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High Dynamic Range Image Rendering with a Luminance-Chromaticity Independent Model

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Abstract. High dynamic range image (HDR) is widely used since it is capable of capturing more fine information. However, problems remain in its display. A good rendering of HDR color images requires careful treatment of both the brightness and chromaticity information. In this work, we first prove that the global logarithmic mapping of the R, G, B channels may result in desaturation. We then propose an improved way for HDR image rendering. Specifically, by keeping the chromaticity fixated, we use a global transformation and the Retinex-based adaptive filter only in the brightness channel. We finally transfer them back to the RGB space after combining the new brightness and the original chromaticity together. Our model works well in keeping the chromaticity information. Global mapping only in the brightness channel is a good way to avoid desaturation. In addition, our model ensures a good independence between brightness and chromaticity. By applying our method on HDR images, the details in both dark areas and bright areas can be well displayed with better appearance in hue and saturation.

Keywords: HDR, tone mapping, retinex, color constancy

1 Introduction

The dynamic range of an image indicates its luminance range. High dynamic range image (HDR) indicates that the dynamic range of an image exceeds the range of reproducing ability of a display device. The human visual system (HVS) has nice adaptation to HDR scenes. In contrast, the traditional display devices have the limited performance on adapting to HDR scenes. When rendering a HDR image directly on a relative low dynamic range (LDR) device, details of the scene may suffer the loss. Thus, how to render an image on traditional LDR display devices is a nontrivial task [11]. To solve this problem, many HDR rendering algorithms with various motivations have been proposed [2].

Simple rendering algorithms globally compress the dynamic range utilizing a logarithmic function, gamma function or piecewise linear function [16]. These global mapping functions are mathematically simple and computationally fast. However, globall mapping may cause a serious loss of contrast, specifically the

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loss of detail visibility on both bright and dark areas of images. In order to overcome the insufficiency of direct global rendering function, a local processing is necessary for compensating the loss of contrast and thus conserving the more visually appealing details of scenes [3,2,17,20]. For example, Reinhard *et al.* [19] developed a local method based on the photographic dodging and burning technique. Fattal *et al.* compacted the dynamic range of HDR image using a gradient attenuation function defined by a multiresolution edge detection scheme [4]. Both of these two methods provide an efficient way of compressing the dynamic range while preserving the local contrast information of scenes. However, in order to obtain good performance, these approaches explicitly require careful parameter tuning. In contrast, HVS has the ability of adaptively dealing with the HDR scenes, which has motivated many algorithms to functionally imitate the mechanisms of HVS to reproduce the HDR images [12,6,14,1,5].

Inspired by the color perception of HVS, the Retinex theory proposed by Land [15] has been considered as the first attempt at designing computational model for lightness image recovering. Various versions of Retinex have been implemented for different applications. The simplest Retinex algorithm is max-RGB [15,7,8], which aims at recovering the true color of scenes [9,10,21]. Horn reformulated the Retinex as a two-dimensional Laplacien operator in logarithmic space [12], which can effectively remove the local uniform color cast of illuminant of scenes and enhance the contrast of images. However, directly applying the single-scale Retinex operator on images may introduce the problem of halo artifacts. In order to reduce this problem, Rahman *et al.* [18,13] suggested to use multiscale Retinex for color restoration (MSRCR) by averaging three single-scale Retinex. This way partially suppresses the halo artifacts but does not ensure a correct rendering of colors [1]. Although some methods [14,1,5] have been proposed to enhance color image by specifically applying the Retinex filter on luminance component of an image that is explicitly expressed in perceptually uniform color space (e.g., HSV/HSL), these color space are not truly luminance-chromaticity independent. Thus, such strategy may also cause color artifacts that magnify color shifts, or lead to color desaturation when processing the luminance.

In 2006, Meylan and Sabine Ssstrunk [16] proposed another Retinex-based algorithm for rendering HDR images. This method is characterized by using principle component analysis (PCA) as a color model and adopting the Retinex-based adaptive filter for local processing. This operator allows better compression in high-contrast areas while increasing the visibility in low contrast areas and can effectively avoid the halo artifacts in dark areas. However, its drawback is the introducing of quite obvious color distortion due to the global compressing of the HDR images.

