Color Image Enhancement Using Multiscale Retinex and Image Fusion Techniques

Chang-Hsing Lee, Cheng-Chang Lien, Chin-Chuan Han

Abstract—In this paper, an edge-strength guided multiscale retinex (EGMSR) approach will be proposed for color image contrast enhancement. In EGMSR, the pixel-dependent weight associated with each pixel in the single scale retinex output image is computed according to the edge strength around this pixel in order to prevent from over-enhancing the noises contained in the smooth dark/bright regions. Further, by fusing together the enhanced results of EGMSR and adaptive multiscale retinex (AMSR), we can get a natural fused image having high contrast and proper tonal rendition. Experimental results on several low-contrast images have shown that our proposed approach can produce natural and appealing enhanced images.

Keywords—Image Enhancement, Multiscale Retinex, Image Fusion.

I. INTRODUCTION

TO enhance low contrast images taken in complex lighting conditions, the retinex theory, which is based on the human visual system and is originally proposed by Land [1], [2], has been exploited for image contrast enhancement. Jobson et al. then evolved Land's retinex theory to single-scale retinex (SSR) [3] and multiscale retinex (MSR) [4], [5]. Generally, MSR is more effective than SSR in both local contrast enhancement and dynamic range compression. From the principle of retinex theory [1], an image $I(x, y)$ can be defined as follows:

$$I(x,y) = L(x,y)\, R(x,y), \qquad (1)$$

where $L(x, y)$ represents the illumination and $R(x, y)$ contains the reflectance characteristics of image objects. Later on, Jobson et al. developed the SSR approach which applies the center/surround retinex model for light and color rendition as well as dynamic range compression [3]. For each pixel, the logarithmic ratio between its pixel value and a weighted average of its surrounding pixel values, which is viewed as the estimated illumination, is computed to represent the estimated reflectance. Mathematically, the retinex output (i.e., the estimated reflectance) can be expressed as follows:

$$SSR_c(x,y) = \log\big(I_c(x,y)/[F(x,y)*I_c(x,y)]\big)$$
$$= \log I_c(x,y) - \log[F(x,y)*I_c(x,y)], \qquad (2)$$

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where $I_c(x, y)$ is the pixel value of the c-th color component, $SSR_c(x, y)$ is the corresponding retinex output value, "$*$" denotes the convolution operation, and $F(x, y)$ represents the surround function given by

$$F(x,y) = K\, e^{-(x^2+y^2)/\sigma^2}, \qquad (3)$$

where σ is the standard deviation of the Gaussian surround function representing the space constant, and K is a constant selected by

$$\iint F(x,y)\,dxdy = 1. \qquad (4)$$

In general, the center/surround retinex model can compensate for lighting variations among different image regions and thus can approximate to some extent the reflectance of each object. Finally, a canonical gain/offset correction procedure is applied to the retinex output to produce the SSR enhanced image. Typically, its quality is influenced by the scale (the space constant) of the Gaussian surround function. By using a small scale, we can locally enhance the image contrast at the cost of losing tonal rendition or producing halo artifacts. On the other hand, a large scale can yield better tonal rendition whereas the image contrast is not effectively improved. Usually, a reasonable compromise can be obtained by using a middle-scale retinex. However, it is difficult to determine the appropriate scale because it is generally image dependent.

MSR, an extension of SSR, tried to combine the merits of small-scale retinex, middle-scale retinex, and large-scale retinex to achieve a graceful balance between dynamic range compression and tonal rendition. The MSR output is defined as a weighted sum of several SSR outputs corresponding to different scales:

$$MSR_c(x,y) = \sum_{s=1}^{S} \omega_s\, SSR_{c,s}(x,y), \qquad (5)$$

where MSR_c is the MSR output of the c-th color component, S is the number of scales, ω_s is the weight for the s-th scale, $MSR_{c,s}$ is the MSR output for the c-th color component and the s-th scale with its surround function given by

$$F_s(x,y) = K_s\, e^{-(x^2+y^2)/\sigma_s^2}, \qquad (6)$$

where σ_s is the Gaussian surround space constant for the s-th scale, K_s is a constant determined by the following equation:

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$$\iint F_s(x, y)\, dxdy = 1. \tag{7}$$

The experiments have shown that a combination of three different scales ($\sigma_1 = 15$, $\sigma_2 = 80$, $\sigma_3 = 250$) with equal weighting ($\omega_1 = \omega_2 = \omega_3 = 1/3$) is sufficient to provide both dynamic range compression and tonal rendition for most images [4], [5]. However, MSR can amplify the noise contained in a large dark area, or can produce an unnatural image in which the global contrast of brightness (i.e., the relative brightness of darker regions and brighter regions) is lost. To solve this problem, adaptive MSR (AMSR) [6] was proposed to enhance the contrast of an image. In AMSR, the weight associated with each SSR output image as well as the input image is adaptively computed according to the pixel value of the input image in order to produce a high-contrast image, denoted by Y^{AMSR}, with proper tonal rendition. However, some noises in dark background will become visible in the enhanced image. To solve this problem, we will propose the edge-strength guided multiscale retinex (EGMSR) method to get an enhance image, denoted by Y^E, without generating visible noises. Further, the image fusion technique will be used to combine the images Y^{EGMSR} and Y^{AMSR} to get a fused image having enhanced contrast, proper tonal rendition, and natural impression.

II. Proposed Color Image Enhancement Approach Using Edge-strength Guided Multiscale Retinex (EGMSR) and Image Fusion Techniques

The proposed EGMSR method tried to combine different SSR output images in a way that the weight associated with each pixel in the SSR output images is pixel dependent. In this paper, the weight of each pixel is determined according to its edge strength. Given a color image, its luminance image, Y, is obtained by using the following transformation function:

$$Y(x, y) = 0.299 \times R(x, y) + 0.587 \times G(x, y) + 0.114 \times B(x, y), \tag{8}$$

where $R(x, y)$, $G(x, y)$, and $B(x, y)$ denote the red, green, and blue values of a pixel at coordinate (x, y). The luminance image Y is then enhanced using the proposed EGMSR approach to yield an enhanced luminance image, Y^E. The enhanced image Y^E will then be fused with the AMSR enhanced image Y^{AMSR} [6] to get the output image Y^{MSRIF}.

Fig. 1 shows the flow diagram of the proposed EGMSR approach. Let SSR_s denote the SSR output corresponding to the s-th scale ($s = 1, 2, 3$). The linear stretching method, which first trims the largest 1% and smallest 1% of SSR output values, will be employed to normalize each SSR output value to the full display range using the following equation [6]:

$$Y_s(x,y) = \begin{cases} 255, & SSR_s(x,y) > P_{99} \\ 255 \times \dfrac{SSR_s(x,y) - P_1}{P_{99} - P_1}, & P_1 \le SSR_s(x,y) \le P_{99} \\ 0, & SSR_s(x,y) < P_1 \end{cases} \tag{9}$$

where P_{99} (or P_1) denotes the 99-th (or first) percentile which is defined as the value where 99 (or 1) percent of the SSR output values less than or equal to it.

Generally, small-scale SSR will greatly improve the local contrast than larger scale SSRs. However, invisible noises will also be amplified as well and may become visible in the enhanced image, which will degrade the perceived image quality.
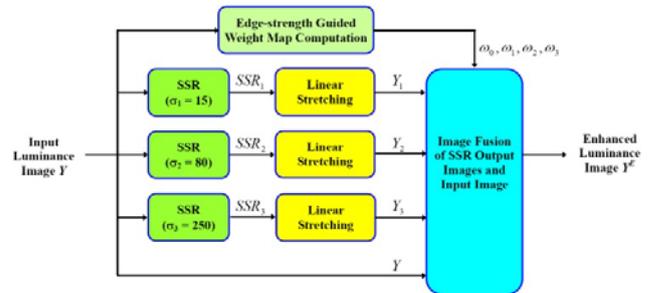

