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Research Article

Color Image Enhancement Algorithm Based on Weighted Guided Image Filtering Under Low and Non-uniform Illumination

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Abstract As the state of the art, grayscale image enhancement algorithms are most commonly adopted in the enhancement of RGB color images suffering from low or non-uniform illumination. While these methods are applied on each of the RGB channels independently, unbalanced inter-channel enhancements (color distortion) can often be observed in the resulting images. Besides, images with non-uniform illumination enhanced by the Retinex algorithm are prone to artifacts such as local blurring, halo and over-enhancement. To address the above-mentioned problems, an improved RGB color image enhancement method based on the weighted guided image filtering (WGIF) is proposed to target the non-uniform illumination or poor visibility conditions. Unlike the conventional Retinex algorithm and its variants, the WGIF used a surround function instead of the Gaussian filter to estimate the illumination component as a strategy to avoid the local blur and halo artifacts thanks to the anisotropy characteristics and adaptive local regularization hyper-parameter. To limit color distortions, the RGB images are first converted to the HSI (hue, saturation, intensity) color space, where only the intensity channel is enhanced, before being converted back to the RGB color space with a linear color restoration algorithm. Experimental results show that the proposed method is effective for both RGB color and grayscale images under low exposure and non-uniform illumination, achieving better visual quality and objective evaluation scores than those from the comparison algorithms. In addition, the efficiency of the proposed method is also improved due to the linear color restoration algorithm.

Keywords color image enhancement; images with non-uniform illumination; images under low illumination; weighted guided image filter; color restoration algorithm.

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1 Introduction

Color images contain richer information than grayscale images. In recent years, color images have been applied more and more in many fields. However, in practice, images are often obtained under undesirable weather and illumination conditions. Images taken under insufficient or non-uniform light, shows low brightness, poor contrast, blurred local details, poor color fidelity and sudden changes in light, even often accompanied by a lot of noise. These make it difficult to extract and analyze information from images by human eyes or machine vision systems[17, 18, 45]. Thus, many scholars devote themselves to color image enhancement nowadays [25, 51].

To enhance the color image of low illumination, it is required to maintain the color information without distortion while increasing the brightness and contrast, and highlight the image details and texture, so that the enhanced image is bright and natural. Conventional color image enhancement directly applies the grayscale image enhancement method to the each channels of the RGB model such as histogram equalization algorithm and its various improved algorithms[4, 26, 36, 46] in spatial domain enhancement, wavelet transform algorithms[2, 3, 41] in frequency domain enhancement, and Retinex algorithm[21] and its some improved algorithms[34, 35, 40]. A better result couldn't be achieved if these grayscale image enhancement algorithms are applied directly to color image due to a strong correlation between the RGB color channels. If each color channel is directly processed by using the grayscale image enhancement algorithm, the different channels will be enhanced imbalancedly, which will lead to color distortion, saturation decrease, obvious block effect and other problems.

To overcome these problems, some scholars process images in other color models such as HSI, HSV, YCbCr, YUV, etc[33, 53, 57]. In these color models, the brightness and color of the image are recorded in different independent channels. The processing of brightness channel will not affect color channel, ensuring no color shift occurs. For example, Yang and Shin et al.[42, 52] proposed an image enhancement method in HSV model. First, in the Value channel the illumination component is obtained by the Gaussian filter, and the reflection component is got by Retinex theory. Then the brightness of the illumination component is increased, the processed illumination component is combined with reflection component again, and the enhanced V channel image is obtained. Finally, the enhanced image is converted to RGB image. This method can better overcome the deficiencies such as color distortion and loss of image light details. However, due to the isotropic characteristics of Gaussian Filtering(GF) when it is used to estimate the background illumination, the blurred edges of the resulting reflection component tend to be appeared, and the enhanced image is subject to halo artifact and low contrast as the non-uniform illumination information of the original image. Consequently, in order to enhance the non-uniform illumination component under low illumination, some researchers have attempted to estimate the background illumination using a filter with anisotropy characteristics such as Bilateral Filtering(BF)[47, 50, 56] or Guided Image Filtering(GIF)[12, 31]. BF may be subjected to "gradient reversal"[5, 7, 42] in image enhancement, because the Gaussian weighted average is unstable if a pixel on an edge has few similar pixels around it, and the efficiency of BF is poor. Meanwhile, while GIF is used to estimate the illumination component of the image, blurred halo and pseudo-edge effect[8] will appear in the edge of windows with large texture differences for the same regularization factor is used in all local filtering windows. Accordingly, variant of GIF, that is, weighted guided image filter(WGIF)[27] was proposed to achieve good edge preserving.

In recent years, with the development of deep neural network, many researchers have proposed low-light image enhancement deep learning-based methods[9, 23, 29]. Wang et al.[48] put forward a Global Light Awareness and Detail Retention Network(GladNet), which can effectively enhance image details but still suffers from unsaturated color and low contrast. Wei et al.[49] put forward a Deep Retinex Network(RetinexNet). This method is data-driven learning and introduces multi-scale cascading technology to adjust lighting, well improving the brightness of low-illumination images. However, due to the ignore of the color information of the image, the enhanced image will have color distortion. Zhang et al. [55] proposed a Kindling darkness(KinD) Network. It employs pairs of datasets taken under different exposure conditions to train image decomposition network, reflection component recovery network and luminance adjustment network, which can effectively remove noise interference, enhance brightness and maintain color reality. Although the deep learning-based method has good generalization performance and better effect, it often needs large-scale dataset for training, is highly dependent on the dataset and requires high computational resources.

In this paper, we present a novel color image enhancement method under low and non-uniform illumination, whose main contributions include the following three aspects:

- GF possesses anisotropic characteristics, so that gradient inversion can be effectively avoided by using it to estimate illumintaion. On the basis, WGIF introduces the adaptive regularization parameters, better avoiding the halo and pseudo-edges as the edge gray difference is large. Therefore, we use WGIF instead of GF to estimate the illumination component and denoise the reflection component, which better maintains the edge and detail information, and avoids local blurring, halo and noise amplification.
- Only intensity channel in HSI color space is processed, and the linear color restoration algorithm is used to calculate the luminance gain coefficient to accurately restore the color of each pixel, can the efficiency be improved while avoiding color distortion.
- The illumination component and the fused image are enhanced by adaptive Gamma correction function and S-hyperbolic tangent function, respectively, to improve image contrast and enhance image details.

The rest of this paper is organized as follows. Section

2 gives a brief review of related work. In Section 3, we depicts the proposed method. Section 4 demonstrates and analyzes the experimental results, followed by conclusion drawn in Section 5.

2 Related work

For the color image under low and non-uniform illumination, proposed method in this paper converts its original color image to HSI model. Only the dark area of the intensity channel image is enhanced, the brightness and clarity of the color image can be improved. Therefore, the enhancement of intensity channel image is the core of the proposed method. Nevertheless, the key to be solved is how to maintain the richer information, and avoid some phenomena such as blurring, halo and over enhancement, occurring in the region of illumination mutation as the brightness of image enhances.

Human perception can construct a visual representation with vivid color and detail across the wide dynamic range regardless lighting variations, which is called color constancy[19, 20]. Some scholars have proposed various image enhancement algorithms under low illumination from the perceptual characteristics of the human visual system, among which Retinex [14, 15] based on color constancy attracts much attention. At the same time, many improved algorithms have emerged[39, 54, 56]. According to illumination-reflection model, the human visual perception of the color depends on the reflection characteristics of the object's surface, and the image can be mathematically represented as the product of the illumination component and reflection component:

$$S_c(x,y) = L_c(x,y) * R_c(x,y) \tag{1}$$

where c is one of the RGB channels, that is, $c \in \{R, G, B\}$. S, L and R are original image, illumination component and reflection component, respectively.

