A TONE MAPPING ALGORITM WITH DETAIL ENHANCEMENT BASED ON RETINEX THEORY

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ABSTRACT

Because of the progress of the digital camera technique recently, we can directly obtain the HDRI (High Dynamic Range Image) from camera. Nevertheless, limited by display, we still transfer the HDRI to the display which can show LDRI (Low Dynamic Range Image). This technique is known as tone-mapping.

The goal of tone-mapping is to compress the luminance dynamic range into low dynamic range while decreasing distortion and preserving detail. We use logarithm first to compress high dynamic range based on background luminance. The retinex local contrast enhancement is thus being performed to enhancement the image in dark regions. Using our method can preserve most of detail without contrast distortion especially dark areas.

Keywords *tone mapping, tone reproduction, high dynamic range image;*

1. INTRODUCTION

The dynamic range is a ratio between the maximum and minimum physical measures. In photography, we use "dynamic range" for the luminance range of a scene being photographed, or the limits of luminance range that a given digital camera or film can capture, or the reflectance range of images on photographic papers.

High Dynamic Range Imaging (HDRI or just HDR) is a set of techniques that allow a greater dynamic range between the lightest and darkest areas of an image than current standard digital imaging techniques or photographic methods. This wide dynamic range allows HDR images to represent more accurately the range of intensity levels found in real scenes.

In this paper, we focus on how to compress the HDR images into the stored image that it can be shown on the common display. This technique is “tone-mapping”. The algorithm for resolving tone-mapping can be classified by two categories: spatial uniform and spatial varying algorithms.

1. Spatially uniform algorithms: They are non-linear functions based on the luminance and other global variable of the image. Once the optimal function has been estimated according to the particular image, every pixel in the image is mapped in the same way. This is a simple way to implement tone-mapping algorithm but sometimes distorts the local contrast.

2. Spatially varying algorithms: The parameters of the non-linear function change in each pixel, according to features extracted from the surrounding parameters. In other words, the effect of the algorithm changes in each pixel according to the local features of the image. Those algorithms are more complicated than global ones, they can show artifacts (e.g. halo effect), the output can look un-realistic, but they can provide the best performance, since the human vision is mainly sensitive to local contrast.

(a) (b)

Fig. 1 (a) spatially uniform algorithm. (b) spatially varying algorithm.

2. RELATED WORK

2.1 TONE MAPPING

Tone mapping problem can be solved by many algorithms. We can classify tone-mapping algorithms into global operator and local operator. Global operators use single non-linear function that such algorithms are efficient but sometimes cause a loss of contrast even part of image may over-saturate or under-saturate. Local operators use function according to the local features of the image. These methods are more complicated than the global operators but it can preserve most of detail. After all, the human vision system is mainly sensitive to local contrast.

The simplest global tone mapping method is bound to linear scaling. Linear scaling reproduces the tone into the dynamic range of display according different mapping functions. Fig. 1 shows the different linear mapping function. We can notice that brightness pixels are saturated; dark pixels are completely black; or the contrast is largely compressed.

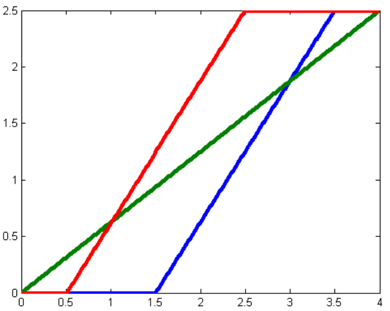


Fig. 2. A linear mapping chart. The red line causes over-saturation, the blue line causes under-saturation, and the green line compresses the complete dynamic range so that it can lose detail of part of the image.

Another simple global tone-mapping function is shown below. This function will map scene radiance values Y in the domain $[0, \infty)$ to a displayable output range of $[0,1)$. This mapping function can be done very fast and flexibly but it has a serious disadvantage that the brightness pixels are over-saturated and the detail is lost [20].

$$L_{display} = \frac{Y_{world}}{1 + Y_{world}} \qquad (1)$$

Ward Larson and Holly Rushmeier [8] proposed a tone reproduction operator that preserves visibility in high dynamic range scenes. Their method introduces a new histogram adjustment technique, based on the population of local adaptation luminance in the scene. The method also incorporates models for human contrast and color sensitivity to reproduce experience of human vision.

