

Image Enhancement Based on Gamma Map Processing

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ABSTRACT

This paper proposes a novel image enhancement technique based on Gamma Map Processing (GMP). In this approach, a base gamma map is directly generated according to the intensity image. After that, a sequence of gamma map processing is performed to generate a channel-wise gamma map. Mapping through the estimated gamma, image details, colorfulness, and sharpness of the original image are automatically improved. Besides, the dynamic range of the images can be virtually expanded.

Keywords: image enhancement, gamma adjustment

1. INTRODUCTION

In the real world, the dynamic range of lightness is usually wider than that of image sensors. The insufficient dynamic range of image sensors may sometimes cause the suppression of image details and the fading of image colors. In order to automatically enhance degraded images, a channel-wise local gamma adjustment algorithm was proposed in [1]. In that approach, gamma adjustment as an image intensity mapping function is performed to simultaneously enhance image details and colorfulness, based on two successive gamma estimations: local gamma estimation and channel-wise local gamma estimation. The content-dependent channel-wise gamma map is generated based on the estimation of local image details and color in the original image.

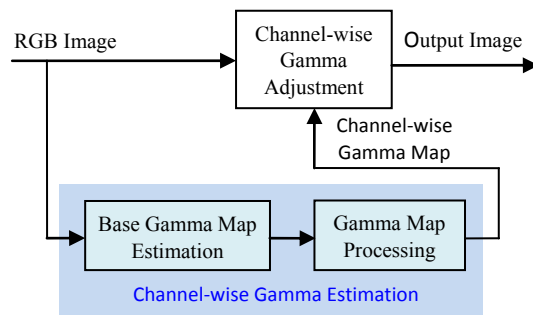


Figure 1. Overview of the proposed system.

In this paper, we evolve the concept of the channel-wise gamma estimation into two major parts: the base gamma map estimation module and the gamma map processing module, as illustrated in Figure 1. In the base gamma map estimation module, a base gamma map is directly generated from the gray-level intensity map of the original image. Following that, in the gamma map processing module, a sequence of spatial filtering and modification is performed over the gamma map to generate a channel-wise gamma map. The estimated channel-wise gamma map is fed into the channel-wise gamma adjustment module to enhance image details, colorfulness, contrast, and sharpness simultaneously.

2. RELATED WORKS

In order to improve the visual quality of digital images, many image processing techniques have been proposed, like gamma adjustment, histogram equalization, adaptive histogram equalization, homomorphic filtering, and Retinex-based algorithms. Among these approaches, the multi-scale retinex with color restoration (MSRCR) is a widely used method

based on Land's theory of human visual perception [2][3]. Inspired by the receptive field structures of neurophysiology, Land introduced in [3] the use of a center/surround spatial kernel for the modeling of human's color vision. Based on the same center/surround spatial kernel, the MSRCR method adopted a set of multi-scale Gaussian filters as the surrounding function to achieve both color constancy and contrast/lightness enhancement at the same time [4][5]. However, the MSRCR method requires high computational complexity and may sometimes cause artifacts such as unnatural color and "halo effects" in the enhanced images.

To avoid halo effects in adjusted images, some non-linear tone mapping operators are proposed. Tumblin et al. proposed a low-curvature image simplifier (LCIS) to extract details from high-dynamic-range images for display [6]. Further in [7], Durand et al. introduced a fast operator based on bilateral filtering [10] to decompose a high-dynamic-range image into a base layer and a detail layer. They preserved the detail layer and adjusted only the base layer for high-dynamic-range imaging. The concept of image decomposition for tone mapping is further applied to many applications, such as tone management [8] for image details and contrast enhancement. However, in these approaches, the adjustment of decomposed base layers is image-dependent and sometimes requires user supervision [6][7] or target-image models [8].

On the other hand, AINDANE (Adaptive and Integrated Neighborhood Dependent Approach for Nonlinear Enhancement) [9] is a new algorithm for the automatic improvement of image quality under extremely low or non-uniform lighting conditions. This method relies on the statistical information of the input image and is composed of two separate processes: adaptive luminance enhancement and adaptive contrast enhancement. If compared to the MSRCR method, this method requires lower computational complexity and may produce fewer artifacts in the enhanced images.

Even though both MSRCR and AINDANE can automatically and successfully improve the local contrast of images for low illumination conditions, they have difficulty in handling overly illuminated situations. These two methods may sometimes overly enhance image contrast and produce unnatural images. To provide more natural-looking enhancement results, a channel-wise local gamma adjustment algorithm was proposed in [1] to enhance both image details and colorfulness based on a spatially varying channel-wise gamma estimation. In that approach, image details are automatically enhanced based on the estimation of local image details in the original image. By individually adjusting the local gamma value over the R, G, and B color channels, image colorfulness can be properly enhanced.