In this work, we start by probing into the Meylan's model by first proving that the global logarithmic mapping on all of the R, G, B channels in Meylan's method results in desaturation. Then we prove that there are serious problems when using PCA as a model to encode the luminance and chromaticity of image. According to these analyses, we then propose improved models for brightness

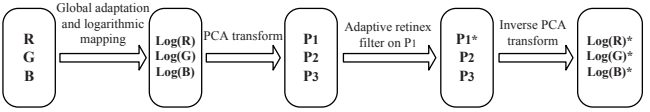

Fig. 1. The flowchart of RBAF algorithm. Adapted from [16].

and chromaticity information. Specifically, by keeping the chromaticity fixated, we use a global transformation and the Retinex-based adaptive filter only in the brightness channel. Since our new pipeline is truly luminance-chromaticity independent, the details in both dark and bright areas of HDR images can be well rendered with better appearance of both hue and saturation information.

The rest of this paper is organized as follows. In section 2, the processing pipeline of Meylan's method [16] is briefly introduced, then we demonstrate that the global logarithmic transformation and PCA-based color model in Meylan's method are the main reasons for producing serious color distortion. Our improved model is introduced and comprehensively evaluated in Section 3. Finally, some discussion and concluding remarks are given in Section 4.

2 RBAF and it's color distortion problem in rendering HDR image

For simplicity, we call Meylan's rendering method [16] as Retinex-Based Adaptive Filter (RBAF). Fig. 1 shows the framework of RBAF, which could be primarily described as four steps. There is a power function based global adaptation on the input HDR images before a global logarithmic transformation. However, we have experimentally found that the power function based global adaptation has little effect on the final reproducing results of RBAF. Thus, we ignore such step in RBAF. The input HDR image thus is first undergone a global logarithmic transformation. Then PCA is used to decorrelate the logarithmic RGB representation of the input image into three principal components. Then, RBAF takes the first principal component (P1) as the luminance, and a Retinex-based adaptive filter is used to enhance the visibility of luminance while keeping the chromatic components (P2 and P3) unchanged. Finally, the original luminance is replaced by the filtered luminance (P1*) and the obtained image is transferred back to logarithmic RGB through inverse PCA to obtain the final output.

The key idea of RBAF is to process only the luminance component of images while keeping the chromatic component unchanged. However, from the experimental analysis we found that RBAF has poor ability of keeping the chromatic component unchanged, thus the final output of RBAF introduces serious color distortion. We found two steps in the pipeline of RBAF that lead to this problem. One is the initial logarithmic transformation imposed on HDR images, which results in desaturation. Another one is that the PCA is not a good chromatic model for separating the luminance and chromaticity components of images. The qualitative analysis and mathematical demonstration are as follows.

Fig. 2. (a) The histogram of an image before and after log transformation. (b) A HDR scene captured with a normal (non-HDR) camera, which is roughly regarded as the ground truth of a rendered HDR image. (c) The result of a HDR image after log transformation. (d) The relationship between R and G.

Fig. 2 (a) shows that directly using the logarithmic mapping on R, G, and B channels will reduce the contrast among color channels, thus resulting in desaturation. Fig. 2 (b) and (c) further indicate that although the global logarithmic mapping on the original HDR images (not shown here) can compress the high intensity areas in images while enhancing the visibility of dark areas, the color of HDR images after logarithmic mapping is seriously desaturated (Fig. 2 (c)) in comparison to the color of the ground truth (Fig. 2 (b)).

Fig. 3 shows two examples of images, which show the color distortion introduced by PCA transformation in RBAF. Although one of the novelties of RBAF is to only process the luminance component of images while keeping the chromatic components unchanged, the experimental results show that the R-BAF results in color distortion while achieving good contrast enhancement on luminance. For example, in comparison to the color of ground truth, the color of objects labeled with an arrow on the bottom row of Fig. 3 is shifted from red to yellow after being processed by RBAF. The reason of color distortion is that the PCA is not good enough to be taken as a model that can effectively separate the luminance from the chromaticity of images. The explanation is as follows.

According to the pipeline of RBAF, the PCA transformation on input logarithmic RGB image could be expressed as the following linear algebraic equation:

$$\begin{cases} P_1 = t_{11}\log R + t_{21}\log G + t_{31}\log B \\ P_2 = t_{12}\log R + t_{22}\log G + t_{32}\log B \\ P_3 = t_{13}\log R + t_{23}\log G + t_{33}\log B \end{cases} \tag{1}$$

Where $[logR, logG, logB]$ are respectively the R, G, B color channels of input image in the logarithmic space. $[t_{ij}]$ indicates the corresponding transform matrix of PCA. $[P_1, P_2, P_3]$ are the first, second, and third principal components respectively. RBAF assumes that the PCA can encode a chromaticity model by treating P_1 as the luminance of images, which is independent of the chromaticity of image described by P_2 and P_3. In other words, the chromaticity of images defined by P_2 and P_3 will form a pure chromatic space, which is not affected by the change of the luminance of images defined by P_1.

