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Improved MSR Model for Image Enhancement in Different Color Spaces

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Abstract: During the process of low-light image enhancement, the classic Multi-Scale Retinex (MSR) suffers from halo effects and insufficient color protection. Therefore, this paper proposes an improved MSR model. The core idea of this paper is to replace the Gaussian filter in MSR with gradient-domain guided filtering. Meanwhile, in the process of image enhancement, the differences among various color spaces are taken into account. Experiments have proven that the improved method proposed in this paper can effectively improve the quality of low-light images. However, when applying the proposed method to different color spaces, the experimental results do not confirm the existence of a universal optimal color space model. In the field of image enhancement, it is still necessary to choose the appropriate color space model according to the characteristics of the specific application scenario.

Keywords: Low-light; Multi-Scale Retinex; Gradient-domain Guided Filtering; Color Space.

1. Introduction

Due to the influence of insufficient lighting, interference signals, haze, and underwater environments, the obtained single-modal images may have low brightness, unbalanced colors, and low contrast. Low-light environments usually lead to low image brightness and quality degradation [1]. Underwater images suffer from color bias, blurriness, and low contrast due to light absorption [2]. The presence of haze causes the light reflected by objects to be absorbed and scattered by particles in the atmosphere during transmission to the imaging device, leading to reduced image brightness, color blur, and loss of detail [3].

For many years, single-modal image enhancement has always been a hot topic of research. The Retinex model [4] is an image enhancement method based on human vision characteristics, with the main theoretical basis being the theory of optical trichromaticity and color constancy.

The classic Retinex model enhances the R (Red), G (Green), and B (Blue) channels of the source color image separately, but this method has some drawbacks. First, there is color distortion (Color Artifacts). Processing the R, G, and B channels separately can lead to an imbalance in color ratios. For example, over-enhancing the red channel can make the image appear overly red, disrupting natural tones (such as abnormal skin colors). Moreover, the RGB channels are not entirely independent in the color space, and processing them separately ignores the spectral correlation between channels. Secondly, there is the luminance-chrominance coupling problem. Luminance changes can cause color shifts, and directly adjusting the RGB channels will simultaneously alter both luminance and chrominance. For example, increasing the brightness of dark areas may also amplify chrominance noise (such as the appearance of colored noise in dark regions). The human eye is more sensitive to luminance than to chrominance, but synchronous processing of RGB channels cannot distinguish. Some special color spaces, such as YIQ/YUV/HSV/YCbCr, may be more suitable.

In addition, there is the issue of abnormal local contrast. Enhancing each channel separately can lead to color fringing or edge artifacts in edge regions. Differences in enhancement levels of the same object in different channels can cause texture confusion. Furthermore, during the image enhancement process, image noise is also amplified. The enhancement process amplifies noise in each channel separately, and when combined in a true color image, the noise from each channel can overlap, potentially resulting in more intense and complex noise (such as colored granular noise).

2. Classical Retinex Theory

The classical Single-Scale Retinex(SSR) model [5] can be represented as:

$$R_{SSR_i}(x,y)=\log S_i(x,y)-\log(G(x,y,c)\otimes S_i(x,y)) \quad (1)$$

$$G(x,y,c)=K_n e^{-(x^2+y^2)tc^2} \quad (2)$$

Where $i\in(R,G,B)$, $G(x,y,c)$ is Gaussian function, $S_i(x,y)$ represents the component of the i-th channel in the low light image, representing the two-dimensional Gaussian function. SSR uses the Gaussian function to estimate the luminance, c represents the scale parameter. When c is large, the SSR can relatively focus on preserving image color, and when c is small, the SSR can relatively focus on preserving image details. However, it is difficult to achieve both under a single parameter.

Different from SSR, Multi-Scale Retinex(MSR)[6] uilizes multiple filters of different scales of c for enhancing the low-light image and then introduces weights W_1,W_2,W_3 to obtain the final lighting image by weighted averaging the brightness maps of different scales, expressed as:

$$R_{MSR_i}(x,y)=\sum_{n=1}^{N} W_n[\log S_i(x,y)-\log(G_n(x,y,c)\otimes S_i(x,y))] \quad (3)$$

$$G_n(x,y,c)=K_n e^{-(x^2+y^2)tc_n^2} \quad (4)$$

In Eq.(3) and Eq. (4), $G_n(x,y,c)$ is the n-th Gaussian function, N represents the number of Gaussian convolution functions, generally 3, representing small, medium, and large scales. W_n represents the weight of each scale, generally set to 1/3. Compared with SSR, MSR has significant advantages and can effectively utilize multi-scale image feature information, thus greatly improving the effect of image enhancement.

