An Improved Image Enhancement Method Based on Lab Color Space Retinex Algorithm

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ABSTRACT

Due to the lack of color and "halo artifacts" in enhancement of low illuminance images based on existing algorithms, this paper presents an image enhancement algorithm based on an improved Lab color space Retinex algorithm. The author innovates the image preprocessing, improves the guided filtering considering the deviation of the guided filtering algorithm, and proposes a new method to enhance the filtered image. The overall idea of image enhancement in this paper is as follows. First of all, the low illumination image is preprocessed so that the obvious dark regions in the image are roughly enhanced and adjusted. Then the preprocessed image is converted to Lab color space and the luminance component (L) and chroma components (a, b) are separated out. Using a modified guided filtering algorithm to estimate the incident component luminance value to obtain the reflected component, after the gamma correction is performed, the image brightness contrast is improved by the adaptive logarithm mapping method. Finally, the brightness component and chromaticity component are recombined and converted to RGB color space. Experiments show that the improved algorithm proposed in this paper has a better image enhancement effect and can solve the "halo artifact" problem of the image.

Keywords: Lab color space, guided filtering, adaptive logarithmic mapping, image enhancement.

1. INTRODUCTION

The Lab color space was established on the basis of the international standards for color measurement developed by the International Commission on Illumination (CIE) in 1931. It is a color model defined by the CIE organization that theoretically includes all colors visible to the human eye. In 1976, it was officially named CIELab[1]. It's worth mentioning that the Lab color space is much larger than the color space of human vision and color range is much larger than RGB, CMYK and other color modes. More importantly, the luminance and chrominance components of the Lab color space do not affect each other. In this way, we do not affect the chrominance component when we perform separate operation on the luminance component, and we can ensure the integrity and consistency of the image after the component combination. Based on this, we will perform image enhancement operations in the Lab color space[2].

On December 30, 1963, E. Land proposed a computational theory of constant perception of color based on the model of brightness and color perception of human vision-Retinex theory. It is composed of retina and cortex[3]. The Retinex theory mainly includes two aspects: the color of an object is determined by its ability to reflect long, medium and short wavelengths of light, rather than by the absolute value of the reflected light intensity; the color of the object is not affected by the non-uniformity of light and has a consistency. Therefore, the essence of Retinex theory of image enhancement is to eliminate or reduce the impact of incident images by some methods and to preserve the reflective properties of the object as much as possible[4].

In 1997, Daniel J. Jobson and Zia-ur Rahman et al. proposed the single-scale Retinex (SSR) algorithm, this algorithm uses low-pass filtering to estimate the incident components and improves the center-around Retinex theory. However, the single-scale Retinex algorithm can't achieve a balance between the color retention of the image itself and the retention of the detail information of the image[5]. Subsequently, a multi-scale Retinex (MSR) algorithm was proposed, the algorithm is theoretically consistent with the SSR algorithm. In this algorithm, multiple SSR algorithms are weighted averagely and the processing results are combined to enhance the image. However, when the MSR algorithm enhances the color image, it will cause global or local color distortion of the image[6]. Therefore, researchers have proposed MSRCR (Multi-Scale Retinex with Color Restoration) algorithm with color restoration factor. The algorithm uses the color restoration factor to enhance the image after the MSR algorithm. Compared with the previous algorithm, the algorithm can preserve the color information of the image better after the enhancement[7]. Afterwards, researchers conducted a series of algorithmic improvements for low-light image enhancement. Although there are improvements,

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there are still some deficiencies. For example, the speed of the algorithm runs slowly, the enhanced part of the image's color information is lost, and “halo artifacts” appear at the edges of the image.

In order to overcome the shortcomings of the traditional image enhancement algorithm, this paper improves the image enhancement algorithm. First, the low-light image is preprocessed so that the image is roughly enhanced, the dark regions of the image is improved in the image. Then the preprocessed image is converted to the Lab color mode and the luminance component (L) and the color component (a, b) are separated. The brightness component is estimated by improved guided filter and then corrected by Gamma, adaptive logarithmic mapping obtains the reflected component reflecting the essence of the image. Finally, the luminance component and color component are combined and converted to RGB color space.