In this paper, we evolve the concept of the channel-wise gamma estimation to a sequence of gamma map processing, which provides an improved enhancement performance with lower computational complexity. Besides, the proposed gamma map processing can also enhance image contrast and sharpness simultaneously and virtually expands the dynamic range of the output images.

3. PROPOSED ALGORITHM

3.1 Base Gamma Map Estimation

In the proposed approach, we adopt an intensity mapping function $I'(x, y) = [I(x, y)]^{\gamma(x, y)}$ to enhance the image detail of the original image. Here, for an RGB image with three color channels: $I^R(x, y)$, $I^G(x, y)$, and $I^B(x, y)$, we define $I(x, y)$ to be an intensity (gray-scale) image expressed as

$$I(x, y) = 0.2989I^R(x, y) + 0.5870I^G(x, y) + 0.1140I^B(x, y). \quad (1)$$

For the image pixel at (m,n), a base gamma value $\gamma_{base}(m,n)$ is estimated to "reset" the intensity value into a default value I_0 , as expressed in (2).

$$I(x, y)^{\gamma_{base}(x, y)} = I_0 \quad (2)$$

Through the intensity mapping function of $\gamma_{base}(x, y)$, the entire intensity image is mapped to a constant image with the value I_0 , where the default value of I_0 is set to be 0.5. Based on (2), the base gamma map $\gamma_{base}(x, y)$ can be deduced to be

$$\gamma_{base}(x, y) = \frac{\log(I_0)}{\log(I(x, y))}. \quad (3)$$

It seems to be unreasonable to transfer images into a constant image as shown in Figure 2 which contains no information of the original image. In fact, the information of the original image never disappears, but is just temporarily stored in the base gamma map $\gamma_{base}(x,y)$. In the next section, we'll introduce how to design a gamma map process to reproduce the image information in the mapped image so that the enhancement of the original image can be achieved at the same time.

3.2 Gamma Map Processing

In this section, we introduce a concept of data transferring between the gamma map and the mapped image. As mentioned before, the original image information is temporarily stored in the corresponding base gamma map. If we apply a Gaussian smooth filtering over the base gamma map, as shown in Figure 2, the image information can be reproduced in the mapped image through the smoothed gamma map. Based on this idea, we design a sequence of gamma map processing to adapt the base gamma map into a channel-wise gamma map. Finally, a channel-wise gamma adjustment is performed to modify the original RGB image base on the estimated channel-wise gamma map. Image details, contrast, sharpness and colorfulness can be automatically enhanced with this channel-wise gamma adjustment.

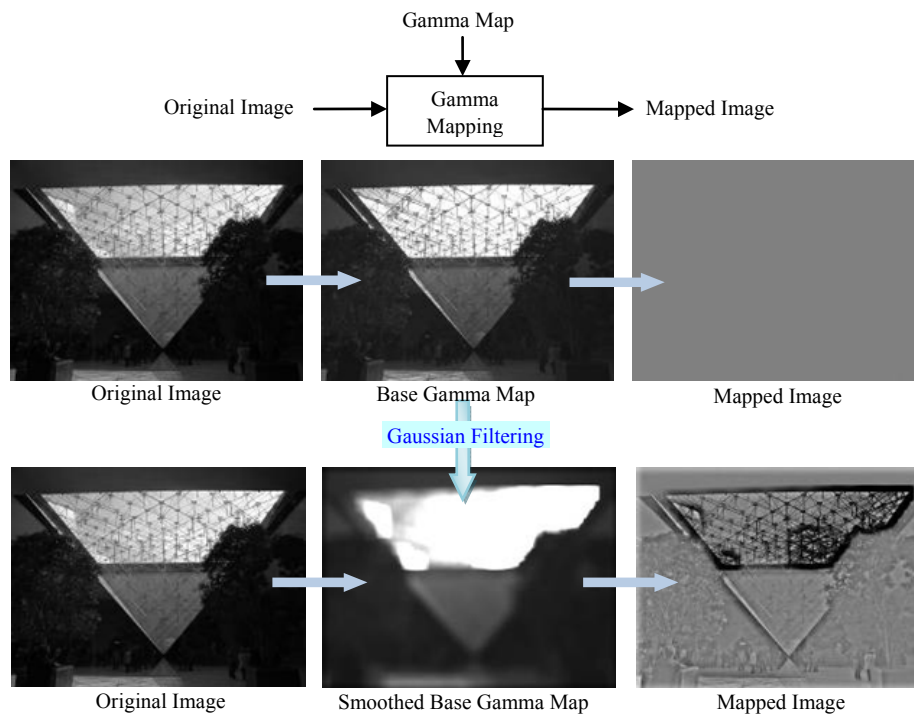


Figure 2. Gamma adjustment of intensity images.