Fig. 1 Flow diagram of the proposed EGMSR approach

Fig. 2 gives an example showing the SSR output images of different scales, Y_s ($s = 1, 2, 3$). Fig. 2 (a) shows the night building image, from which we can see that the background is relatively dark compared to the tower in the foreground. From Fig. 2 (b), we can see that by using small-scale SSR the local contrast can be enhanced (please see the building in the bottom left corner of the image) at the expense of producing many visible noises (please see the dark sky region). Such noises can be suppressed to some extent by using large-scale SSR (please see Fig. 2 (d)). That is, small-scale SSR may over-amplify invisible noises (i.e., small edges/textures in the input images) contained in smooth regions. To deal with this phenomenon, for small-scale SSR output image, if the edge strength of a pixel is not obvious, we should assign a small weight value to it in order not to over-enhance the noises. To this end, for each pixel, we first compute the maximal edge gradient among its eight neighbors (denoted by $N_8(x, y)$):

$$g_{\max}(x, y) = \max_{(p,q) \in N_8(x,y)} \left| f(x, y) - f(p, q) \right|. \tag{10}$$

According to $g_{max}(x, y)$, each pixel will be classified into one of three edge groups G_1, G_2, and G_3, which indicate strong-edge group (denoted by G_1), moderate-edge group (denoted by G_2), and weak-edge group (denoted by G_3), respectively. Then, we define the likelihood probability p_i for each edge group G_i ($i = 1, 2, 3$) as follows:

$$p_1(x, y) = \begin{cases} 1, & \text{if } g_{\max}(x, y) \ge 128 \\ e^{-(g_{\max}(x,y) - 128)^2 / 2\sigma_E^2}, & \text{otherwise} \end{cases}, \tag{11}$$
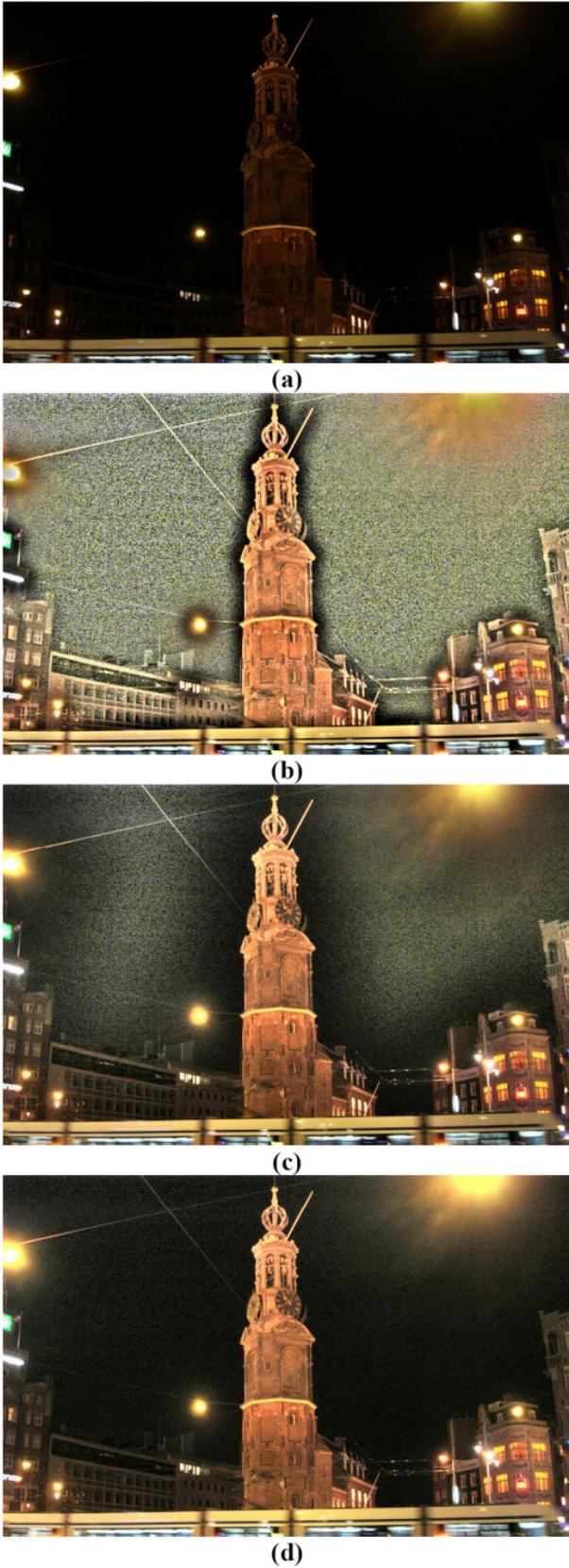
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Fig. 2 Input image (Y) and SSR output images (Y_1, Y_2, Y_3) for different scales. (a) Y (b) Y_1 (c) Y_2 (d) Y_3
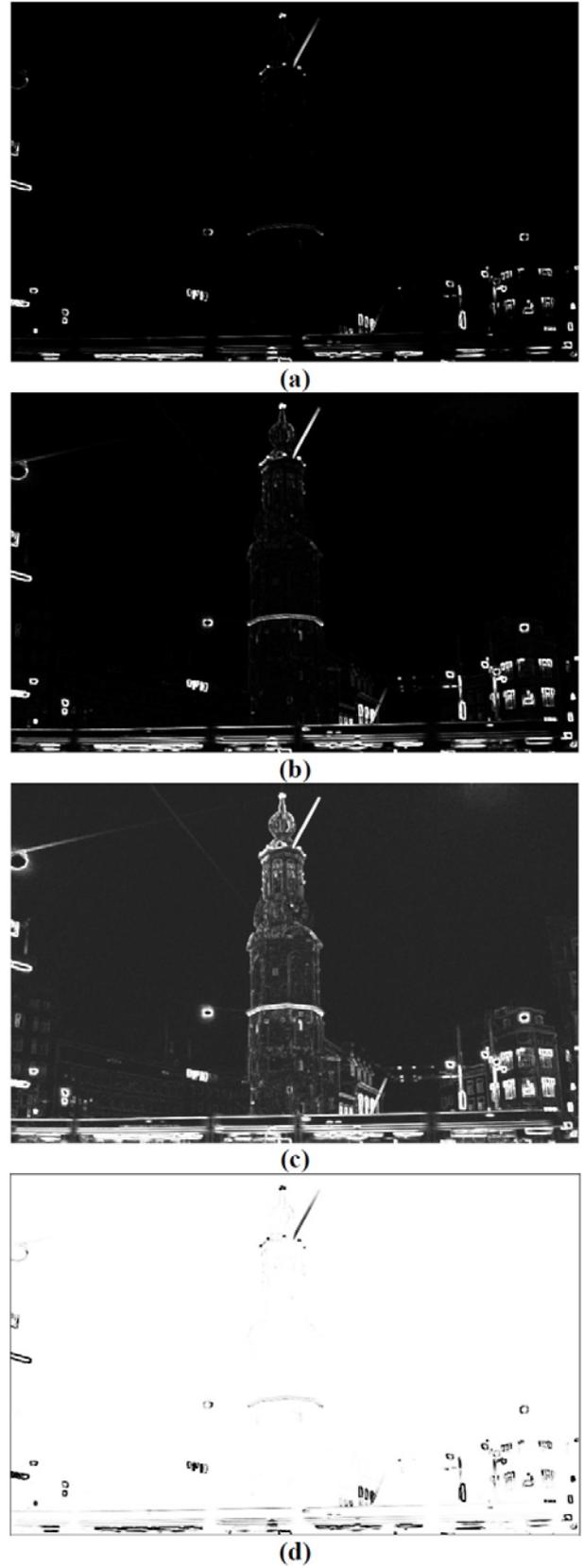