2. IMAGE ENHANCEMENT PREPROCESSING

Image preprocessing is often implemented before feature extraction, segmentation, and matching[8]. The main purpose of preprocessing is to eliminate unrelated information in the image, to restore useful real information, to enhance the detectability of the information and to simplify the data to the maximum extent. Thus the reliability of feature extraction, image segmentation, matching and recognition can be improved. The preprocessing process generally has digitization, geometric transformation, normalization, smoothing, restoration, and enhancement[9]. The algorithm uses a color image linear transformation.

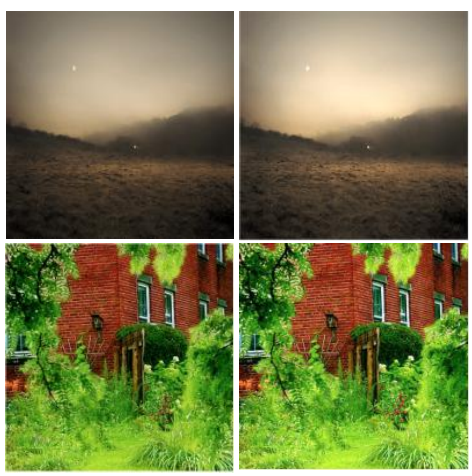
Linear transformation function expression

$$F(x)=k*x+b. \tag{1}$$

Here, x is the input image, k is the enhancement coefficient, and b is the compensation parameter. For the brightness value of different images, the two parameter values of k and b can be set as needed to obtain better results.

The algorithm proposed in this paper is directly enhanced on color images, and the algorithm is simple, fast and practical.

The results of the algorithm are as follows



(a) Original image (b) Processed image

Figure 1. Image enhancement preprocessing

Fig.1(a) is the original images, and Fig1(b) is the pre-processed images. It can be seen from figure 1 that the brightness of the preprocessed images are improved, and the enhancement effect in the dark regions are particularly obvious.

3. LAB COLOR SPACE PROCESSING

The Lab color model is device-independent and has a wide color gamut. It includes not only all the gamut of RGB and CMYK, but also the colors that they can't represent. The brightness channel (L) in Lab's color model is responsible for the brightness of the entire image, the color channels a and b are only responsible for the color. The channel represents the range from magenta (white in the channel) to dark green (black in the channel); b channel represents the range from coked yellow (white in the channel) to indigo (black in the channel)[10].

The advantages of the Lab channel

a. Lab mode can pick most images that RGB channels can pick, otherwise it will not be established;
b. In any single-tone background, it is very easy to use the Lab mode to complete the channel with a distinct color difference;
c. Any operation (such as sharpening, blurring, etc.) on the lightness (L) channel in the Lab mode will not affect the hue[11].

Based on the various advantages of the Lab channel, the operation of image enhancement in the Lab color space is obviously superior to other color spaces in general, so this algorithm will perform image enhancement in the Lab space.

In fact, RGB images can't be directly converted to Lab color space, it need to be converted to XYZ color space and then converted to Lab color space.

The formula for converting RGB images to XYZ space[12] is as follows

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} . \tag{2}$$

$$\begin{cases} X = 0.412453 * R + 0.357580 * G + 0.180423 * B \\ Y = 0.212671 * R + 0.715160 * G + 0.072169 * B \\ Z = 0.019334 * R + 0.119193 * G + 0.950227 * B \end{cases} \tag{3}$$

From the formula (3) we can see that the sum of the coefficients is 0.950456 which is very close to 1. We know that the range of R/G/B is [0,255]. If the coefficient sum is equal to 1, the range of X must also be between [0,255]. Therefore, we make the sum of the coefficients equal to 1 so that we can map the XYZ and RGB in the same range.

$$\begin{cases} \mathbf{R} = \mathbf{gamma}\left(\frac{r}{255}\right) \\ \mathbf{R} = \mathbf{gamma}\left(\frac{g}{255}\right) \\ \mathbf{R} = \mathbf{gamma}\left(\frac{b}{255}\right) \end{cases} . \tag{4}$$

$$\text{gamma}(x) = \begin{cases} \left(\frac{x+0.55}{1.055}\right)^{2.4}, (x > 0.04045) \\ \frac{x}{1.292}, (Other) \end{cases} . \tag{5}$$

In order to improve image contrast, we use the gamma function to make nonlinear hue editing.