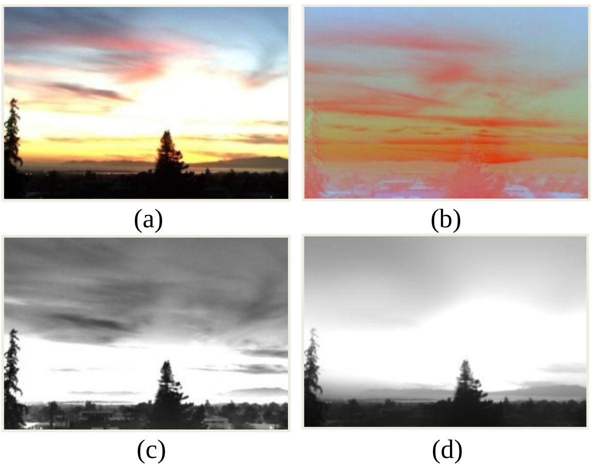
Tumbling and Turk [10] build a similar hierarchy using multiple instances of a new low-curvature image simplifier (LCIS) to increase the local contrast while avoiding halo artifacts. LCIS uses a form of anisotropic diffusion to enhance boundaries but smoothing insignificant intensity variations. This method does not take into account whether details are visibly significant so that the resulting images look unnatural and have serious edge artifacts.

F. Drago and K. Myszkowski [2] presented a global tone-mapping algorithm based on logarithm with different bases. The formulation of this algorithm is shown below:

$$L_d = \frac{0.01*L_{dmax}}{log_{10}(L_{wmax}+1)} * \frac{\log(L_w+1)}{\log\left(2+\left(8*\left(\frac{L_w}{L_{wmax}}\right)^{\frac{\log(b)}{\log(0.5)}}\right)\right)} \qquad (2)$$

where L_{wmax} and L_{dmax} are the maximum luminance of world and display; L_d and L_w denote the output luminance of image and world luminance in the scene; and b is the bias parameter which can influence expression of brightness and darkness regions in the output image.

F. Durand and J. Dorsey [3] present a tone-mapping operator that reduces contrast while preserving most of detail. This algorithm belongs to local operators and no parameter should be set. They use an edge-preserving filter called bilateral filter in logarithm of luminance. This is a non-linear filter that is composed of a Gaussian filter in spatial domain and an influence function in intensity domain that calculates the difference light between pixels. After that, they obtain the low frequency and high frequency information which is subtracted from the intensity of image and low frequency information. The low frequency image is then compressed while the high frequency information is preserved. However, the color is still saturation through this method due to the severe gamma compression.



(a) (b)

(c) (d)

(e)

(f)

Fig. 3 (a) The high dynamic range input image. (b) The color of input image. (c) The intensity of input image. (d) The low frequency based on bilateral filter. We can notice that the edge is preserved while the noise and texture are eliminated. (e) The detail image which is different between intensity and low frequency image. The compression step is done by reducing based layer domain while preserving the detail of high dynamic range image. (f) The final result after bilateral filter tone compression [5].

Raanan Fattle et al. [4] proposed a tone-mapping algorithm which is processed in gradient domain. They observed that the drastic change in the luminance must involve the large magnitude gradients. Nevertheless, they consider that the magnitude can be attenuated by a gradient domain function that is penalizing larger magnitude gradients than smaller and keeping the gradient orientation. This conduct additionally avoids some artifacts such as halos, gradient reverses, and edge flaws but need parameter tuning.

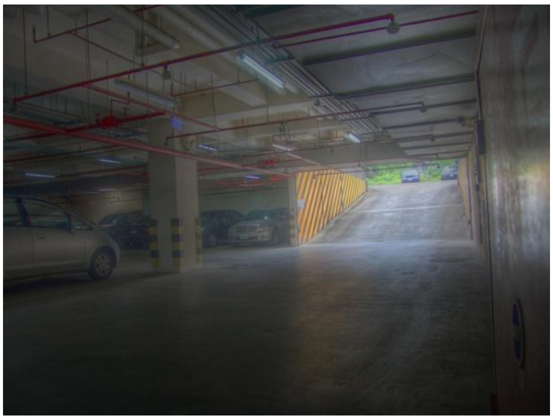


Fig. 4 gradient domain tone compression.

