HDR Image Compression by Integrated Surround Retinex Model

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Abstract

In this paper, we propose a novel HDR image compression method by Fast Integrated Surround Retinex model. The proposed method has two novelties. First, multi-scale surround images are integrated to a single surround field, which is applied to Center/Surround Single-Scale Retinex model. The method reduces the "banding artifact" seen in normal SSR and simplifies the complicated computational steps in conventional Multi-Scale Retinex. Second, the introduction of Gaussian Pyramid cuts the computation time for generating a large-scale surround by tracing a "reduction" and "expansion" sequences using down and up sampling. The proposed model worked well in compressing the dynamic range and improving the visibility in heavy shadow areas of natural color images while preserving pleasing contrast.

Introduction

Human visual system can see over five orders in magnitude simultaneously and gradually adapt to scenes with over nine orders in magnitude. The conventional display devices, such as CRT, can capture the dynamic range of about 100:1. To recreate the viewer's sensation of the original scene, a high dynamic range (***HDR***) has to be compressed to low dynamic range (***LDR***) of the display devices.

HDR to ***LDR*** Tone Mapping Operator (***TMO***) can be classified into global and local operators. Global ***TMO*** compresses the dynamic range by operating a spatially-invariant tone reproduction curve (***TRC***) with point-wise on the image based on the global adaptation of human vision such as average luminance[1,2], which is simple and efficient while losing local contrast. Alternatively, local ***TMO*** uses a spatially-variant structure of the image data, such as Gaussian decomposition, to preserve local image contrast[3] while at the expense of time consumption.

This paper presents a novel local ***TMO*** based on ***Retinex*** theory[4,5], which suggested to recover the surface reflectance by removing the non-uniform spatial distribution of illumination. Though various ***TMO***s have been proposed, its key feature is the treatment of the spatial distribution of illumination.

The ***Center/Surround*** (***C/S***) model simply estimates the illuminant distribution ***L*** around a pixel in attention by averaging the image ***I*** with Gaussian filter G_m. Since the image ***I*** is equivalent to the product of the scene reflectance ***R*** and illumination ***L***, the ***C/S*** ratio ***I/L*** recovers ***R***. NASA[6-8] developed a Multi-Scale Retinex (***MSR***) by a weighted sum of multiple Single-Scale Retinex (***SSR***) with different standard deviation σ_m to suppress the banding artifacts in high contrast edges caused by ***SSR***. The basic NASA model is described as follows.

$$R^i_{MSR}(x,y) = \sum_{m=1}^{M} w(\sigma_m) R^i_{SSR}(x,y,\sigma_m);\; i = R,G,B \qquad (1)$$

$$R^i_{SSR}(x,y,\sigma_m) = \log \frac{I_i(x,y)}{I_i(x,y) \otimes G_m(x,y)} \qquad (2)$$

$$G_m(x,y) = K_m \exp\{-(x^2+y^2)/\sigma_m{}^2\}, \qquad (3)$$

$$\iint G_m(x,y)dxdy = 1, \qquad \sum_{m=1}^{M} w(\sigma_m) = 1 \qquad (4)$$

The symbol ⊗ denotes convolution. Since the optimization of weights is not easy[9], conventional MSR simply applies equal weights to all scales of SSR but doesn't always give the satisfactory images. In addition, logarithmic conversion is unstable for the dark noise level in shadow and the independent ***C/S*** process in R, G, and B channel causes the color imbalance. The adaptive *scale-gain* ***MSR*** model [10,11] succeeded in stable and excellent color reproduction in linear space without logarithmic conversion. In this model, the surround image generated only from luminance image is used for R, G, and B channel, which keeps the color balance well. They also proposed an automatic setting method for weights adapted to the scale-gain. However, since the computation of weights needs the histograms of luminance ***SSR***s corresponding to the multiple scales which takes too much time with increasing of Gaussian kernel size, it still needs improvement for practical use.