XYZ space conversion to Lab space is as follows

$$\begin{cases} L^* = 116 * F\left(\frac{Y}{Y_n}\right) - 16 \\ a^* = 500\left[F\left(\frac{X}{X_n}\right) - F\left(\frac{Y}{Y_n}\right)\right]. \\ b^* = 200\left[F\left(\frac{Y}{Y_n}\right) - F\left(\frac{Z}{Z_n}\right)\right] \end{cases} \quad (6)$$

$$F(t) = \begin{cases} t^{\frac{1}{3}}, \text{ if } t > (\frac{6}{29})^3 \\ t, \text{ otherwise} \end{cases}. \quad (7)$$

L^*、 a^*、 b^* are the values of the three channels of the final Lab color space, X_n、 Y_n、 Z_n generally default to 95.047, 100.0, 108.883.

In the Lab space we separate the L component for image enhancement, the separated images are shown below

(a)Preprocessed image (b)L channel component (c)A channel component (d)B channel component

Figure 2. Gaussian scale-space pyramid create an interval in the difference-of-Gaussian pyramid.

The luminance and chromaticity components of each image in the Lab space are shown in Fig. 2.

4. IMPROVED RETINEX ALGORITHM

4.1 Retinex Theory basis

Retinex theory holds that color perceptual perception is only related to the perception of the object's reflection properties by the visual system and is not affected by changes in ambient light. The Retinex theory holds that the image S of an object seen by the observer is reflected by the incident light L on the surface of the object. The reflectivity R is determined by the object itself and is not changed by the incident light L. However, the image we get is often an image with incident interference, which requires us to remove the incident component from the obtained image and get the reflection component that conforms to the nature of the human eye. So that we can achieve the purpose of image enhancement.

The schematic diagram of the theoretical model of Retinex[13] is shown in figure 3

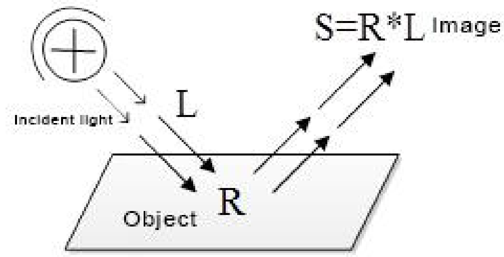


Figure 3. Retinex theoretical image composition.

The process of improving the Retinex algorithm in this paper is shown in figure 4

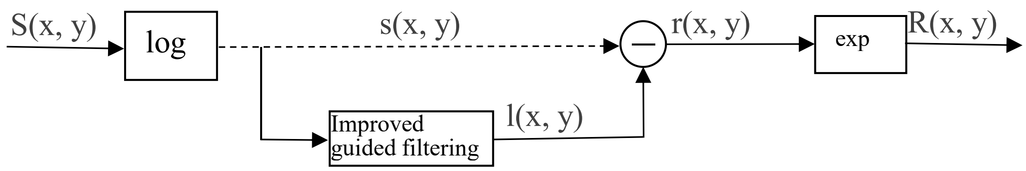


Figure 4. Retinex theoretical image composition.

The Retinex theory assumes that the original image S is the product of the light image L and the reflectivity image R, that is, the image S (x, y) consists of two parts: illumination component(L) and reflectance component(R).

The expression formula is as follows

$$S(x, y) = I(x, y) \cdot R(x, y). \tag{8}$$

Here, (x, y) represents the coordinate points of the image and $S(x, y) \leq I(x, y)$.

The purpose of image enhancement based on Retinex theory is to estimate the illumination L from the original image S and get the reflection component R. Eliminating the uneven illumination and improving the visual effect of the image, just like the human visual system.

Usually, in order to simplify the computation steps, we need to transform them into log fields and transform product relations into summation relations.

The logarithmic domain conversion formula is obtained

$$\text{Log } S(x, y) = \text{ Log } L(x, y) + \text{ Log } R(x, y). \tag{9}$$

The deformation of the formula (9) can be obtained

$$\text{Log } R(x, y) = \text{ Log } S(x, y) - \text{ Log } L(x, y). \tag{10}$$

It can be seen from formula (10) that when the image does not depend on the influence of ambient light, it can reach a constant color. Therefore, we need to remove incident interference components from the original image to obtain clear images that are in line with the nature of human vision. The core of the Retinex method is to estimate the illumination component L, that is to say, we should estimate the L component from the original image S, remove the L component and get the original reflection component R that conforms to the nature of the human eye.