The proposed flowchart of gamma map processing is illustrated in Figure 3, which is split into three major modules: the smoothing module, the shaping module, and the channel-wise modification module. These modules are to be described in detail in the following subsections.

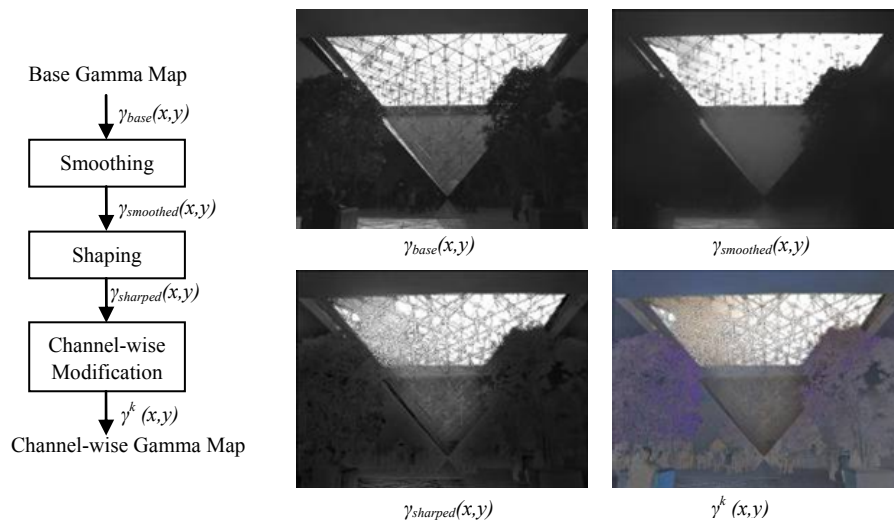


Figure 3. Flowchart of Proposed Gamma Processing.

3.2.1 Gamma-Map Smoothing Module

In the smoothing module, based on the idea of data transferring, we apply smoothing filtering over the base gamma map to generate a smoothed gamma map $\gamma_{smoothed}(x,y)$. To illustrate how this smoothing module works, we show a 1-D example of intensity mapping in Figure 4, where an intensity signal is transferred through three different gamma mapping functions, the base gamma function and two smoothed gamma functions. As transferred through the base gamma function, which is calculated based on (3), the mapped signal turns to be a constant value with no data information. If the base gamma function is filtered by a smoothing filter, such as Gaussian filter or bilateral filter [10], details of the original signal can be transferred to the mapped signal. Furthermore, global intensity variance could be removed through these mappings. This is why we can handle ill-lighting conditions by removing the global illumination.

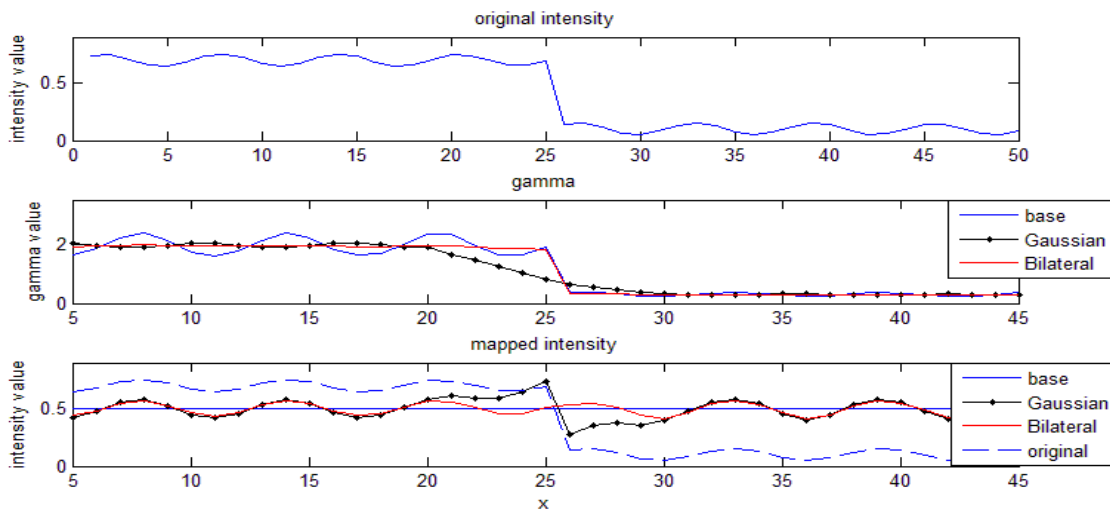


Figure 4. 1-D example of gamma mapping with three different mapping functions, the base one, a Gaussian smoothed one, and a bilateral smoothed one.