The main idea of Retinex theory is to calculate and eliminate the illumination component from the original image. For the calculation of illumination component, however, an under-determined equation has to be solved, which only can be estimated approximately instead of being accurately calculated. Jobson et al.[15] put forward the Single-Scale Retinex (SSR) algorithm, using GF as the center/surround function to estimate the background illumination. Scale parameter in Gaussian function is the only input parameter of the SSR algorithm, so the smaller the value, the more obvious the compression of dynamic range of image, and the larger the value, the more obvious the enhancement of image contrast. Subsequently, the Multi-Scale Retinex algorithm(MSR)[14] was proposed, which combines the dynamic range compression and the tonal rendition, with a weighted sum of several different SSR results. In practice, the MSR is just approaching human vision's performance in dynamic range compression. It would fail to process the images with local or global graying-world violations effectively. In some cases, the "graying out" effect is severe and an unexpected color distortion may occurs. Therefore, Multi-Scale Retinex algorithm with Color Restoration(MSRCR) is proposed by Rahman and Jobson et al.[39], which improves MSR with a universally applied color restoration factor to eliminate the color distortions and gray zones evident.

In the classical Retinex methods mentioned above, the lighting is usually considered to be uniform, so GF is used as center/surround function to estimate the illumination component. However, illumination mutation may occur at the edge of an object in the image, thus the gradient variation in all directions around the pixels would be different. If the isotropic filter such as GF is used to estimate the illumination component, inaccurate results will be produced in the light mutation region, leading to halo defect[47]. In fact, we need to preserve the edges of illumination while smoothing the other small fluctuations unrelated to light. Thus, many studies have focused on estimating the illumination component by low-pass filters with anisotropic properties. Thus preserving the more edge image related to the light jump, and smoothing some useless details and textures independent of the light mutation. If BF is used to estimate the illumination component[50, 54, 56], the halo effect may be overcome to some extent. However, on the one hand, BF may be subjected to "gradient reversal" in image enhancement, that is because the global mapping is adopted in that method, the Gaussian weighted average is unstable if a pixel on an edge has few similar pixels around it, and the detail information of the illumination component will be lost. On the other hand, the efficiency of BF is poor. Wang et al.[43]put forward a bright-pass filter to estimate the illumination component, which was further optimized by using a relative illumination error function, thus preserving naturalness while enhancing image details. Sun et al.[44] proposed to estimate the illumination component using a guided image filter in gradient domain(GDGIF) and to correct by using gamma and sigmod functions, which effectively avoided edge artifacts and enhanced the contrast. Nevertheless, noise often exists in low illumination

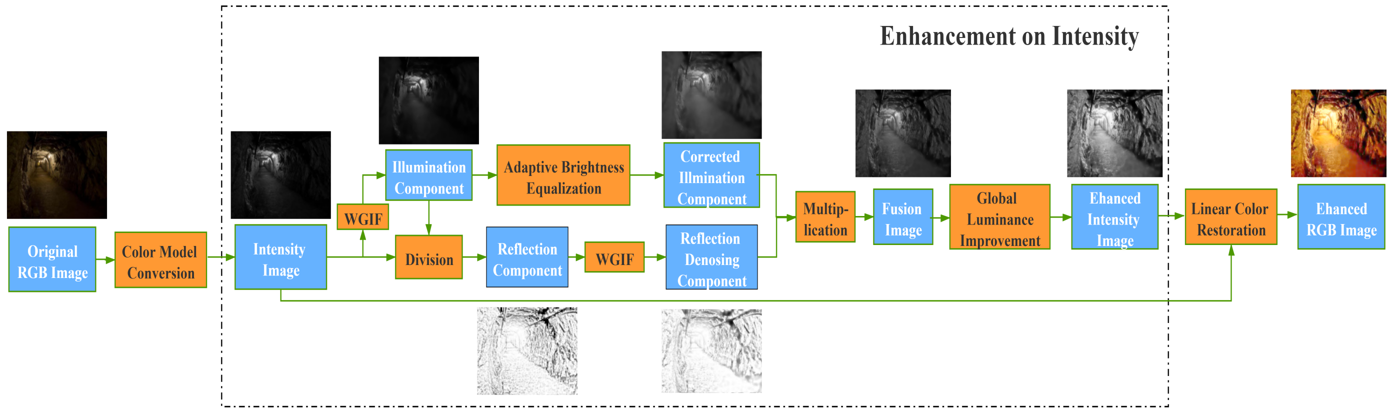


Fig. 1 The basic description of the proposed method, in which the orange box and the blue box are the operation methods and input or output images of each stage, respectively.

components, andnnoise amplification tends to occur after enhancement. To avoid noise amplification, Liu et al.[24] put forward a structure-revealing enhancement method based on the rubost retinex decomposition model, using fidelity terms, region smoothing terms, and structure information terms to construct an optimization function. This method can effectively suppress noise, but will cause the image to produce regional blurring, resulting in loss of detail information. Yu et al.[1] proposed a physical lighting model to recover low-illumination images. Having iteratively adjusted the environmental light and light-scattering attenuation rate by information loss constraint, WGIF is uesd to refine them, which effectively removes noise interference, highlights texture details, and maintains relatively natural colors.

GIF[12] is an image filtering method with anisotropic characteristics. It consists of a local linear transfer model between the guidance image and the output image, such that the gradient direction of the output image is the same as that of the guidance image to effectively avoid the gradient reversal problem in BF[28, 30]. The regularization hyper-parameter of the cost function is set by the user to determine the relative edge-preserving and smoothing effects of the image. Generally speaking, in “high variance” regions, lower regularization hyper-parameter values can be chosen to penalize the linear coefficients’ amplitudes. Whereas in “flat patch” regions, higher regularization hyper-parameter values are preferred to coerce lower approximation errors. However, this hyper-parameter is most often fixed for all local windows, and when the GIF is used to estimate the illumination component of the image, blurring edges could occur in windows with large texture differences. The WGIF[27] combines the advantages of both global and local filtering in that it adaptively adjusts this regularization hyper-parameter based on the variance of the current window. Therefore, the WGIF proposed in this paper can also be considered as the illumination component estimation by removing the noises from the reflection component.

3 Our method

In this paper, a novel color image enhancement method based on WGIF under low and non-uniform illumination is proposed. First, the original color image is transferred from RGB color model to HSI color model, and the Intensity, Hue and Saturation channels in HSI are obtained. We only use WGIF to estimate the illumination component of the intensity image and remove the noise contained in the reflection component. Ultimately, a linear color restoration method is used to transform the enhanced intensity image into the original RGB color model and obtain the final enhanced color image. The description of the proposed method is shown in Fig. 1. The area surrounded by the dashed box in the Fig. 1 is the core of the proposed method in this paper, which is the process of enhancing the original intensity image based on WGIF. Firstly, the WGIF is used to obtain the illumination component of the intensity image, and the adaptive brightness equalization methods of Gamma correction and linear stretching are used to process the obtained illumination results. Then, the reflection component is calculated by the illumination component, and the noise is also removed by WGIF. Finally, the new illumination component and reflection component are fused and the obtained result is globally enhanced. The flow of the proposed method in this paper is shown in Tab. 1.

Tab. 1 The Basic Procedure of the Proposed Method.

ALGORITHM: WGIF-Based Color Image Enhancement Method
Begin
1) Load original RGB color image $S(x,y)$, convert the original image to HSI color model, obtain Intensity Image $S_I(x,y)$.
2) **Enhancement on intensity image**
Compute and process illumination componet
① Use WGIF to estamate illumination component of intensity: $S_{ILi}(x,y) = \overline{a}_i S_{Ii}(x,y) + \overline{b}_i$
Adaptive brightness equalization
② Corrected the illumination component by adaptive Gamma fuction function: $S_{ILG}(x,y) = (S_{IL}(x,y))^{\phi(x,y)}$
③ Global linear stretching: $S_{ILGf}(x,y) = \frac{S_{ILG}(x,y) - min(S_{ILG}(x,y))}{max(S_{ILG}(x,y)) - min(S_{ILG}(x,y))}$
Compute and process reflection component image
④ Compute reflection component: $S_{IR}(x,y) = \frac{S_I(x,y)}{S_{IL}(x,y)}$
⑤ Denoise reflection component by WGIF: $S_{IRHi}(x,y) = \overline{a}_i S_{IR}(x,y) + \overline{b}_i$
3) **Image Fusion**
Fuse the processed illumination component and reflection component
①get the enhanced intensity image: $S_{IE}(x,y) = S_{ILGf}(x,y) \times S_{IRH}(x,y)$
②Improve the brightness of the fused image by the S-hyperbolic tangent function:
$b = \frac{1}{m*n}\sum_{x=1}^{m}\sum_{y=1}^{n} S_{IE}(x,y) \qquad S_{IEf}(x,y) = \frac{1}{1+e^{-8*(S_{IE}-b)}}$
4) **Color Restoration**
① Calculate brightness gain coefficient: $\alpha(x,y) = \frac{S_{IEf}(x,y)}{S_I(x,y)}$
② Convert the enhanced HSI image to RGB color model by color linear restoration process.
$R_1(x,y) = \alpha(x,y)R_0(x,y) \qquad G_1(x,y) = \alpha(x,y)G_0(x,y) \qquad B_1(x,y) = \alpha(x,y)B_0(x,y)$
End

From the description and flow charts(Fig. 1&Tab. 1) of the proposed method, it can be seen that the image enhancement of intensity channel and the linear restoration algorithm are the key points of the proposed method in this paper. Here, the enhancement process of the intensity image mainly consists of illumination estimation, local brightness enhancement and image fusion. The details will be described below.

