A SINGLE BACKLIT IMAGE ENHANCEMENT METHOD FOR IMPROVEMENT OF VISIBILITY OF DARK PART

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ABSTRACT

This study proposes a simple and fast backlit image enhancement method that improves the visibility of dark parts. The proposed method uses gamma correction and histogram equalization to make an intensity-adjusted image and a contrast-enhanced image, respectively. Then, an alpha-blended image of the two images is obtained. Finally, an output image is obtained by fusing the original image and the blended image using alpha blending to avoid causing artifacts in bright parts. The weight for fusion is calculated by using Otsu's method and the guided filter. We verify the effectiveness of the proposed method through comparative experiments.

Index Terms— Backlit image, image enhancement, weight map, alpha blending

1. INTRODUCTION

When shooting with a general digital camera under a backlight environment, the unexposed subject part to light becomes exceptionally dark, and an image with low visibility may be acquired. This is because the dynamic range of the camera is narrower than that of the human eye. To use HDR (High Dynamic Range) images is practical to acquire images with high visibility even under backlight, but multiple LDR (Low Dynamic Range) images taken at the same shooting position with different exposures to be combined are needed.

On the other hand, many methods for improving the visibility of a single LDR image have been proposed so far [1, 2, 3, 4]. Although gamma correction is a typical intensity correction method and can improve the intensity of dark parts, it does not sufficiently improve the contrast of the entire image. Histogram Equalization (HE) [5], [6] and Contrast Limited Adaptive Histogram Equalization (CLAHE) [7] are typical contrast enhancement methods. Although these methods significantly improve the visibility of the entire image, they may cause artifacts by over-enhancement. Multiscale Retinex with Color Restoration (MSRCR) [8] is an image enhancement method based on the Retinex theory that uses local brightness information. However, it tends to cause halo artifacts. Although the method of Paris *et al.* [3] is an edge-aware image enhancement, the smoothness of flat parts tends to be impaired. Wang *et al.*'s method [4] for backlit image enhancement may cause artifacts to appear in bright parts.

This study proposes a fast enhancement method that improves the visibility of dark parts in backlit images while suppressing the artifacts mentioned above. An enhanced intensity image with balanced intensity and contrast is first generated using gamma correction and histogram equalization in the proposed method. Next, focusing on the intensity histogram of the backlit image, a binary image is created by Otsu's method. The edge-preserving smoothed version of this image is used as a weight map to suppress the artifacts at the edge parts. Finally, an output image is obtained by alpha blending between the input image and the enhanced intensity image using the weight map. The effectiveness of the proposed method is verified through comparative experiments with the conventional image enhancement methods.

2. PROPOSED METHOD

Let $\boldsymbol{I}_{ij}^{RGB} = (I_{ij}^R, I_{ij}^G, I_{ij}^B)^\mathsf{T}$ $(i=1,2,\cdots,M; j=1,2,\cdots,N)$ be a pixel value of an input 24-bit RGB color backlit image. First, the pixel values of the intensity image I_{ij} of an input image $\boldsymbol{I}^{RGB}$ are calculated as follows:

$$I_{ij} = (I_{ij}^R + I_{ij}^G + I_{ij}^B)/3. \tag{1}$$

Now, let h be the histogram of an intensity image $\boldsymbol{I}$; and each bin is denoted by $h(U), U \in \{0, 1, \cdots, 255\}$. Figures 1(a) and 1(b) are examples of $\boldsymbol{I}$ and h of a backlit image, respectively. Generally, backlit images tend to have a bimodal distribution as shown in Fig 1(b). The following subsections describe the details of the proposed method.

2.1. Generation of enhanced intensity image

First, the following gamma correction is applied to I_{ij}:

$$I_{ij}^{gamma} = 255 \cdot (I_{ij}/255)^{\frac{1}{\gamma}}. \tag{2}$$

Figures 1(c) and 1(d) are resulting image $\boldsymbol{I}^{gamma}$ and its histogram, respectively. The pixel distribution moves to the right, and the blackish pixels moderately decrease. However, the dynamic range cannot be effectively utilized only by gamma correction. Therefore, the contrast is further improved using histogram equalization as shown in Figs. 1(e) and 1(f). After that, the pixel values of an enhanced intensity image $\boldsymbol{O}$ is calculated as follows:

$$O_{ij} = (1-\alpha) \cdot I_{ij}^{gamma} + \alpha \cdot I_{ij}^{HE}, \tag{3}$$

where I_{ij}^{HE} is a pixel value of an image processed by histogram equalization. Figures 1(g) and 1(h) are the enhanced image $\boldsymbol{O}$ and its histogram, respectively. While the contrast is improved by effectively utilizing the dynamic range, the image quality in the bright parts is significantly reduced.