2.2 RETINEX THEORY

The original retinex theory is proposed by E. H. Land with intent on reproducing the perception to color stimuli by the Human Vision System [1]. The word "retinex" is a portmanteau formed from "retina" and "cortex", suggesting that both the eye and the brain are involved in the processing. The ancestor of retinex model in digital image is described below:

$$R(x) = \frac{1}{N}\sum_{k=1}^{N} f(\frac{I(x)}{max_{y\epsilon N} I(y)}) \quad (3)$$

where $R(x)$ is Retinex value; $I(x)$ is the intensity value in pixel x; N is a path that surrounding around pixel x; and f is an increasing function which can be manipulated by power law or logarithm.

Another formula of retinex model of color vision is proposed by E. H. Land himself, who modified the formula of the original one [5][1]. He observed that the Human Vision System (HVS) is associated with the brightness surrounding around the pixel so that the formula is becoming:

$$R(x) = log(\frac{I(x)}{< \{I(y), y \in Surround\} >}) \quad (4)$$

where the <,> denotes the average weighting function. Other variation of Retinex formula replaces the average operator by Gaussian weighting functions proposed by Jobson et al. [6]:

$$R(x) = log(\frac{I(x)}{(G * I)(x)}) \quad (5)$$

where G function is Gaussian function, and $*$ operator denotes the convolution operator.

In Jobson *et al.*'s single-scale retinex (SSR) [5][1][7], the formulation is mentioned in fig. 5. Another algorithm is called multi-scale retinex (MSR) which is proposed by Jobson himself that have better color rendition [5]. In MSR, the output color image $f_{MSR_i}(x,y)$, $i \in \{R, G, B\}$ is obtained as the weighted sum of the several SSR output color images using Gaussian filter having different support regions as follows:

$$R_{MSR_i}(x,y) = \sum_{n=1}^{N} w_n f_{n_i}(x,y),\ i \in \{R,G,B\} \quad (6)$$

Where N denotes the number of scales; $f_{n_i}(x,y)$ is the SSR output color image with the nth scale and ith color channel; and w_n is a weighting parameter for SSR.

MSR algorithm is good enough for gray images; however, it's not desirable for color images. The RGB proportion is out of balance because the RGB ratios is unknown equal to the retinex values of RGB ratios. The solution is done by applying multi-scale retinex with color restoration (MSRCR) shown below [5]:

$$R_{MSRCR_i}(x,y) = C_i(x,y) R_{MSR_i}(x,y)\ i \in \{R,G,B\} \quad (7)$$

where $R_{MSR_i}(x,y)$ is MSR output for each color and $C_i(x,y)$ denotes the color restoration function which is represented:

$$C_i(x,y) = \beta \log(\propto I'_i(x,y))$$

which β and $\propto$ are the constants, and $I'_i(x,y)$ is the specific weight defined by:

$$I'_i(x,y) = I_i(x,y) / \sum_{x=1}^{3} I_x(x,y),\ i \in \{R,G,B\} \quad (8)$$

where $I_i(x,y)$ is the pixel value for each color channel.

The SSR color enhancement is suitable for gray images but hard to keep the color balance on color proportion for color images while MSR is better than

SSR due to the better color rendition. MSRCR improves the color images because of the color restoration and better contrast. However, they usually dedicate to enhance the foggy images.

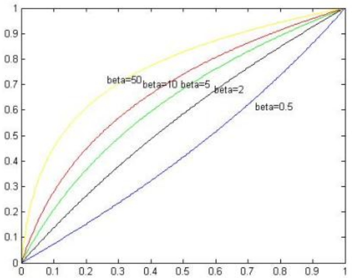


Fig. 5. Logarithmic curve with different β values.

3. OUR METHOD

In this chapter, we will present my algorithm to derive the Low Dynamic Range Image (LDRI). The flowchart is shown on Fig. 3. First, we use logarithm compression whose parameters are determined by background luminance image to reduce the tone into the [0, 1] range. Second, we focus on the dark regions which are insufficient to reveal detail contrast. We apply a detail enhancement similar to retinex theory to enhance the detail contrast.