3.1 Illumination Estimation

WGIF is applied to estimate illumination component in the proposed method. Both the guide and input images are intensity image S_I, and output $\widehat{q}_i$ is the estimated illumination component, which is marked as S_{IL}.

$$S_{ILi}(x,y) = \widehat{q}_i(x,y) = \overline{a}_k S_{Ii} + \overline{b}_k, \forall i \in w_k \qquad (2)$$

where a_k and b_k are the linear coefficients. Its cost loss function is:

$$\mathrm{E}(\mathrm{a}_k, b_k) = \sum_{i \in w_k}((a_k S_{I_i} + b_k - p_i)^2 + \frac{\varepsilon}{\Gamma_{S_I}(i)} a_k^2) \qquad (3)$$

Where ε is a regularization factor penalizing large a_k, which determines the criterion of a “flat path” or a “high variance” area. An edge-aware weighting $\Gamma_{S_I}(i)$ is defined in the local window w_k centered on the pixel i as follows:

$$\Gamma_{S_I}(i) = \frac{1}{N}\sum_{i'=1}^{N} \frac{\sigma_{I,1}^2(i) + \zeta}{\sigma_{I,1}^2(i') + \zeta} \qquad (4)$$

Where I is the guidance image, $\sigma_I^2(\cdot)$ is the variance of I in the 3×3 local window, and N is the number of pixels; ζ is a constant and its value is selected as $(0.001L)^2$. while L is the dynamic range of input image, and i' takes all pixels of the image.

For the pixel i in the high variance region with large texture variation and rich information, the corresponding edge weight $\Gamma_{S_I}(i)$ is larger, so the smaller regularization term $\frac{\varepsilon}{\Gamma_{S_I}(i)}$ is obtained in Eq. (3), and the edge of the image can be preserved well. If pixel i is at flat area, the edge weight factor $\Gamma_{S_I}(i)$ is smaller, so a greater $\frac{\varepsilon}{\Gamma_{S_I}(i)}$ is obtained, thus the smoothing effect is more obvious.

Thanks to the adaptive adjustment of the regularization term is implemented, the solution of the linear coefficient of the WGIF is more stable than the GIF. Estimating the illumination component of the image by WGIF not only better preserves the edge details of the image, but also avoids the appearance of artifact edge in the image, and the reflection component can be also calculated more accurately. Besides, the computational complexity of the WGIF is the same as the GIF, which is also $O(N)$.

In classic Retinex algorithms, Eq. (1) is transformed into logarithmic domain, and multiplication is transformed into addition. This operation can simplify the calculation process, but may cause the loss of gray information of the image. Therefore, the reflection component is S_{IR} obtained directly from the estimated illumination component S_{IL} according to Eq. (1):

$$\mathrm{S}_{IR}(x,y)=\frac{S_I(x,y)}{S_{IL}(x,y)} \tag{5}$$

3.2 Adaptive Brightness Equalization

To avoid gray information being lost, the proposed method does not directly remove the illumination component in the logarithmic domain, but corrects the illumination component.The brightness of the estimated illumination component S_{IL} itself is often very low, so the proposed method uses adaptive Gamma correction function[37] to correct S_{IL}, which maps the input dark color in a narrow range to a wider range, and obtains the corrected illumination component S_{ILG}. Its expression is:

$$\mathrm{S}_{ILG}(x,y)=S_{IL}(x,y)^{\phi(x,y)} \tag{6}$$

$$\phi(x,y)=\frac{S_{IL}(x,y)+a}{1+a} \tag{7}$$

$$a\text{=1-1/}m\text{*}n\sum_{x=1}^{m}\sum_{y=1}^{n}S_{IL}(x,y) \tag{8}$$

Where $S_{ILG}(x,y)$ is corrected illumination component, m,n are the height and width of the original image, respectively. $\phi(x,y)$ is Gamma correction function, and parameter a is the gray mean value of S_{IL}.

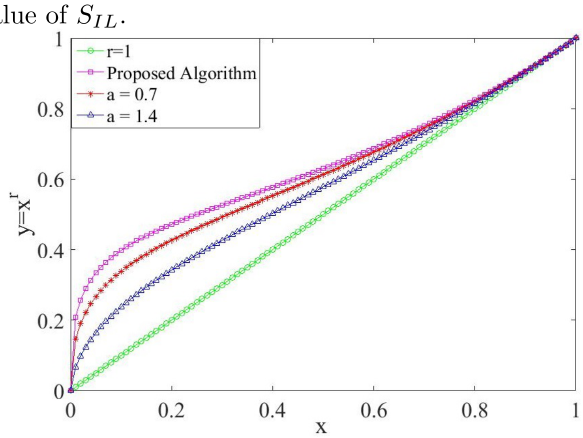


Fig. 2 Curve of Adaptive Gamma Correction(comparison of adaptive parameter a with fixed parameter $a = 0.7$ and $a = 1.4$)

It can be seen from Eq. (6), Eq. (7) and Eq. (8) that the parameters of Gamma correction can be adaptively adjusted by the values of illumination components in the proposed method. The intensity values are obviously enhanced in the dark region, while in the bright region the enhancement is suppressed. Thus, the more details can be exhibited in dark areas, and the over-enhancement wouldn't occur in the bright area. The curve of adaptive Gamma brightness correction function is shown in Fig. 2. Where $y = x^r$ denotes Gamma correction function, $r = \frac{x+a}{1+a}$ refers to the parameter value of Gamma function, $a = 1 - \sum_{i=1}^{n} x_i$ is the mean of input x.

After the adaptive Gamma correction, the dark area of the image is effectively enhanced, and the dynamic range of the image is also compressed, so the contrast of the image is reduced. It is necessary to enhance the global contrast of the brightness-adjusted image. Thus the corrected illumination component S_{ILG} is stretched linearly to obtain the result image S_{ILGf}.

$$\mathrm{S}_{ILGf}(x,y)=\frac{S_{ILG}(x,y)-min(S_{ILG}(x,y))}{max(S_{ILG}(x,y))-min(S_{ILG}(x,y))} \tag{9}$$

Here, max and min represent the evaluation functions of the minimum and maximum values of the pixels in the image S_{ILG}, respectively.

3.3 Image Fusion

Noise must be removed for avoiding its amplification before image fusion. Since noise mainly exists in the reflection component S_{IR} , the reflection component S_{IR} obtained by Eq. (5) is processed by WGIF, and the denoised reflection component is S_{IR}.

$$\mathrm{S}_{IRH}=\widehat{q}_{S_{IR_i}}=\overline{a}_iS_{IR}+\overline{b}_i \tag{10}$$

Then, the processed illumination component S_{ILGf} is multiplied with the denoised reflection component S_{IRH} to get the fused intensity image S_{IE}.

$$\mathrm{S}_{IE}(x,y)=S_{ILGf}(x,y)*S_{IRH}(x,y) \tag{11}$$

Finally, the S-hyperbolic tangent function[13] is used to improve the brightness of the fused image S_{IE}, and the enhanced intensity image S_{IEf} is obtained.

$$\mathrm{S}_{IEf}(x,y)=\frac{1}{1+e^{-8*(S_{IE}-b)}} \tag{12}$$

$$b\text{=1/}m\text{*}n\sum_{x=1}^{m}\sum_{y=1}^{n}S_{IE}(x,y) \tag{13}$$

Where b is the mean intensity value of S_{IE}, m and n are the height and width of image S_{IE}, respectively.