2.2. Generation of weight map

In the proposed method, intensity correction that enhances the dark parts is performed while avoiding deterioration of image quality in the bright parts mentioned above. First, Otsu's method [9] is used to divide the intensity image into dark and bright parts. The number of pixel of black class ω_1, that of white class ω_2, a mean of black class m_1, and that of white class m_2 are calculated; and then a threshold t which maximizes $\omega_1\omega_2(m_1-m_2)^2$ is found. Using this threshold t, a binary image $\boldsymbol{W}$ is generated by the following equation:

$$W_{ij} = \begin{cases} 1, & I_{ij} < t \\ 0, & \text{otherwise}\ . \end{cases} \tag{4}$$

To obtain a weight map $\tilde{\boldsymbol{W}}$, the guided filter [10] is applied to $\boldsymbol{W}$ with $\boldsymbol{I}$ as a guide image as follows:

$$\tilde{W}_{ij} = \overline{a}_{ij} \cdot I_{ij}^{nor} + \overline{b}_{ij}, \tag{5}$$

$$a_{ij} = \frac{\frac{1}{(2r+1)^2}\sum_{(k,l)\in\Omega_{ij}} I_{kl}^{nor} \cdot W_{kl} - \overline{I}_{ij}^{nor} \cdot \overline{W}_{ij}}{\frac{1}{(2r+1)^2}\sum_{(k,l)\in\Omega_{ij}} \left(I_{kl}^{nor} - \overline{I}_{ij}^{nor}\right)^2 + \epsilon}, \tag{6}$$

$$b_{ij} = \overline{W}_{ij} - a_{ij} \cdot \overline{I}_{ij}, \tag{7}$$

where Ω_{ij} is a $(2r+1)\times(2r+1)$ square region centered at (i,j); a normalized image $I_{ij}^{nor} = \frac{1}{255} \cdot I_{ij}$; $\overline{I}_{ij}^{nor}$, $\overline{W}_{ij}$, and $\overline{a}_{ij}$, $\overline{b}_{ij}$ are filtered I_{ij}^{nor}, W_{ij}, a_{ij}, and b_{ij} by a $(2r+1)\times(2r+1)$ box-filter at (i,j) with the integral image [11]. This filtering is conducted to suppress the artifacts at the edge parts. Figures 2(a) and 2(b) are the weight maps before and after applying the filter. Due to the edge-preserving smoothing, the edge structure becomes closer to the original image.

2.3. Image composition using the filtered weight map

Using $\tilde{\boldsymbol{W}}$, the final intensity image $\tilde{\boldsymbol{O}}$ is composed by the following equation:

$$\tilde{O}_{ij} = \tilde{W}_{ij} \cdot O_{ij} + (1-\tilde{W}_{ij}) \cdot I_{ij}. \tag{8}$$

Then $\tilde{\boldsymbol{O}}$ is colorized by the following equation:

$$\tilde{\boldsymbol{O}}_{ij}^{RGB} = \boldsymbol{I}_{ij}^{RGB} \cdot (\tilde{O}_{ij}/I_{ij}). \tag{9}$$