Integrated-Surround Retinex Algorithm

In this paper, we propose an ***Integrated-Surround Retinex*** model as shown in Fig.1.

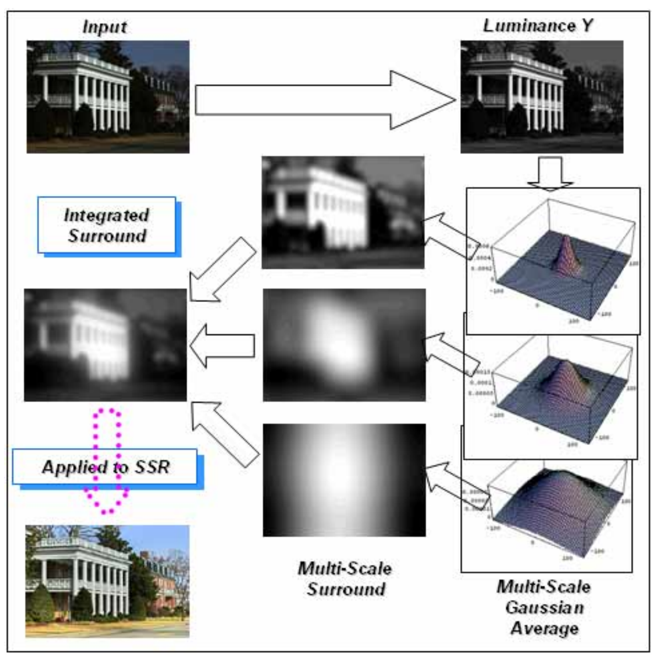

Figure 1. *The overview of Integrated-Surround Retinex*

Instead of weighting multiple ***SSR***s with different scale σ_m, the proposed model integrates m=1~M different surround image S_m generated by different scale σ_m into a single surround image S_{sum} with the scale-dependent weight $w(\sigma_m)$. To keep color balance, S_m is calculated by convoluting luminance image $Y(x,y)$ with Gaussian Filter G_m with standard diviation σ_m as Eq.(7) expressed. Eq.(5) denotes the ***C/S*** ratio of center pixel I_i to integrated luminance surround S_{sum} in the proposed model.

$$SSR_{sum}(x,y,\sigma_m) = A\frac{I_i(x,y)}{S_{sum}(x,y,\sigma_m)} \tag{5}$$

$$S_{sum}(x,y,\sigma_m) = \sum_{m=1}^{M} w(\sigma_m) S_m(x,y,\sigma_m) \tag{6}$$

$$S_m(x,y,\sigma_m) = \langle G_m(x,y) \otimes Y(x,y) \rangle; \tag{7}$$

In the proposed method, M times division in the computation of multiple ***SSR***s is replaced by the easy summation instead.

Optimum Parameters

Retinex model aims to reproduce the original scene reflectance, but in practice, the original scene is usually unknown unless the observer sees the captured scene standing at the same place and the same time. However the setting of the optimum parameters is difficult without the original image. As illustrated in Fig.2, we synthesized a visual target image C on screen to match the real scene A by modifying the digital camera image B taken under non-uniform illumination in our laboratory using Photoshop by trial and error[11].

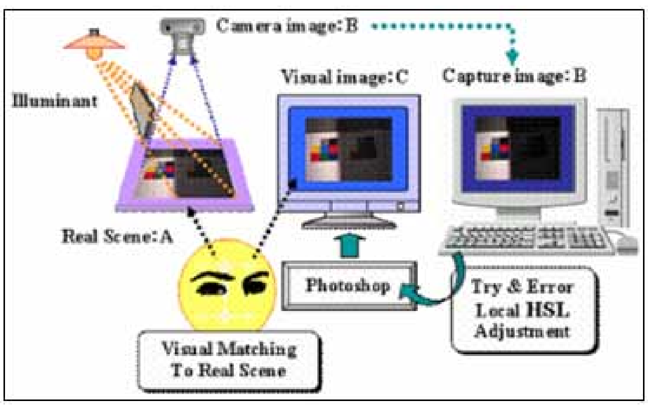

***Figure 2**. Scheme of target image visually matched to real scene*

To make a quantitative estimation for the proposed model and find the optimum parameters, the color differences ΔE^*_{ab} between the visual target image C and the processed images for the camera image B are evaluated in CIELAB color space.

