Over-exposure image correction with automatic texture synthesis

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***Abstract*—A novel over-exposure image correction algorithm combining synthesized texture information in over-exposed regions is presented. In this algorithm, intensity image is decomposed into structure and detail layers by weighted least squares method. Modified exemplar-based texture synthesis method is applied to the detail layer in order to synthesize texture details in over-exposed regions. The synthesized texture is combined with the original texture and fed to the lightness and color correction modules to get the final result. An efficient diffusion-like color correction method is presented. Qualitative and quantitative experimental results show that the proposed method produces vivid details which are absent in previous methods without human assistance in over-exposed regions. This improves the overall appearance of the recovered image.**

Keywords-image restoration; image enhancement; over-exposure correction

I. INTRODUCTION

The natural world contains a wide range of light intensities which can not be captured by most of the consumer grade photographic sensors. For example, the relative brightness of an outdoor scene in a sunny day is about 400,000. Even for the normal indoor environment, the relative brightness will still reach to about 1,500 [1]. However, the dynamic range of common digital camera is only 1000:1. As a result, over-exposure is inevitable in daily-life photography.

In order to overcome the above mentioned difficulties, High Dynamic Range (HDR) imaging techniques were proposed. Popular HDR algorithms gather multiple shots with different exposure values [2-4]. Firstly, image registration is applied in order to register multiple shots [5] so that different exposure values of the same pixel can be obtained. Then tone mapping technique [6] is used to fit the HDR image to low dynamic range devices such as LCD monitor. Recently, Mertens *et al.* proposed a simple and direct method to fuse a bracketed exposure sequence into a high quality image guided by simple quality measures like saturation and contrast without assembling the HDR image first [7]. Since multiple images are required, these methods are restricted to nearly static scenes [2][7]. Otherwise, some complicated methods are applied in order to compensate for the relative motion between images. For example, gradient-based optical flow method whose computational complexity is quite high is applied in [3] in order to find corresponding pixels between neighboring images. Heo *et al.* utilized the global intensity transfer functions obtained from joint probability density functions between different exposure images [4].

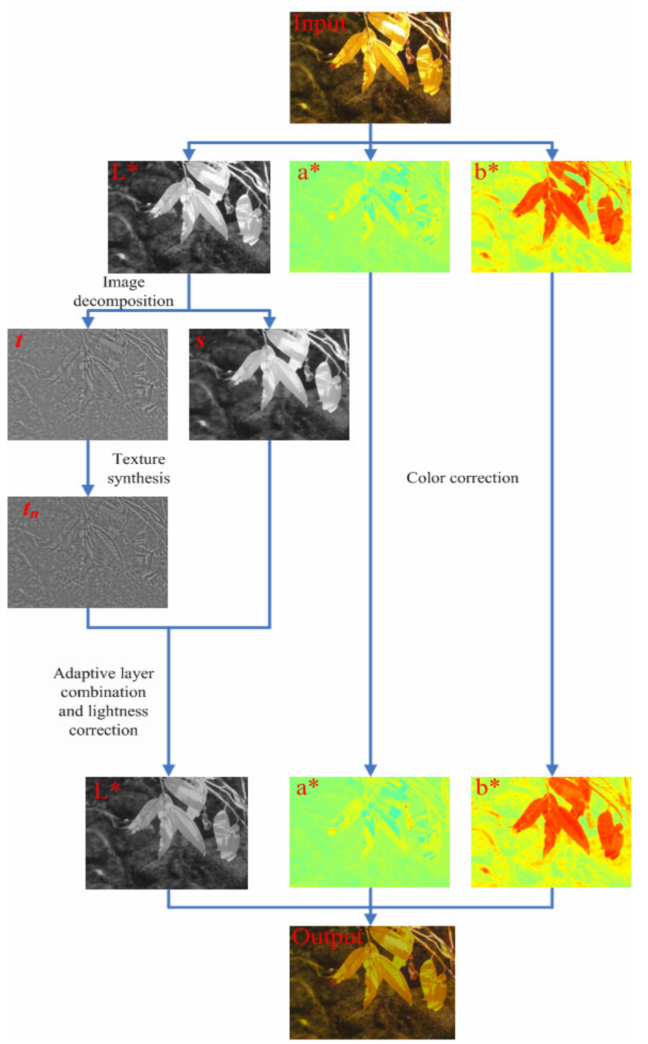


Figure 1. The workflow of our algorithm. (Images are scaled for visualization purpose.)

