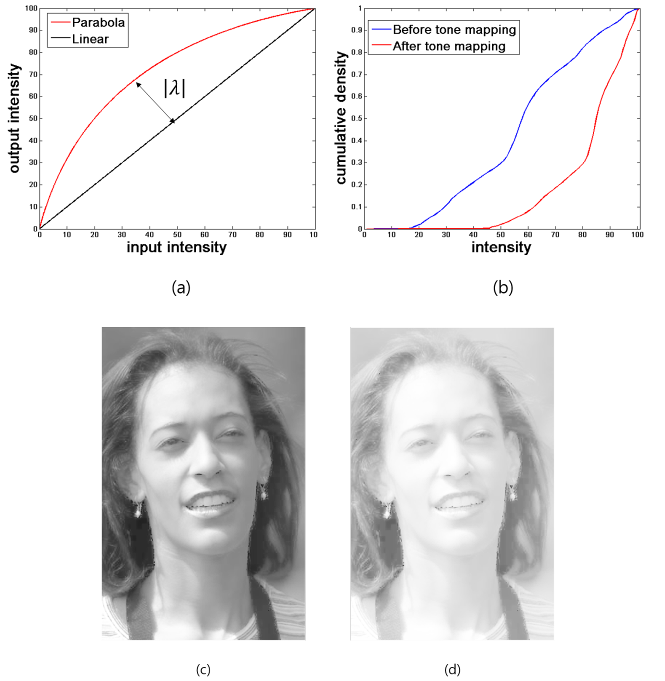

Fig. 1. Parabola-based tone mapping. (a) Intensity transfer functions, (b) cumulative density functions of intensity values, and the corresponding images (c) before and (d) after tone mapping.

resulting estimated reflectance values lie within the available range of $[0, 1]$ according to (6). Moreover, we can further preserve the details and edge structures in an input image by only consider the neighboring pixels having similar colors to the target pixel.

We can obtain reflectance from (6) as

$$R_{\mathrm{lum}}(x, y) = \frac{I_{\mathrm{lum}}(x, y)}{\hat{L}_{\mathrm{lum}}(x, y)}. \tag{11}$$

C. Tone Mapping

We enhance the contrast of input image by improving the dynamic range of intensity histogram of the estimated illumination image $\hat{L}_{\mathrm{lum}}$. Traditional histogram equalization or cumulative density function (CDF) matching [12] can be used to this end, however, these methods often result in unnatural images since populated similar intensity values may be changed quite differently.

In this work, we employ a parabola-based tone mapping curve. As shown in the transfer function domain in Fig. 1(a), we define a red parabola curve on the blue line with the $45°$ slope, whose vertex is deviates from the blue line up to $|\lambda|$. Thus the parabola curve has relatively steep slopes for low intensity values and slowly changes for high intensity values. We adaptively find a proper parabola curve to an input image, by computing λ as

$$\lambda = \int_0^{100} T_{\mathrm{ill}}(z) - T_{\mathrm{unif}}(z)\ dz \tag{12}$$

where $T_{\mathrm{ill}}(z)$ is the CDF of $\hat{L}_{\mathrm{lum}}(x, y)^3$ values and $T_{\mathrm{unif}}(z)$ is the CDF of uniform distribution, respectively. Note that the integration range is $[0, 100]$, since we consider the L channel in Lab color space.

We transform the initially estimated illumination values of $\hat{L}_{\mathrm{lum}}(x, y)$ into a new one $\tilde{L}_{\mathrm{lum}}(x, y)$ according to the computed parabola-based tone mapping curve. If λ becomes positive, it means that an input image is a low light level image, and thus we increase the intensity values by parabola-based transfer function, and vice versa. Moreover, the absolute value of $|\lambda|$ controls the level of enhancement: larger $|\lambda|$ changes intensity more severely. In addition, to preserve the order of pixel values in the resulting image, we make $|\lambda|$ not to exceed a threshold μ, which is set to 35.3 empirically. Fig. 1(b) compares the CDFs of $\hat{L}_{\mathrm{lum}}(x, y)$'s (before tone mapping) and $\tilde{L}_{\mathrm{lum}}(x, y)$'s (after tone mapping) corresponding to the images shown in Figs. 1(c) and (d), respectively. We see that the resulting illumination becomes brighter and exhibits a wider dynamic range of intensity values than initially estimated one.

Finally, we obtain an enhanced luminance image $\tilde{I}_{\mathrm{lum}}$ by using the computed reflectance R_{lum} in (11) and the enhanced illumination $\tilde{L}_{\mathrm{lum}}$.

$$\tilde{I}_{\mathrm{lum}}(x, y) = R_{\mathrm{lum}}(x, y) \cdot \tilde{L}_{\mathrm{lum}}(x, y). \tag{13}$$

We combine the enhanced luminance $\tilde{I}_{\mathrm{lum}}$ and the original chrominance components of I_a and I_b together, which are then transformed into RGB color space.

IV. Experimental Results

We evaluate the performance of the proposed algorithm compared with that of Wang *et al.*'s algorithm [12], on the three test low light level images: 'Woman' in Fig. 2(a), 'Man' in Fig. 3(a), and 'Dog' in Fig. 4(a), respectively.

