A FUSION-BASED METHOD FOR SINGLE BACKLIT IMAGE ENHANCEMENT

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ABSTRACT

In this work, a new simple but effective fusion-based strategy for enhancing single backlit image is proposed. The fundamental idea of proposed strategy is to blend different features into a single one to improve the specific quality of image. Most of existing methods are based on the modification of histogram to enhance the contrast of low light images. However, the backlit images are different from low light images, which have wide dynamic ranges of light regions, thus the existing methods cannot achieve good enhanced results of backlit images. To improve performance of enhanced results, the proposed method considers numerous features of images and processes the dark and bright regions, respectively. Furthermore, proposed method introduces weight maps to increase the visibility. Experimental results show that proposed method is superior to existing methods, which achieves better results both in visual effects and processing time.

Index Terms— backlit image, image enhancement, image fusion

1. INTRODUCTION

Since objects and details cannot be seen clearly in very dark regions due to the non-uniform illumination, backlit images have the similar degradation with back lighting. However, different from normal low light images, backlit images have a wide dynamic range which contains both very dark and bright regions in the same scene. To improve normal images with undesired illumination, many image enhancement algorithms have been proposed, such as the well-known histogram equalization algorithm [1], to enhance the contrast at the cost of destroying the global structure. To address this drawback, Celik [2][3][4] and Lee et al. [5] constructed a 2D histogram using mutual relationship between each pixel and its neighborhood pixels to increase the grey-level differences. Although [2]-[5] can increase the brightness and contrast while keeping the histogram structure, they may yield over-enhancement when the histogram contains peaks. Retinex-based algorithms (e.g. SSR [6], MSR [7] and MSRCR [8]) have a good performance in general. However, when the image is under back lighting condition, especially with low light, the result tends to be a gray-out image. To solve the problem of backlit enhancement, some specific methods such as [9]-[10] have been proposed. Besides, a new method for non-uniform illumination images enhancement is proposed in 2013. The method decomposed an image into reflectance and illumination using bright-pass filter, and employed the bi-log transformation for illumination adjustment, namely naturalness preserved enhancement algorithm (NPEA) [11]. Although the NPEA has the advantage of enhancing the details and preserving the naturalness, but it has the drawback of expensive computation due to the patch-based calculation.

In this paper, a novel enhancing approach that focuses on a single backlit image based on a multi-scale fusion is introduced. Since the fusion technology depends on the choice of the inputs and the weight maps, features of backlit are investigated to choose the appropriate inputs and weights. Firstly, three derived inputs are obtained by improving the luminance on original value layer of HSV space. Secondly, one weight map is designed to measure exposure feature in the derived inputs. Finally, to effectively blend different types of useful information into a single one, the derived inputs and weight are fused to obtain the enhanced image. A multi-scale strategy is also adopted in the fusion process to suppress artifacts. Experimental results demonstrate that the enhanced image has a decent balance between luminance improvement and naturalness preservation. In addition, the proposed method is straightforward to implement due to most calculations are pixel-wise operations.

The rest of the paper is organized as follow. We describe a fusion-based algorithm for backlit image in Section II. Next, in Section III, we present the comparisons of the proposed with several enhancement algorithms. Finally, we conclude the paper in Section IV.

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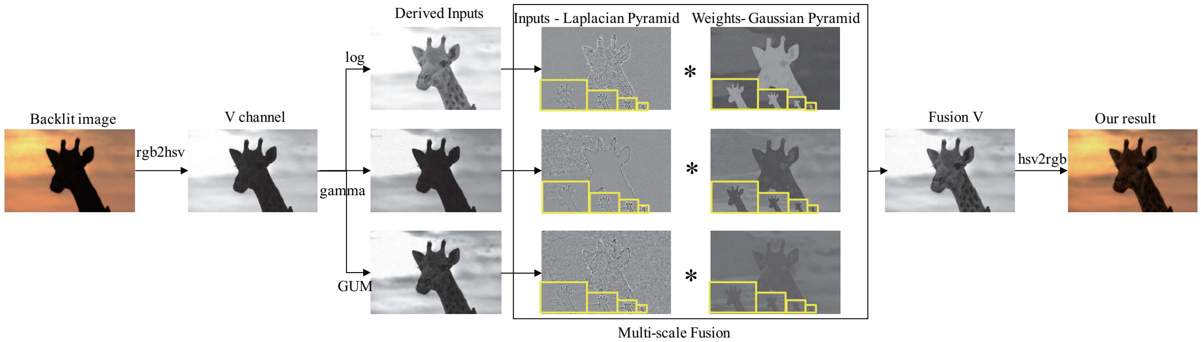


Fig. 1. The outline of the algorithm.