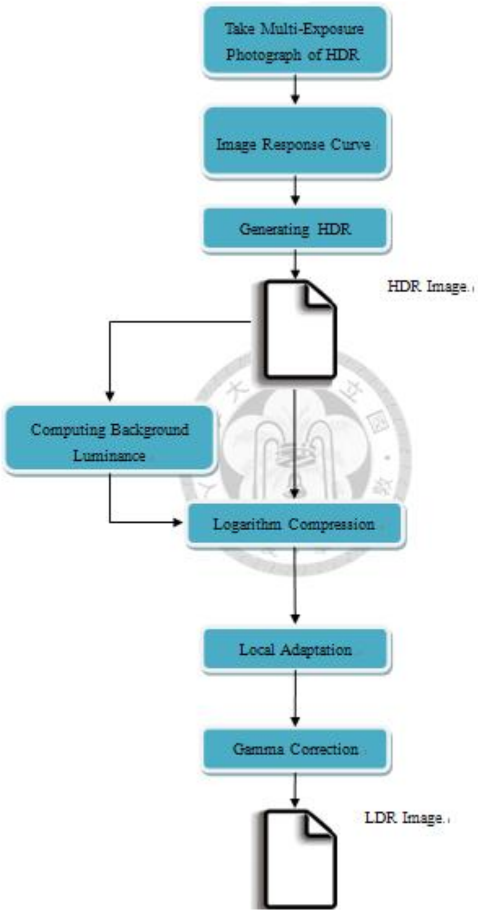


Fig. 6. Complete flowchart.

3.1 Logarithm Compression Based on Background Luminance

In real world, the high dynamic range brings out large gradient margin in the high dynamic range image. In traditional tone reproduction, this issue is dealt with by compression of both high and low luminance. However, modern tone mapping has abandoned these ‘s’-shaped transfer curves in favor of curves that compress mainly in high luminance while preserving low luminance [9].

We first view the log-average luminance as a useful approximation to the key of the scene. The following equation calculates the log-average luminance:

$$L_{average} = \frac{1}{MN}\exp\left(\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\log(\sigma + L_w(x,y))\right) \qquad (9)$$

where $L_{average}$ is the average luminance for the image; MN are the number of pixels in the image; $L_w(x,y)$ is the “world” luminance for pixel (x,y); and σ is a small value that prevents the black pixel from logarithm function. Thus we can map the luminance to middle-gray of the image. The mapping equation is shown below:

$$L(x,y) = \frac{\alpha}{L_{average}} L_w(x,y) \qquad (10)$$

where $L(x,y)$ is the scaled luminance value, and α is a parameter whose range is zero to one.

We use the logarithm function in Section 2.1.1, which is similar to the logarithm function proposed by F. Drago [2]:

$$L_o = \frac{\dfrac{\log(L_{in}(x,y)+1)}{\log\left(a + b * \left(\frac{L_{bilateral}(x,y)}{L_{max}}\right)^{\gamma}\right)}}{\log(L_{max}+1)} \qquad (11)$$

where L_{max} is the maximum luminance in the scene; L_{in} and L_o are the world luminance and displayed luminance; a, b, and γ are bias, scale, and exponent parameters to adjust luminance; and $L_{bilateral}$ is the L_{in} luminance through bilateral filter processing:

$$L_{bilateral}(p) = \frac{1}{k(p)}\left(\sum_{q\in C} g\sigma_s(||p-q||)g\sigma_s(||I_p - I_q||)\right)I_q \qquad (12)$$

where p, q are the positions of processed pixel and neighbor pixels; I_q is the neighbor intensities of pixels in window C; I_p is the intensity of processed pixel; $g\sigma_s$ measures the spatial closeness between pixels p and q; $g\sigma_s$ denotes the intensity closeness between p and q; and k is the normalization term which makes sure that the total sum of the weight of all pixels in domain equals one:

$$k(p) = \left(\sum_{q\in C} g_{\sigma_s}(||p-q||)g_{\sigma_r}(||I_p - I_q||)\right) \qquad (13)$$

3.2 Retinex-Based Local Adaptation

After logarithm compression, we perform a surround-based Retinex method to enhance detail. Here is the following equation:

$$L_{new}(x,y) = \log_{\beta}\big(L_o(x,y)\big) - \alpha * \log_{\beta}(\text{mask}(x,y)) \quad (14)$$

