Appearance Improvement of Color Image by Adaptive Linear Retinex Model

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Abstract

The electronic camera can't catch the details in the heavy change of highlight and shadow, while human vision can see a very wide range of luminance scenes with keeping the color constancy. This paper presents a method to improve the image appearance based on ***Adaptive Scale-Gain MSR*** (*Multi-Scale Retinex*) model and discusses the design of optimum parameters based on visual appearance experiments. Conventional Retinex model needs for careful adjustment in parameters and hasn't any clear target to be reproduced. In this paper we get a target image by adjusting the camera image on screen to be visually close to a test scene set up in our laboratory. The kernel sizes and weights for ***MSR*** are optimized to match the target image in minimum color difference. The proposed model

Introduction

The electronic camera can't catch the details in the heavy change of highlight and shadow, while human vision can do. ***Retinex*** model proposed by Land and McCann[1] controls the scene dynamic range automatically not by "pixel-to-pixel" but by ***"spatial-to-pixel"*** process like as human vision. Jobson,[2] Rahman,[3] Funt,[4] and others have advanced the single-scale Retinex (***SSR***) into multi-scale Retinex (***MSR***) based on the center/surround (***C/S***) model.

In the basic MSR, the Retinex output Ri(x, y) is given by

$$R_i(x,y) = \sum_{m=1}^{M} W_m \cdot log \frac{I_i(x,y)}{\langle G_m(x,y) * I_i(x,y) \rangle}, \; i = R, G, B \quad (1)$$

$$G_m(x,y) = Kexp[-(x^2+y^2)/\sigma_m{}^2], \; \iint G_m dxdy = 1 \quad (2)$$

RGB output is calculated by the weighting sum of ***C/S*** ratio for center pixel $\boldsymbol{C}=I_i(x, y)$ vs surround $\boldsymbol{S}=\langle G_m * I_i \rangle$.

G_m denotes Gaussian averaging filter with ***scale*** m of standard deviation σ_m for surround field and the symbol * denotes convolution. However, the conventional ***MSR*** have the following difficulties in practical use.

- Unstable ***Log*** function (for dark noise or offset level)
- Ambiguous weights and gain factors in multi-scales
- Chromatic unbalance in RGB channel process.

Adaptive Linear Retinex Model

To improve the above problems, we have developed an adaptive linear MSR model. This model is described by

$$R_i(x,y,\sigma_m) = A \sum_{m=1}^{M} W(\sigma_m) \left\{ \frac{I_i(x,y)}{S_m(x,y,\sigma_m)} \right\} \quad (3)$$

$$S_m(x,y,\sigma_m) = \langle G_m(x,y) * Y(x,y) \rangle \quad (4)$$

In this model, output is calculated directly by the linear (***C/S***) ratio. So, unstable *Log* function is not needed and clipping become simple. Furthermore, common use of luminance *Y* for all *RGB* channels enables to keep the color balance.

The key point of this model is to determine the weighting function $W(\sigma_m)$ adaptive to the scale σ_m. Actually, the Retinex outputs are not determined by the min/max surround levels but by ***C/S*** ratio in each pixel.

Here we considered that the Retinex effect in each scale depends on the distribution of the SSR and the weighting function is given by the ***C/S histogram*** as follows.

$$W(\sigma_m) = M \left\{ \Sigma_{C/S}(\sigma_m) / \sum_{m=1}^{M} \Sigma_{C/S}(\sigma_m) \right\} \quad (5)$$

where, we introduced the standard deviation in the histogram of $Y_{C/S}(x,y,\sigma_m)$ to the weight of Retinex output for each scale m as follows.

$$\Sigma_{C/S}(\sigma_m) = \sqrt{\frac{1}{XY} \sum_{x=1}^{X} \sum_{y}^{Y} [Y_{C/S}(x,y,\sigma_m) - Ave\{Y_{C/S}(x,y,\sigma_m)\}]^2} \quad (6)$$

To reduce the computation costs, the C/S histogram was examined only for the luminance *Y* image. The C/S ratio for *Y* image is calculated by

$$Y_{C/S}(x,y,\sigma_m) = Y(x,y)/S_m(x,y,\sigma_m) \quad (7)$$

By this establishment of weighting function, we could obtain stable MSR images (Fig. 1). In our MSR, the shadow areas in the original image are improved very well and sky-blue or the color of earth are reproduced better than the result by NASA. However, in practice, there are no clear color targets to be reproduced, because most of original scenes are unknown. Although, any definitive solution for deciding the optimum parameters i.e., the number of SSR and the weights, or the size of scales, doesn't exist, experimentally it is known that at least, three different scales should be combined for creating a stable MSR.