In order to investigate the independence of chromatic components, we simultaneously fixate P_2 and P_3 in linear algebraic Eq. (1) while P_1 could be arbitrary

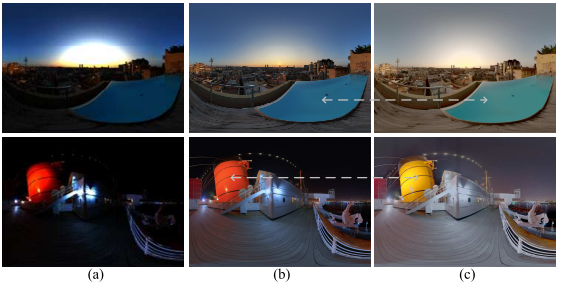

Fig. 3. (a) Original HDR images (b) Ground truth images of (a), which are captured using normal (non-HDR) cameras without any processing. (c) The results obtained by processing the original HDR images (a) with RBAF.

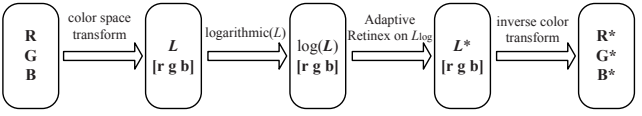

Fig. 4. The proposed pipeline for HDR image rendering.

values. Thus, we derive the Eq. (1) as follows:

$$\begin{cases} P_2 = t_{12}\log R + t_{22}\log G + t_{32}\log B \\ P_3 = t_{13}\log R + t_{23}\log G + t_{33}\log B \end{cases} \tag{2}$$

We solve this linear algebraic equation and get

$$\begin{cases} R = c_1 G^{x_1} \\ B = c_2 G^{x_2} \end{cases} \tag{3}$$

P_2 and P_3 are fixed, thus x_1, x_2, c_1, and c_2 are decided by P_1. If P_2 and P_3 are independent of P_1, the chromatic space defined by P_2 and P_3 should not be changed when P_1 is changing. For example, we probe the color space $[R\ G\ B]$ when setting $c_2 = 0$, $c_1 = 1$, $x_1 = 0.33$. Note all of coefficients in Eq. (3) are decided by P_1 and thus can reflect the changing of P_1. We get

$$\begin{cases} R = G^{0.33} \\ B = 0 \end{cases} \tag{4}$$

If P_2 and P_3 can really represent a luminance independent chromatic space, $[R\ G\ B]$ defined by Eq. (4) should have the same chromaticity. Fig. 2 (d) shows the relationship between R and G, and the corresponding chromatic space. Obviously, the defined chromatic space $[R\ G\ B]$ with fixed P_2 and P_3 does not have same chromaticity but has undergone the color change that is shifted from red to yellow. This phenomenon is well consistent with the color distortion in Fig. 3, in which the color of objects labeled with the arrow in ground truth image is shifted from red to yellow after being processed by RBAF.

3 Improving RBAF by using a luminance-chromaticity independent model

In section 2, we point out that the global logarithmic mapping utilized in RBAF results in desaturation. We also indicate that the PCA based color model is not good enough to separate the luminance from the chromaticity of images, which is the reason that leads to the color distortion in the results of RBAF. In this section, we improve RBAF by using a luminance-chromaticity independent model that can truly process brightness and chromaticity independently. Fig. 4 shows the pipeline of the proposed algorithm.

Different from RBAF, here we first use a simple color model to express luminance of image and the chromaticity of image respectively. We will prove that this color model is truly luminance-chromaticity independent. The luminance-chromaticity independent model means that the chromaticity of an image is not affected by the change of luminance of the image.

