An Improved Retinex low-illumination image enhancement algorithm

ShaoQuan Wang, DeYong Gao, YangPing Wang and Song Wang
School of Electronics and Information Engineering Lanzhou Jiaotong University, Lanzhou China
Gansu Provincial Engineering Research Center for Artificial Intelligence and Graphic & Image Processing, Lanzhou China
Gansu Provincial Key Lab of System Dynamics and Reliability of Rail Transport Equipment,Lanzhou China
E-mail:1878873431@qq.com Tel:+86-13919076586

Abstract— **Low-illumination images are generally low-quality images. The retinex algorithm can cause halo artifacts and loss of details in processing. Therefore, an improved Retinex algorithm is proposed. Firstly, the HSI color space which is more in line with the human visual characteristics is selected instead of the RGB image, that is, the luminance component I is processed. Then, the illuminance image is estimated by using a guided filter that fuses the edge detection operator, and the edge detection operator can be better positioned. At the edge, an illuminance image with rich edge information can be obtained; after obtaining the illuminance image, the reflected image can be obtained by the Retinex principle, the obtained reflected image is subjected to low-rank decomposition, and the low-rank property of the image is used to suppress the enlarged halo and the enhancement process. Noise; finally, the visual effect is further improved by local contrast enhancement. Experiments show that the algorithm can effectively improve the brightness and contrast of the image, preserve the details of the image, and also suppress the noise interference in the enhancement process. The subjective visual effect and objective evaluation results of the image have also been greatly improved.**

I.Introduction

Due to the limitations of hardware devices, images in low-light environments such as nights and dusks are generally characterized by dark colors and inconspicuous image details. The subsequent work requires a clear, low-noise image, so the image preprocessing stage It makes sense to be able to enhance the image very well.

At present, the low illumination image enhancement methods mainly include the Retinex method [1][2][3][4][5][6], the histogram method [7], and the deep learning method [8][9]. Among them, the Retinex algorithm has effects in dynamic range compression, edge enhancement and color constant, so it is widely used in image defogging, enhancement and other fields. The Retinex algorithm is based on the theory of color perseverance. The theory holds that the reflection property of the object itself determines the true color of the object. The acquisition of the reflection image is closely related to the illuminance image. Therefore, how to obtain the illuminance image is the most critical step. Based on this, a large number of researchers have improved it. Land[10]proposed a center-circumferential Retinex algorithm, which uses a low-pass filter to obtain illuminance images. The algorithm has low complexity and better estimates of illuminance images. The resulting reflected image has a higher quality. On this basis, researchers have proposed SSR[1], MSR[2], MSRCR[3]and MSRCP[4].Although the experimental results have been improved, there are still phenomena such as halo artifacts and color shifts, and the image drying and edge preservation cannot be consistent.

In view of this, an improved Retinex image enhancement algorithm is proposed in this paper in order to better restore the true color of low-illumination images and suppress the noise and artifacts generated in the enhancement process. This algorithm is improved on the basis of MSR. Firstly, an optimized guidance filter is used to replace the Gaussian filter in the original Retinex to better estimate the illumination image. Then low-rank decomposition is used to suppress the noise generated in the enhancement process and eliminate the "halo artifact" effect. Finally, the local contrast of the image is enhanced to highlight the sensitive details of human eyes and improve the visual effect of the image.

II. RELATED WORKS

The traditional Retinex enhancement algorithms, including SSR and MSR, are introduced briefly

A. Single scale Retinex(SSR)

Retinex theory believes that the perceived color of human beings is determined by the ability of objects to reflect red, green and blue. A pair of images S can be divided into two parts, the illuminance image L and the reflected image R, and the product of the illuminance image and the reflected image. Is a complete image, i.e

$$S(x,y)=R(x,y)\cdot L(x,y) \tag{1}$$

Accurately estimate the illuminance image L as the focus of Retinex, and after obtaining L, the reflected image R can be calculated. Usually, in the process, the image S is transferred to the logarithmic domain, ie $s = \log S$, $r = \log R$, $l = \log L$, thereby converting the product relationship into a relation of sum, there are:

$$r(x,y)=s(x,y)-l(x,y) \tag{2}$$

How to obtain an illuminance image is mathematically an underdetermined problem [11] and can only be obtained by estimation. The center-circumvented Retinex algorithm obtains the estimated illuminance image by convolving the original image with a low-pass filter to obtain:

$$r(x,y)=s(x,y)-s(x,y)*G(x,y) \tag{3}$$

Where $*$ is a convolution operation; G is expressed as a Gaussian surround function, which has:

$$G(x,y)=\exp(-\frac{x^2+y^2}{2c^2}) \quad (4)$$

Where c is the scale parameter of the Gaussian function, and its size determines the enhancement effect of the SSR.

B. Multi-Scale Retinex(MSR)

Because of c unique value, you can't balance color fidelity with detail. Based on this, MSR (Multi-Scale Retinex) has been developed on the basis of SSR. The MSR algorithm combines SSRs of different scales by linear weighting, i.e

$$r(x,y) = \sum_{d=1}^{D} W_d \{s(x,y) - s(x,y) * G_d(x,y)\} \quad (5)$$

Among them, D is the number of Gaussian surround functions, and its value is usually 3, which can maintain the SSR three-scale advantage. If D=1, the MSR is equivalent to the SSR, and W_d is the SSR weight for each scale, and the sum is 1.

In summary, the performance of the filter has a great impact on the final image quality. In order to obtain a better quality image, it is important to select the correct filter.

III. METHOD

Aiming at the problems of traditional Retinex algorithm in dealing with low illumination images, this paper proposes an improved Retinex low illumination image enhancement algorithm. 1 first converting the low illumination image from the RGB color space to the HSI color space; 2 then using the improved guided filtering and the luminance component I to perform a convolution operation to estimate the illumination component of the image; 3 then using the low-rank decomposition to calculate the reflected image, Contains noise and artifacts; 4 Finally, use local contrast enhancement, enhance contrast, and transfer HSI color space to RGB space to get the final image. The algorithm flow is shown in Fig. 1:

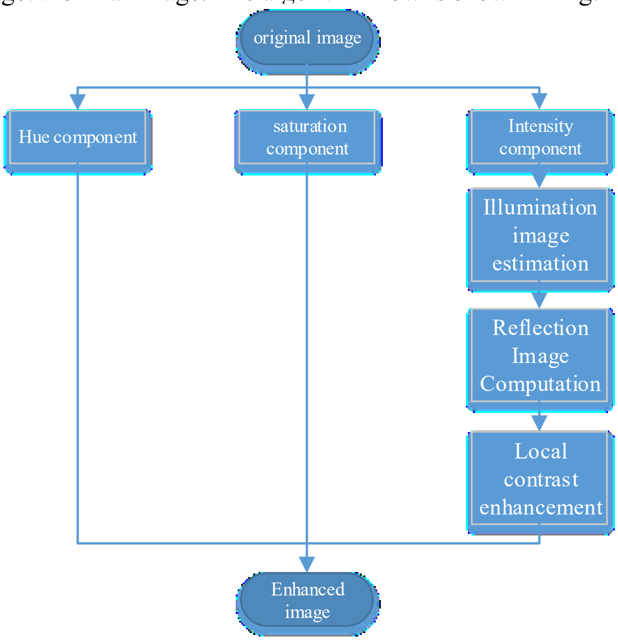

Fig.1 Algorithm framework in this paper

A. Illumination image estimation

Accurate estimation of illuminance image is the key of the Retinex algorithm. Due to the isotropic characteristics of the Gaussian filter [11], it is impossible to accurately estimate the illuminance image. In order to obtain accurate illuminance image, an improved guidance filter is proposed instead of the Gaussian filter.