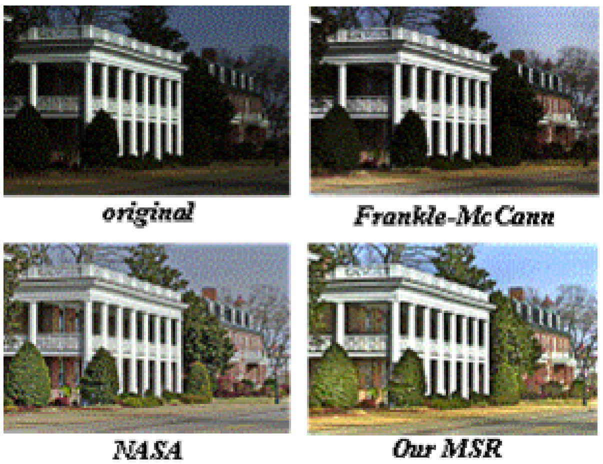

Figure 1. Comparison in MSR models

Optimal MSR Using A Few SSRs

The fewer SSR are used, the more MSR becomes practical. Here, we compared the minimum MSR using only two scales (***large*** and ***small***) with that by three scales (***large***, ***medium***, and ***small***). A typical sample is shown in Fig. 2. These MSRs are clearly better than SSR. But the minimum MSR using two scales is deficient in the reproduction of shadow area. Hence we assume if three scales of SSR are composed appropriately, a low cost but practical MSR may be obtained. Next we examined the optimal combination of three SSRs.

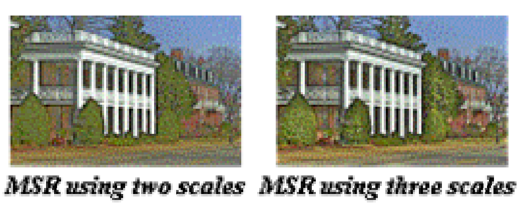

Figure 2. Comparison of MSR with M=2 and M=3

Optimization in Color Reproduction for MSR

Using Original Image as a Substitute for Large Kernel SSR

As the scale is larger, the SSR approaches closer to the original image, because the surround approaches to a constant gray in overall average. So we can use the original image as a substitute for a large scale SSR.

Synthesis of Target Images

For an optimization of MSR parameters, we tried to produce a target image on CRT screen just as we are seeing the same target placed at experimental room. Setting up a test target under a non-uniform illumination in the laboratory, the digital camera image on screen is partially corrected by try and error using Photoshop to produce the target image as visually close as possible to the real scene (Fig. 3). We used three typical test targets; (A) color blocks, (B) color glass balls and (C) color chart. An example of the input camera image and the generated target image are shown in Fig. 4.

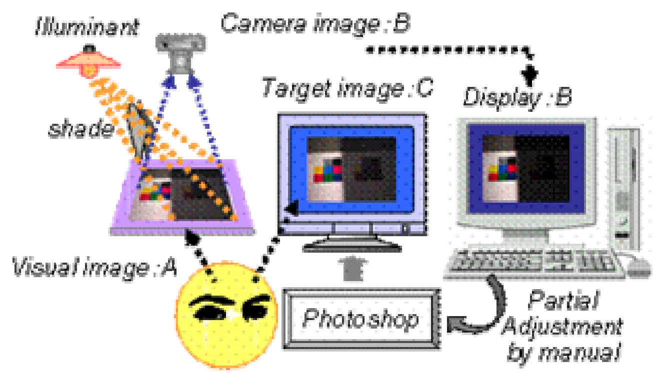

Figure 3. Synthesis of target image by visual matching

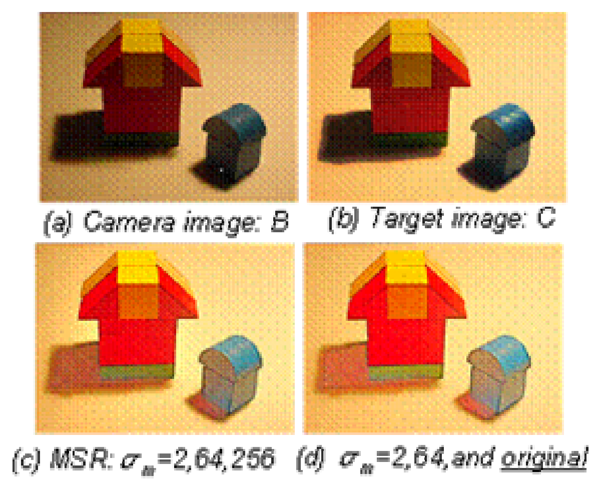

Figure 4. Synthesis of target image by visual matching

Determination of Optimal Central SSR

In general, the contrast enhancement effect in SSR appears strongly in local area but loses tonal reproducibility for a smaller kernel size of σ_m, because the ***C/S*** ratio converges to around 1.0. While the Retinex effect is weakened for a larger kernel size of σ_m, because the surround ***S*** reflects the global average of luminance image.