$$\Delta E^*_{ab}(P,V) = RMS(\|LAB(P) - LAB(V)\|) \tag{8}$$

P can be any results of proposed method, such as our proposed method or NASA. V stands for the visual target image C.

Considering the computation expense and processing speed, it is hoped to produce ***MSR*** image from a small number of ***SSR***s. Empirically, to produce a ***MSR*** image without banding artifact, at least three ***SSR*** images are needed. As well, we used three scales (M=3) of surround images, small (σ_1=2), middle (σ_2=16), and large (σ_3=128) to get an integrated surround in the proposed method. The gain A and the weight $w(\sigma_m)$ are optimized to minimize the color difference. When A=0.8 and $w(\sigma_1)$=0.3, $w(\sigma_2)$=0.1, $w(\sigma_3)$=0.6, we obtained the smallest color difference ΔE^*_{ab} =8.6. From the tendency of color difference changes we can draw a conclusion that the smallest color difference corresponding to each combination tends to increase with the decrease in $w(\sigma_3)$ and goes up fast for $w(\sigma_3) < 0.5$. Hence $w(\sigma_3) \geq 0.5$ and large scale σ_3=128 are indispensable. This conclusion is almost the same as reported by Ref.[11]. In addition, we also tested the color reproducibility for a different set of three scales (σ_1=8, σ_2=32, σ_3=128). The smallest color difference ΔE^*_{ab} = 8.9 is obtained when A=0.8 and $w(\sigma_1)$=0.2, $w(\sigma_2)$=0.1, $w(\sigma_3)$=0.7.

Fig.3 shows the results. Our model (d) showed the better result than NASA (i) and close to our previous *adaptive scale-gain* ***MSR*** (f).

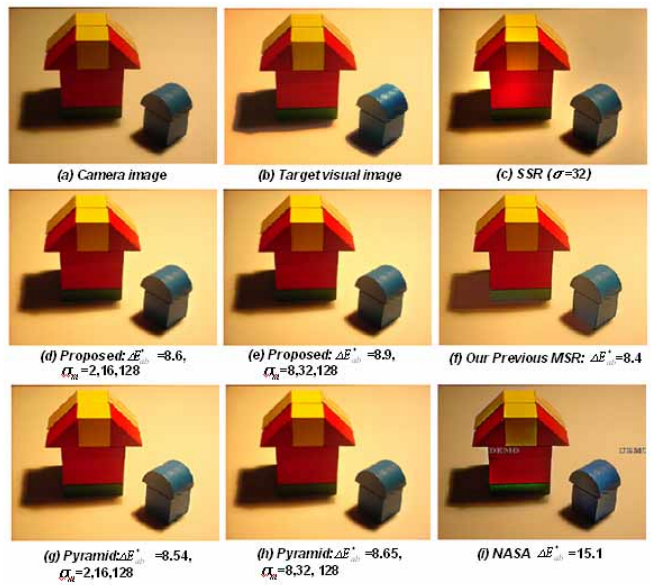

***Figure3**. Color reproducibility results*

Improvement in fast computation

Retinex algorithm is very time consuming due to a convolution between original image and Gaussian filters for calculating the larger scale surround images. Particularly, as the kernel size of Gaussian filter increases, the convolution time dramatically increases. The proposed model has the same problem too. For example, when using Gaussian filter with σ=128 (kernel size=4σ+1=513×513 pixels) for image size 1280×960, it took more than one hour (Pentium 1GHz, Memory 512MB, MATLAB). Because the time is mainly consumed in calculating the surround image, Gaussian Pyramid method is introduced to accelerate the convolution speed in this paper.