3.4 Color Restoration

After the above steps, the enhanced intensity image is obtained, it is necessary to be re-converted to RGB color model before the final enhancement output. Therefore, in order to avoid the color distortion caused by the inconsistent increase of RGB channels[10], the brightness gain coefficient α[6, 10, 16] is calculated from the original and enhanced intensity images by a linear method as follows:

$$\alpha(x,y)=\frac{S_{IEf}(x,y)}{S_I(x,y)} \tag{14}$$

Then, α is adopted to convert the enhanced image back to the RGB color model, which preserves the linear proportion of the original and enhanced color images in the RGB channels. The linear color restoration process is shown in the Eq. (15).

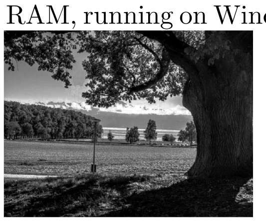
$$\begin{cases} R_1(x,y) = \alpha(x,y)R_0(x,y) \\ G_1(x,y) = \alpha(x,y)G_0(x,y) \\ B_1(x,y) = \alpha(x,y)B_0(x,y) \end{cases} \tag{15}$$

Where it is assumed that the RGB three-channels of original and enhanced color images are $[R_0, G_0, B_0]$ and $[R_1, G_1, B_1]$, respectively.

Moreover, the time cost of color model conversion is also reduced.

4 Results and discussion

In order to verify the effectiveness of proposed method, the experiments of illumination estimation, reflection denoising and image enhancement are carried out in this paper. MATLAB 2019b is adopted for programming, and a computer with an eight-core CPU, Intel 3.6GHz, 8G RAM, running on Windows 10 is used.



(a) Original Image

(b) Image filtered by GF

(c) Image filtered by BF

(d) Image filtered by GIF

(e) Image filtered by WGIF

Fig. 3 Comparison of the estimated illumination component by GF, BF, GIF and WGIF.

4.1 Experiment of Illumination Estimation

In order to verify the effect of WGIF in estimating illumination component, we use GF, BF, GIF and WGIF to estimate illumination component and reflection component of a image, respectively. The results of illumination estimation experiment are shown in Fig. 3 and Fig. 4.

(a) Original Image

(b) GIF

(c) WGIF

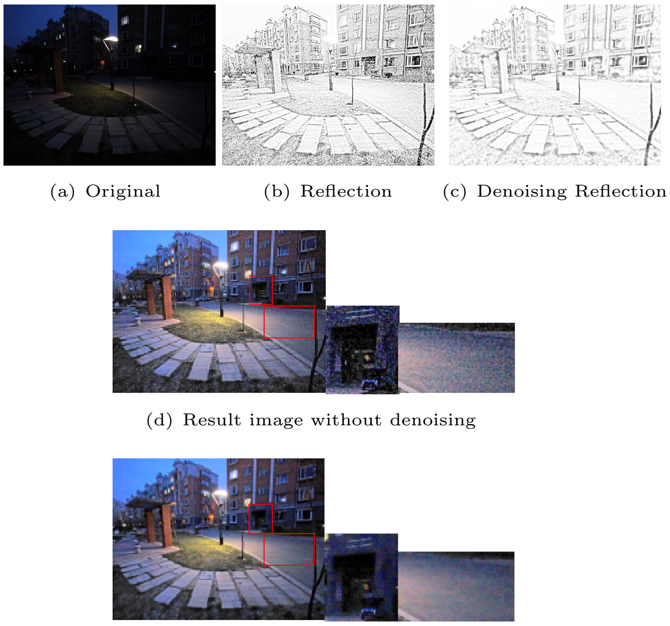
Fig. 4 In HSI color space, the illumination component and reflection component estimated by GIF and WGIF are only for I channel.

Fig. 3 illustrates some examples of the estimated illumination by different image filters. It can be observed that the result of GF is blurring at the step edge, which would lead to halo. The edge preserving effects of BF and GIF are better than that of GF, but many details unrelated to light are also preserved. In the result of WGIF, the strong edges are well preserved while the weaker textures are smoothed. Therefore, more accurate illumination component can be obtained using WGIF compared to other filters mentioned above.

Fig. 4 is the result of illumination component and reflection component obtained by using GIF and WGIF for intensity image S_I. Among them, Fig. 4(a) is intensity channel image. Fig. 4(b) and Fig. 4(c) show the illumination and reflection components obtained by GIF and WGIF. It can be seen that the illumination component estimated by GIF preserves more detailed textures, thus there are few details in the reflection component. By comparison, the illumination component estimated by WGIF is clear at the step edge, while the more details are preserved in the reflection component.

4.2 Experiment of Reflection denoising

To verify whether the reflection component denoising affects the enhancement results, the reflection component is denoised and not denoised respectively to observe the result image. The experimental results are shown in Fig. 5. Fig. 5(a)-Fig. 5(e) show the original image, the reflection component, the denoised



(a) Original (b) Reflection (c) Denoising Reflection

(d) Result image without denoising

(e) Result image with denoising

Fig. 5 The effect of reflection component denoising and non-denoising on the result images.

reflection component, the result image without denoising, and the result image after denoising in turn. From Fig. 5, it can be seen that there is a lot of noise in the reflection component because the original image was taken in low illumination. After denoising the reflection component using WGIF, most of the noise in the ground and the entrance of right unit building is removed, and the result after denoising is obviously better than the result image before denoising.

4.3 Experiment of Image Enhancement

In this paper, low-light color images and grayscale images with uniform and non-uniform illumination in different scenes are used as experimental objects. To ensure the diversity of data sources, we randomly select some public datasets of color images from NASA Research Center, LIME-Data (Low-light Image Enhancement-Data)[11], DICM (DIgital CaMeras)[22], and MEF (Multi-Exposure image Fusion)[32]. For enhancement of grayscale images, CMU-PIE and YaleB face databases are used as the experimental objects, with Face1 and Face3 from CMU-PIE dataset, and Face2 and Face4 from YaleB dataset. In our work, we only care about the illumination problem, thus we just select Face2 and Face4 with same pose ($P00$) and different light ($0^\circ - 77^\circ$) from the YaleB face dataset.

For the color enhancement algorithms, the proposed method is compared with traditional and deep learning-based methods, including MSR[14], MSRCR[39], CLAHE[26], NPE[43], Liu[24]; RetinexNet[49], GladNet[48], KinD[55], respectively. And for the grayscale image enhancement algorithms, the proposed method is compared with SSR[15], MSR[14] and CLAHE[26]. To ensure the fairness of the experiments, the relevant methods are downloaded from the authors' website, and the default parameters in the authors' article are used for the comparison experiments. The parameters for our experiment are set as follows: the window radius $r = 5$, and regularization factor $\varepsilon = 0.1^2$, $\zeta = 0.065536$ constant in the WGIF.

4.3.1 Subjective Evaluation

Fig. 6 and Fig. 8 respectively show the results of the proposed method and the traditional methods under uniform and non-uniform low-illumination color images. Fig. 7 is the zoom-in patch of the image in Fig. 6. Fig. 9 shows the results of the proposed method and deep learning-based methods. Due to the limitation of space, only the representative results under various illuminations are shown.