4.2 Improved Guided Filtering

Previous scholars who have studied Retinex theory estimated the illuminance L by bilateral filtering of the image and Gaussian filtering as the center-surround function. Their results often found common problems such as "halo artifact", slow speed, and color loss in high contrast areas. Guided filtering algorithm is superior to bilateral filtering in image smoothing and edge preserving, the speed of the guided filtering is not related to the size of the filter window[14]. Considering the advantages of guided filtering and the problems that arise with other approaches, this paper uses an improved guided filter to estimate the incident components of the image.

The guided filtering algorithm requires a guidance image for filtering. The guidance image can be a separate image or the input image itself. The mathematical expression of the bootstrap filter is obtained[15]

$$\mathrm{Pj} = Ai * I\mathrm{j} + \mathrm{B}i. \tag{11}$$

Here, Pj is the output image, $I\mathrm{j}$ is the guided image, Ai and $\mathrm{B}i$ are the invariant coefficients of the linear function when the center of the window is located at I. The assumption of this method is that there is a local linear relationship between Pj and $I\mathrm{j}$ in the window centered on pixel I, Ai and $\mathrm{B}i$ can't be the same.

In order to get the coefficients Ai and $\mathrm{B}i$ in formula (11), it is assumed that Oj is the result of Pjfiltering and satisfy the minimum difference between Oj and Pj. According to the method of unconstrained image, restoration can be transformed into the optimization problem, the value function is obtained.

$$\begin{cases} \mathrm{Pj} = \mathrm{Oj} - \mathrm{Nj} \\ E(Ai, \mathrm{Bi}) = \sum_{\mathrm{j}\in\partial_i}((Ai * I\mathrm{j} + \mathrm{Bi} - \mathrm{Oj})^2 + w_1 Ai^2) \end{cases} \tag{12}$$

Here, Nj is noise, Oj is a degraded image of Pj contaminated by noise Nj, limit j to window ∂_iso that the Ai value is not too large.

The solution formula (12) can be obtained

$$\begin{cases} Ai = \dfrac{\frac{1}{N_{\partial_i}}\sum_{\mathrm{j}\in\partial_i} I\mathrm{j}^2 - Vi^2}{\eta_i^2 + \delta} \\ \mathrm{Bi} = (1 - Ai)Vi \end{cases}. \tag{13}$$

Here,$Vi$and $\eta_i$represent the mean and variance of the guided image in the local window, N_{∂_i} represents the total number of pixels in the window ∂_i, δ is a smoothing parameter that balances the degree of edge and smoothness. The larger δ is, the better the smoothness is, and the worse the opposite edge is.

To calculate the mean value of the whole image

$$f_i\big(I(x,y)\big) = \frac{1}{W_\partial}\sum_{\mathrm{j}\in\partial_i}(Ai * I\mathrm{j}\ (\mathrm{x,y}) + \mathrm{Bi}). \tag{14}$$

Based on the improved guided filter, the mathematical expression of the reflection component is obtained

$$R_i(x,y) = \mathrm{LogI(x,y)} - \mathrm{Log}[f_i(I(\mathrm{x,y}))] + \frac{1}{\alpha}\mathrm{Log}[f_i(I(\mathrm{x,y}))](i = 1,2,3; \alpha > 1). \tag{15}$$

Here, i represents the number of filtering, I (x, y) is the brightness of the original image, α is a weight coefficient that can be adjusted according to the image.

When the traditional algorithm subtracts the incident component of the image, there may be errors in the calculation process so that excessive incident components are subtracted which results in missing image information. For this phenomenon, this paper adds the illuminance component that can adjust the parameters according to the image quality on the basis of subtracting the incident component. In this way, the information needed for the essence of the image can be preserved and the image problem caused by excessive loss of image information can be avoided.

The reflection component estimation can be obtained by inverse transformation of the reflection component

$$R_i'(\mathrm{x,y}) = \exp(R_i(\mathrm{x,y})) \,. \tag{16}$$

4.3 Reflection Component brightening

The reflection component image obtained by the above method is usually darker , which requires us to adjust the brightness of the image. Here, we first use the Gamma correction algorithm to correct the image and then use the adaptive logarithmic mapping method to improve the image brightness.