Guided filtering has the characteristics of edge preservation and low complexity, so it is often applied to image preprocessing. An important assumption of the bootstrap filter is that the result of the edge-preserving filter and the guided image exhibit a linear relationship within the filter window:

$$q_i = a_k I_i + b_k, \quad \forall i \in \omega_k \quad (6)$$

Where I_i is the guide image, q_i is the output image, ω_k is the window with k as the center pixel, and a_k and b_k are the linear coefficients corresponding to the window. In order to obtain the output image q closest to the input image p, the least squares method is used to fit the linear relationship in the equation, and the cost function is:

$$E = \sum_{i\epsilon\omega_k}((a_k I_i + b_k - p_i)^2 + \varepsilon a_k^2) \quad (7)$$

Here, ε is a regularization parameter for preventing a_k from being excessively large, and its value is artificially set by the call. Although guided filtering is a fast edge-preserving filter, it is often easy to produce "vignetting" at the edges.

The Reference [12] pointed out that the regularization parameter ε in (7) is fixed, and does not consider the difference between different windows, which causes the pilot filter to produce vignette after processing the image. To solve this problem, the reference [12] proposed a weighted guidance filter. This method changes the denominator of the regular term parameter ε and introduces a weight $T(i)$ thereto to form $\varepsilon/T(i)$. Then (7) becomes:

$$E = \sum_{i\epsilon\omega_k}((a_k I_i + b_k - p_i)^2 + \frac{\varepsilon}{T_G(i)} a_k^2) \quad (8)$$

The weighting factor $T_G(i)$ defined therein is defined as:

$$T_G(i) = \frac{1}{N}\sum_{i=1}^{N}\frac{\sigma_{G,1}^2(i)+\gamma}{\sigma_{G,1}^2(i\prime)+\gamma} \quad (9)$$

Where $\sigma_{G,1}^2(i)$ is the local area variance with i as the center radius of 3×3, γ is taken as $(0.001\times L)^2$, and L is the dynamic range of the image. If the image is 8 bits, Then $L = 256$. A pixel that is usually at the edge has a T value greater than 1, while a pixel in the smooth region has a T value less than one. Finally, a Gaussian filter is applied to remove possible blockiness.

Because the variance weighting factor introduced can adjust a_k, the edge can be better protected than the original guidance filter. $T_G(i)$, the weighting factor, is based on the local variance within the window. Although it can reflect the edge information to a certain extent, it is found in the experiment that the area with large variance does not correspond to the edge one by one, so it is not very suitable to use variance as the penalty factor. In reference[13], edge detection operators such as Sobel, Canny and Log operators are proposed to replace variance as penalty factors to form weighted guided filtering for edge detection [13]. The enhanced finger-vein image has clearer edges, better highlights the texture details, and inhibits the noise to some extent. Inspired by this, this paper proposes an improved guidance filter based on an edge detection operator. The absolute amplitude response of the Dog(Difference of Gaussian) operator is adopted to replace the local regional variance. Dog operator is a second order differential operator, which is a simplified calculation of Log operator and has a stronger ability to locate edges. And low computational complexity. In this paper, the Dog operator is used to locate edges more accurately. Therefore, the weighting factor in (9) is redefined as:

$$\Psi(i) = \frac{1}{N}\sum_{i=1}^{N}\frac{|DoG(i)|+\gamma}{|DoG(i')|+\gamma} \tag{10}$$

The (8) becomes:

$$E = \sum_{i\in\omega_k}((a_k I_i + b_k - p_i)^2 + \frac{\varepsilon}{\Psi(i)}a_k^2) \tag{11}$$

In the formula: Dog denotes the Gauss differential edge detection operator; N is the number of pixels of the image; |•| is the operation of taking absolute value; I is the central pixel i', which takes all the pixels of the image.

B. Reflection Image Computation

The reflection image can be obtained from the illumination image estimated by A, but there are many noises in the low illumination image. It is easy to magnify the original image noise and affect the visual effect in the enhancement process. In order to prevent noise interference in the subsequent image processing process, this paper introduces the method of low-rank matrix decomposition to remove the noise. If a clear image is regarded as a matrix, then it has low-rank, because there are many similarities in the clear image, and there are correlations between the corresponding matrix rows. Therefore, low-rank decomposition can be used to remove the noise in the enhancement process. In this paper, RPCA is used to solve the problem. The greatest advantage of RPCA is that it can restore the low-rank matrix with any size and sparse enough noise matrix. Then the low-rank matrix can be written as the following minimization problem:

$$\min rank(A) + \lambda||E||_0, s.t\ R = A + E \tag{12}$$

Where A and E are respectively the low-rank component and the sparse error matrix of R, rank(·) is the rank of the matrix, λ is the regularization parameter, and ||·|| represents the l_0 norm.