The convolution process in Gaussian Pyramid is illustrated in Fig.4. First, the original luminance image $g_0(x, y)$ is placed at the bottom, and each successive higher level is smaller version scaled down by 1/2 in width and height of the previous level. Through the K *steps* sequences, image group: g_1, g_2, …, g_K is constructed, which characterizes the multi-resolution pyramid structure. The process from g_0 to g_1, …, g_K is finished by down sampling for the low-passed image by Gaussian filter **w** with 1/2 rate.

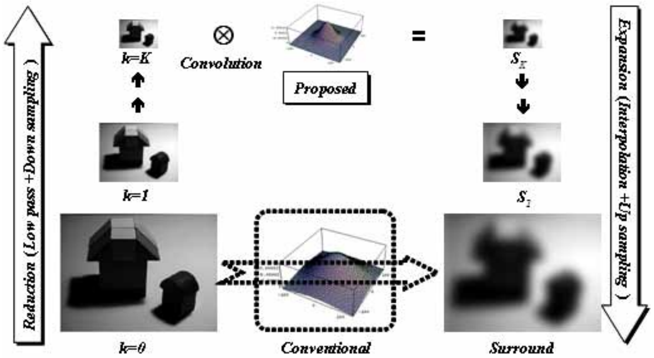

Figure 4*. Fast computation method for surround by Gaussian Pyramid*

Letting the 1/2 reduction function be *Reduce*, the upward down-sampling Gaussian pyramid is expressed by Eq. (9).

$$g_k = Reduce(g_{k-1}) = Downsample_{1/2}\{Lowpass(g_{k-1})\}$$
$$Lowpass(g_{k-1}) = \mathrm{m} \otimes g_{k-1}; \quad \otimes \text{ means convolution.}$$
$$\mathrm{m} = [m_{ij}] = [w_i \cdot w_j]; i, j = 1, 2, ..., 5 \tag{9}$$
$$\mathrm{w} = [w_i] = [0.05, 0.25, .0.4, .0.25, .0.05]$$

When the reduced image g_k at required level K is obtained, the convolution by small-sized Gaussian filter with standard deviation σ_K creates the reduced surround image S_K corresponding to level K. Then S_K is expanded to twice in width and height by interpolation and up sampled by twice rate until the surround image S_0 with the same size as the original image is obtained. This downward up-sampling process is expressed by Eq. (10) and (11).

$$S_K = g_K \otimes G_m(x, y, \sigma_K) \tag{10}$$

$$S_{k-1} = Expand(s_k) = Upsample_2\{Interpolate(s_k)\} \tag{11}$$

The surround S_m expressed in Eq. (7) can be substituted by S_0. According to Gaussian pyramid, S_0 can be obtained by *K-steps* up-sampling processes after convoluting g_K with Gaussian filter $G_m(\sigma_K)$. Due to the sizes of both g_K and $G_m(\sigma_K)$ reduced to $2^{-K}\times2^{-K}$, the computation time is dramatically reduced.

We limited the down sampled image size to 32×32 to avoid the loss of original image information. Table.1 gives examples of the computation time before and after Gaussian Pyramid for two different size images. For the original image g_0 with size of 256×192, the size of top image g_2 is reduced to 64×48 after K=2 steps down sampling. Because of $\sigma_m=\sigma_K\times2^K$, in this case of K=2, we need to compute the convolutions for σ_K=2, 4, 8, 16, 32, equivalent to σ_m=8, 16, 32, 64, 128, respectively. For σ_m=64 and 128, before and after Gaussian Pyramid the computation time is reduced to about 1/10 and 1/15 respectively. The time is getting much more reduced with increasing σ_m. For larger image size 1280×960, after K=4 steps down sampling, the size of top image g_4 is reduced to 80×60. As Table.1 illustrated, we need only to compute σ_K =2, 4, 8, equivalent to σ_m=32, 64, 128 respectively. The computation time is saved to about 1/10, 1/45, and 1/450 after Pyramid respectively. The computation time is getting more dramatically reduced not only with increasing σ_m, but also with increasing image size. As shown in Table.1, to image size 1280×960, the computation time is reduced to 1/443 for σ_m=128 after Pyramid.