2. A NEW FUSION-BASED IMAGE ENHANCING ALGOROTHM

The poor quality of the backlit images mainly manifests in two aspects: One is the lack of luminance in back lighting regions; the another one is contrast degradation near the under-exposed regions. Therefore, a luminance improving and a contrast enhancing techniques are applied according to the two factors, respectively. The fundamental idea is to combine three input images weighted by specific maps into a single one. Before processing appropriate input images and weight maps, we transform the RGB space into the HSV space first. Then both inputs and weights operate in value layer. After the multi-scale fusion processing, the image is transformed back to RGB space. The outline of the new algorithm is shown in Fig. 1.

2.1. Inputs

Since backlit images contain dark and bright regions in the scene, we apply a method which can increase the luminance of dark pixels and compress the dynamic range simultaneously. The first input I^1 is obtained by adjusting the value using a logarithm function, which yeilds an extreme slope in dark region. Therefore, the first input image can be defined as:

$$I^1(x,y) = \log(\alpha(V(x,y)+1)), \tag{1}$$

where $V(x,y)$ is the original value layer of the HSV space at the location of (x,y), and α is the coefficient representing the brightness of the image, default value is 0.5. And one is added to make sure I^1 is positive.

Since equation (1) can enhance the details by stretching the dark values and compressing the bright values, input I^1 has over-enhancement in dark regions as shown in Fig.2. To solve this problem, we apply gamma correction with the inverted version of the original image. By inverting the original image, the bright regions in the original image become dark and vice versa. Thus, we apply gamma correction which is monotonic increase and can decrease large values effectively. Therefore, input I^2 can be expressed as:

$$I^2(x,y) = 255 - (255 - V(x,y))^{\gamma}, \tag{2}$$

where γ is the adaption factor, it depends on the number of low pixels, i.e.,

$$\gamma = \frac{N - \mathrm{n}}{N}, \tag{3}$$

where N and, n represent the total number of pixels and the number of pixels whose value are less than 50, respectively.

Although equation (1) and (2) have improved the luminance, contrast degradation occurs near the over-enhancement and under-enhancement regions. To enhance the contrast, a generalized unsharp masking algorithm (GUM) [12] is applied to generate the third input I^3.

2.2. Weight

Luminance improving and contrast enhancing are preprocessings step to the image. To make result image more satisfied for the human visual perception, we use the specific weight map to measure and extract more details of the input image. Since the nature of the problem is backlit, which is more related to light exposure. Therefore, exposedness is chosen as weight map to receive those regions with good exposure from derived inputs.

The exposedness weight map represents the degree of exposure. Generally, we firstly normalize the value within [0,1]. Then set the values close to the average value of 0.5. The pixels usually have a good exposure. To obtain the weight map, the distance between input value $I(x,y)$ and the average value (0.5) for each pixel is computed as follows:

$$W_E^k(x,y) = \exp\left(-\frac{(I^k(x,y) - 0.5)^2}{2\sigma^2}\right), \tag{4}$$

where k indexes the derived inputs, $I^k(x,y)$ represents the value of the input I^k and the default value of the standard

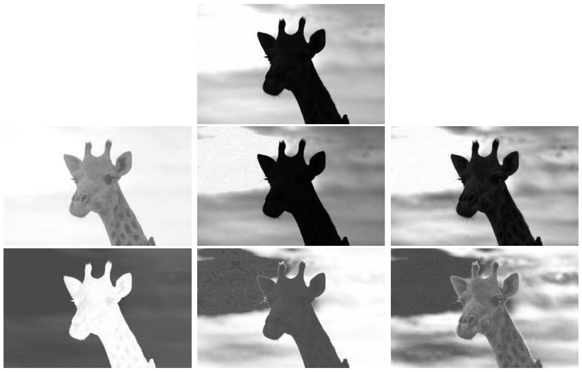


Fig. 2. Top: V channel of original image. Middle: three inputs I^1, I^2 and I^3. Bottom: the exposedness weight maps.

deviation is $\sigma = 0.3$. After that, small values are assigned to pixels with under-exposed and over-exposed regions while most normal-exposed pixels get high values. The example for the exposedness weight map shows in Fig. 2.