As shown in Figure 4, since the Gaussian filtering has smoothed global edges in the gamma function, halo effect may occur around edges in the mapped results. On the contrary, bilateral filtering preserves edges during smoothing and may

avoid halos in the output images. Hence, in our approach, we apply bilateral filtering as our main smoothing processing and this operation is denoted as

$$\gamma_{smoothed}(x, y) = bf(\gamma_{base})_p \quad (4)$$

In this equation, $bf(I)_p$ denotes the bilateral filtering of image I at pixel $p=(x, y)$. As defined in [10], the bilateral filtering is expressed as

$$bf(I)_p = \frac{1}{k} \sum_{q \in I} [g_{\sigma_s}(\|p - q\|) \cdot g_{\sigma_r}(|I_p - I_q|) \cdot I_q]$$

with $k = \sum_{q \in I} [g_{\sigma_s}(\|p - q\|) \cdot g_{\sigma_r}(|I_p - I_q|)]$ and $g_{\sigma_r}(x) = \exp(-x^2 / \sigma_r^2)$. (5)

In (5), σ_s is a spatial smoothing factor, σ_r is a range (intensity) smoothing factor, and k is a normalization term. Here we select σ_s to be 5% of the image size and σ_r to be 0.1. Although the bilateral filter preserves edges during smoothing, details with high intensity variance may still be preserved in the gamma maps. This may cause loss of high-contrast details. To solve this problem, we cascade a Gaussian filter of a small kernel size after the bilateral filter. The standard deviation of the Gaussian filter is chosen to be 1 in our experiments. For this Gaussian filter, the smoothed regions around the edges are quite small and visible halos can thus be avoided. In addition, the inclusion of the Gaussian smoothing operation can even enhance the sharpness of edges.

However, from the intensity domain to the gamma domain, a non-linear transform (3) is applied. This influences the smoothing ranges of the bilateral filtering. To handle this problem, a transfer function T is performed to the base gamma before the smoothing process, and the corresponding inverse transform T^{-1} is performed after the smoothing process, as illustrated in Figure 5. The transfer function T and the corresponding inverse function T^{-1} are defined as

$$T(x) \equiv \begin{cases} \left(\frac{x}{\gamma_c}\right)^{t_0} & \text{for } x < \gamma_c \\ 1 & \text{otherwise} \end{cases} \quad \text{and} \quad T^{-1}(x) \equiv \gamma_c x^{\frac{1}{t_0}}, \quad (6)$$

where t_0 is a transferring factor and γ_c is a clipping constant representing the upper-bound of the gamma value. Here, we select $t_0=4$ and $\gamma_c=5$.

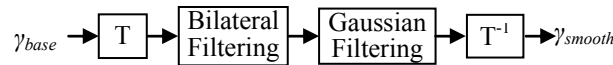


Figure 5. Flowchart of gamma-map smoothing module.

3.2.2 Gamma-Map Shaping Module

As demonstrated above, the local details removed from the gamma map get transferred to the output image. Hence, if we subtract details in the gamma map, the subtracted details will appear in the output image. In other words, if we want to increase detail response in the output image, we only need to further suppress the details in the gamma map. Based on this idea, a gamma-map shaping module is proposed. In this module, we first compute the detail gamma map $\gamma_{detail}(x, y)$, which is defined as

$$\gamma_{detail}(x, y) \equiv \gamma_{base}(x, y) - \gamma_{smoothed}(x, y). \quad (7)$$

In order to enhance details, contrast, and sharpness of the output image, we properly subtract γ_{detail} from the smoothed gamma map to get the shaped gamma map, as expressed in (8).

$$\gamma_{shaped}(x, y) = \begin{cases} \gamma_{min} & \text{if } \gamma_{base}(x, y) - c_1 \gamma_{detail}(x, y) < \gamma_{min} \\ \gamma_{base}(x, y) - c_1 \gamma_{detail}(x, y) & \text{otherwise,} \end{cases} \quad (8)$$

where $\gamma_{\min}=0.01$ is the default constant to prevent negative shaped gamma. The parameter c_1 controls the magnitude of the enhanced details which is proportional to the degree of contrast enhancement. To show how this shaped gamma mapping works, we also take a 1-D example as shown in Figure 6. Here, an intensity signal is transferred through three different gamma functions: base, smoothed, and shaped gamma functions. As expected, details are enhanced through the shaped gamma function.

