Tone Mapping Algorithm for Luminance Separated HDR Rendering Based on Visual Brightness Functions

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Abstract - *Tone mapping algorithms are used in image processing that reduces the range of high dynamic range (HDR) image to be displayed on low dynamic range (LDR) devices. The retinex method is one of the tone mapping algorithms to provide dynamic range compression, color constancy, and color rendition. It has been developed from single scale methods to multi-scale methods. Retinex algorithms still have drawbacks like the noise and desaturation. In this paper, we propose a new local tone mapping algorithm for enhancement of contrast, saturation, and noise of HDR rendered images. In proposed algorithm, an RGB image is converted into an HSV image. The V component provides intensity information of images and it can be easily used to estimate the global and local illuminants. The new algorithm introduces an adaptive gamma correction method as a function of local illuminants*.

Keywords: Tone mapping, Retinex, Brightness function, Local adaptation

1 Introduction

The real world has wide dynamic range about 10,000:1 from highlights to dark shadows and human eyes can directly perceive it. However, images captured by a digital camera are different from the human perception for the original scene. Because the dynamic range of image sensors and displays is much narrower than that of the human eyes, images are easily saturated in the highlights and shadows areas for lack of the dynamic range in the indoor and outdoor situations.

Tone mapping methods have been developed for rendering the high dynamic range (HDR) images on low dynamic range (LDR) devices. Tone mapping can be simply realized by histogram equalization, power-law transformation, and compression by logarithmic or sigmoid functions. These algorithms are suitable for overall enhancement of LDR images but insufficient for local area enhancement and HDR compression. Histogram equalization causes color distortion due to limited application for luminance components. And the power-law transformation is difficult to adjust appropriate gamma value for each image [1]. So, additional local tone mapping method is necessary because global tone mapping can cause loss of contrast and detail.

Retinex theory, the model of lightness and color perception of human vision, is developed by Land [2]. This algorithm improves the brightness, contrast and sharpness of an image in addition to the dynamic range compression. Single scale retinex (SSR) is based on the center/surround algorithm which computes the difference in the logarithm domain between each pixel and weighted average value of its surround [3]. It is appropriate for gray-scale images. Multi-scale retinex (MSR) is introduced for improvement of detail but it is not enough for color images. Multi-scale retinex with color restoration (MSRCR) is developed to correct undesired color distortion in MSR [4]. However, MSRCR uses many parameters for the compensation of color distortion and it is difficult to select the optimal value. Retinex in the RGB space deals R, G, and B signals separately, accordingly there are color artifacts that exaggerate color shifts and desaturation [5]. Another color spaces such as YUV and HSV also have luminance and chrominance channels. These color spaces can preserve the color elements and reduce the number of computation because they apply retinex processing only to the luminance channel. Comparing the two color spaces, HSV space shows better performance than YUV. The HSV space considers the perception of human vision, therefore each H (Hue), S (Saturation), and V (Value) components are less correlation [6]. HSV retinex also is influenced by the Gaussian filter size. When the filter size is small, the detail is improved but the halo artifact more appears. On the other, the center/surround method in logarithm domain increases the noise in dark areas and decreases the color saturation in highlights areas. B. Sun [7] has presented the luminance based MSR (LBMSR) to reduce the noise in dark areas but it still has low contrast problems in highlights areas. To enhance the image quality and generate neutral image, compensation methods of these noise and desaturation are needed.

In this paper, we propose an adaptive tone mapping algorithm for enhancement of HDR image rendering. This algorithm includes the local luminance estimation parameters, the minimum luminance threshold, the maximum luminance threshold, and the visual gamma function. The minimum and maximum threshold parameters provide the boundaries of perceptual luminance according to relative local illuminations. The visual gamma function is considered to the variation of the surround luminance level. And only the intensity component of the HSV space is used to reduec the hue shifts. And multi-scale method is applied to improve the performance of proposed algorithm. Finally, we compared our algorithm with conventional algorithms.