To obtain consistent results, we normalize the value of $W_E^k(x,y)$ ($\overline{W}^k(x,y) = W_E^{\mathrm{k}}(x,y)/\sum_k W_E^k(x,y)$), so that they add up to one at each pixel (x,y).

2.3. Image Fusion

After obtaining three inputs I^{k} and weight maps W^{k}, the output image is computed by the formula: $V(x,y) = \sum\limits_k \overline{W}^{\mathrm{k}}(x,y) I^k(x,y)$. The results contain uncomfortable halos by directly using this naive blending. So we adopt a multi-scale fusion inspired by Burt and Adelson [13] to solve the problems. By applying a Laplacian operator to decompose inputs into a pyramid and a Gaussian pyramid for weight maps. So the result of $V(x,y)$ are obtained by blending the Laplacian inputs and Gaussian weight maps for each level separately:

$$V^l(x,y) = \sum_k G^l\{\overline{W}^{\mathrm{k}}(x,y)\} L^l\{I^k(x,y)\} \tag{5}$$

where *l* represents the number of the pyramid levels. $G\{\overline{W}\}$ is a Gaussian pyramid of the normalized weight map $\overline{W}$, and $L\{I\}$ is a Laplacian pyramid of the input *I*.

Finally, we transform the new HSV image into RGB space to obtain the final enhanced color image.

3. EXPERIMENTS

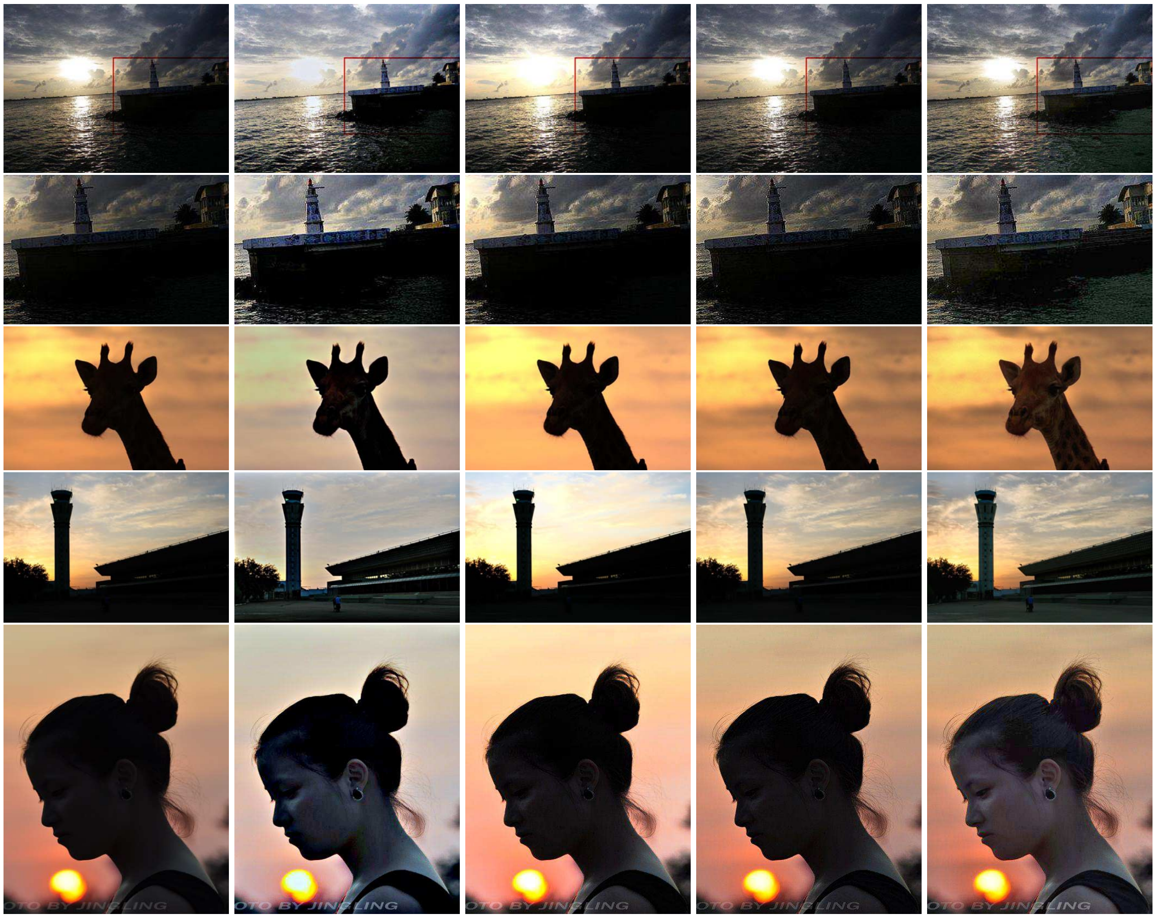
To demonstrate the effectiveness of the proposed new method, a large number of backlit images are tested. Due to space limitation, we only choose four representatives as shown in Fig. 3. All the experimental images are processed by Matlab R2012a on a PC with a 3.30GHz Intel Pentium Dual Core Processor and 16GB RAM. More experimental results and code can be found on our website: ***http://smartdsp.xmu.edu.cn/backlitimage-enhancement.html***.

