DARK CHANNEL PRIOR-BASED SPATIALLY ADAPTIVE CONTRAST ENHANCEMENT FOR BACK LIGHTING COMPENSATION

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ABSTRACT

In this paper, we present a novel contrast enhancement method for backlit images that consists of three steps: i) computation of the transmission coefficients using the dark channel prior, ii) generation of multiple images having different exposures based on the transmission coefficients, and iii) image fusion. Compared to global intensity transformation methods and spatially invariant contrast enhancement algorithms, our approach first extracts under-exposed regions using the dark channel prior map, and then performs spatially adaptive contrast enhancement. As a result, the contrast of the image is increased, especially for backlit scenes and those with very wide dynamic range, while still preserving image details and color.

***Index Terms*—** Contrast enhancment, backlighing compensation, dark channel prior

1. INTRODUCTION

Contrast enhancement is one of the most important issues in low-level image processing, and is developed to adjust the dynamic range of an image for better human visual perception [1]. It is a fundamental function of image processing, video processing, medical imaging, aerial image processing, and computer vision.

Existing contrast enhancement algorithms based on histogram modification can be classified into: global and local approaches [2]. Since the global approach enhances the contrast based on the global intensity distribution of the image, it may cause another contrast degradation such as under- and over-exposures. On the other hand, the local approach can better enhance the contrast than global approach because of the spatially adaptive contrast stretching. For this reason, local enhancement methods can be applied to compensate backlit images, which have a very wide dynamic range. Both global and local histogram modification-based methods, however have two fundamental problems; i) color distortion and ii) average brightness change.

Although conventional histogram equalization (HE) method is widely used for contrast enhancement, it may result in serve under- or over-exposure and color distortion because of the globally modified histogram. As a result, a number of modied histogram equalization methods have been proposed. Kim has introduced a mean-preserving bi-histogram equalization algorithm (BHE) that involves the decomposition of an image into two subimages, the one with samples with intensities less than the mean and the other with intensities greater than the mean [3]. Histogram equalization is separately performed in each subimage. Wan has proposed dualistic sub-image histogram equalization (DSIHE) that separates the image into two subimages based on the median intensity [4]. In spite of evenly distributed histograms in two subimages, neither of these approaches are able to meet the higher degree of brightness preservation without undesired artifacts. Chen has introduced an improved contrast enhancement method referred as recursive mean-separate histogram equalization (RMSHE) that recursively separates the image based on the mean [5]. Major drawback of the RMSHE method is the indefinite processing time because of its recursion steps. Kim has proposed a gain controllable clipped histogram equalization (GC-CHE) method that adaptively controls the maximum value of the histogram and the intensity transformation function by clipping histograms [6]. Although the set of modified versions of histogram equalization methods can enhance the contrast while preserving brightness, they still generate color distortion and loses image detail. A high dynamic range (HDR) imaging method fuses multiple images with different exposures for virtually increasing the dynamic range [7-10]. However, the HDR method requires at least two low dynamic range (LDR) images and results in ghost artifacts because of motion in the scene. For removing motion-induced ghost artifacts, Im has proposed a single image-based HDR imaging algorithm, that generates multiple, differently exposed images by intensity-adaptive histogram equalization and then fusing them into a single, HDR image [11]. However, this method also contains color distortion because of the inher-

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ent global intensity transformation of histogram equalization. Moreover, it cannot enhance completely over- or under-exposed regions because differently exposed LDR images are generated from a single input image.

In a wide dynamic range scene containing back lighting, contrast degradation occurs near the under-exposed region because of the short integration time. On the other hand, the proposed approach enhances the contrast only in the under-exposed region for back lighting compensation. The under-exposed regions are extracted using a transmission map, which is based on a dark channel prior originally proposed in [12]. In order to enhance the contrast, we generate two differently exposed images based on the transmission map. We can then fuse these images together with the input image to generate the resulting image.

Because the proposed method enhances the contrast using a transmission map as the weighting factor, it can simultaneously enhance over- and under-exposed region by extending the dynamic range. Fig. 1 shows the block diagram of the proposed contrast enhancement algorithm for backlit images.

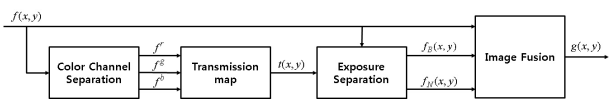


Fig. 1. The method for computing the proposed descriptor based on combined depth and color features.