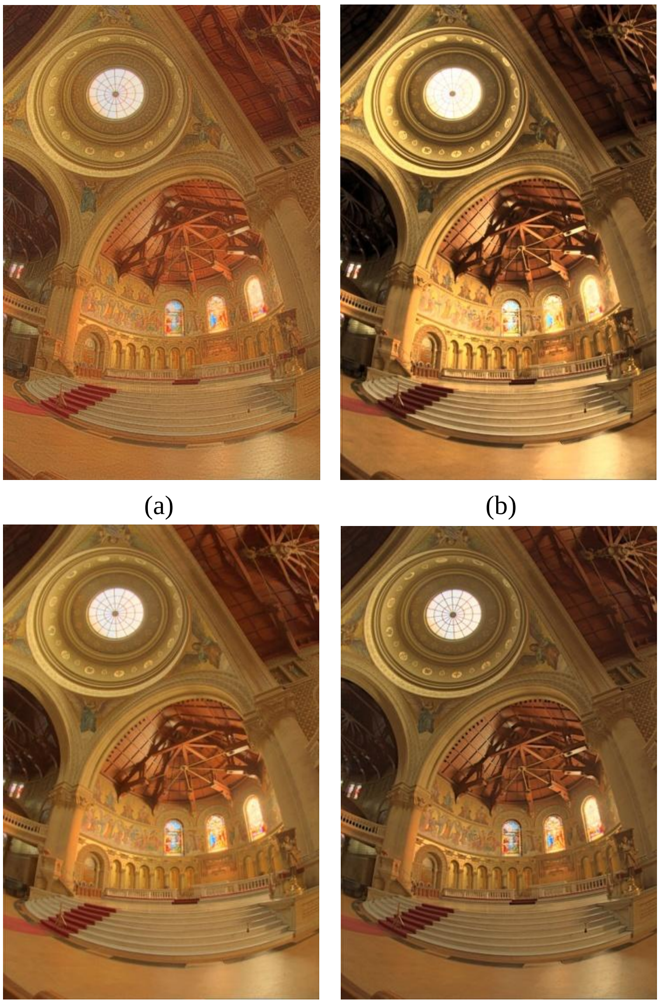
where $L_{new}(x,y)$ and $L_o(x,y)$ are the displayed luminance and luminance from Eq. (4.1.3); α is a scale parameter; $\text{mask}(x,y)$ is computed by convolving the luminance $L_o(x,y)$ with surround function; and $\log_{\mathrm{b}}(x,y)$ is computed by:

$$\log_{\beta}\big(L(x,y)\big) = \frac{\log(L(x,y) * (\beta - 1) + \beta)}{\log(\beta)} \quad (15)$$

where b is a parameter that higher value causes high-key images. Logarithm curve obeys the Weber-Fechner law of Just-Noticeable Difference (JND) response in human vision. Fig. 2 shows the logarithm curves with different b values.

Finally, we need to do the gamma correction, a nonlinear operation used to encode and decode luminance or tristimulus values in video or still image systems.

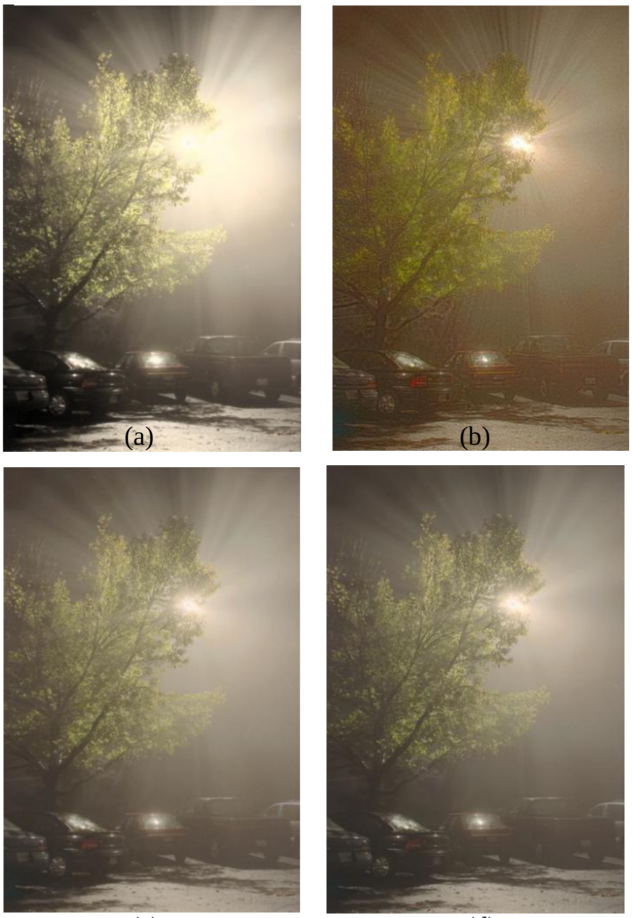
4. EXPERIMENTAL RESULTS



(a) (b)

(c) (d)

Fig. 7 (a) LCIS. (b) G.W. Larson's method. (c) Adaptive logarithm. (d) Our method.