Since (11) is a NP problem, the NP problem is transformed into a relaxed convex optimization problem.

$$\min\ ||A||_* + \lambda||E||_1, s.t\ R = A + E \tag{13}$$

Where $||\cdot||_*$ represents the kernel norm of the matrix, and $||\cdot||_1$ is 1 norm. In this paper, we use the augmented Lagrangian multiplier method to solve, and then we can get the low-rank component A, which is a clear image.

C. Local contrast enhancement

Because the dynamic range of the image is compressed, the contrast of the image is low and the image appears "gray-white", so it is necessary to enhance the contrast of the image. In the objective world, human beings are more sensitive to the local contrast. The line of sight often focuses on subtle changes. According to this characteristic, the local contrast enhancement of the image can achieve a better visual effect. In this paper, the adaptive contrast enhancement (ACE) algorithm is used to enhance the local contrast of the image. The ACE algorithm uses anti-sharpening masking technology, which essentially divides the image into the low-frequency part and high-frequency part, and then enhances the high-frequency part representing details. For high-frequency part enhancement, it multiplies it with a certain gain value, enlarges high-frequency information, and finally obtains the enhanced image. Therefore, the calculation of the high-frequency part gain value is the most important part of the ACE algorithm. The high-frequency part of the image can be obtained by subtracting the low-frequency part from the original image. Generally, the low-frequency image can be obtained by calculating the local center of the pixel.

In this paper, we first take the processed image pixel value f (i, j) in 3.2 as the local contrast enhancement. We define a local area with (i, j) as the center, and a window size of $(2n + 1) * (2n + 1)$, where n is an integer. The local average can be expressed as:

$$M_{i,j} = \frac{1}{(2n+1)^2}\sum_{k=i-n}^{i+n}\sum_{t=j-n}^{j+n} f(k,t) \tag{14}$$

The local variance is:

$$\sigma_x^2(i,j) = \frac{1}{(2n+1)^2}\sum_{k=i-n}^{i+n}\sum_{t=j-n}^{j+n}[f(k,t) - M_{i,j}]^2 \tag{15}$$

The enhanced pixels are represented as:

$$h(i,j) = M_{i,j} + \frac{\theta}{\sigma_x(i,j)}[f(i,j) - M_{i,j}] \tag{16}$$

In the formula above, theta is a constant, so the enhancement of the high-frequency part is adaptive and inversely proportional to the local standard deviation. In order to prevent ringing effect and pixel saturation, theta is taken as the global average value in the experiment, and $\frac{\theta}{\sigma_x(i,j)} \leq 3$ is defined.

IV. EXPERIMENT

In this paper, several groups of low illumination images are selected for the experiment, and the image quality is evaluated after the experiment. At present, image quality evaluation is mainly divided into the subjective evaluation and objective evaluation. The subjective evaluation mainly relies on people's subjective feelings to evaluate the image "good or bad", and objective evaluation designs quantitative indicators according to the model.

A. Subjective evaluation of experimental results

Low illumination images are generally dim and blurred. According to the distribution of illumination, it can be roughly divided into two categories: non-uniform illumination image and uniform illumination image. In order to verify the effectiveness of this algorithm for low illumination image enhancement, two groups of images are selected according to the illumination distribution for the experiment, and then the experimental results obtained by this algorithm are compared with those obtained by other algorithms, and the relevant experimental conclusions are obtained. This paper uses LOW Light data set (LOL) [14]. The experimental hardware is Intel (R) Core (TM) i5-4200M, memory 8.00GB, system Windows 10, and software is MATLAB R2016a.