Fig. 3 Weight images for SSR output images (denoted by W_1, W_2, and W_3) and the input image shown in Fig. 2 (denoted by W_0). (a) W_1 (b) W_2 (c) W_3 (d) W_0

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$$p_2(x,y) = e^{-(g_{\max}(x,y)-96)^2/2\sigma_E^2}, \qquad (12)$$

$$p_3(x,y) = e^{-(g_{\max}(x,y)-64)^2/2\sigma_E^2}, \qquad (13)$$

where σ_E is the standard deviation of the Gaussian function ($\sigma_E = 32$ in this paper). Finally, the weight associated with each pixel of the SSR output images is defined as follows:

$$\omega_1(x,y) = p_1(x,y), \qquad (14)$$

$$\omega_2(x,y) = \max\{p_1(x,y), p_2(x,y)\}, \qquad (15)$$

$$\omega_3(x,y) = \max\{p_1(x,y), p_2(x,y), p_3(x,y)\}. \qquad (16)$$

Note that we usually assign larger weights to larger-scale SSRs than small-scale SSRs. In addition, the weight associated with the input image is given by

$$\omega_0(x,y) = 1 - \omega_1(x,y). \qquad (17)$$

Thus, for those pixels having a large edge value $g_{max}(x, y)$, the small-scale SSR output image will have a larger weight. On the other hand, for those pixels having a small edge value, the

input image and large-scale SSR output image will get a larger weight.

Fig. 3 shows the weight images associated with each SSR output image and the input image shown in Fig. 2. Note that the weight value is pixel dependent, which is computed based on the edge strength of each image pixel. Further, we can see that the weight image associated with small-scale SSR will exhibit large weights only for those pixels having strong edge strength (please see Fig. 3 (a)), whereas the weight image for the input image will present large weights for those pixels in the smooth dark/bright areas (please see Fig. 3 (d)). As a result, for small-scale SSR, those pixels in smooth areas will have small weight values to prevent from over-enhancement, whereas those pixels having strong edge strength will present large weight values. Finally, the input image and all SSR output images will be fused together to obtain the enhanced luminance image by using the following equation:

$$Y^E(x,y) = \frac{\omega_0(x,y)\,Y(x,y) + \sum_{s=1}^{3}\omega_s(x,y)\,Y_s(x,y)}{\sum_{s=0}^{3}\omega_s(x,y)}. \qquad (18)$$

Fig. 4 Enhanced results of a night building image shown in Fig. 2(a). (a) Y^{MSR} (b) Y^{AMSR} (c) Y^E (d) Y^{MSRIF}

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Based on Y^E, the R, G, B color values will be reconstructed by using the following formula in order to prevent relevant hue shift and color de-saturation [7]:

$$R^r(x,y) = \frac{1}{2}\left(\frac{Y^E(x,y)}{Y(x,y)}(R(x,y)+Y(x,y))+R(x,y)-Y(x,y)\right), \quad (19)$$

$$G^r(x,y) = \frac{1}{2}\left(\frac{Y^E(x,y)}{Y(x,y)}(G(x,y)+Y(x,y))+G(x,y)-Y(x,y)\right), \quad (20)$$

$$B^r(x,y) = \frac{1}{2}\left(\frac{Y^E(x,y)}{Y(x,y)}(B(x,y)+Y(x,y))+B(x,y)-Y(x,y)\right). \quad (21)$$

These reconstructed color component images R^r, G^r, and B^r will then be combined to form the output color image.

Note that the main objective of the proposed EGMSR approach is to enhance a low-contrast image without introducing any visible noises in smooth dark/bright regions. However, by carefully observing the enhancing results by using AMSR and EGMSR, we have found that AMSR can provide higher contrast than EGMSR in those edge/texture areas. To provide a better enhancement in the whole image, we can combine the enhanced image Y^E and Y^{AMSR} to yield the enhanced luminance image Y^{MSRIF}:

$$Y^{MSRIF}(x,y) = \frac{1}{2}\left(Y^E(x,y) + Y^{AMSR}(x,y)\right). \quad (22)$$