The rest of the paper is organized as follow. We present a dark channel prior-based contrast enhancement algorithm in section 2. Section 3 summarizes experimental results to confirm the validity of the proposed by comparing with existing histogram equalization-based methods [3-6], and section 4 concludes the paper.

2. DARK CHANNEL PRIOR-BASED CONTRAST ENHANCEMENT

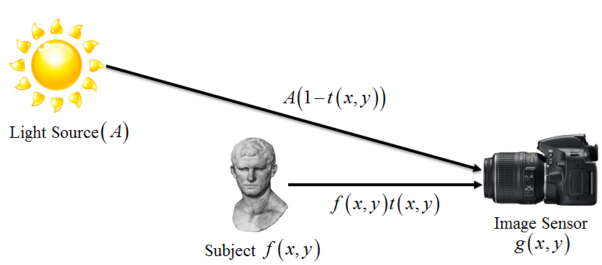


Fig. 2. Illustration of the backlit image formation model.

The backlit image formation model is illustrate in Fig. 2. We assume that the acquired image $g(x,y)$ by an image sensor is the weighted sum of the reflecting component by the subject $f(x,y)$ and the constant sunlight or airlight A as

$$g(x,y) = f(x,y)\,t(x,y) + A\left(1 - t(x,y)\right), \tag{1}$$

where (x,y) represents image coordinate, and $t(x,y)$ the space-variant transmission, coefficients that serve as the weighting factor at each pixel. This image formation model is inspired by the original dehazing [12]. In the region of backlit objects, the transmission coefficient $t(x,y)$ is close to zero since the corresponding region becomes dark regardless of $f(x,y)$. If we can extract the region that has small transmission coefficients, we can enhance the contrast of only under-exposed region.

For extracting the dark backlit regions, we use the dark channel prior originally proposed in [12]. We observe that in most of the non-sky regions, at least one color channel has some pixels whose intensity is very low and close to zero. Therefore, a region containing very low intensity values can be considered as the backlit subject region, and the background sky region is over-exposed containing much higher intensity values than the subject region.

In most backlit images, subject regions tend to be under-exposed because of the back lighting. Therefore, if we apply the dark channel prior to the enhancement of backlit images based on the observation that a pixel in the under-expose region has very low intensity in all three color channels. To formally describe this observation, the dark channel prior can be defined as

$$f^{dark}(x,y) = \min_{c\in\{r,g,b\}} f^c(x,y), \tag{2}$$

where f^c represents a color channel of f. Using this definition, the dark channel prior can be stated that if f does not contain saturated region, the corresponding value becomes low, and tends to become zero. An example of dark channel image is shown in Fig. 3(b).

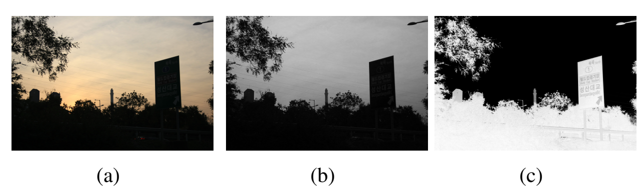


Fig. 3. (a) An input backlit image, (b) the corresponding dark channel image, and (c) the corresponding transmission map.

In order to enhance the under-exposed region without unnatural boundary artifacts, we need to use the weighting function. We compute the weighting function using the transmission coefficient as

$$t(x,y) = 1 - \min_{c\in\{r,g,b\}} \left(\frac{g^c(x,y)}{A^c}\right), \quad c \in \{r,g,b\}. \tag{3}$$

Fig. 3(c) shows the transmission map of a backlit image. We can observe that the bright background region in a backlit image has very small or zero transmission coefficients, whereas the dark backlit region transmission coefficients. Therefore, we can generate the weighting function using the transmission coefficient as

$$W(x, y) = e^{t(x,y)}. \tag{4}$$

Because the transmission coefficient has values between zero and one, the weighting function has values between 1 and 2.7. In order to assign the transmission coefficient value higher than 2.7 for stronger contrast enhancement, we generate two types of weighting functions as

$$W_b\left(x, y\right) = \frac{e^{t(x,y)}}{L} \quad \text{and} \quad W_n\left(x, y\right) = \frac{e^{t(x,y)}}{1-L}, \tag{5}$$

where $W_b\left(x, y\right)$ and $W_n\left(x, y\right)$ respectively represent the weighting functions for generating over- and normal-exposed images. L is the parameter for changing the brightness of the image, and has values between zero to one. We used $L = 0.3$ for most experiments.