Since the traditional HDR imaging techniques all need multiple images with different exposures. It restricts their applications in some conditions. As a result, researches on correcting the over-exposed regions with one image gradually emerge. Masood et al. [8] utilized spatial-variant ratios to correct over-exposed channels with one image. It could only deal with partial over-exposed regions which rarely appear in real images instead of fully over-exposed regions. Guo et al. [9] corrected lightness and color information separately with one image by solving large scale linear systems. However, over-exposed regions lack texture information after correction.

In this paper, we introduce a novel over-exposure image correction algorithm with one image automatically. The original color image is converted into CIELab color space. We decompose the L* channel of original image into structure and detail layers. A modified exemplar-based texture synthesis method is proposed in order to reproduces texture details in over-exposed regions of the detail layer. Furthermore, a diffusion-like color correction method is proposed which can produce similar results with [9] and is much faster. Finally the reconstructed L*, a* and b* channels are recombined together to get the corrected image. The workflow of our algorithm is illustrated in fig. 1.

This paper is organized as follows. In section 2, texture synthesis algorithm in detected over-exposed regions is described in details. Lightness correction and an efficient diffusion-like color correction method is described in section 3. Section 4 provides qualitative and quantitative experimental results and we draw conclusions in section 5.

II. Texture synthesis in over-exposed regions

Firstly, we detect the over-exposure regions in the original image. We convert the original image into CIELab color space where the L* channel represents lightness information and a* and b* channels represent the color information [10]. Over-exposure likelihood map is estimated by analyzing brightness and color information as proposed in [9]. Threshold is applied to the map to get the over-exposed regions Ω. Over-exposure image has dramatically different lighting conditions. So texture synthesis based on original image directly is difficult and inaccurate. For this reason, we decompose L* channel into structure and detail layers by minimizing the following equation:

$$\sum_{\boldsymbol{p}}(|\boldsymbol{t}(\boldsymbol{p})|^2+\lambda(\boldsymbol{a}_x(\boldsymbol{p})(\partial(\boldsymbol{u}(\boldsymbol{p})-\boldsymbol{t}(\boldsymbol{p}))/\partial x)^2+\boldsymbol{a}_y(\boldsymbol{p})(\partial(\boldsymbol{u}(\boldsymbol{p})-\boldsymbol{t}(\boldsymbol{p}))/\partial y)^2)) \tag{1}$$

where $\boldsymbol{u}$ is the L* channel of the original image, $\boldsymbol{t}$ is the detail layer, $\boldsymbol{p}$ is the pixel location, λ controls the balance between two terms, $\boldsymbol{a}_x()$ and $\boldsymbol{a}_y()$ are location dependent smoothness weights. Equation (1) contains two parts. The first part $|\boldsymbol{t}(\boldsymbol{p})|^2$ is the data term that enforces the texture layer only to capture intricate texture details of the image. The rest part is the regularization term strives to achieve smoothness of the residual image (structure layer) so that the different exposures are encoded in it. Equation (1) can be solved with weighted least squares [11]. With the calculated detail layer, structure layer can be calculated as:

$$\boldsymbol{s}(\boldsymbol{p}) = \boldsymbol{u}(\boldsymbol{p}) - \boldsymbol{t}(\boldsymbol{p}) \tag{2}$$

The detail layer is single channel and captures gray scale texture details. It usually contains homogeneous regions which lack texture. So the discrimination power is less than traditional color image when applying sum of squared differences in exemplar-based image inpainting technique [12]. For this reason, we propose an adaptive window scheme instead of the static window size in [12] so that the search window size can be adapted to the texture information. The search window size $h_{\boldsymbol{p}}$ at pixel $\boldsymbol{p}$ is chosen as:

$$h_{\boldsymbol{p}} = \min_w \mathrm{Var}(\boldsymbol{t}(w, \boldsymbol{p})) > \beta \quad (5 \le w \le 19) \tag{3}$$

where $\boldsymbol{t}(w, \boldsymbol{p})$ is a $w \times w$ window centered at pixel $\boldsymbol{p}$ of the detail layer. Var() is the variance of the values in the window. β is a threshold which can be set as the average variances of 9×9 windows in the original detail layer. We constrain the value of w so that $h_{\boldsymbol{p}}$ will not be too large which will cause difficulties in finding matching window. The window size also should not be too small so that there is not enough supporting information provided by the neighborhood areas when searching for the matching window. With the above modified exemplar-based image inpainting technique, texture information can be synthesized in over-exposed regions of detail layer. The synthesized detail layer is adaptively enhanced and combined with the structure layer to get the new L* channel:

$$\boldsymbol{u}_{\mathbf{n}}(\boldsymbol{p}) = \boldsymbol{s}(\boldsymbol{p})+k_1\times\boldsymbol{t}_{\mathbf{n}}(\boldsymbol{p})\times\delta(\boldsymbol{p}\in\Omega)+ k_2\times\boldsymbol{t}_{\mathbf{n}}(\boldsymbol{p})\times\delta(\boldsymbol{p}\notin\Omega) \tag{4}$$

where $\boldsymbol{t}_{\mathbf{n}}$ is the synthesized detail layer, $\delta(x)$ is indicator function. In the following lightness correction module, gradient information will be compressed so that the recovered image is not as sharp as the original one. For this reason, we enhance high frequency component in L* channel by choosing $k_2 > 1$. Meanwhile, even more emphasis should be put on over-exposed regions as original image lacks detail information in these regions. In this paper, we choose $k_1 = 3$ and $k_2 = 2$.

III. Lightness and color correction

Lightness correction is applied to the reconstructed L* channel. The idea is to attenuate image gradient non-linearly while keep the intensity in over-exposed regions as close as possible to the original value. Similar with [9], the above idea can be transformed to the minimization of least squares problem. Color correction is applied to a* and b* channels separately. The method in [9] needs to solve an extremely large scale linear system which is quite challenging. To cope with this difficulty, we propose an efficient diffusion-like method:

Step 1. Calculate over-exposure binary image $\boldsymbol{M}_{\mathbf{b}}$. We set 0 in over-exposed regions and 1 elsewhere. Calculate distance transform image $\boldsymbol{D}$ corresponding to $\boldsymbol{M}_{\mathbf{b}}$ [13].

Step 2. For each isocontour in $\boldsymbol{D}$ from the minimum value to the maximum value, we visit every pixel $\boldsymbol{p}$ of this isocontour. First, we calculate weights of every pixel $\boldsymbol{q}$ which is in the 8-neighbourhood of $\boldsymbol{p}$:

$$wt_c(\boldsymbol{q}) = N_d(\|\boldsymbol{p}-\boldsymbol{q}\|_2)N_c(\|\boldsymbol{c}(\boldsymbol{p})-\boldsymbol{c}(\boldsymbol{q})\|_2)\boldsymbol{M}_{\mathbf{b}}(\boldsymbol{q}) \tag{5}$$

where c stands for color channel, it can be a* or b*. $N_d()$ and $N_c()$ are 2 Gaussian distributions which evaluate the differences of spatial distances and color distances respectively. $\|.\|_2$ is the L2 norm. Then we update the value of $\boldsymbol{p}$ in color channel c:

$$\boldsymbol{c}_{\mathbf{n}}(\boldsymbol{p}) = \sum_{\boldsymbol{q}\in\partial\boldsymbol{p}}(wt_c(\boldsymbol{q})\boldsymbol{c}(\boldsymbol{q}))/ \sum_{\boldsymbol{q}\in\partial\boldsymbol{p}}wt_c(\boldsymbol{q}) \tag{6}$$

where $\partial\boldsymbol{p}$ is 8-neighbourhood of $\boldsymbol{p}$. After all the pixels in the isocontour have been processed by above equations. We update $\boldsymbol{M}_{\mathbf{b}}$ to be 1 for all the pixels in this isocontour.

Step 3. Iterate step 2 until the average relative change of each pixel is smaller than a predefined threshold (We choose 0.1%.).

After we correct the lightness of L* channel and the color information of a* and b* channels, we can convert the CIELab color space back into RGB color space and get the final corrected over-exposure image.

IV. Experimental Results

Our proposed algorithm is implemented in MATLAB and tested on a laptop equipped with Intel Core2Duo P7350 2GHz CPU and 2 GB RAM. Fig.2~4 show 3 demonstrations. All these images are from [9]. From these figures we can conclude that the overall color is similar between our algorithm and the method [9]. However, in fig. 2, the skeleton of the leaf which is missed by [9] is clearly reconstructed through our texture synthesis technique. In fig. 3, our result is sharper than [9] especially in coral regions. In fig. 4, the details of the slide fastener are reconstructed together with the wrinkles of the jacket nearby which improves the visual effect of the whole image. Our method vividly reconstructs the details in over-exposed regions and improves the overall performance of the corrected image. Table 1 shows quantitative comparison results between the color correction module of our proposed algorithm and the method in [9]. The color correction module proposed in [9] is implemented in MATLAB by us. As a result, we can compare the computational time of color correction module between our method and [9]. We also calculate the average absolute differences in a* and b* channels between them (The range of a* and b* channels is from -128 to 127.). From the table we can conclude that our method can produce similar color correction results with much lower computational complexity. This proves the effectiveness of our proposed algorithm.