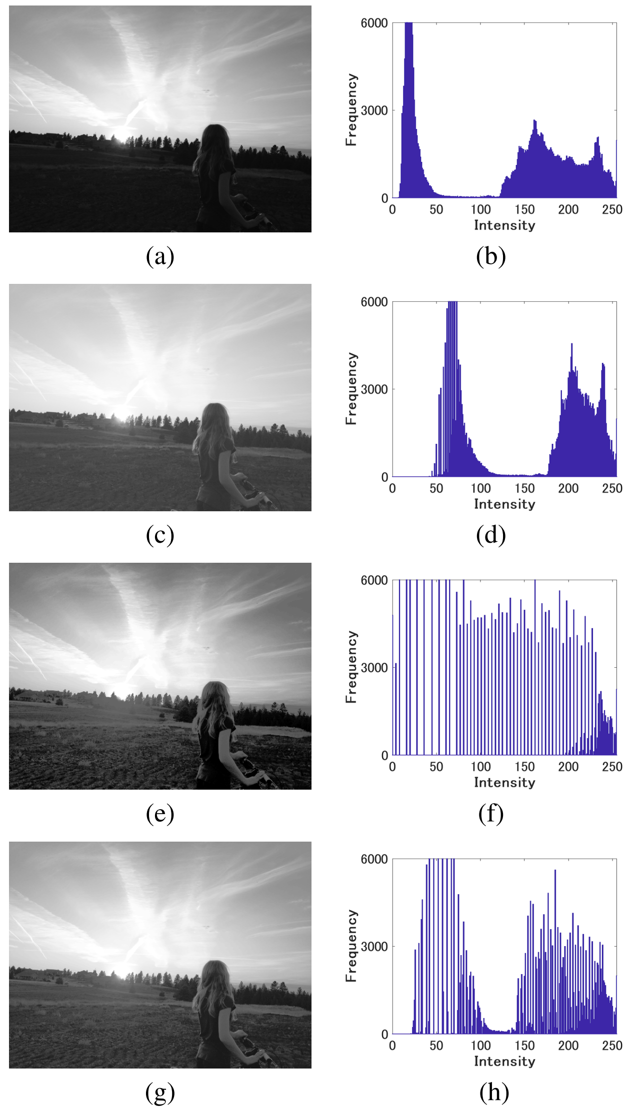
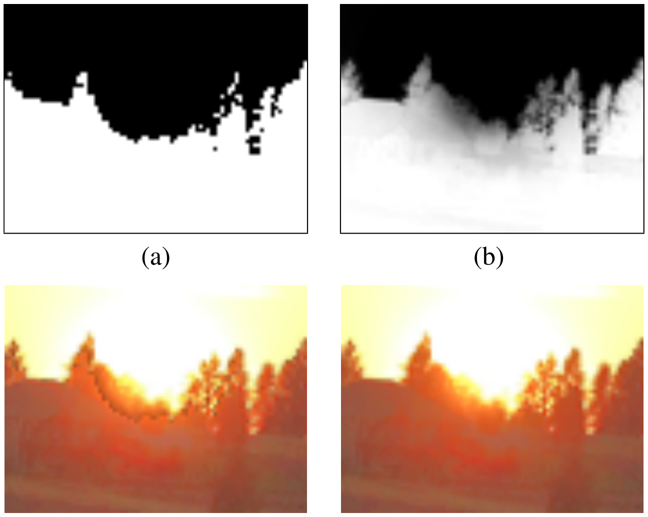


Fig. 1. Processed backlit images and their histograms. (a) Intensity image $\boldsymbol{I}$. (c) Result of gamma correction for $\boldsymbol{I}$. (e) Result of histogram equalization for $\boldsymbol{I}$. (g) Enhanced image obtained by alpha blending. (b), (d), (f), and (h) are the histograms correspond to (a), (c), (e), and (g), respectively.

Figures 2(c) and 2(d) are magnified output images obtained by applying the raw and the filtered weight maps, respectively. From these results, the suppression of artifacts by edge-preserving smoothing is confirmed.

3. EXPERIMENTAL CONDITIONS

In this experiment, we used four backlit images shown in Fig. 3. The size of each image is as follows: Image 1: 640×480, Image 2: 721×480, and Image 3 and 4: 720×480. As comparative methods, HE, CLAHE, MSRCR, Paris's method, and Wang's one were used. The parameters of the comparative



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

Fig. 2. Effect of the guided filter. (a) Raw weight map. (b) Filtered weight map. (c) Artifact caused by the raw weight map. (d) Enhanced image using the filtered map without artifact.

Table 1. LOE.

	Image 1	Image 2	Image 3	Image 4
HE	310	475	423	157
CLAHE	1045	1763	1443	1222
MSRCR	1563	2634	2520	2387
Paris	602	1144	821	844
Wang	619	749	1144	526
Ours	**134**	**217**	**258**	**65**

Table 2. Q value (bright parts).