Two differently exposed images are obtained as

$$\begin{aligned} &g_B\left(x, y\right) = g\left(x, y\right) \cdot W_b\left(x, y\right) \\ &\text{and} \\ &g_N\left(x, y\right) = g\left(x, y\right) \cdot W_n\left(x, y\right), \end{aligned} \tag{6}$$

where $g_B\left(x, y\right)$ and $g_N\left(x, y\right)$ respectively represent over- and normal-exposed images. Fig. 4 shows the results of generating differently exposed images using the proposed method describe in (5) and (6).

We can find that each image in Fig. 4 represents contains different types of details because of different exposures. Therefore, in order to enhance the backlit image while preserving visual continuity, the proposed method fuses differently exposed images in the pixel level similar to HDR imaging as [11]

$$\hat{f}\left(x, y\right) = \frac{\sum\limits_{n \in \{O,N,I\}} g_c^n\left(x, y\right) W\left(Y_c^n\left(x, y\right)\right)}{\sum\limits_{n \in \{O,N,I\}} W\left(Y_c^n\left(x, y\right)\right)}, \tag{7}$$

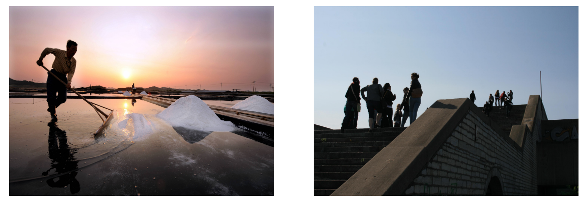
where g_c^n, for $c \in \{r, g, b\}$, and for $n \in \{O, N, I\}$ represents the over-exposed, normal-exposed, and input images, repsectively. The weighting factor $W\left(Y_c^n\right)$ is a function of Y_c^n, and Y_c^n represents intensity of I_c^n. The weighting factor is computed by using Gaussian-shaped function.

3. EXPERIMENTAL RESULTS

In order to illustrate the effectiveness of the proposed method to contrast enhancement of backlit images, we used two backlit images for the experiment as shown in Fig. 5. Each image is of size 2816×1880, and we refer to them as Saltern and Stair. We compare the proposed contrast enhancement method with BHE [3], DSIHE [4], RMSHE [5], and GC-CHE [6].

(a) (b) (c)

Fig. 4. Differently exposed images: (a) Input, (b) normal-exposed, and (c) over-exposed images.



(a) (b)

Fig. 5. Two test images with back lighting; (a) Saltern and (b) Stair.

Fig. 6 shows the results of various contrast enhancement methods. The man is under-exposed by the sunlight in the background. The mean and median values of the input image are 124.56 and 157, respectively. The red box of Fig. 6(a) represents the cropped region.

(a) (b) (c)

(d) (e) (f)

Fig. 6. Experimental results of various contrast enhancment methods; (a) Input image, (b) BHE, (c) DSIHE, (d) RMSHE, (e) GC-CHE, and (f) the proposed method.

Fig. 7 shows the cropped and enlarged version of Fig. 6. Both BHE and RMSHE algorithms divide input histogram into multiple sub-histograms using the mean intensity. Since sub-histograms of the Saltern image are not concentrated, the results are not sufficiently enhanced as shown in Figs. 7(b) and 7(d). On the other hand, DSIHE divides the input histogram into sub-histograms using median intensity, and its result is not sufficiently enhanced either as shown in Fig. 7(c). GC-CHE enhances the contrast by adjusting gain, which is larger than threshold. The threshold of the Saltern image is $90,062$, but most of luminance distribution is less than the threshold as shown in Fig. 7(e). Therefore, the number of clipped gain is small, and the result of enhancement becomes insufficient. On the other hand, the proposed method generates two images with different exposures, and fuses them together with the input image. Since all three images contain different details, the fused image can represent all the details in three images.