In our new approach, firstly, the best ***medium*** scale SSR is determined to work as the most important ***optimal central SSR*** according to the following steps.

[1] Generate M different scales SSR with $\sigma_m = 2^m$ ($m=1 \sim M$)

$$SSR(x,y,\sigma_m) = A(\sigma_m)\left\{\frac{I_i(x,y)}{S_m(x,y,\sigma_m)}\right\} \tag{8}$$

[2] Adjust the gain $A(\sigma_m)$ to minimize the *rms* color difference $\Delta E^*_{ab}(rms)$ between each $SSR(x, y, \sigma_m)$ and the target image $R_{vis}(x, y)$ as

$$A_{opt}(\sigma_m) = A(\sigma_m) \text{ for } \min_{m=1}^{M}\left\{\Delta E^*_{ab}\left\langle SSR, R_{vis}\right\rangle\right\} =$$

$$\min\left[\frac{1}{XY}\sum_{x=1}^{X}\sum_{y=1}^{Y}\left\| LAB\{SSR(x,y,\sigma_m)\} - LAB\{R_{vis}(x,y)\}\right\|^2\right]^{1/2} \tag{9}$$

The SSR with minimal color difference is denoted as $SSR_{opt}(x,y,\sigma_m)$.

$$SSR_{opt}(x,y,\sigma_m) = A_{opt}(\sigma_m)\left\{\frac{I_i(x,y)}{S_m(x,y,\sigma_m)}\right\} \tag{10}$$

[3] The SSR image whose color difference is minimal in $SSR_{opt}(x,y,\sigma_m)$ is selected as the optimal core SSR as

$$SSR(\sigma_{core}) = SSR_{opt}(x,y,\sigma_m);$$

$$m = core \text{ for } \min_{m=1}^{M}\left\{\Delta E^*_{ab}\left\langle SSR_{opt}(x,y,\sigma_m), R_{vis}\right\rangle\right\} \tag{11}$$

Experimental Results

Estimation of Optimal Scale

Figure 5 shows how a measured color difference denoted as $\Delta E^*_{ab}\left\langle SSR, R_{vis}\right\rangle$ between a $SSR(x, y, \sigma_m)$ and the target $R_{vis}(x, y)$ changes with the gain $A_{opt}(\sigma_m)$ in Eq.(9).

The optimal gain value increases along with the scale m (kernel size σ_m). In this sample, optimal $SSR_{opt}(x,y,\sigma_m)$ is obtained at $A_{opt}(\sigma_m) \cong 0.25 \sim 0.3$ in case of $m=6$ ($\sigma_m=64$).

Figure 6 illustrates the changes in color difference $\Delta E^*_{ab}\left\langle SSR_{opt}, R_{vis}\right\rangle$ vs. scale m for each $SSR_{opt}(x,y,\sigma_m)$.

Psychophysical Estimation by Paired-Comparison

Since we could obtain the optimal core $SSR(\sigma_{core})$ by the above experiment, we tried to produce a best new MSR dividing the weights by the following ratio

$$MSR_{new} = 0.5(1-k)SSR(\sigma_{small}) + kSSR(\sigma_{core}) + 0.5(1-k)SSR(\sigma_{large}) \tag{12}$$

By setting $k > 1/3$, the greatest weight k is assigned to the optimal core SSR and the remaining $0.5(1-k)$ to the others.

Although the greater k is, the smaller the color difference is, banding artifacts are striking. It is because the ***MSR*** approaches to the single-scale Retinex (***SSR***) with core kernel size. So the optimal weight k can't be decided by not only the color difference, but also lesser banding effects.

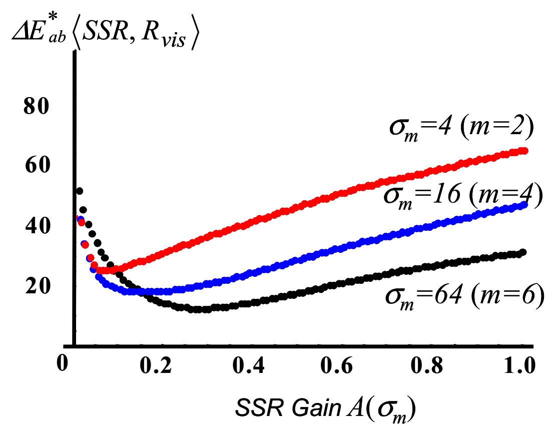

Figure 5. Changes in $\Delta E^*_{ab}\left\langle SSR, R_{vis}\right\rangle$ vs. gain $A(\sigma_m)$