Our model extracts the luminance component of an image by calculating the maximum value among R,G,B channels for each pixel.

$$L(x,y) = max\{R(x,y), G(x,y), B(x,y)\} \tag{5}$$

Then, the computed luminance of each pixel is used to normalize each of the R, G, and B color values.

$$r(x,y) = \frac{R(x,y)}{L(x,y)}, g(x,y) = \frac{G(x,y)}{L(x,y)}, b(x,y) = \frac{B(x,y)}{L(x,y)} \tag{6}$$

Then a globally logarithmic mapping is only applying on $L(x,y)$ while keeping the normalized chromaticity $[r(x,y), g(x,y), b(x,y)]$ unchanged, which is different from RBAF. After global logarithmic processing on $L(x,y)$, local adaptation is performed on $L(x,y)$ using the surround-based Retinex method designed in RBAF [16], which is expressed as

$$L^*(x,y) = log(L(x,y)) - \beta(x,y) \cdot log(L_{Gauss}(x,y)) \tag{7}$$

Where $log(L(x,y))$ indicates the logarithmic mapping on $L(x,y)$, $log(L_{Gauss}(x,y))$ is computed with surround mask. For simplicity, we directly use the technique in RBAF [16] for computing surround mask $log(L_{Gauss}(x,y))$. $\beta(x,y)$ weights the surround mask based on the pixel value at coordinate (x,y)

$$\beta(x,y) = 1 - \frac{1}{1 + e^{-7\cdot(L(x,y)-0.5)}} \tag{8}$$

We finaly replace the original luminance $L(x,y)$ with $L^*(x,y)$ and recover a RGB image for displaying by

$$\begin{cases} R^*(x,y) = L^*(x,y) \cdot r(x,y) \\ G^*(x,y) = L^*(x,y) \cdot g(x,y) \\ B^*(x,y) = L^*(x,y) \cdot b(x,y) \end{cases} \tag{9}$$

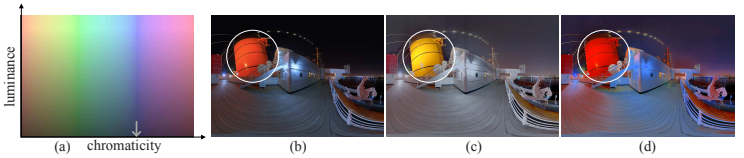

Fig. 5. (a) chromaticity diagram. (b) The ground truth of the scene. (c) Result processed by RBAF. (d) Result processed by our algorithm.

Fig. 6. Top: The rendering results when taking the max of RGB values as luminance. Bottom: The results when taking the mean of RGB values as luminance.

3.1 Analysis of the independence of luminance and chromaticity

Our algorithm takes the color coefficient $[r(x,y), g(x,y), b(x,y)]$ normalized by luminance $L(x,y)$ as chromatic component, which is truly independent from brightness component. Fig. 5 shows the relationship between the color coefficient $[r(x,y), g(x,y), b(x,y)]$ and the luminance $L(x,y)$. This figure demonstrates that the chromaticity keeps almost unchanged when the luminance is changing.

For example, the chromaticity (e.g., the point labeled with arrow) almost keeps same when the luminance on vertical coordinate varies. Moreover, as analyzed above, the PCA-based color model is not good enough to separate the luminance from chromaticity of images and thus results in color distortion (Fig. 5(b) and (c)). In contrast, our algorithm overcomes the color distortion of RBAF and achieve good performance on color fidelity (Fig. 5 (d)).

To evaluate our luminance model, another common way for computing the luminance of image is used, i.e., the mean of RGB values of each pixel is adopted as luminance component. Fig. 6 shows the reproducing results by taking two different strategies for luminance computation. From this figure we can obviously observe that taking the max of RGB values as luminance obtains better performance of rendering than taking the mean of RGB values as luminance. In contrast to other linear combination based luminance model (e.g., mean and PCA), the results also indicate that the luminance model $L(x,y)$ is more effective on controlling the dynamic range of images, which can greatly enhance the luminance contrast and visibility of HDR images.

3.2 Experimental results and comparison

We compared our method with other typical tone mapping methods, including: the MSRCR of Rahman *et al.* [18,13], the RBAF of Meylan [16]. Fig. 7 totally