TABLE I. Quantitative Comparison Results for Color Correction Module

Image index	1	2	3
Image resolution	500×375	600×450	356×397
Computational time of [9] (s)	606.00	1300.95	324.51
Computational time of our method (s)	2.74	2.90	0.46
Average a* channel absolute differences	4.75	4.08	3.89
Average b* channel absolute differences	4.77	3.98	4.63

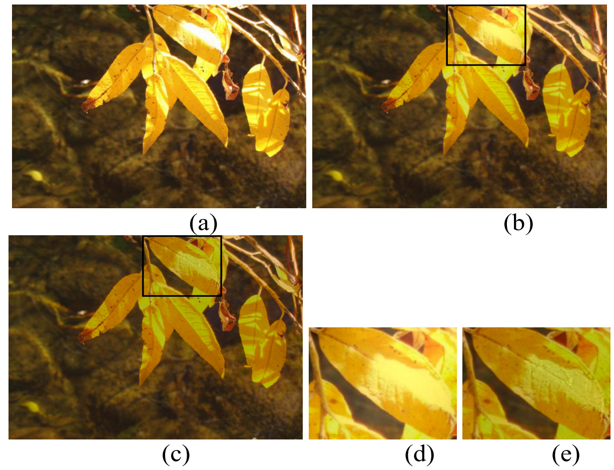


Figure 2. The first result of correcting over-exposure. Note that the skeletons are reconstructed by our algorithm. (a) original over-exposure image, (b) correction result by [9], (c) correction result by our proposed algorithm, (d) zoomed in version of the area labeled as black rectangle in (b), (e) zoomed in version of the area labeled as black rectangle in (c).

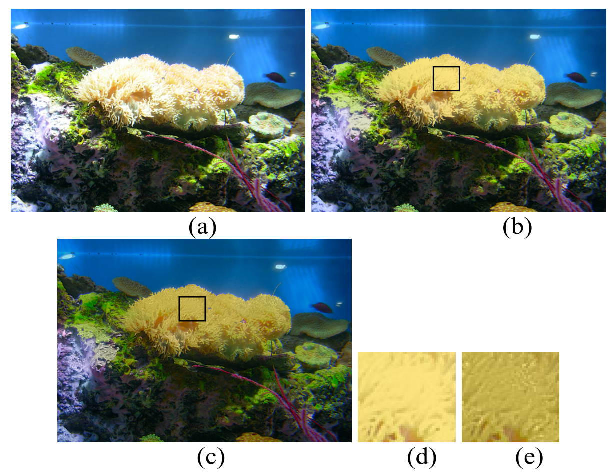
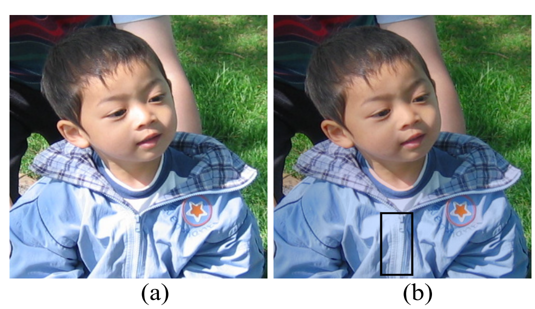


Figure 3. The second result of correcting over-exposure. Our algorithm produces sharper result and synthesize the details of the coral. (a) original over-exposure image, (b) correction result by [9], (c) correction result by our proposed algorithm, (d) zoomed in version of the area labeled as black rectangle in (b), (e) zoomed in version of the area labeled as black rectangle in (c).



(c) (d) (e)

Figure 4. The third result of correcting over-exposure. Our algorithm synthesize the texture of slide fastener and wrinkles of the jacket naturally. (a) original over-exposure image, (b) correction result by [9], (c) correction result by our proposed algorithm, (d) zoomed in version of the area labeled as black rectangle in (b), (e) zoomed in version of the area labeled as black rectangle in (c).

V. Conclusions

In this paper, we propose a method that can correct over-exposed regions with only one image automatically. Thanks to the modified exemplar-based texture synthesis algorithm, texture information of over-exposed regions can be recovered in detail layer. The recovered detail layer is adaptively enhanced and combined with the structure layer. Lightness and color corrections are applied to the combined image in order to produce the final result. A diffusion-like color correction method which is much faster is proposed and the performance is similar compared with [9]. Experimental results show the superior overall performance of our method. In the future, we plan to develop more advanced texture synthesis algorithm based on machine learning techniques so that our method is suitable for a wider range of images.

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