MSR performs a good effect on improving image brightness, but easily leads to excessive enhancement or color distortion. Multi-Scale Retinex with Color Restoration (MSRCR) [6] can effectively correct the color ratio of the restored image by calculating the proportion of various color channels, avoiding serious color cast and distortion. However, MSRCR involves image blurring and contrast adjustment at multiple scales, resulting in high computational complexity. Meanwhile, halo artifacts may appear in areas with strong light and shadow transitions, and color cast may still occur even after local contrast enhancement. It has low sensitivity to high light areas and limited effectiveness in improving details, and has limited adaptability to image types.

In [7], an improved Retinex mine image enhancement algorithm was proposed to reduce effectively over-enhancement. An enhanced Retinex model for the underwater image method was combined with improved homomorphic filtering [8]. A novel Bayesian Retinex algorithm was constructed for enhancing underwater images with multi-order gradient priors of reflectance and illumination [9]. Another novel Retinex model was proposed for dehaze combining the dark channel prior and guided filter [10].

As is well known, the classical Retinex model applies Gaussian filters to estimate the illumination components, which can easily lead to inaccurate estimation results under complex illumination conditions, which is an important reason for a series of problems.

3. Improved MSR

In response to the above issues, this study has made extensive improvements to the classic MSR model, using the YIQ color space as an example. The overall research approach is as follows.

(1) Color Preprocessing

The simplest white balance treatment [11] is applied to the source image to be enhanced, achieving the effect of eliminating color bias and maintaining color authenticity. This step is crucial because it helps in normalizing the color distribution of the image, thereby reducing the initial color disparities that might be present due to varying lighting conditions.

(2) Color Space Transformation

The source color image is transformed from the RGB space to the YIQ color space(taking YIQ as an example), separating and processing the hue components (I, Q) and the luminance component (Y) separately. This transformation is beneficial because the YIQ color space is designed to separate luminance information from chrominance information, which allows for more effective processing of each component independently.

(3) Luminance Enhancement

The gradient domain guided image filter [12] is used to replace the Gaussian filter in the original MSR, constructing a new luminance enhancement method (simplied as MSR_Gd). This approach leverages the gradient information of the image to guide the filtering process, which helps in preserving edges and details while enhancing the luminance. This is a significant improvement over the traditional Gaussian filter, which tends to blur edges and may not preserve the fine details effectively.

(4) Image Denoising

The fast non-local means filter (FNLM) [13] is used to filter the luminance enhanced by MSR_Gd, eliminating the noise amplified during the image enhancement process. This step is critical because image enhancement processes often amplify existing noise in the image. By applying a denoising filter, we can mitigate this effect and improve the overall quality of the enhanced image.

(5) Chrominance Expansion

The chrominance components (I,Q) are enhanced separately using a nonlinear gamma function to expand the display range. This step helps in improving the color representation of the image by adjusting the gamma values of the chrominance components, thereby enhancing the overall visual appeal of the image.

(6) Color Space Inverse Transformation

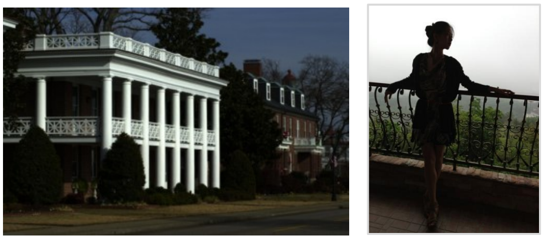
For the three new components Y, I, and Q processed in the above steps, the image is transformed from the YIQ color space back to the RGB. This step ensures that the final enhanced image is in the standard RGB color space, which is widely used and compatible with most display devices.

(7) Edge Sharpening

The Laplace operator is used to sharpen the edges of the color image processed in the sixth step, obtaining the final image enhancement result. Edge sharpening is an important step in enhancing the visual quality of the image, as it helps in highlighting the boundaries of objects within the image, making them more distinct and clear.

4. Conclusion

As shown in Figure 1, two commonly used low-light images were selected as test subjects and processed using the proposed image enhancement method.



(a) House (b) Lady

Figure 1. Low-light images of House and Lady

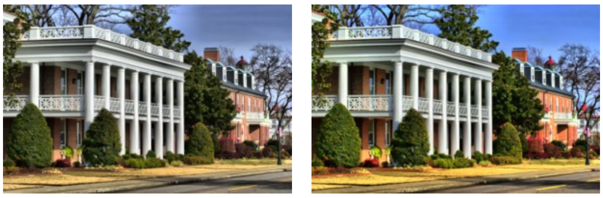
(1) Subjective Evaluation

Figure 2 shows the results of the House image enhanced in different color spaces. The source image contains a white cylindrical structure on the left side (with ample lighting) and a red brick wall (with insufficient lighting). The right side of the image also features a red brick wall, and due to the overall low lighting conditions, the visual quality of the red wall and trees in the source image is poor.

(a) House (b) Enhanced in RGB

(c) Enhanced in YIQ (d) Enhanced in YUV

(e) Enhanced in YCbCr (f) Enhanced in LAB



(g) Enhanced in HSI (h) Enhanced in HSV

Figure 2. Enhancement of Figure 1(a) in different color space.