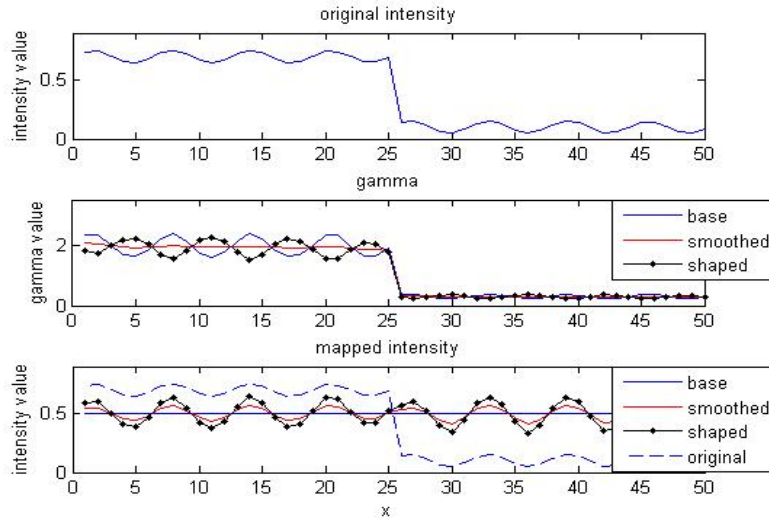


Figure 6. 1-D example of gamma mapping with three different gamma functions.

3.2.3 Channel-wise Modification Module

After mapping through the shaped gamma function, we can enhance local details and remove global illumination. However, completely removing global illumination may make the adjusted image look unnatural. On the other hand, in order to enhance the colorfulness of output images, a channel-wise modification module adapted from [1] is proposed. In this module, we propose a modification to transfer $\gamma_{shaped}(x,y)$ into a channel-wise gamma map $\gamma^k(x,y)$, which is formulated as

$$\gamma^k(x,y) = \gamma_{shaped}(x,y) \cdot M^k(x,y). \quad (9)$$

In (9), $k \in \{R, G, B\}$ and $M^k(x,y)$ denotes a channel-wise modification term. The estimated channel-wise gamma map is fed into the channel-wise gamma adjustment module as an RGB tone mapping function. The function $M^k(x,y)$ denotes the ratio between the intensity image $I(x,y)$ and the color channel $I^k(x,y)$. That is, we define

$$M^k(x,y) \equiv \frac{I_{\max}(x,y)}{I^k(x,y)}, k \in \{R, G, B\}, \quad (10)$$

$$\text{with } I_{\max}(x,y) \equiv \max\{I^R(x,y), I^G(x,y), I^B(x,y)\}.$$

In Figure 7, we show how Equation (9) works in a bright region and a dark region, respectively. In a dark region, as shown in Figure 7 (a), the shaped gamma value γ_{shaped} will be a value smaller than 1 so that the image contents over small intensity values can be properly expanded. In this example, the red channel $I^R(x,y)$ is larger than the other two channels and thus $M^R(x,y)$ is smaller than $M^G(x,y)$ and $M^B(x,y)$. Hence, the channel-wise adjustment in (9) assigns the red channel a smaller local gamma value than the other two channels. This assignment increases the value of the red component and makes the enhanced image redder. Similarly, over a bright region, as shown in Figure 7 (b), the shaped gamma value will be a value larger than 1 in order to expand the image contents over large intensity values. Over this bright green region, $M^G(x,y)$ is smaller and thus the local gamma value in the green channel is smaller than that of the other two channels. This assignment causes the increase of the green value and makes the enhanced image greener.