It can be seen that the brightness enhancement effect of MSR algorithm is distinctive, while MSR algorithm over enhances the image, resulting in the losing of some details in the brighter area, the occurring of strong noise, and the appearing of obvious halo in the step edge (the sky in the Tower image of Fig. 6, the clouds in the Girl image of Fig. 8). Compared to MSR algorithm, MSRCR algorithm improves brightness and preserves the color. However, the contrast of the enhanced image is low and some details are lost. Moreover, MSRCR is subject to the most severe halo (the chandelier in the Coffee House image of Fig. 6, the candle wick in the Candle image of Fig. 8). Though the CLAHE algorithm has appropriate brightness enhancement and is close to the true color, it may appear blur and color disorders in the dark and detailed information areas (the wooden floor in the Factory image of Fig. 6, the idol of the Madison image in Fig. 8). The enhanced images of NPE, Liu[24] and the proposed method are obviously better than others in terms of visual effects, and the images are more natural and realistic. However, some of the images enhanced by the NPE are too vivid in color and the noise is amplified, resulting in the loss of some detailed information and severe halo (the robot arm in the Robot image of Fig. 6, the wall and light in the Factory image of Fig. 8). The enhanced image of Liu[24] has natural colors and effectively removes noise interference, but causes some blurred details.(the distant tall buildings in the Apartment image of Fig. 6, the stone gate in the Eiffel Tower image of Fig. 8).

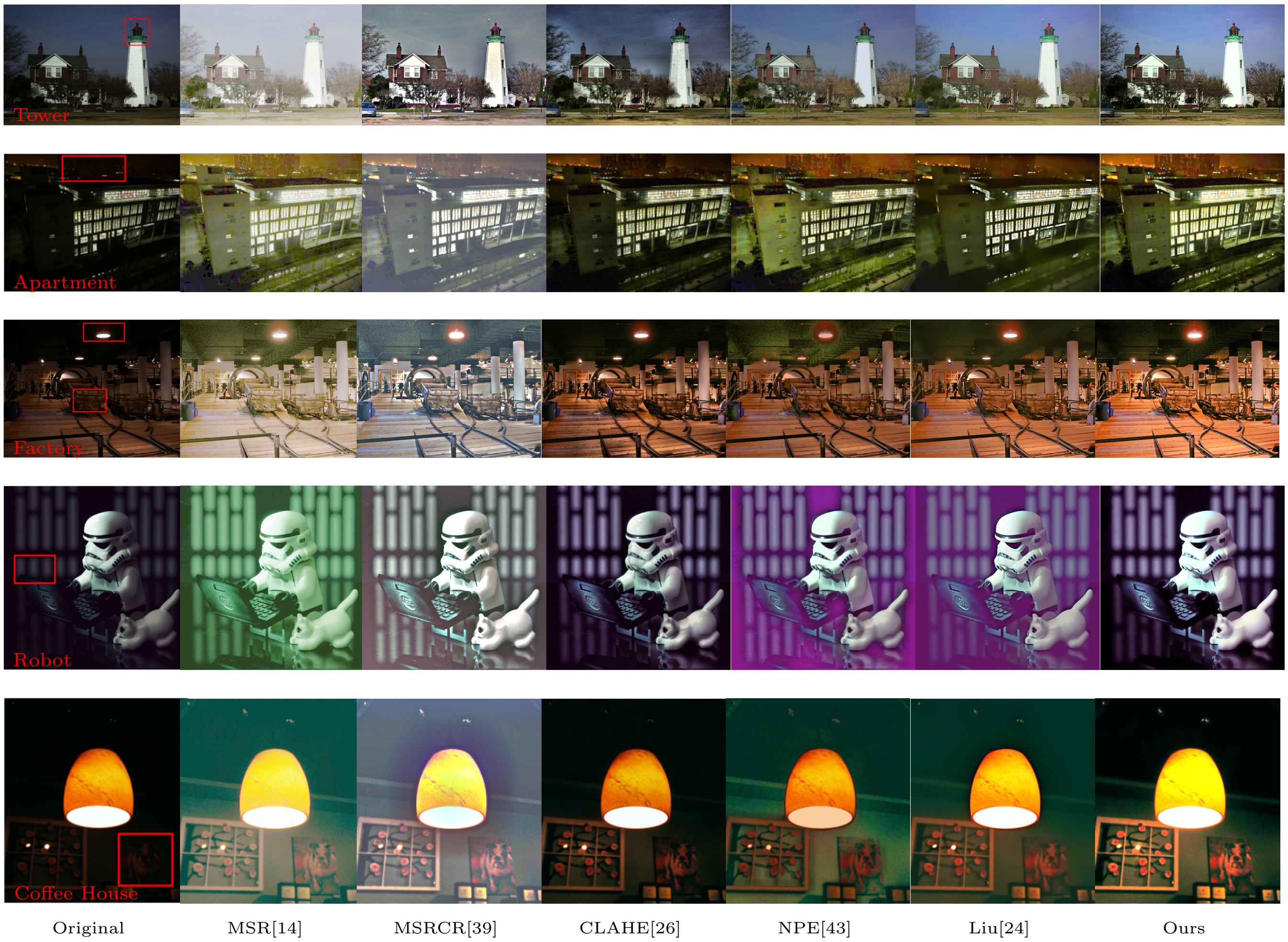


Fig. 6 Comparison of the proposed method with the traditional methods on low illumination color images with uniform light, where the leftmost column is the original image, with the name in the left corner and the detail display area in the red box in Fig. 7

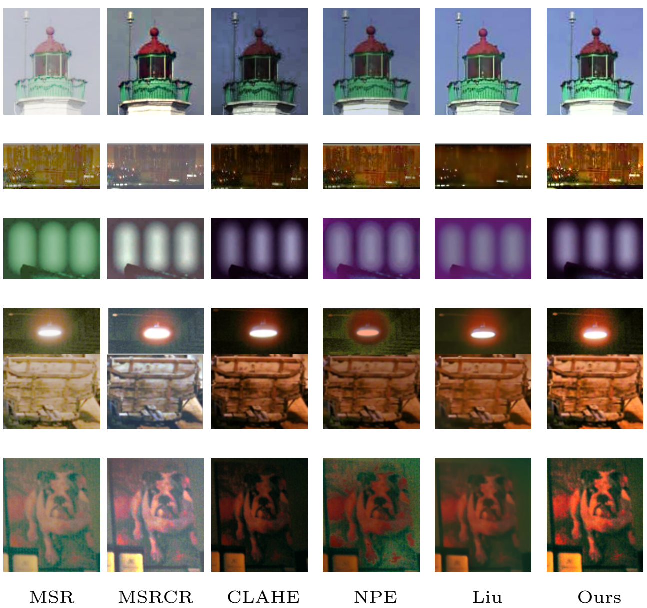


Fig. 7 Detailed display of Image Enhancement of Fig. 6.

As shown in Fig. 9, the RetinexNet algorithm effectively improves the overall brightness of the image, but the noise is obviously amplified after the enhancement, resulting in serious color distortion and poor visual effect. Compared with RetinexNet, the brightness of GladNet and KinD algorithms are improved appropriately, and the details of dark areas are clear, but the color of the enhanced image is unsaturated and the overall contrast is low.

Combined with the detail in Fig. 7, it can be seen that the proposed method adaptively improves the local brightness and contrast with effectively enhancing of the dark area and well-preserved details of bright area. In addition, the halo problem is also avoided, the noise is not significantly amplified, and the color of the enhanced image is vivid and natural. However, the detail enhancement effect is poor when the light is extremely non-uniform and the dark area is too dark (the bookshelf in the Cadik image of Fig. 8).