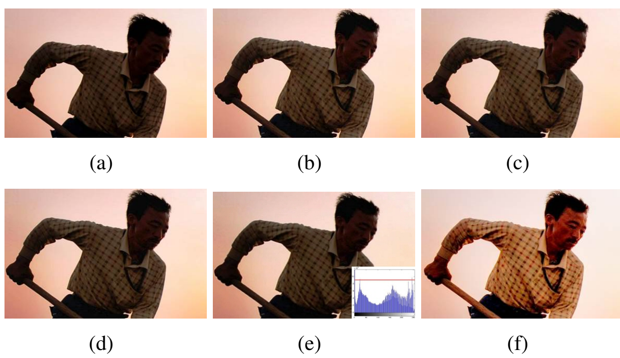


Fig. 7. Cropped and enlarged experimental results of Fig. 6 using different contrast enhancement methods; (a) Input image, (b) BHE, (c) DSIHE, (d) RMSHE, (e) GC-CHE, and (f) the proposed method.

Fig. 8 shows the results of the same experiment using Stair image. Because camera gazes at the sky, the region of people, the vertical wall, and the stair becomes darker. We can find that the proposed method best enhanced the contrast among all existing methods. For clearer comparison, we cropped and enlarged the red box in Fig. 8(a), and the corresponding results are shown in Fig. 9.

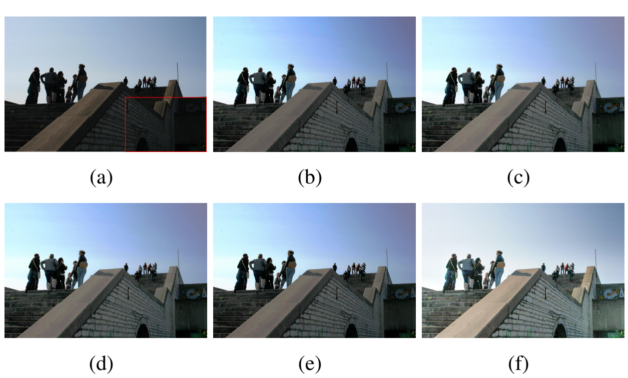


Fig. 8. Experimental results using different contrast enhancement methods; (a) Input image, (b) BHE, (c) DSIHE, (d) RMSHE, (e) GC-CHE, and (f) the proposed method.

Fig. 9 shows the cropped and enlarged version of Fig. 8. The mean and median intensity of the input image is 107.84 and 128, respectively. Because sub-histograms of BHE, DSIHE, and RMSHE are concentrated around a particular value, resulting images are enhanced as shown in Figs. 9(b)-9(d). However, texture of the wall is not clear enough. In the result of GC-CHE, since most luminance distribution is less than threshold, that is $79,636$ as shown in Fig. 9(e), enhancement in the under-exposed region is not sufficient. On the other hand, we can find that the proposed method can successfully restore the texture of the wall. Because the proposed method generates differently exposed images using the transmission map, it can change the brightness of each image for correctly restoring texture of the under-exposed region. By fusing differently exposed images together with an input image, the proposed method can successfully enhance the contrast as shown in Fig. 9(f).

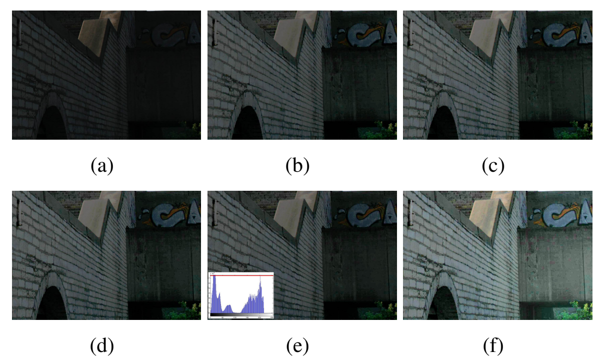


Fig. 9. Cropped and enlarged experimental results of Fig. 8 using different contrast enhancement methods; (a) Input image, (b) BHE, (c) DSIHE, (d) RMSHE, (e) GC-CHE, and (f) the proposed method.

4. CONCLUSION

In this paper, we proposed a novel contrast enhancement method to enhance the contrast of the backlighting images by extracting the under-exposed region. Various histogram equalization-based methods cannot successfully enhance the contrast of severely saturated region because of their inherent limitations. Although HDR imaging can partially solve such problem, it requires two or more differently exposed images under assumption that the scene is stationary while multiple images are acquired. For overcoming the limitations, the proposed method fuses differently exposed images together with the input back lighting image to enhance the contrast of the under-exposed region. For extracting under-exposed region, the proposed method estimates the transmission coefficients using the dark channel prior. Therefore, the proposed method can enhance contrast of only under-exposed regions in the back lighting image while preserving details and color of the bright region.

5. REFERENCES

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