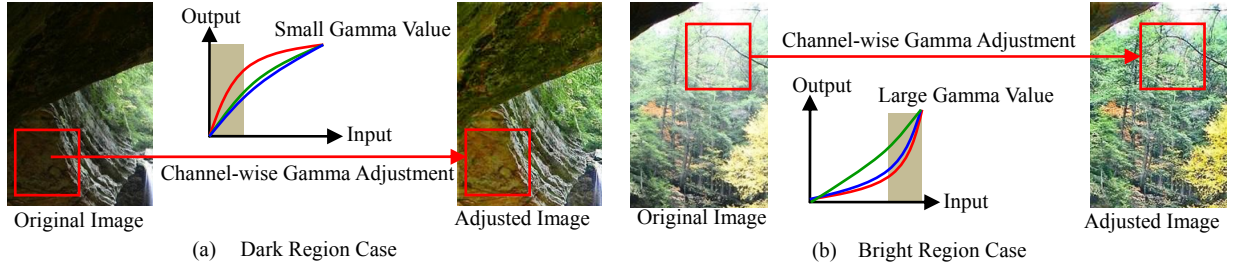


Figure 7. Channel-wise gamma adjustment for (a) a dark region, and (b) a bright region.

However, if we enhance every color in the image, it may make the adjusted image look somewhat unnatural. To maintain the naturalness of the enhanced image, we further modify the formula of channel-wise gamma modification as

$$\gamma^k(x, y) = \frac{\gamma_{shaped}(x, y) \cdot [I_{\max}(x, y) + S_1(x, y)]}{I^k(x, y) + S_1(x, y)}, \quad (11)$$

where $S_1(x, y)$ is a suppressing term defined as

$$S_1(x, y) = c_2 \cdot (\bar{I}(x, y) - I_{\min}(x, y))$$

$$\text{with } \bar{I}(x, y) \equiv \frac{1}{3} [I^R(x, y) + I^G(x, y) + I^B(x, y)] \text{ and } I_{\min}(x, y) \equiv \min \{I^R(x, y), I^G(x, y), I^B(x, y)\} \quad (12)$$

In (12), c_2 controls the magnitude of the suppressing term. This suppressing term $S_1(x, y)$ corresponds to the colorfulness of the image data at (x, y) . If the pixel of the original image is already very colorful, $S_1(x, y)$ will be large and the channel-wise gamma may be close to the shaped gamma for each color channel. This automatically reduces the degree of colorfulness enhancement.

In order to prevent overly removing the global illumination and to preserve the original image color with low colorfulness, such as black and white, we further modify (12) as

$$\gamma^k(x, y) = \frac{\gamma_{shaped}(x, y) \cdot [I_{\max}(x, y) + S_1(x, y)] + S_2(x, y)}{I^k(x, y) + S_1(x, y) + S_2(x, y)}, \quad (13)$$

where $S_2(x, y)$ is the second suppressing term defined as

$$S_2(x, y) = c_3 \cdot \gamma_{base}(x, y) + c_4. \quad (14)$$

In (14), c_3 and c_4 control the magnitude and bias value of $S_2(x, y)$. With a larger value of $S_2(x, y)$, the channel-wise gamma may be held around 1. This reduces the degree of adjustment.

In the proposed approach, we provide a few tunable controlling parameters for users. In general case, for automatic enhancement, the default value of these parameters is shown in Table 1.

Table 1 Default controlling factors

c_1	c_2	c_3	c_4
1	3	0.3	0.1

4. RESULTS

To analyze the adjusted chrominance of the proposed algorithm, we made an experiment as shown in Figure 8. In this experiment, we took one under-exposed image and one properly exposed image of the Macbeth color-checker. The proposed algorithm was applied to the under-exposed picture to get an enhanced image. The chrominance distribution of

the color patches of the 2nd and 3rd columns are respectively plotted for all three images. This distribution shows that the proposed algorithm does successfully enhance the colorfulness of the faded colors in the under-exposed image.

We apply the proposed algorithm to enhance images shown in Figure 9 and Figure 10 for performance evaluation and comparison with the MSRCR method [5], the AINDANE method [9], and the local gamma based adjustment algorithm [1]. In these two examples, our proposed method effectively improves image details and colorfulness and generates more natural-looking results. In addition, in Figure 10, we show that our approach can be used to deal with ill-exposed images.

In Figure 11, we apply the proposed algorithm to enhance an image with different settings of the controlling factors. In this example, in order to improve the quality of the dark regions, we reduce c_3 and c_4 to lighten the suppressing term S_2 . We can observe that the details and colorfulness in the dark regions are improved. Besides, the bright regions are held with only a slight change due to the spatial varying gamma adjustment. Moreover users can tune the other controlling factors to obtain a preferred adjustment. For example, choosing a larger value of c_1 provides a higher degree of contrast enhancement, and choosing a lower value of c_2 provides a higher degree of color enhancement. The proposed algorithm provides an automatic enhancement for general cases and allows an easy control for different purposes.