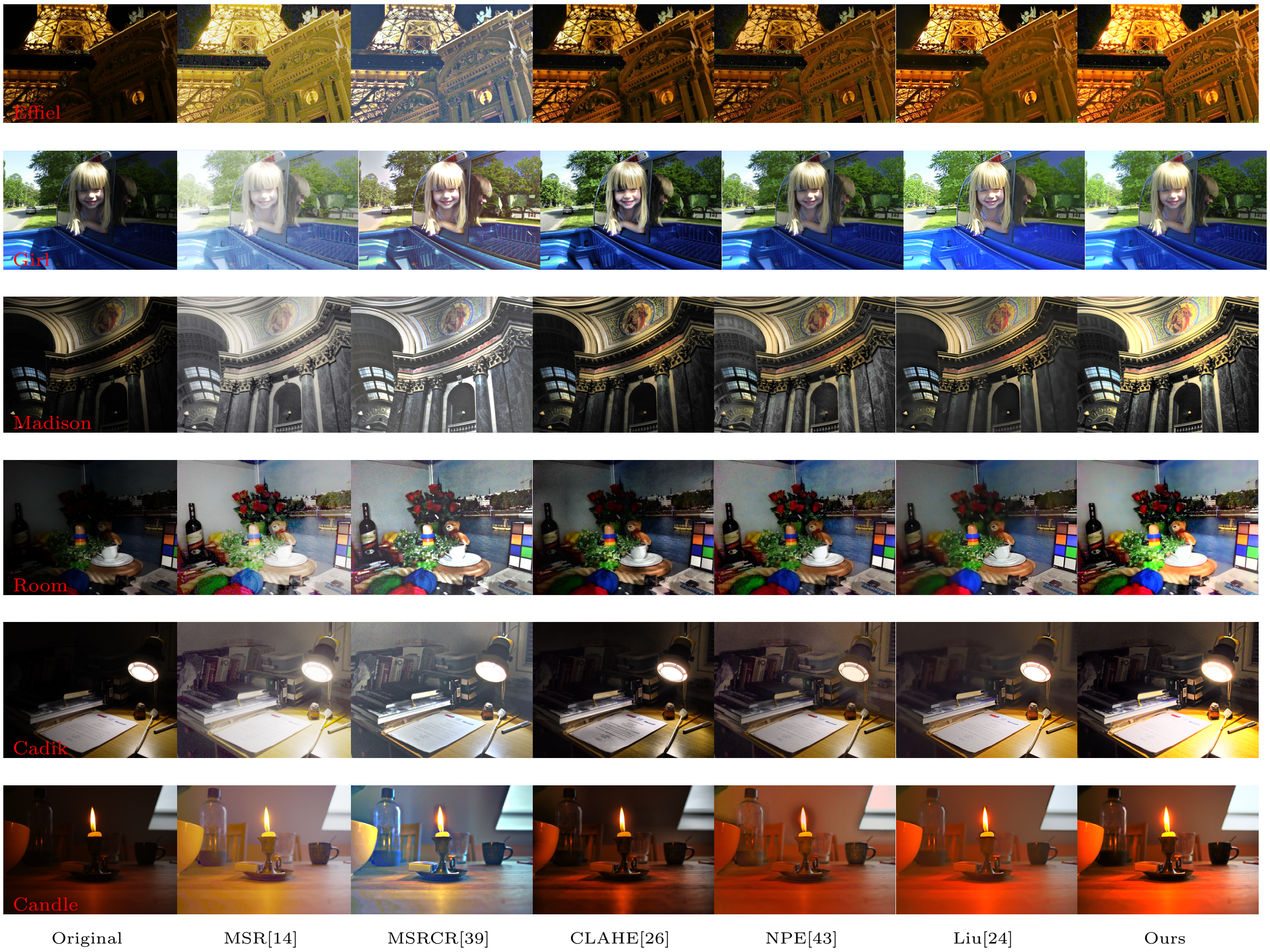


Fig. 8 Comparison of the proposed method with the traditional methods on low illumination color images with non-uniform light.

Fig. 10 and Fig. 11 are the results of the low illumination grayscale image enhancement with uniform and non-uniform lighting, respectively. Fig. 12 is the zoom-in patch of the Face1 image in Fig. 10.

It can be seen from Fig. 10 and Fig. 12 that SSR algorithm improves the brightness of images under uniform illumination, but its effect is poor with amplified noise under non-uniformly illumination. The MSR algorithm over enhances the image, thus the contrast is decreased, and some details are lost. It can be observed that the noticeable halo appears in the sharp edge (as shown in Fig. 12), and the noise is very obvious. The enhanced image of CLAHE has clearer details of the face, but its tones are unevenly with halos at the edges. By comparison, the proposed method improves both brightness and contrast, resulting in a bright and clear image. For images under very non-uniform lighting, however, the enhancement effect in dark area is still limited.

Fig. 13 is the scan results of the 30th line pixel of image Face1 processed by the aforementioned algorithms. It can be seen that the pixel intensity values in the original image are the lowest. Hopefully, they are improved significantly after being processed by SSR, MSR, CLAHE and the proposed method. Among them, MSR algorithm improves the brightness values maximally, but the curve of the line is the flattest, meaning the image contrast is the lowest. SSR and CLAHE algorithms have poor smoothing effect in the low frequency region, that is, the effect of de-noise is poor. The proposed method improves the intensity values significantly in the high frequency region, while in the low frequency region they are well smoothed. Thus the details in the dark areas are presented and the noises are removed. In addition, it can be seen from the figure that the brightness is moderately improved using the proposed method.

Fig. 9 Comparison of the proposed method and deep learning-based methods in different images.

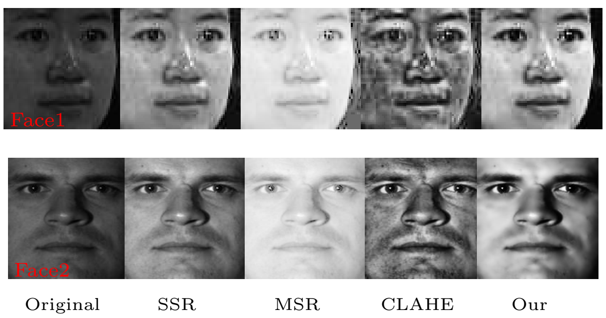


Fig. 10 Low illumination grayscale image enhancement with uniform Light.

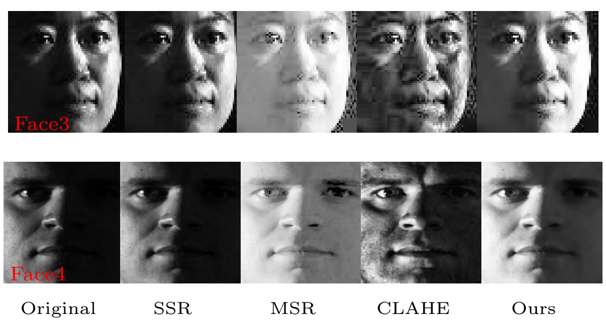


Fig. 11 Low illumination grayscale image enhancement with non-uniform light.

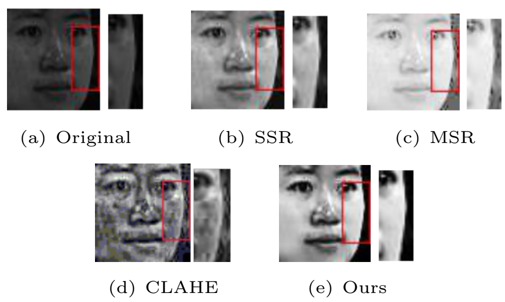


Fig. 12 Enhancement detail contrast of Face1

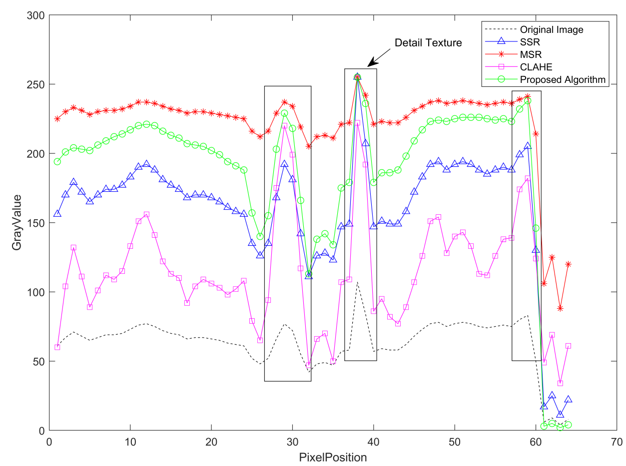


Fig. 13 Pixel Scan Results of the 30th Line of Image Face1

Tab. 2 Objective quality evaluation of different enhancement methods for low illumination color images with uniform light.