3.1. Subjective Assessment

We compare the performance of MSRCR [8], Content-Aware Dark Image Enhancement Through Channel Division (CD) [14] and Spatial Entropy-Based Global and Local Image Contrast Enhancement (SECEDCT) [4] algorithms. As shown in Fig. 3(b), the results tend to be a grayer image by multi-scale retinex method. Meanwhile, in line 5, the girl's face is obviously color distortion. This is because the MSRCR method uses the reflectance as the enhanced image without considering the illumination. The CD algorithm produces a content aware channel division transformation for each image to enhance dark images. But as shown in Fig. 3(c), it increases the background only while the foreground is still dark. We can see in line 4 that details of the clouds are lost due to over-enhancement. Fig. 3(d) shows the enhanced results of SECEDCT algorithm. However, through comparing the corresponding results with original images, it is obvious to see that the effect of SECEDCT algorithm is poor. The results of proposed method are presented in Fig. 3(e), which are superior to the results of other three methods. As shown in third line of Fig. 3, the proposed method can effectively enhance the backlit object without introducing color or content distortion. Furthermore, through comparing the results of second line in Fig. 3, although the upper region in the result of M-SRCR algorithm is enhanced well, the rest regions of result is poor. Comparing to MSRCR algorithm, the proposed method enhances the luminance of the whole image without local regions, and tradeoffs the enhancement well between the salient and non-salient objects so as to preserve the naturalness.

3.2. Objective Assessment

Since subjective assessment depends on human visual system, it is difficult to find an objective assessment that is consistent with the subjective assessment. Here, we used a blind image quality assessment called natural image quality evaluator (NIQE) [15] as an objective evaluation method. NIQE uses measurable deviations from statistical regularities observed in images and lower value indicates higher quality. From Table I, it is found that our method produces lowest NIQE and standard deviation values as compared to the other three methods. Hence, our method gives better visual quality images. Furthermore, in order to illustrate the stability of our proposed method, we show the average and standard deviation of 100 images in eighth and ninth lines of Table I. In addition, our proposed method has highest time efficiency as shown in Table II. Experimental results show that the proposed method not only provides good visual representation but also has lower computational time such that it can be applied to a real-time system.



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

Fig. 3. (a) Input image with back lighting, (b) the enhanced image by MSRCR [8], (c) the enhanced image by CD [11], (d) the enhanced image by SECEDCT [4], (e) the enhanced image by the proposed method.

Table 1. ASSESSMENT RESULTS OF NIQE [15].

	Original	MSRCR	CD	SECEDCT	Proposed
Sea	3.58	**3.13**	3.45	3.95	3.22
Giraffe	7.51	6.97	8.09	7.49	**5.29**
Airport	5.99	6.54	6.64	5.03	**4.18**
Girl	6.59	6.07	6.73	6.00	**4.94**
Avg.	5.92	5.68	6.23	5.62	**4.41**
Avg. of 100	4.32	3.82	4.38	4.31	**3.71**
Std. of 100	2.00	1.77	2.08	1.99	**1.67**

Table 2. CPU EXECUTION TIME (seconds).