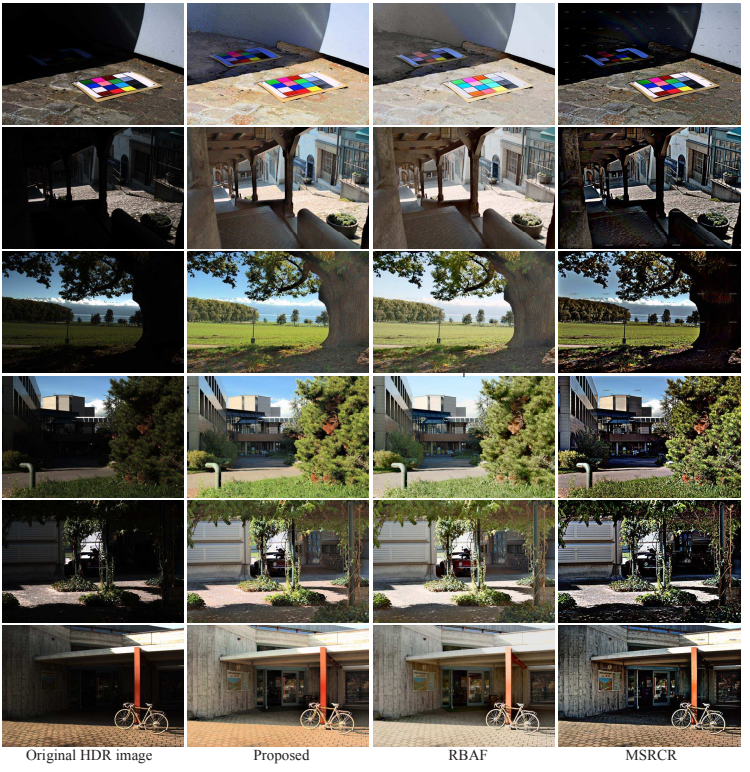

Fig. 7. Results of different methods. From left to right: Original HDR images, the results of the proposed algorithm, RBAF [16], and MSRCR [18,13], respectively.

show six commonly used HDR images. From the viewpoint of luminance contrast enhancement, the MSRCR performs very poor on luminance enhancement on all of the HDR images listed here. There are serious halo artifacts in the outputs of MSRCR, mainly because that MSRCR is based on a fixed Retinex filter [16,18].

In contrast, both RBAF and our method employ an adaptive Retinex filter to enhance the luminance and thus avoid the problem of halo artifacts. Although both RBAF and our method achieve very good performance on luminance enhancement, our method performs better than RBAF on local luminance contrast enhancement(e.g, the local contrast between sky and cloud in the third and fourth rows of Fig. 7)

We further investigated the performance of color fidelity between RBAF and our method. Both RBAF and our method perform well on enhancing the luminance visibility of scenes. However, RBAF obtains poor performance on keeping the color fidelity in comparison to our method. The results of RBAF on color enhancement are consistent with the previous analysis that the global logarithmic mapping on all of the R,G,B channels results in desaturation (e.g., the color checker in the first row of Fig. 7). In contrast, by applying our method, the details in both dark areas and bright areas are well enhanced while remaining

better hue and saturation. Moreover, there is contrast loss of color information in the results of RBAF, since the PCA is not a good color model for separating the luminance from chromaticity of images. For example, all of the images in Fig. 7 seem grayer and unnatural after be enhanced by RBAF. However, our method provides a good appearance of colors on all of the processed images.

4 Conclusion and discussion

HDR image rendering has been widely studied and a large number of algorithms exist. They enhance the quality of the rendered images, but still suffer from various problems. One of the common drawbacks is the color distortion when enhancing the local contrast and luminance visibility on both bright and dark areas. We provided in this work a method to render HDR images by improving the Retinex based adaptive filter (RBAF). RBAF was inspired from by the Retinex theory of color vision and has its efficiency in increasing the local luminance contrast while preventing halo artifacts.

However, RBAF performs poor on color enhancement. We proved that global logarithmic mapping on R,G,B channels utilized by RBAF is the main reason of resulting in desaturation. Moreover, we also pointed out that PCA is not a good model for separating the luminance from the chromaticity of images and it is the key reason of serious color shift in the results of RBAF. In order to overcome the problems of RBAF, we improved the RBAF by adopting a model which is truly color and luminance independent. In particular, our method uses the max among R,G,B values of each pixel as luminance component of images and utilizes it to normalize the R,G,B values of each pixel to obtain the chromaticity component of images. In comparison to other models (e.g, PCA-based [16] or HSV-based [14,1,5]), this simple model is really luminance-chromaticity independent and thus it can minimize the chromatic changes induced by the processing of luminance. Moreover, we only apply the global logarithmic mapping on the luminance channel, which can avoid the problem of desaturation introduced by global logarithmic mapping on all of the R,G,B color channels.

We tested our method on various HDR images, compared it with other typical algorithms and showed that it efficiently increases the luminance visibility while preventing color distortion. As an important future direction, we are interested in quantitatively testing the color fidelity of an image after being processed by HDR rendering algorithms. A feasible way is to use the angular error, which is frequently utilized in color constancy literature [9,7], to measure the color difference between the original HDR image and the enhanced image.

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