In order to verify the effectiveness of non-uniform illumination image enhancement, the proposed algorithm, MSR, MSRCR and MSRCP algorithms were selected for comparison experiments. The experimental results are shown in Figure 2.

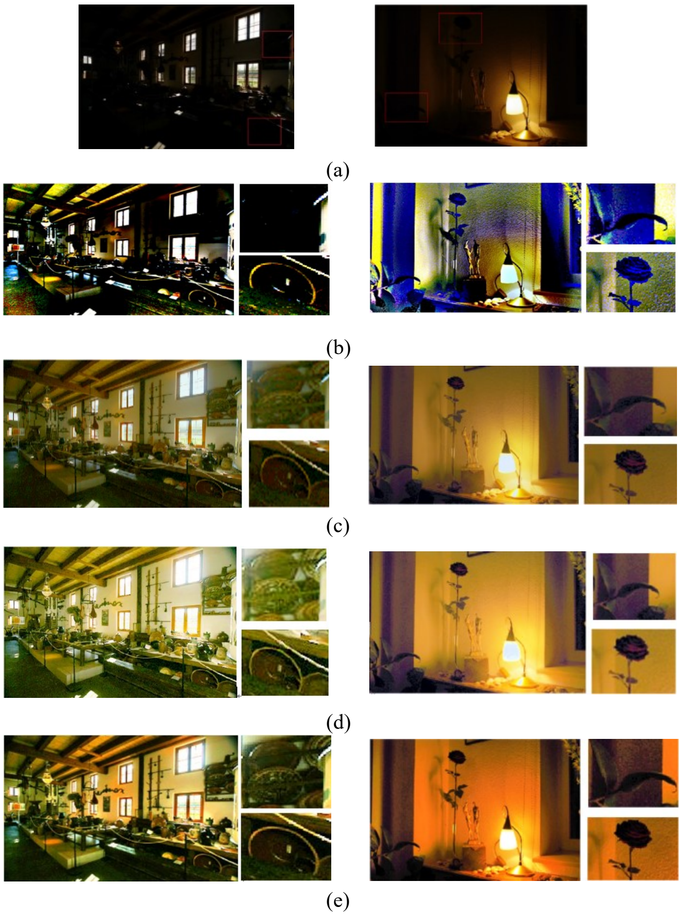

Fig.2. Contrast experiment of low illumination image enhancement with uneven illumination. (a) Original image(I Π) (b) MSR (c) MSRCR (d) MSRCP (e)Proposed

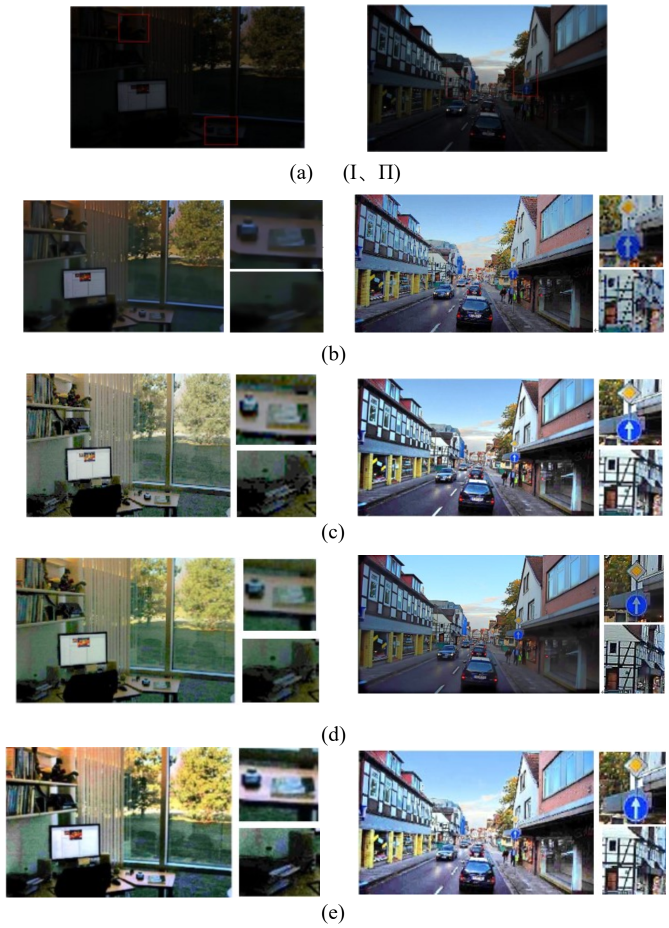

Fig.3 Contrast experiment of low illumination image with uniform illumination.(a) (b) (c) (d) (e) are [15] [16] [17] and our results