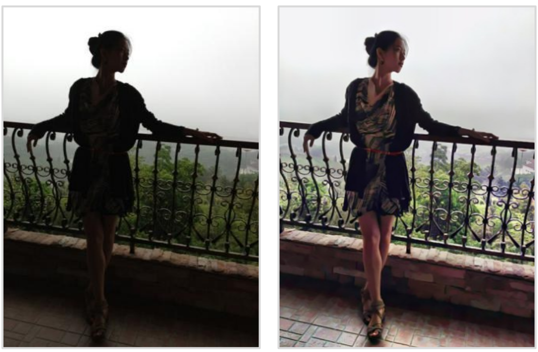
Figure 2(b) shows the enhanced image using the proposed MSR_Gd algorithm in the RGB color space. Figures 2(c) to 2(h) show the enhanced images in different color spaces. It can be observed that Figures 2(b), 2(e), 2(f) have improved brightness but lower color saturation, resulting in a less visually appealing image. Figures 2(c), 2(d), and 2(g) have similar visual effects and are more in line with conventional visual habits. Figure 2(h) has overly high color saturation.

Figure 3 shows the results of the Lady image enhanced in different color spaces. Similar to the House image test, the proposed MSR_Gd method was applied to the Lady image in different color spaces, and the results are shown in Figures 3(b) to 3(h). The visual quality of the enhanced images is consistent with the results observed in Figure 2.

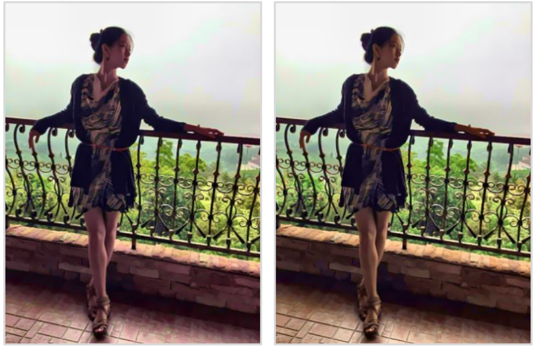
(2) Objective Evaluation

To objectively evaluate the impact of different color spaces on the proposed image enhancement method, several metrics were considered, including information entropy (EN), average gradient (AG), image visual quality (VIF), peak signal-to-noise ratio (PSNR), and structural similarity index (SSIM). The results are shown in Tables 1 and 2.

The top three values for each metric are highlighted in bold in Tables 1 and 2. Unfortunately, no single color space consistently outperformed the others in all metrics.



(a) Lady (b) Enhanced in RGB



(c) Enhanced in YIQ (d) Enhanced in YUV

(e) Enhanced in YCbCr (f) Enhanced in LAB

(g) Enhanced in HSI (h) Enhanced in HSV

Figure 3. Enhancement of Figure 1(b) in different color space.

Table 1. Evaluation of House image Enhancement

Color Space	EN	AG	VIF	PSNR	SSIM
RGB	0.0695	15.8124	**0.7233**	**12.7384**	**0.5247**
YIQ	**0.3928**	**17.3874**	0.6776	11.6919	0.4911
YUV	**0.3588**	**17.6493**	0.6911	11.5252	0.4873
YCbCr	**0.4326**	**18.0151**	0.6820	11.4441	**0.4978**
LAB	0.0564	15.4410	**0.6999**	**12.5382**	**0.5418**
HSI	0.1845	14.0614	**0.7081**	**11.8250**	0.4906
HSV	0.1818	14.3300	0.6424	10.9919	0.4896

Table 2. Evaluation of Lady image Enhancement

Color Space	EN	AG	VIF	PSNR	SSIM
RGB	0.1192	9.4141	**0.7827**	14.4430	**0.6804**
YIQ	**0.1750**	**10.4702**	0.7721	**15.1042**	0.6488
YUV	**0.1830**	**10.3667**	**0.7784**	**15.6980**	0.6427
YCbCr	**0.3965**	**10.7329**	0.7450	13.2437	0.6422
LAB	0.0689	9.246	0.7454	14.5804	**0.6998**
HSI	0.0618	8.8797	**0.7758**	14.3039	0.6375
HSV	0.0583	9.0422	0.6985	**15.8405**	**0.6544**

Despite this, as can be seen from Tables 1 and 2, in terms of EN and AG, YIQ, YUV, and YCbCr perform better. In terms of VIF, the metrics for the RGB and HSI color spaces are better; in terms of SSIM, the RGB and LAB color spaces are better. However, the results of objective evaluation do not completely match those of subjective evaluation.

This study focuses on the performance of the improved MSR method in different color spaces. First, it can be affirmed that the improved MSR, taking the YIQ color space as an example, can effectively improve the visual quality of low - light images. However, when the improved MSR is applied to different color spaces, different enhancement effects are obtained. The experiments in this paper show that the enhancement effect of the improved MSR should be determined according to the specific application scenario.

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