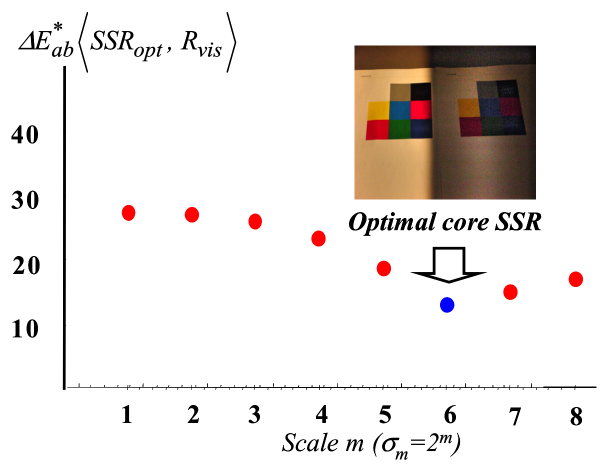

Figure 6. Example of optimal scale $SSR(\sigma_{core})$ with minimum ΔE^*_{ab}

In order to find the appropriate k value, we estimated the Z-score for the $\{MSR_{new}\}$ test samples by paired-comparison method (Fig. 7). The results in paired-comparison experiments are summarized in Fig. 8.

The core $SSR(\sigma_{core})$ image was obtained for $m = 7$ ($\sigma_{core} = 128$) for a test image ***"color block"*** shown in Fig. 7. Here seven different MSR_{new} images are generated for $k = 1/3 \sim 1.0$.

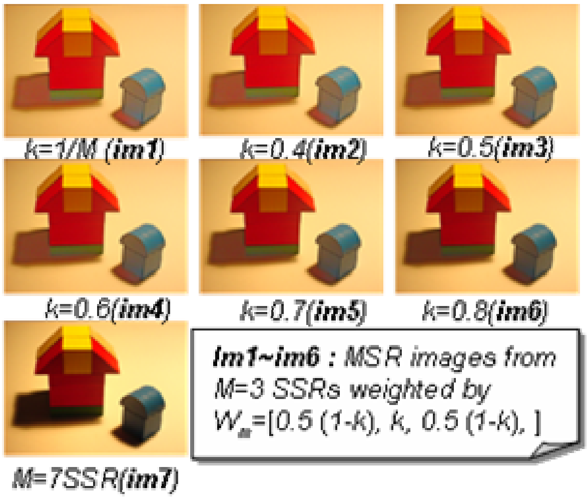

Figure 7. MSR test samples for psychophysical experiment

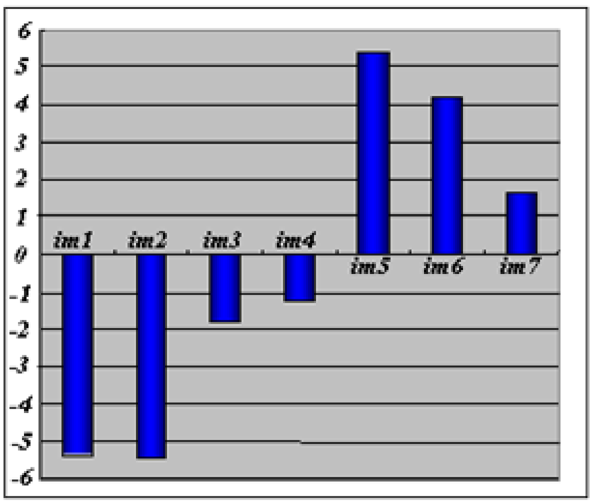

Figure 8. Result in pared-comparison experiments

Where ***im1*** and ***im7*** corresponds to the minimum $k = 1/3$ and the maximum $k = 1$. In this case, ***im7*** reflects the ***core SSR*** itself. As clearly shown in Fig. 8, ***im5*** ($k = 0.7$) got the best score. We used $m = 1$ ($\sigma_{small} = 2$) and original image as a substitute for largest kernel $m = 8$ ($\sigma_{large} = 256$). This means a visually ***best MSR*** is obtained by the combination of

$$MSR_{best} = 0.15SSR(\sigma_{small}) + 0.7SSR(\sigma_{core}) + 0.15SSR(\sigma_{large}) \cong 0.15SSR(\sigma_{small} = 2) + 0.7SSR(\sigma_{core} = 128) + 0.15 original \quad (13)$$

Conclusion

Through the above approach, we could remove the ambiguity of a parameter notably and get a design rule for getting the visually better ***MSR***.

As future works, we are going to verify the robustness of our model for a variety of natural scenes and study on the reduction in banding artifacts. Our goal is to develop the automatic decision algorithm of optimum parameters depending on the image content.

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Biography

Masato Yoda received his B.E. degree from Information and Image Sciences, Chiba University, Japan in 2003. Since 2003, he has been a Master course student in Graduate School of Science and Technology, Chiba University. His current research interests include digital image processing, color research and application.