It can be seen from the comparison experiment in Fig. 2 that the image after the MSR algorithm is enhanced is severely deteriorated, and the colors of "flower" and "leaf" in (b) are reversed to blue, which is inconsistent with the actual situation.The MSRCR and MSRCP algorithms can improve the brightness of the image as a whole, and have better enhancement effects. However, it can be observed from the partial enlargement that the image details are not clear, the noise is more, and the local contrast is not obvious. The image enhanced by the algorithm in this paper has natural color, high contrast, less noise, and more edge information, and the overall visual effect is relatively good.

In order to verify the effectiveness of uniform illumination image enhancement, this paper selects reference [15], reference [16], reference[17] and the algorithm of this paper for experiments. The experimental results are shown in Figure 3.

It can be seen from Fig. 3 that the reference [15] does not have good denoising, the details of the image are not obvious, and there is a halo phenomenon. The overall clarity of the reference [16] is high, but the image edge blur is observed from the partial enlargement in (c), and there is a phenomenon of amplified noise. Although the reference [17] has a better enhancement in image detail and contrast, a black circle of appears below the right image in (d). The algorithm in this paper restores the details better and suppresses noise and artifacts. The effect is more natural.

B. *Objective evaluation of experimental results*

In the objective evaluation, this paper adopts the objective evaluation index of mean, average gradient, and information entropy. Mean value reflects the brightness of the image, and the bigger the value, the bigger the brightness of the image. Mean gradient reflects the clarity of the image. The bigger the average gradient, the clearer the image is. Information entropy is used to measure the richness of image information [18]. The objective evaluation is shown in Tables 1 and 2.

The data in Table 1 and Table 2 indicate that the selected algorithms have their own strengths. Except for the average brightness in Π in Table 1 and the average gradient in 2 in Table 2, all other indicators are the first, indicating that the algorithm can enhance the low-illumination image better than other algorithms.

V. CONCLUSION AND FUTURE WORK

Aiming at the halo artifacts, noise amplification and color

TABLE 1
Objective Evaluation of Illumination Non-uniformity Image Experiments

experiment	algorithm	mean	average gradient	information entropy
I	MSR	47.94	13.98	4.82
	MSRCR	88.34	15.67	6.52
	MSRCP	90.98	15.59	6.91
	Proposed	**93.26**	**19.36**	**7.34**
Π	MSR	85.34	18.35	7.00
	MSRCR	96.37	15.27	7.12
	MSRCP	**101.68**	16.64	7.62
	Proposed	97.23	**18.85**	**7.85**

TABLE 2
OBJECTIVE EVALUATION OF UNIFORM ILLUMINATION IMAGE

experiment	algorithm	mean	average gradient	information entropy
I	[16]	87.36	14.67	5.29
	[17]	95.43	13.75	7.71
	[18]	100.39	15.93	7.64
	Proposed	**116.88**	**18.24**	**7.79**
Π	[16]	100.31	10.81	4.38
	[17]	80.49	17.64	7.65
	[18]	88.42	**18.68**	7.29
	Proposed	**181.33**	17.34	**7.95**

distortion of Retinex algorithm in low illumination image processing, this paper proposes a low illumination image enhancement algorithm based on Retinex algorithm, which performs different processing in three stages: illumination image estimation, reflection image acquisition, and post-processing. Experiments show that this method can effectively suppress noise and avoid color deviation, and has a good visual effect. However, the running time of this algorithm is long, and there is a problem of noise amplification when dealing with images with more light loss, which is the direction of the next work.