	MSRCR	CD	SECEDCT	Proposed
Sea	**0.35**	2.43	0.42	**0.35**
Giraffe	0.79	3.78	0.82	**0.62**
Airport	15.73	55.98	14.59	**8.57**
Girl	0.39	1.70	0.40	**0.31**
Avg.	4.31	15.97	4.06	**2.46**
Avg. of 100	1.11	5.88	1.26	**0.89**

4. CONCLUSIONS

In this paper, a new effective and efficient method for backlit image enhancement based on a multi-scale fusion is proposed. Other enhancement algorithms often result in under-enhancement when images contain very dark regions. To overcome this limitation, our new method fuses appropriate input images weighted by specific maps. Experimental results demonstrate that our method not only enhances the contrast in under-exposed regions but also preserves details in bright regions. In addition, the proposed method requires only one input and the computation is inexpensive since our operation is mostly in per-pixel fashion.

5. REFERENCES

[1] S. M. Pizer, E. P. Amburn, J. D. Austin, and et al., "Adaptive histogram equalization and its variations," *Computer vision, graphics, and image processing*, vol. 39, no. 3, pp. 355–368, 1987.

[2] T. Celik, "Two-dimensional histogram equalization and contrast enhancement," *Pattern Recognit*, vol. 45, no. 10, pp. 3810–3824, 2012.

[3] T. Celik and T. Tjahjadi, "Contextual and variational contrast enhancement," *IEEE Transactions on Image Processing*, vol. 20, no. 12, pp. 3431–3441, 2011.

[4] T. Celik, "Spatial entropy-based global and local image contrast enhancement," *IEEE Transactions on Image Processing*, vol. 23, no. 12, pp. 5298–5308, 2014.

[5] C. Lee, C. Lee, and C.S. Kim, "Contrast enhancement based on layered difference representation of 2d histograms," *IEEE Transactions on Image Processing,*, vol. 22, no. 12, pp. 5372–5384, 2013.

[6] D. J. Jobson, Z.U. Rahman, and G.A. Woodell, "Properties and performance of a center/surround retinex," *IEEE Transactions on Image Processing*, vol. 6, no. 3, pp. 451–462, 1997.

[7] D. J. Jobson, Z. U. Rahman, and G. A. Woodell, "A multiscale retinex for bridging the gap between color images and the human observation of scenes," *IEEE Transactions on Image Processing*, vol. 6, no. 7, pp. 965–976, 1997.

[8] M. Elad, R. Kimmel, D. Shaked, and R. Keshet, "Reduced complexity retinex algorithm via the variational approach," *Journal of visual communication and image representation*, vol. 14, no. 4, pp. 369–388, 2003.

[9] Li Tao, Richard Tompkins, and Vijayan K. Asari, "An illuminance-reflectance model for nonlinear enhancement of color images," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) - Workshops*, 2005, p. 159.

[10] Zhenhao Li, Kai Cheng, and Xiaolin Wu, "Soft binary segmentation-based backlit image enhancement," in *IEEE International Workshop on Multimedia Signal Processing*, 2015.

[11] S. Wang, J. Zheng, H. Hu, and B. Li, "Naturalness preserved enhancement algorithm for non-uniform illumination images," *IEEE Transactions on Image Processing*, vol. 22, no. 9, pp. 3538–3548, 2013.

[12] G. Deng, "A generalized unsharp masking algorithm," *IEEE Transactions on Image Processing*, vol. 20, no. 5, pp. 1249–1261, 2011.

[13] P. J. Burt and E. H. Adelson, "The laplacian pyramid as a compact image code," *IEEE Transactions on Communications*, vol. 31, no. 4, pp. 532–540, 1983.

[14] A. R. Rivera, B. Ryu, and O. Chae, "Content-aware dark image enhancement through channel division," *IEEE Transactions on Image Processing*, vol. 21, no. 9, pp. 3967–3980, 2012.

[15] A. Mittal, R. Soundararajan, and A. C. Bovik, "Making a "completely blind" image quality analyzer," *IEEE Signal Processing Letters*, vol. 20, no. 3, pp. 209–212, 2013.