In Fig. 2, the hair region is associated with compact distribution of low intensity values, and thus becomes blurred

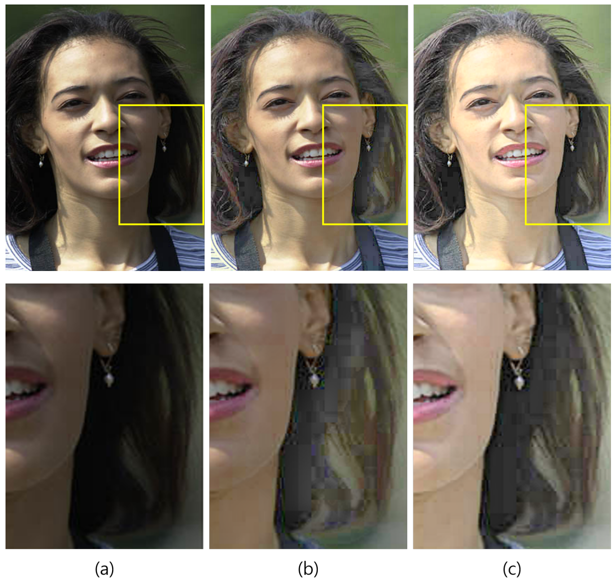

Fig. 2. Contrast enhancement results on 'Woman' image: (a) Input low contrast image, and the enhanced images by (b) [12] and (c) the proposed algorithm, respectively. The proposed algorithm preserves the details of the hair region faithfully.

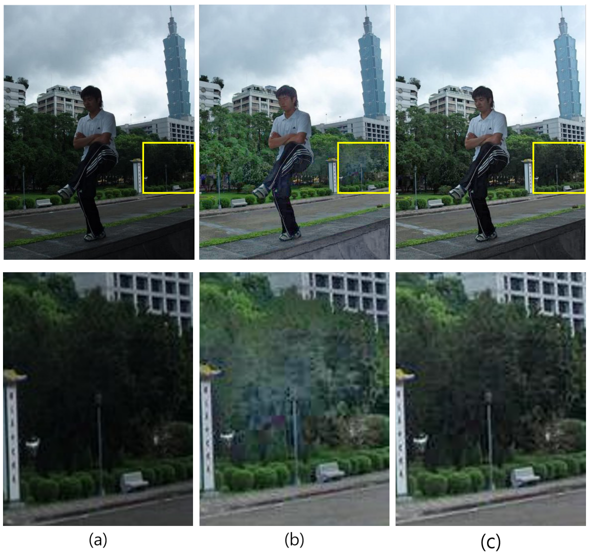

Fig. 3. Contrast enhancement results on 'Man' image: (a) Input low contrast image, and the enhanced images by (b) [12] and (c) the proposed algorithm, respectively. The proposed algorithm preserves naturalness and color constancy in the tree region.

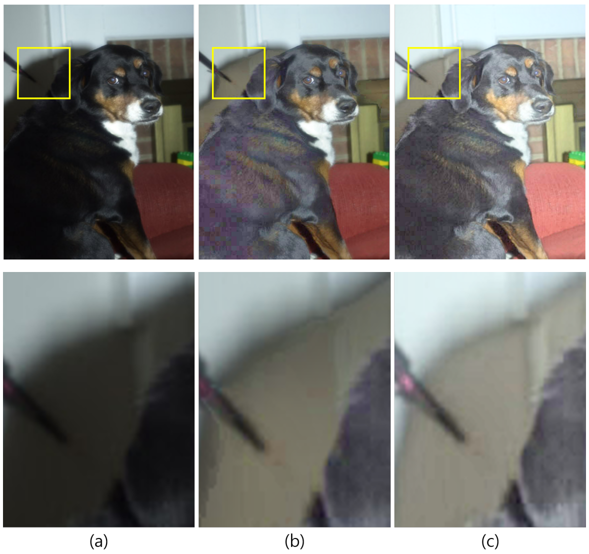

Fig. 4. Contrast enhancement results on 'Dog' image: (a) Input low contrast image, and the enhanced images by (b) [12] and (c) the proposed algorithm, respectively. The proposed algorithm preserves naturalness in the shadow region.

and unnatural in the Wang *et al.*'s algorithm as shown in Fig. 2(b). However, as shown in Fig. 2(c), the proposed algorithm preserves the details of hair region by adaptively selecting neighboring pixels for bilateral filtering. Similarly, while the Wang *et al.*'s algorithm distorts the colors of trees as shown in Fig. 3(b), the proposed algorithm preserves color constancy in the tree region and yields a natural result as shown in Fig. 3(c). Also, we observe that the shadow region exhibit largely different brightness values in the Wang *et al.*'s algorithm as shown in Fig. 4(b), however, the proposed algorithm alleviates this artifact and preserves the natrualness of dark shadow region as shown in Fig. 4(c).

The experimental results show that the proposed contrast enhancement algorithm can preserve color constancy and naturalness in the resulting images, since it adaptively applies the bilateral filtering and changes the pixel values according to an optimally selected parabola-based tone mapping curve.

V. Conclusions

In this work, we proposed a Retinex-based image contrast enhancement algorithm to preserve color constancy. We first decomposed an input image into luminance and chrominance components using Lab color space. Then we estimated the illumination by applying bilateral filtering adaptively according to the color similarity and luminance distribution among neighboring pixels. Moreover, we improved the contrast of luminance image by performing parabola-based tone mapping to the estimated illumination image. Finally, we generated an enhanced color image by combining the enhanced luminance and the original chrominance together. Experiment results demonstrated that the proposed algorithm enhances the contrast of input low contrast images, while preserving image details and natural colors faithfully. However, when an input image has a very low light level, the proposed algorithm often yields an over-enhanced result. We will address this problem as a future work.

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