(a) (b)

(c) (d)

Fig. 8(a) G.W. Larson's method. (b) LCIS. (c) Adaptive logarithm. (d) Our method.

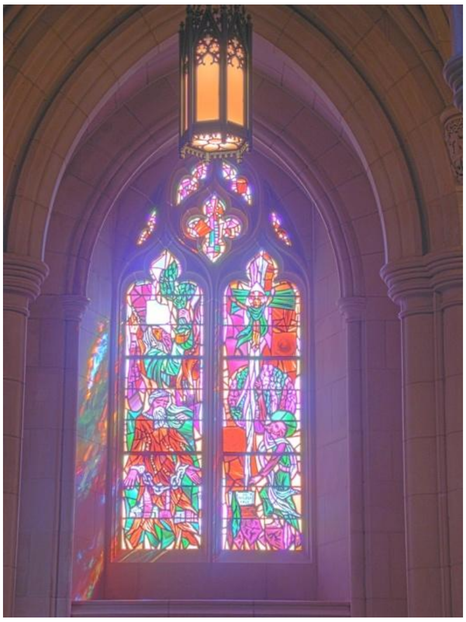
(a)

(b)

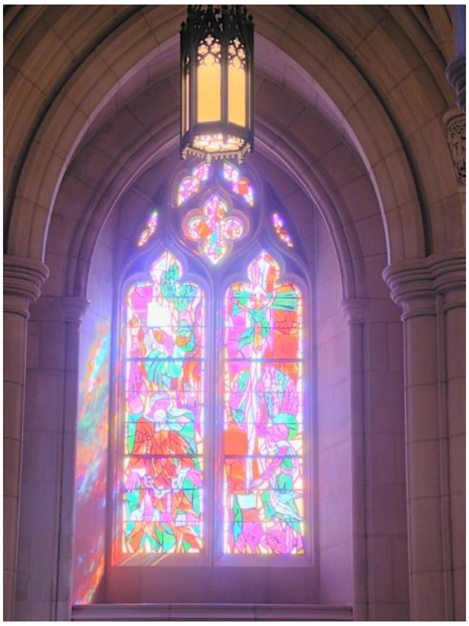
(c)

(d)

Fig. 9 (a) G.W. Larson's method. (b) Result after LCIS. (c) Result after adaptive logarithm. (d) Our method.



(a)



(b)

Fig. 10 (a) Bilateral filter proposed by F. Durand et al. (b) Our method.

(a)

(b)

Fig. 11 (a) Result after bilateral filter tone mapping. (b) Our method (c) Result after HDR Tools [11].

(c)

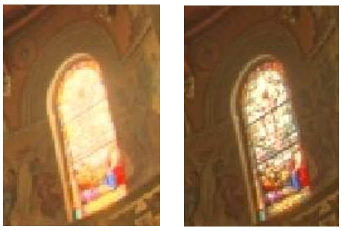
5. CONCLUSION AND FUTURE WORK

We implement a tone-mapping algorithm which is simple, effective, and similar to human vision system. Besides, the human vision system is sensitive to the contrast and detail that we enhance in dark regions. Because of the perception of human vision system, HDR image is considered “foggy” or “artistic” by human due to the serious contrast reduction for gradient domain compression.

The tone-mapping of high dynamic range image is seriously image-dependent that some people always focus on decision of parameters. Our method has fewer parameters to settle but still needs to provide the maximum and minimum dynamic range values. The default is the maximum and minimum values for the input (.hdr file). We experiment with the dynamic range problem using Gaussian distribution that the maximum value is $\mu + 3\sigma$, where μ is the log-encoding of average of luminance, and σ is the standard deviation. The drawback of this method is that we cannot assume the image has normal distribution.

However, the disadvantage of our algorithm is that the details are sacrificed at high illumination for some HDR images because of the log encoding of dynamic range compression. The appearance is shown in Fig. 6. Another drawback is the edge artifact in high contrast region. The solution is to replace the mask filter in local adaptation by bilateral filter. Instead of retinex color enhancement, we also resolve this problem by another detail enhanced algorithm.

In other hand, we can replace retinex-based algorithm with another detail enhancement. We can also replace the logarithm in equation (11) with another dynamic range compression such as gamma compression. The parameters of gamma compression can be determined by local background luminance that the luminance in dark regions increases the value more than the luminance in bright regions but might cause the color saturation due to the severe local light compensation.



(a) (b)

Fig. 12 Compared with (a) our method and (b) bilateral filter [3]. Our method loses the details at high illumination.

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