5. CONCLUSIONS

In this paper, we proposed a new image enhancement technique, which improves image detail, colorfulness, contrast, and sharpness simultaneously through a channel-wise gamma mapping. The channel-wise gamma map is generated from the original image with a sequence of gamma map processing, which can be implemented with low computational complexity. Compared to prior arts, the proposed method can be used to deal with over-bright and over-dark cases and can well preserve the naturalness of the enhanced images.

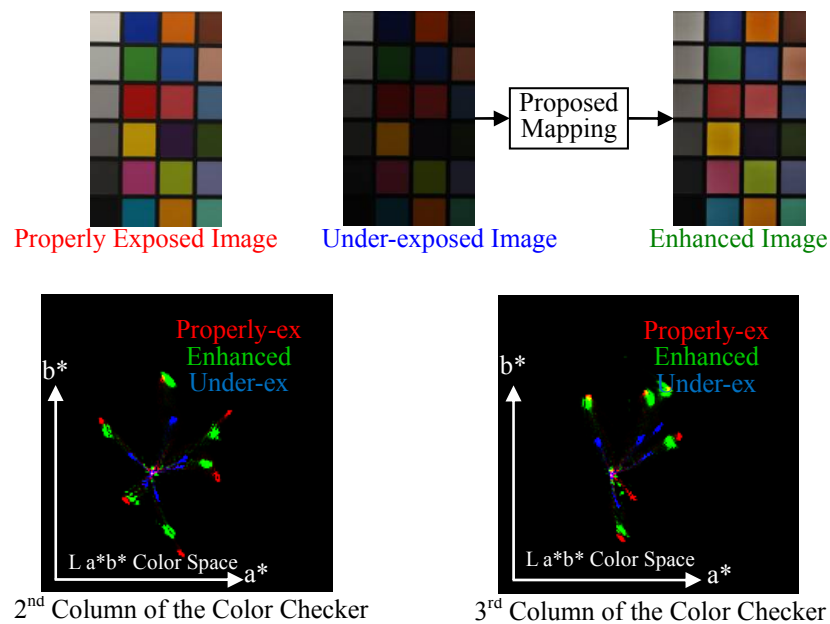


Figure 8. Chrominance analysis of the Color-Checker experiment.



Figure 9. (a) The original image and the enhanced images by (b) MSRCR, (c) AINDANE, (d) the local gamma based approach [1], and (e) the proposed algorithm.

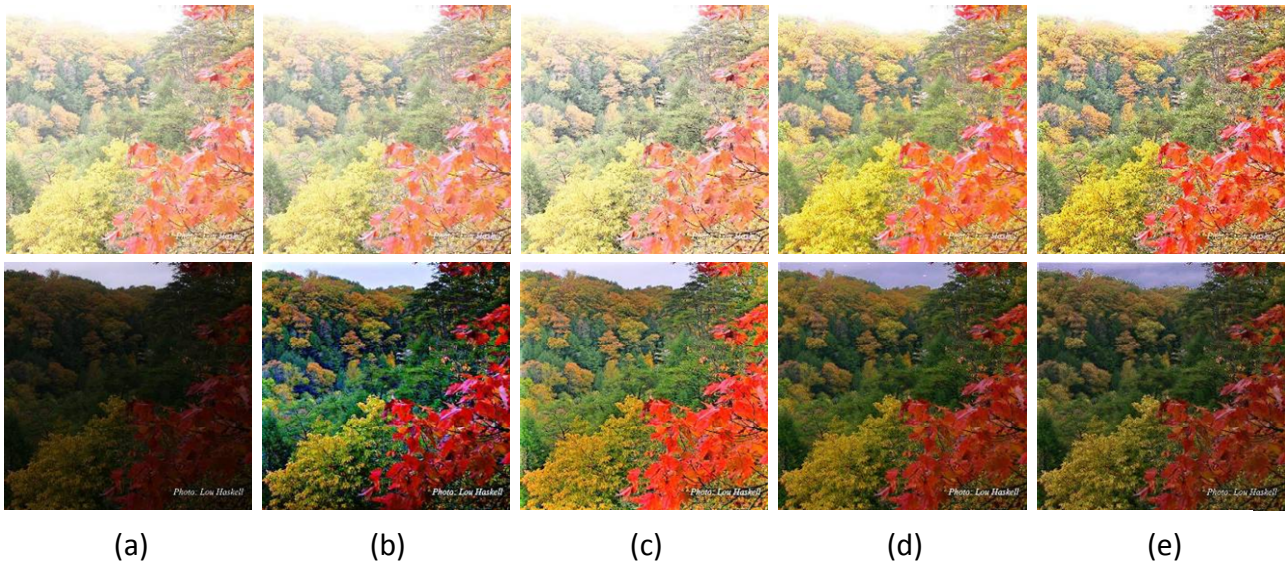


Figure 10. (a) The original images and enhanced images by (b) MSRCR, (c) AINDANE, (d) the local gamma based approach [1], and (e) the proposed algorithm.