Gamma correction algorithm[16] formula

$$\mathrm{I} = \sum_{i=1}^{3} w_i \, (R_i'(\mathrm{x,y}))^{\frac{1}{\gamma}}. \tag{17}$$

Here, I is the enhanced reflection component which also represents the enhanced luminance component.

Improving Luminance contrast of Image by Adaptive Logarithm Mapping. First, we need to convert the reflection components obtained in the Lab space to XYZ space. The conversion formula is as follows

$$\begin{gathered} Y = Y_n * f^{-1}\left(\frac{1}{116}(L^* + 16)\right) \\ X = X_n * f^{-1}\left[\frac{1}{116}(L^* + 16) + \frac{1}{500}\, a^*\right]. \\ Z = Z_n * f^{-1}\left[\frac{1}{116}(L^* + 16) - \frac{1}{200} b^*\right] \end{gathered} \tag{18}$$

$$f^{-1}(\mathrm{t}) = \begin{cases} t^3, \ \text{if}\ \mathrm{t} > \frac{6}{29} \\ 3\left(\frac{6}{29}\right)^3 (\mathrm{t} - \frac{4}{29}), \ \text{otherwise} \end{cases}. \tag{19}$$

At this point, we highlight the reflected component in the XYZ space. The brightening formula is obtained

$$L_{\mathrm{d}} = \frac{0.01 * L_{d\max}}{\log_{10}(1 + L_{d\max})} * \frac{\log(1 + L_{\mathrm{w}})}{\log[2 + (\frac{L_{\mathrm{w}}}{L_{d\max}})^{\frac{\log b}{\log 0.5}} + 8]} \,. \tag{20}$$

Here, L_{dmax} indicates the maximum display capability of the display device. For an ordinary CRT monitor, we directly set the value to 100. L_{dmax} and L_w represent the maximum brightness and average brightness of an image.

4.4 Image combination

The formula for converting XYZ into RGB space is obtained

$$\begin{bmatrix} \mathrm{R} \\ G \\ B \end{bmatrix} = \begin{bmatrix} 3.240479 & -1.537150 & -0.498535 \\ -0.969256 & 1.875992 & 0.041556 \\ 0.055648 & -0.204043 & 1.057311 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} . \tag{21}$$

According to equations (18) and (19), we convert the color components (a, b) to the XYZ color space and combine the enhanced luminance component (L) with the color components (a, b). According to formula (21), we convert the complete image after integration to RGB color space.

The step of image enhancement algorithm in this paper

a. A linear transformation of color image is used for image preprocessing;
b. Transform the image from RGB color space to Lab color space and separate the three components;

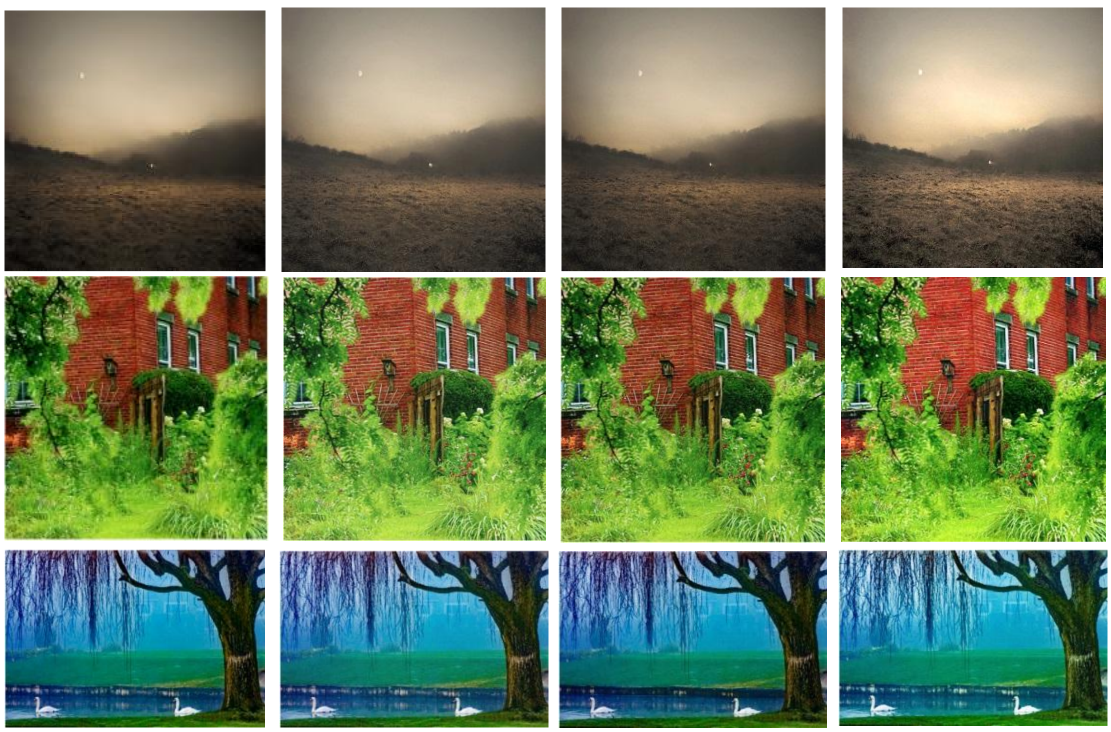
c. Convert the L-channel component to the logarithmic domain and use the modified bootstrap filter to calculate the reflected component;