2 Retinex Based Algorithms

The center/surround method uses the difference between each pixel and a weighted surround image in logarithm domain. The basic equations of the SSR are shown as follows.

$$R_{SSR}(x,y) = \log I_i(x,y) - \log\left[F(x,y) * I_i(x,y)\right], \tag{1}$$

$$F(x,y) = K\exp\left[-(x^2+y^2)/\sigma^2\right], \tag{2}$$

$$K = 1/\sum_x\sum_y \exp\left[-(x^2+y^2)/\sigma^2\right], \tag{3}$$

where I_i is the input image in i th spectral band, R_{SSR} is retinex output, F is the Gaussian LPF function, and the symbol "*" is convolution operation. K is a normalized factor and σ is standard deviation of the filter and controls the degree of blurring. If σ is smaller, the detail and dynamic range compression are improved but the quality of color rendition is lower.

The MSR is the weighted sum of several SSRs with different Gaussian filter size. It has good performance for gray scale images. However, MSR is not desirable for color images because the RGB channel is unbalanced due to the SSR processing for each RGB component. As a result, the retinex processing causes the gray-out of the image in entire or specific regions. To solve the problem, Jobson *et al*. [4] have been added the color restoration part to the MSR. It makes transition from logarithmic domain to the display domain through canonical gain and offset adjustment as followings.

$$R_{MSR}(x,y) = \sum_{n=1}^{N}\omega_n R_{SSRn}, \tag{4}$$

$$R_{MSRCR}(x,y) = G\left[C_i(x,y)R_{MSR}(x,y) + b\right], \tag{5}$$

$$C_i(x,y) = \beta\log\left[\alpha I_i(x,y)\right] - \log\left[\sum_{i=R,G,B} I_i(x,y)\right], \tag{6}$$

where N is the number of scales, R_{SSRn} is the SSR of the n th scale, R_{MSR} is the output of MSR, ω_n is the weighting factor. C_i is the color restoration function for each RGB channel, β is a gain constant, α controls the strength of the nonlinearity, and R_{MSRCR} is the output of MSRCR. G and b are the final gain and offset value respectively.

B. Sun *et al*. introduced the LBMSR. The LBMSR algorithm processes only luminance channel. It subtracts sum of convolution results from intensity image in logarithm domain as following equation.

$$R_{LBMSR}(x,y) = \frac{1}{N}\left[\log I(x,y)^N - \log\left(\sum_{n=1}^{N} F_n(x,y) * I(x,y)\right)\right], \tag{7}$$

where R_{LBMSR} is the output of LBMSR, N is the number of Gaussian filter, F_n is the n th Gaussian filter, and I is the luminance channel of input image.

3 Brightness Functions

Stevens investigated the relation between brightness and luminance [8]. The experiments were measured by magnitude estimation with one eye dark-adopted and the other light-adopted. As a result of experiment, the brightness is related to power function of the target luminance. Eq. (8) shows the brightness function in a simple field.

$$B = k(L - L_o)^n, \quad L > L_o, \tag{8}$$

where B is brightness, L is luminance, and L_o is the absolute threshold. k is constant of proportionality and n is the power function exponent. In the dark adaptation, the minimum value of L_o is approximately 0.1 *bril* [9].

Bartleson and Breneman conducted an experiment of the brightness perception in complex stimulus configuration according to luminance variation [10]. Their experiment result shows that brightness function in the complex scene does not coincide with Stevens's brightness function (simple power function). It describe the brightness perception is changed by variations of viewing conditions. The function can be described in a logarithmic form.

$$\log B = 2.037 + 0.1401\cdot\log L - \left[a\exp(b\log L)\right], \tag{9}$$

where a and b are allowed to vary as functions of illuminance.

4 Local Adapted Luminance Estimation

4.1 Luminance Threshold Estimation

Images have usually complex scenes. Therefore, the Bartleson-Breneman's brightness function is more useful for brightness analysis than the Stevens's function. The Bartleson-Breneman's brightness function shows that the human vision is affected by the contrast of the image rather than physical luminance. To know the brightness contrast of images, we need to define the maximum and minimum luminance levels of images.