According to Y^{MSRIF}, we can get the R, G, B color values by using (19)-(21) to reconstruct the output color image.
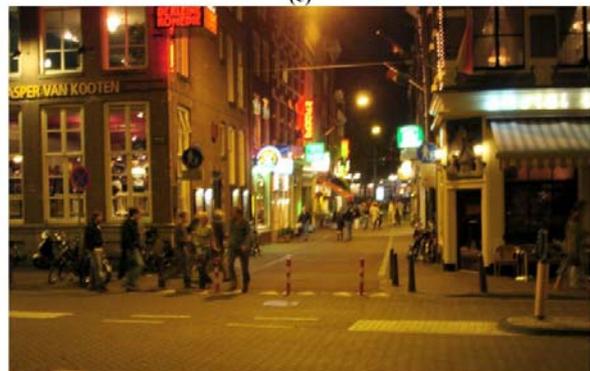

Fig. 5 Enhanced results of a night street scene image. (a) Input image Y (b) Y^{MSR} (c) Y^{AMSR} (d) Y^E (e) Y^{MSRIF}

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Fig. 6 Enhanced results of a backlighting image. (a) Input image Y (b) Y^{MSR} (c) Y^{AMSR} (d) Y^E (e) Y^{MSRIF}

III. EXPERIMENTAL RESULTS

In this paper, several low-contrast images, taken in the night time or in a backlight condition, will be used for performance comparison. The proposed EGMSR approach will be compared with MSR [4] and AMSR [6].

Fig. 4 shows the enhanced results of the night building image shown in Fig. 2 (a), using different enhancement methods. In Fig. 4 (a), MSR makes the dark buildings become clear but also amplifies noises in the dark sky region. AMSR can reduce the noise to some extent (see Fig. 4 (b)) but will suffer from the halo effects near the bright lights. The proposed EGMSR can well reduce the noise at the expense of reducing the visibility of dark buildings (see Fig. 4 (c)). By fusing together the enhanced images Y^E and Y^{AMSR}, we can get a better balance between noise removal and the visibility of dark buildings (see Fig. 4 (d)).

Fig. 5 (a) shows a night street scene image where the foreground subjects and objects exhibit insufficient illumination due to the existence of some bright streetlights in the background. MSR can enhance the contrast of the dark region at the cost of poor tonal rendition (see Fig. 5 (b)). AMSR makes the foreground objects clear at the cost of slightly losing the contrast of the whole image (see Fig. 5 (c)). Our proposed approach yields a natural image with enhanced contrast and proper tonal rendition (see Figs. 5 (d) and (e)).

Fig. 6 shows an image taken indoors with bright outdoor scenes as well as the enhanced images using different methods. From Fig. 6 (a), we can see that, due to the backlight condition, the foreground objects and faces have relatively insufficient illumination and thus are dark and unclear. In Fig. 6 (b), we can see that MSR will make the faces become clear but also

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introduce some visible noises. AMSR can enhance the dark region to some extent without producing apparently visible noises; whereas the enhanced image reveals slightly washed-out appearance (see Fig. 6 (c)). The proposed EGMSR method can suppress the noises and produce a high contrast image but the foreground faces become unclear (see Fig. 6 (d)). By fusing together the enhanced results of AMSR and EGMSR, a better balance between contrast enhancement and tonal rendition can be obtained (see Fig. 6 (e)).

IV. Conclusion

In this paper, we propose the EGMSR approach for color image contrast enhancement. From the experimental results, we can see that EGMSR can prevent from over-enhancement of the noises contained in the smooth dark/bright regions. On the other hand, AMSR [6] can well enhance the contrast of edge regions. Thus, by fusing together the enhanced results of AMSR and EGMSR, we can get a fused image having high contrast and proper tonal rendition in the whole image. In this paper, the image fusion rule is just simple pixel averaging, which does not carefully consider the image characteristics in different regions. Thus, an extension of this research is how to design appropriate image fusion method to produce a fused image with enhanced contrast, proper tonal rendition, and without producing any noises.

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