Method \ Indicators		Information Entropy	ΔB	ΔC	ΔH	Avergae Gradient	Edge Intensity	$Std \times Gray (\times 10^4)$
Tower/Apartment	Original	6.64/5.44	\	\	\	3.69/8.04	32.48/63.78	9.72/3.69
	MSR	6.68/7.29	**2.09**/3.80	-0.09/0.70	0.0016/0.0600	4.86/11.77	41.09/88.58	24.09/27.10
	MSRCR	7.12/6.27	1.18/**4.94**	0.61/0.11	0.0199/1.4140	8.53/10.49	74.39/83.24	34.80/22.13
	CLAHE	7.07/6.67	0.67/0.96	0.13/0.57	\	5.11/12.10	67.67/94.05	13.14/11.72
	NPE	6.73/7.25	0.74/2.33	-0.06/0.49	0.0214/0.0005	5.77/15.15	48.55/113.66	14.79/20.17
	Liu[24]	6.99/6.63	1.11/1.62	0.19/0.82	**0.0011**/0.0932	5.89/13.37	50.98/104.89	21.51/17.42
	RetinexNet	6.84/7.36	1.30/3.14	-0.34/0.09	0.0038/0.0084	**13.72/20.94**	**76.74/140.78**	15.05/18.04
	GladNet	7.19/7.12	1.02/1.77	0.33/0.83	0.0459/0.0309	7.66/12.32	57.86/96.97	24.21/18.29
	KinD	7.05/7.22	1.01/1.81	-0.15/0.50	0.0299/0.0823	8.23/10.62	64.63/90.35	17.28/14.94
	Ours	**7.37/7.49**	1.13/2.88	**0.95/1.84**	0.0013/**0.0001**	6.47/**17.35**	56.41/134.99	**37.24/43.47**
Robot/Factory	Original	5.77/6.03	\	\	\	2.42/4.08	24.67/33.47	6.43/2.26
	MSR	5.57/6.84	4.33/1.54	1.01/-0.51	0.3250/0.0350	**8.12**/9.17	68.49/66.06	16.55/39.33
	MSRCR	7.14/7.40	**4.59**/0.92	1.32/-0.36	3.4170/0.0680	7.35/10.83	**68.86**/77.37	17.59/38.96
	CLAHE	6.91/7.13	0.64/1.12	0.75/1.94	\	4.64/9.55	47.21/75.43	17.89/14.24
	NPE	7.00/6.91	1.85/1.36	-0.08/0.76	**0.0010/0.0123**	4.61/10.85	44.86/75.67	19.23/9.41
	Liu[24]	6.73/7.12	1.75/1.75	-0.16/1.63	0.0016/0.0470	3.70/7.39	36.45/64.88	17.72/16.11
	RetinexNet	6.85/7.06	2.25/2.33	-0.23/0.69	0.0060/0.0179	5.76/**17.53**	51.84/111.91	20.28/11.64
	GladNet	7.02/7.55	1.45/2.61	0.38/3.86	0.0479/0.1644	4.22/11.61	42.03/86.73	22.93/36.36
	KinD	6.98/7.23	1.18/2.21	0.09/2.81	0.0227/0.0425	4.68/7.08	47.77/64.99	15.84/27.36
	Ours	**7.24/7.50**	1.05/**2.72**	**1.91/5.69**	0.0023/0.0360	5.02/15.06	51.44/**114.67**	**36.91/57.97**
Coffee House	Original	4.26	\	\	\	1.44	12.42	9.28
	MSR	5.55	2.82	-0.07	0.0400	4.83	32.98	31.29
	MSRCR	6.22	**3.98**	-0.44	0.6200	4.50	33.64	26.26
	CLAHE	5.45	0.31	-0.08	\	2.88	22.27	10.94
	NPE	5.68	1.22	-0.41	0.0300	4.45	29.59	12.77
	Liu[24]	5.91	1.27	-0.12	**0.0190**	2.01	19.05	19.18
	RetinexNet	6.12	2.43	-0.38	0.0053	**7.33**	**44.12**	18.34
	GladNet	6.00	0.82	0.14	0.1100	2.94	23.08	18.39
	KinD	6.21	1.27	-0.08	0.1790	2.25	22.67	19.15
	Ours	**6.30**	1.18	**0.48**	0.0200	4.31	35.31	**33.60**

4.3.2 Objective Evaluation

In this section, some objective criteria such as information entropy, brightness, contrast, mean gradient, edge intensity, and the $Std \times Gray$[16] are adopted to evaluate the different enhancement algorithms. To calculate $Std \times Gray$, each image is divided into several non-overlapping blocks with the same size, the average deviations and average gray of all blocks are calculated, and the product of the two averages is $Std \times Gray$. The greater the value of $Std \times Gray$, the higher the quality of the image.

In order to evaluate color image, the indicators ΔB[16], ΔC[16] and ΔH[38] are used to measure the change rates of the brightness, contrast, and hue. The calculation equations are as follows:

$$\Delta B = \frac{Mean(I_{out}) - Mean(I_{in})}{Mean(I_{in})} \tag{16}$$

$$\Delta C = \frac{Var(I_{out}) - Var(I_{in})}{Var(I_{in})} \tag{17}$$

$$\Delta H = \left| \frac{Mean(H_{out}) - Mean(H_{in})}{Mean(H_{in})} \right| \tag{18}$$

The objective evaluation results of the color and grayscale image enhancement in low illumination environment are shown in Tab. 2 - Tab. 4, respectively. Here, the bold fonts represent the best result in each group of experiments. The ΔH of the CLAHE denoted by '\' and is not discussed here, because the CLAHE used in this paper processes only the intensity channels in HSI and keeps the hue change ratio close to 0.

It can be seen that compared to other algorithms, the information entropy, ΔC and $Std \times Gray$ of the proposed method are obviously superior, and the results of ΔB, ΔH, average gradient and edge intensity of color images are optimal or close to optimal on most images. Therefore, the proposed method not only retains rich detail information but also has good color fidelity while significantly improving brightness and contrast. The color images processed by MSR, MSRCR and RetinexNet have larger ΔB, average gradient and edge intensity, and the image brightness is significantly improved to show more details in dark areas, but the ΔH is generally too large and the color bias is more serious. The color fidelity of NPE and Liu[24] algorithms is relatively good, but the detail performance ability, brightness and contrast improvement are slightly inferior to the proposed method and MSRCR. The brightness of the grayscale images processed by the proposed method is lower than that of the MSR, but combined with the visual effect, it is shown that just increasing brightness would lead to over enhancement instead of better enhancement results.

Tab. 5 shows the average time for processing low-

Tab. 3 Quality evaluation of different enhancement methods for low illumination color images with non-uniform light.