The minimum luminance level can be derived from the Stevens's function that shows the threshold of brightness in dark adaptation [9]. The human perceives the brightness change when the difference of brightness variation extends about 100:1 [11],[12]. The smallest threshold of brightness change in Stevens's experiment is 0.1 *bril* . The maximum brightness level is 10 *bril* [9]. And corresponding luminance levels for each 0.1 and 10 *bril* vary according to the adaptation luminance level. From these experimental data, we formulate the corresponding luminance values for minimum and maximum brightness levels and propose the minimum and maximum luminance values L_{min} and L_{max} as following modeling equations.

$$L_{min} = 0.0212 + 0.0185 L_{an}^{1.0314}, \tag{10}$$

$$L_{max} = 25.83 + 30.82 L_{an}^{0.6753}, \tag{11}$$

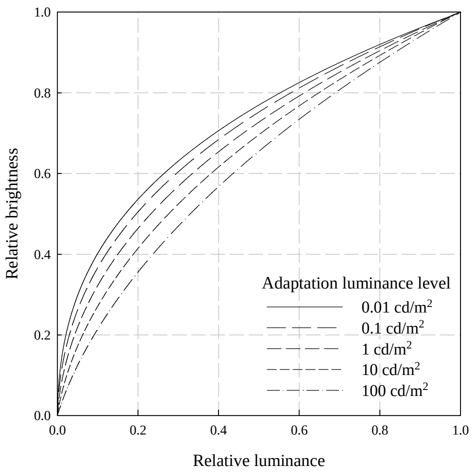

Fig. 1. Changes in relative brightness contrast as a function of adaptation of relative luminance and adaptation luminance levels according to the result of Bartleson and Breneman.

where L_{min} is the minimum luminance level. L_{an} is the normalized adaptation luminance which derived from Gaussian low pass adaptation image at each pixel location, and the maximum value is 100. L_{max} is the maximum luminance level.

4.2 Visual Gamma Estimation

The human eye's visual gamma is also changed by relative luminance for various adaptation conditions. Fig. 1 illustrates the change of relative brightness according to the relative luminance, and the visual gamma increases when adaptation luminance is lower. This shows that the different gamma is locally required for variation of luminance. Therefore, we propose the visual gamma function γ_v as following equation.

$$\gamma_v = 0.444 + 0.045\ln(L_{an} + 0.6034) \qquad (12)$$

This equation is formulated by fitting the curve of the Bartleson-Breneman's brightness functions for simple gamma.

5 Luminance Separated Tone Mapping

5.1 Single Scale Tone Mapping

Fig. 2 shows the center/surround SSR method in the HSV color space. Only the V channel is used in this retinex processing. It can reduce the computation time and preserve the hue and saturation of the original image. But, this algorithm increases the noise in dark areas and decreases the color saturation in highlights areas. To reduce the noise and enhance the color saturation, we propose a single scale tone mapping (SSTM) method, and Fig. 3 shows the block diagram of SSTM. SSTM use the V channel in HSV color space to preserve the hue and saturation. First, luminance parameters, L_{min}, L_{max}, and γ_v in Eqs. (10)-(12), for tone mapping are calculated from local luminance estimation. Second, a tone

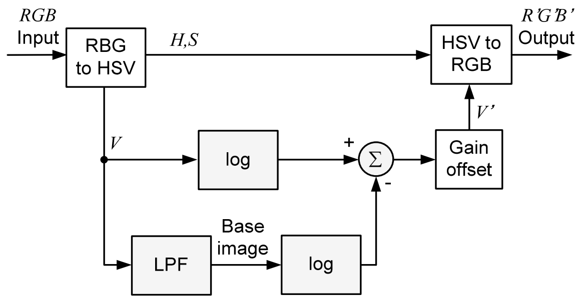

Fig. 2. Singe scale retinex in the HSV color space.

mapping function for local tone compression is proposed. It includes the local gamma function, the maximum and minimum white luminance values for the surround luminance level. The equation is shown as

$$V_o(x,y) = I_{o\_gain} \times \left| \left(\frac{V_n(x,y) - L_{min}(x,y)}{L_{max}(x,y) - L_{min}(x,y)} \right) \right|^{\gamma_v(x,y)} + I_{o\_offset}, \qquad (13)$$

where V_n is normalized input image of the V channel and V_o is the output image. L_{max} is the maximum luminance level, L_{min} is the minimum luminance level, and γ_v is the visual gamma function. I_{o_gain} and I_{o_offset} are constant values that control the range of post local gamma correction. Then, the clipping function was used to remove any extremely bright pixel or dark pixel. We used the image data from 1st to 99th percentile.