Table.1 Reduction in process time by Gaussian Pyramid

Size / scale	256×192 (sec)		1280×960 (sec)	
σ_m	normal	Pyramid (64×48)	normal	Pyramid (80×60)
8	0.29	0.24	x	x
16	0.75	0.24	x	x
32	2.40	0.39	59.10	5.13
64	9.13	0.90	236.1	5.34
128	166.3	10.65	4118	9.29

Figure 5 (a) and (b) give the results of after Gaussian Pyramid. We get almost the same accuracies even through Gaussian Pyramid.

Figure 5*. Examples of proposed model*

High Dynamic Range Image Compression

We adapted also our model to ***HDR*** image. To cope with the high dynamic range, the post-process is necessary. First, we compute the *integrated surround* ***Retinex*** image $Y_R(x, y)$ from ***HDR*** luminance channel by Eq. (12).

$$Y_R(x, y) = \frac{Y(x, y)}{S_{sum}} \tag{12}$$

Then we make use of Y_R to get the condition to compress the ***HDR*** image to ***LDR*** image for display device. We found that the histogram of Y_R mostly concentrated in the lower range, while scattered in the middle to higher ranges for our tested ***HDR*** images. Thus we divided the higher range of Y_R by large interval and the lower range by small interval not to lose the details. First, the histogram of Y_R is divided into two parts **[*****Min-Mean*****]** and

[***Mean***- ***Max***] by the mean value ***Mean***. Second, the pixel numbers Num_1 less than ***Mean*** and Num_2 larger than ***Mean*** are calculated respectively. Thirdly, the ratios of Num_1 and Num_2 to all pixel numbers of image are calculated by Eqs. (13). Then, the bins are calculated by Eqs. (14).

$$ratio_1 = \frac{Num_1}{Num_1 + Num_2}, \quad ratio_2 = \frac{Num_2}{Num_1 + Num_2} \tag{13}$$

$$bin_1 = 255 * ratio_1; \quad bin_2 = 255 * ratio_2 \tag{14}$$

Then the two ranges of [***Min-Mean***] and [***Mean-Max***] are uniformly divided into $\boldsymbol{bin_1}$ and $\boldsymbol{bin_2}$ respectively. Accordingly, the Y_R image is divided into 255, which is a ***LDR*** image can display on normal display devices, expressed by $Y_d(x,y)$. Finally, the compressed color image $I_{di}(x,y)$ is reproduced by Eq. (15), where γ denotes a gamma correction coefficient to control the color saturation. In this paper γ=0.5 is used.

$$I_{di}(x, y) = (\frac{I_i(x, y)}{Y(x, y)})^{\gamma} Y_d(x, y). \tag{15}$$

Two examples of our results are compared with those by Larson's histogram adjustment[12] in Fig.6. For Belgium, our result shows better than Larson's in preserving the contrast, though the visibility in shadows is not well as Larson's. But for Memorial Church, our result shows better contrast and details than Larson's result.

Figure 6. *Examples of HDR image compression*

Conclusions

A concise and fast Retinex algorithm different from conventional MSR is proposed by integrating multi-scale surround images into a single surround. The proposed model worked as well as MSR in suppressing the banding artifacts. The computation time was dramatically reduced by introducing Gaussian Pyramid. The proposed model worked nice in appearance improvement for both normal LDR and HDR images with dynamic range compression. To find optimum parameters, we synthesized a target image on display visually matched to the real scene observed by naked eye in experimental room and used it to evaluate the color reproducibility. Finding the more robust and stable parameters in full automatic through psychophysical tests for more complicated target images is left to future works.

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