	Image 1	Image 2	Image 3	Image 4
Ori.	2986	2943	**7389**	3315
HE	2957	3455	5506	3191
CLAHE	**3807**	4060	7130	**3977**
MSRCR	1341	1212	2814	1387
Paris	3524	**4645**	6932	3237
Wang	2964	3025	6931	3163
Ours	2600	2496	5654	3011

methods were set according to each paper. In the proposed method, the parameters were set as follows: $\gamma = 2$, $\alpha = 0.5$, $r = 20$, and $\epsilon = 0.001$. For quantitative evaluation, Lightness Order Error (LOE) [12], Q value [13], and Naturalness Image Quality Evaluator (NIQE) [14] were used. LOE is an index showing the change in the order relationship of lightness between the original and processing results. The lower the LOE value, the better the method in that the order of intensity is not broken. Q value is an evaluation index of image quality. In this experiment, using the binary image in the

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

Fig. 3. Test images. (a) Image 1. (b) Image 2. (c) Image 3. (d) Image 4.

Table 3. Q value (dark parts).

	Image 1	Image 2	Image 3	Image 4
Ori.	359	2212	1796	2755
HE	1368	2405	3449	1936
CLAHE	872	**3556**	**3887**	**4484**
MSRCR	**2087**	2792	2583	3752
Paris	914	2351	2352	4044
Wang	1187	2872	2829	3502
Ours	1220	2632	3037	3046

Table 4. NIQE.

	Image 1	Image 2	Image 3	Image 4
Ori.	2.67	3.93	2.07	2.65
HE	3.18	4.53	2.37	3.28
CLAHE	2.66	3.98	2.09	2.78
MSRCR	2.51	**3.43**	2.04	2.82
Paris	2.93	5.22	2.67	2.98
Wang	2.47	4.32	2.13	2.92
Ours	**2.31**	3.89	**1.78**	**2.5**

proposed method, the Q value is calculated separately for the dark and bright parts. NIQE is an index for calculating the non-reference image quality score, and the better the perceptual quality, the smaller the score.

4. EXPERIMENTAL RESULTS

The results for Image 1 and 2 are shown in Figs. 4 and 5, respectively. The following is a description of the overall processing trends. Although HE tends to improve visibility in dark parts, it may cause artifacts in bright parts. CLAHE significantly improves the visibility of the entire image. How-

Fig. 4. Results for Image 1. (a) HE, (b) CLAHE, (c) MSRCR, (d) Paris, (e) Wang, and (f) Ours.

Fig. 5. Results for Image 2. (a) HE, (b) CLAHE, (c) MSRCR, (d) Paris, (e) Wang, and (f) Ours.

ever, it shows noticeable over-enhanced artifacts. MSRCR significantly desaturates the entire image and gives unnatural results. In the results of Paris, the details are enhanced; the visibility of the dark parts is improved. However, the contrast of the flat parts is over-enhanced, resulting in unnatural results. Wang improves visibility and contrast in dark parts. However, it can cause artifacts in bright parts. The proposed method improves the visibility of dark parts without the appearance of artifacts.

Table 1 shows the LOE scores. The boldfaced and underlined scores show the minimum and maximum ones, respectively. MSRCR shows the highest scores, and there are many changes in the order of intensity. On the other hand, the proposed method shows the smallest scores and little changes in the order of intensity.

Tables 2 and 3 are the Q values of the bright and dark parts, respectively. The boldfaced and underlined scores show the maximum and minimum ones, respectively. The Q value of the bright part tends to increase most in CLAHE. The Q value of the bright part in the proposed method tends to decrease due to the decrease of the standard deviation in the block at the edge between light and dark parts. The Q value of the dark part tends to increase most in CLAHE, and our method also shows the same tendency.

Table 4 shows the NIQE scores. The boldfaced and underlined scores show the minimum and maximum ones, respectively. The method of Paris *et al*. shows that highest scores (*i.e.*, poor perceptual quality), while the proposed method shows lowest ones (*i.e.*, good perceptual quality).

The average processing times for the four images were as follows: HE: 0.005 [sec.], CLAHE: 0.014 [sec.], CLAHE: 0.844 [sec.], Paris: 30.424[sec.], Wang: 0.216 [sec.], and Ours: 0.036 [sec.]. The execution environment is as follows: CPU: Intel®Core™ i7-6950X 3.00GHz, Memory: 32.0GB, OS: Window 10 Pro, and Language: MATLAB R2019. Consequently, the balanced performance between image quality and processing speed of our method was confirmed.

5. CONCLUSION

In this study, we proposed a fast method for improving the visibility of dark parts in backlit images. In the proposed method, an enhanced image was created by using both intensity correction and contrast enhancement, and the dark part was enhanced by composing the enhanced image and the original one based on a weight map that was conscious of suppressing artifacts. The effectiveness of the proposed method was verified through comparative experiments. The future task is to devise a method to enhance the bright part naturally.

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