d. The reflected component is corrected by the Gamma correction algorithm and the adaptive reflection map is used to further enhance the image;

e. Merge and convert each channel image to RGB color space to get the final bright image.

5. EXPERIMENTAL RESULTS

This algorithm is implemented in Matlab (R2016a) software on the computer with operating system of Windows 7, processor frequency of 3.40GHz, and system memory of 8G. Among them, the image preprocessing stage $k = 1.2$, $b = 2$; guide filter Ai, Bi value is calculated by formula (13), $\alpha = 50$; smooth parameter $\delta = 0.01$; Gamma correction parameter $\gamma = 3$.



(a) Original image (b) MSR algorithm (c) MSRCR algorithm (d) Our algorithm

Figure 5. The algorithm is compared with MSR algorithm and MSRCR algorithm.

From Fig.5, it can be seen with the naked eyes that the image obtained by this algorithm is superior to the MSR algorithm and the MSRCR algorithm both in terms of brightness and color saturation. Although the brightness of the image obtained by the MSR algorithm is improved, the phenomenon of "halo artifact" will appear at the highlight of the image. The image obtained by MSRCR algorithm is better than that by MSR algorithm, but the whole image obtained by MSRCR algorithm will have the phenomena of low brightness and over-enhancement of color, and so on. The image obtained by this algorithm can better solve the "halo artifact" phenomenon and avoid the over enhancement of the image. It can better enhance the image quality and have a good visual effect.

From the objective image quality assessment direction, we compare the MSR algorithm, the MSRCR algorithm, and the enhancement algorithm of this paper to the third image of Figure 5 in terms of speed, mean, and standard deviation. The mean of the image represents the brightness, the standard deviation of the image represents the contrast and the gray-scale entropy of the image represents the amount of detail information.

Table 1. The numerical comparison between the algorithm and other algorithms

Enhancement algorithm	Mean	Standard deviation	Gray entropy	Speed
Original picture	85.1891	41.9265	5.6832	
MSR algorithm	107.0096	46.4695	6.2147	8.0314s
MSRCR algorithm	94.5232	48.8324	6.5973	9.6152s
Our algorithm	112.0942	52.9243	6.9561	0.6347s

As shown in Table 1, the algorithm in this paper in the brightness, contrast, detail retention and speed compared with the previous algorithm has been improved, especially the speed improved significantly.

6. CONCLUSION

In view of the fact that the low illumination image does not meet the requirement of application, this paper presents an image enhancement algorithm based on the improved Lab color space Retinex algorithm, which seriously affects the application value of the image. First of all, we preprocess the low illumination image and roughly enhance and adjust the obvious dark areas in the image. Then the pre-processed image is converted to Lab color space and the luminance component (L) and chroma components (a, b) are separated out. The improved guide filter algorithm is used to estimate the incident component luminance value, obtain the reflection component and perform gamma correction, and then use adaptive logarithm mapping to improve the image brightness contrast. Finally, the luminance and chrominance components are recombined and converted to RGB color space.

The experiment shows that the improved algorithm proposed in this paper has better image enhancement effect and can solve the "halo artifact" problem of the image, and the speed of the algorithm in this paper is much faster than that of other algorithms. However, the details of this article have not retained the expected results. We will continue to study the details of image enhancement after the retention problem.

7. ACKNOWLEDGEMENT

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