5.2 Multi-Scale Tone Mapping

The results of SSTM rendering are depend on the Gaussian filter size. The small size filters produce the enhancement of detail and the large size filter produce better rendition of images. To increase both the detail and rendition, we also introduce the multi scale method that has been usually used to other retinex models as shown in Eq. (14).

$$MSTM = \sum_{n=1}^{N} \omega_n SSTM_n, \qquad (14)$$

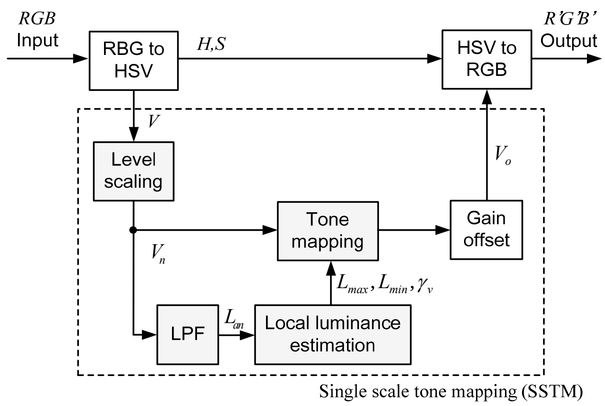

Fig. 3. Prosposed tone mapping algorithm in the HSV color space.

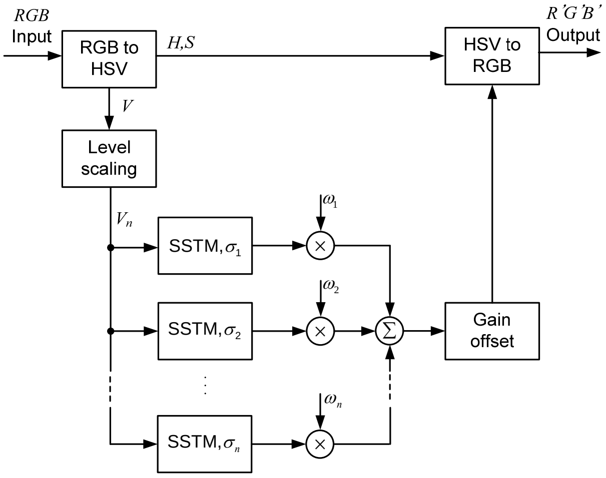

Fig. 4. The flowchart of multi-scale tone mapping method.

where $MSTM$ is the output of multi-scale tone mapping, $SSTM_n$ is the output of n th single scale tone mapping, and ω_n is n th weighting factor. The flowchart is shown in Fig. 4.

6 Simulation Results

We evaluated the performance of the three kinds of test algorithms, HSV based MSR, LBMSR, and our proposed method. We used test color images for indoor and outdoor situations. The standard deviations of LPF filters are 15, 80, 250 and each weighting factor, ω_n is 1/3 for N=3.

In Fig. 5(a), the image shows the strong different brightness between color box and under the desk. In Fig. 5(b), the HSV based MSR method increases local contrasts and compresses global tone well, but the noise in dark areas is emphasized and the color saturation and contrast in light box areas are lower. The LBMSR method reduces the noise under the desk in Fig. 5(c). However, the color saturation and local contrast in bright areas is worse than the case of the HSV based MSR. In Fig. 5(d), we confirmed that the proposed method enhances the contrast and color saturation in entire image and reduces the noise as much as LBMSR.

In Fig. 6(a), the image shows the high contrast between inside and outside tree. In Fig. 6(b), the global contrast of image is enhanced. However, the noises of tree and grass areas are increased. The details of the forest and the ground in bright areas are reduced. In Fig. 6(c), the noises in dark areas are reduced but the details are still low and it causes week edge around bright areas. In Fig. 6(d), the proposed method shows global and local contrast increase as well as noise reduction.

7 Conclusions

In the proposed algorithm, the adjusted visual gamma and perceptual luminance thresholds are used as a function of adaptation luminance. This algorithm enhances the image quality when the adaptation luminance range of image varies highly from dark to bright. And the multi-scale method is used to enhance the detail of image. We simulated our method on various images and compared it with conventional models. As a result, the proposed method reduces the noise in dark areas and enhances the color rendition and contrast in highlights areas better than other models.

(a)

(b)

(c)

(d)

Fig. 5. Original image and rendered images. (a) Original image, (b) HSV based MSR, (c) luminance based MSR, and (d) proposed method.

(a)

(b)

(c)

(d)

Fig. 6. Original image and rendered images. (a) Original image, (b) HSV based MSR, (c) luminance based MSR, and (d) proposed method.

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