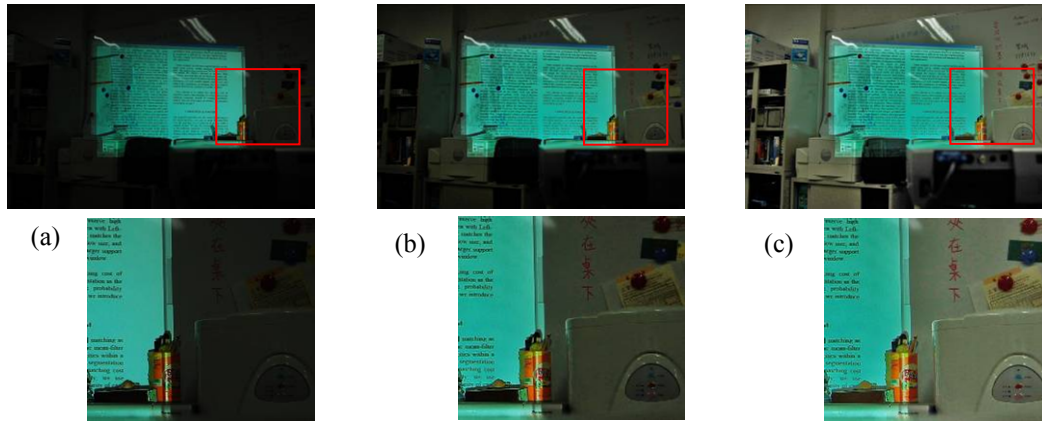


Figure 11. (a) The original image and the enhanced images by the proposed algorithm, with (b) the default controlling factors, and (c) the factor setting with $c_3=0.03$ and $c_4=0.005$.

6. ACKNOWLEDGEMENT

This research was supported by Ministry of Economic Affairs, R. O. C. under Grant Number 98-EC-17-A-02-S2-0047.

REFERENCES

- [1] C. Tseng, S. Wang, Y. Lai, and Y. Zho, "Image Detail and Color Enhancement Based on Channel-wise Local Gamma Adjustment," *SID'09*, 67.5, 1022-1025(2009).
- [2] E. H. Land and J. J. McCann, "Lightness and retinex theory," *Journal of the Optical society of America*, 61, 1-11 (1971).
- [3] E. Land, "Recent advances in retinex theory," *Vision Research* 26(1), 7-21(1986).
- [4] D. J. Jobson, Z. Rahman and G. A. Woodell, "A multiscale Retinex for bridging the gap between color images and the human observation of scenes," *IEEE Transactions on Image processing*, 6, 965-976 (1997).
- [5] Z. Rahman, D. J. Jobson, and G. A. Woodell, "Retinex processing for automatic image enhancement," *Journal of Electronic Imaging*, 13(1), 100-110 (2004).
- [6] J. Tumblin, and G. Turk, "Lcis: A boundary hierarchy for detail-preserving contrast reduction," In *Proc. of ACM SIGGRAPH conf 99*, Annual Conference Series, 83-90 (1999).
- [7] F. Durand and J. Dorsey, "Fast bilateral filtering for the display of high-dynamic-range images". In *Proc. of ACM SIGGRAPH conf 02*, ACM Trans. on Graphics, 21(3), 257-266 (2002).
- [8] S. Bae, S. Paris, and F. Durand, "Two-scale tone management for photographic look," In *Proc. of ACM SIGGRAPH conf 06*, ACM Trans. on Graphics, 25(3), 637 - 645, (2006).
- [9] L. Tao and V. K. Asari, "An adaptive and integrated neighborhood dependent approach for nonlinear enhancement of color Images," *SPIE Journal of Electronic Imaging*, 14, 043006 (2005).
- [10] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," In *Proc. IEEE Int. Conf. on Computer Vision*, 836-846 (1998).
- [11] <http://www.easyhdr.com>
- [12] <http://www.truview.com> reference linking