ACKNOWLEDGMENT

This research was supported by the National Nature Foundation of China (Grant No. 41761082, 61162016, 61562057), the Gansu Science and Technology Project (Grant No. 18JR3RA104, 1504FKCA038), the Science and Technology Project of Gansu Education Department (Grant No. 2017D-08) and Lanzhou Talent Innovation and Entrepreneurship Project(2015-RC-86). all support is gratefully acknowledged.

REFERENCES

[1] JOBSON D J, RAHMAN Z, WOODELL G A. Properties and Performance of a Center/surround Retinex[J]. IEEE Transactions on Image Processing a Publication of the IEEE Signal Processing Society, 1997, 6(3): 451—462.

[2]Jobson D J, Rahman Z ,Woodell G A.A multiscale retinex for bridging the gap between color images and the human observation of scenes[J].IEEE Transactions on Image Processing,1997,6(7):965-976.

[3]Rahman Z U, Jobson D J, Woodell G A.Retinex processing for automatic image enhancement[C].Human Vision and Electronic Imaging VII.Human Vision and Electronic Imaging VII 2002:100—110.

[4] PETRO A B,SBERT C,JEAN-MICHEL M.Multi-scale Retinex [EB/OL].Image Processing on Line,2014(4):71-88.

[5]H Zhao, C Xiao, J Yu, et al.A Retinex algorithm for night color image enhancement by MRF[J].Optics and Precision Engineering, 2014,22(04):1048-1055.

[6]J Zhang, P Zhou, M Xue. Low-light Image Enhancement B ased on Directional Total Variation Retinex[J]. Journal of Computer-Aided Design & Computer Graphics,2018,30(10):1 943-1953.

[7]W He. Low-light Image Enhancement Based on Improve Histogram[J]. Computer Science,2015,42(S1):241-242+262.

[8]W Mao, X Zhao.Enhancement algorithm for low-illumination color image based on neural network[J]. Optical Technique,2010,36(02):225-228.

[9]H Ma,S Ma,Y Xu,et al.Low-Light Image Enhancement Bas ed on Deep Convolutional Neural Network[J]. Acta Optica Sinica,2019,39(02):99-108.

[10] Land E H. An Alternative Technique for the Computation of the Designator in the Retinex Theory of Color Vision[J]. Proceedings of the National Academy of Sciences of the United States of America, 1986, 83(10):3078.

[11]Q Mu,Y Wei,J Li,et al.Research on the Improved Retinex Algorithm for Low Illumination Image Enhancement [J]. Journal of Harbin Engineering University,2018,39(12):20 01-2010.

[12]LI Z, ZHENG J, ZHU Z, et al. Weighted guided image filtering[J].IEEE Transactions on Image Processing,2015,24 (1):120-129.

[13]W Cao, H Wang, J Shi, et al.Enhancement Algorithm of Finger Vein Image Based on Weighted Guided Filter with Edg e Detection[J]. Laser & Optoelectronics Progress,2017,54(02): 172-180.

[14]Wei C, Wang W, Yang W, et al. Deep retinex decomposit ion for low-light enhancement[J]. arXiv preprint arXiv:1808.0 4560, 2018.

[15]Dongyue M , Zhengxiang X , Xiangqian H , et al. Adapti ve bilateral logarithm transformation with bandwidth preservi ng and low-illumination image enhancement[J]. Journal of Im age and Graphics, 2017.

[16] Fu X , Sun Y , Liwang M , et al. A novel retinex based ap proach for image enhancement with illumination adjustment [C]// ICASSP 2014 - 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 20 14.

[17] Wang D , Wang J , Xu Z , et al. Adaptive correction algo rithm for non-uniform illumination images[J]. Xi Tong Gong

Cheng Yu Dian Zi Ji Shu/Systems Engineering and Electronic
s, 2017, 39(6):1383-1390.
[18]S Zhang, P Zeng, X Luo, et al.Multi-Scale Retinex
with Color Restoration and Detail Compensation[J]. Journal
of Xi'an Jiaotong University,2012,46(04):32-37.