Method \ Indicators		Information Entropy	ΔB	ΔC	ΔH	Avergae Gradient	Edge Intensity	$Std \times Gray(\times 10^4)$
Effiel/Girl	Original	6.19/7.14	\	\	\	8.10/8.82	65.19/67.01	6.92/30.77
	MSR	7.18/7.31	2.90/**1.59**	0.47/-0.58	0.6500/0.0351	12.84/9.09	95.47/65.46	33.9/34.06
	MSRCR	7.09/7.45	**3.32**/0.92	0.29/-0.36	2.6400/0.0694	13.45/**15.34**	108.42/114.49	30.84/38.92
	CLAHE	7.19/7.62	0.93/0.30	0.47/-0.07	\	13.29/12.44	106.57/92.87	19.26/38.49
	NPE	6.92/7.48	0.82/0.37	-0.23/-0.22	**0.0100/0.0002**	11.20/11.47	87.72/85.07	10.03/34.32
	Liu[24]	7.31/7.53	1.36/0.83	0.45/-0.25	0.1600/0.0093	13.02/13.75	102.68/97.99	23.46/44.26
	RetinexNet	6.98/7.60	2.59/0.83	-0.20/-0.46	0.0290/0.0182	**15.95/17.84**	114.95/**122.76**	11.85/36.40
	GladNet	7.40/7.62	2.45/0.38	1.04/-0.06	0.3809/0.0386	12.14/10.23	97.23/79.27	23.41/40.37
	KinD	7.44/7.66	2.31/0.62	0.57/-0.26	0.3518/0.0293	9.54/12.21	86.09/98.06	19.57/40.27
	Ours	**7.60/7.69**	2.00/0.62	**0.74/0.16**	0.0400/0.0076	14.52/14.81	**116.33**/111.65	**38.95/62.14**
Madison/Room	Original	5.75/6.01	\	\	\	5.79/2.97	45.82/25.92	3.22/2.72
	MSR	6.28/7.32	3.94/3.96	1.45/2.62	1.1100/0.1642	11.36/8.68	86.02/69.37	35.23/47.24
	MSRCR	7.04/7.38	**4.03/3.77**	1.52/1.78	0.9500/0.3200	13.54/**9.98**	107.25/83.72	35.77/36.18
	CLAHE	6.89/7.04	1.03/1.04	1.23/1.06	\	11.51/6.78	89.76/56.76	14.80/11.64
	NPE	7.26/7.31	2.13/2.15	0.97/1.65	**0.0041**/0.0043	15.18/8.18	112.44/66.86	19.91/22.31
	Liu[24]	7.21/7.03	1.71/1.91	1.07/0.95	0.0194/0.0352	11.41/5.55	89.43/50.67	18.20/15.21
	RetinexNet	7.31/7.45	3.01/3.16	0.31/1.55	0.0988/0.0142	**20.11/12.73**	**135.88/93.71**	16.99/27.89
	GladNet	7.42/7.68	2.42/2.85	2.18/2.45	0.2669/0.0328	12.35/8.03	98.32/68.40	32.47/34.72
	KinD	7.25/7.46	1.80/2.35	1.27/2.30	0.1819/0.0593	10.55/6.39	91.27/58.97	19.65/29.95
	Ours	**7.21/7.68**	2.78/3.26	**3.87/3.31**	0.0139/**0.0031**	16.88/8.73	131.89/74.37	**60.99/50.79**
Cadik/Candle	Original	5.85/5.90	\	\	\	2.99/1.14	24.99/10.48	13.83/4.52
	MSR	7.33/7.02	**2.75/3.09**	-0.01/0.12	0.2500/3.2500	6.21/2.44	42.23/18.86	52.57/19.52
	MSRCR	7.28/7.34	2.71/3.15	-0.08/0.15	0.7377/5.2600	7.33/**4.21**	53.27/**33.77**	35.80/24.57
	CLAHE	6.73/6.53	0.62/0.42	-0.08/0.06	\	5.48/2.49	42.05/20.84	19.77/6.88
	NPE	7.31/6.67	1.31/1.73	0.23/0.03	0.0041/0.2500	6.94/2.61	47.99/19.85	22.42/12.47
	Liu[24]	7.03/6.74	1.25/1.80	0.07/0.02	0.0043/0.0750	4.43/1.53	36.40/14.87	34.39/12.63
	RetinexNet	7.36/6.55	1.72/2.28	-0.39/-0.32	0.0858/0.0266	**11.09**/3.53	**68.04**/24.39	24.00/9.68
	GladNet	7.28/7.09	1.06/1.92	0.59/0.55	0.1701/0.5919	5.20/2.37	41.31/19.99	44.89/19.94
	KinD	7.33/6.94	0.99/1.66	0.18/0.01	0.3553/0.2000	4.18/1.79	37.60/18.27	32.71/12.40
	Ours	**7.38/7.46**	1.90/1.99	**0.53/1.04**	**0.0034/0.0036**	7.01/2.94	52.53/25.23	**72.24/28.57**

Tab. 4 Quality evaluation of different enhancement methods for low illumination grayscale images.

Method \ Indicators		Information Entropy	Brightness	Contract	Avergae Gradient	Edge Intensity	$Std \times Gray(\times 10^4)$
Face1/Face2	Original	6.11/6.62	48.94/65.59	20.36/25.58	5.24/2.97	44.71/27.78	2.03/4.29
	SSR	6.13/6.64	126.09/117.55	50.10/42.08	12.72/4.88	108.32/45.70	31.65/20.82
	MSR	5.99/6.18	**204.16/205.43**	38.49/25.04	9.22/3.07	71.65/27.74	30.24/12.88
	CLAHE	7.39/7.41	105.52/103.98	46.72/42.00	13.88/4.99	126.27/51.91	23.03/18.34
	Ours	**7.48/7.78**	143.91/128.97	**65.16/63.77**	**15.94/5.22**	**139.81/54.04**	**70.33/52.45**
Face3/Face4	Original	6.79/6.32	64.06/46.69	71.73/46.81	14.20/2.76	118.31/26.11	39.26/10.23
	SSR	6.72/6.42	74.31/65.00	74.75/60.69	14.79/3.51	122.64/33.29	41.52/23.94
	MSR	6.28/6.08	**163.32/156.26**	53.13/53.59	13.27/3.58	96.32/33.50	46.09/44.87
	CLAHE	7.05/7.21	93.22/74.28	62.74/61.77	13.50/4.02	121.48/44.19	36.69/28.34
	Ours	**7.16/7.33**	100.20/116.85	**90.45/82.17**	**16.32/4.75**	**137.18/46.46**	**81.96/78.90**

illumination images on the LTSM dataset using the comparsion algorithms. It can be seen that the average time for processing each image by the proposed method is longer than that of MSR and CLAHE, but significantly shorter than that of MSRCR, NPE, Liu[24], and the deep learning-based methods. The deep learning-based mehods running on GPU can significantly reduce the processing time. Combined subjective vision with objective analysis, the overall enhancement effect of MSR and CLAHE is general; NPE and Liu[24] have good effect, but the algorithm complexity is high, requiring much time to process each image; deep learning-based method is highly dependent on computing resources, and its effect is moderate. However, the proposed method can not only obtain better results, but also take less time to process the image.

The efficiency of the color model conversion algorithm is compared on the LTSM dataset in Fig. 14. Obviously, the efficiency of the linear color restoration algorithm is higher than that of the non-linear color restoration algorithm. On the whole, the proposed method in this paper improves the brightness and contrast of the image appropriately, and the enhanced image has the best hue retention, natural and vivid color, and can shows more details, while being highly efficient.

Tab. 5 Average running time of Different enhancement methods on LIME dataset(Unit:s)).

Methods	Traditional methods(*CPU*)					deep learning-based methods(*CPU/GPU*)			Ours(*CPU*)
	MSR	MSRCR	CLAHE	NPE	Liu[24]	RetinexNet	GladNet	KinD	
Time	0.3614	3.4013	0.2732	15.2111	35.6210	3.3114/0.4819	9.1196/1.7376	6.6036/2.5538	0.6024

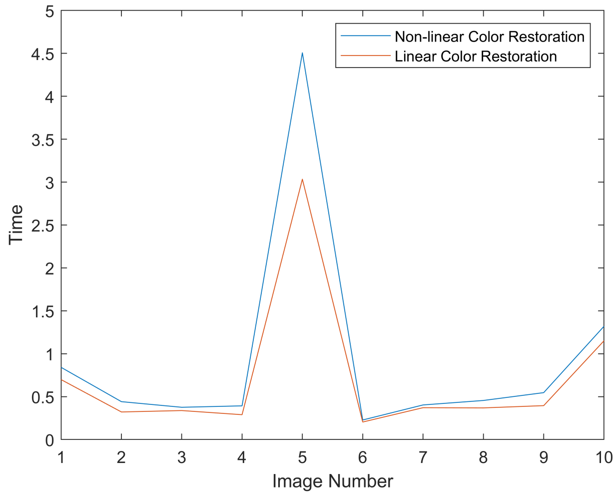


Fig. 14 Time comparison between linear color recovery method and non-linear color recovery method.

5 Conclusion

A novel low and non-uniform illumination image enhancement method based on WGIF is presented in this paper. WGIF is adopted to estimate illumination and remove noise, which effectively overcome some problems such as halo defect, detail loss and noise amplification. To avoid color distortion, images are processed in intensity channel of HSI color model, and the linear color restoration algorithm is adopted. The linear algorithm not only ensures the color is not distorted but also helps to achieve higher efficiency. To prevent the loss of gray information, the proposed method does not eliminate the illumination component directly in the logarithmic domain. Instead, it adaptively improves the brightness according to the illumination component, which effectively avoids over enhancement of the bright area. The experimental results show that the proposed method can efficiently enhance both color and greay images with low illumination. Both the subjective and objective evaluation have achieved good results. Nevertheless, if the illumination is very uneven, the enhancement effect of the local dark region would be limited. Thus, the further research should be carried out in the future.

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