DESIGN OF LOW ILLUMINATION IMAGE ENHANCEMENT ALGORITHM BASED ON DARK CHANNEL DEFOGGING

Shaoyu Chen[1], Fengqian Xu[1], Qingshan Li[1], Yu Zheng[1]*
[1]Quzhou Power Supply Company, State Grid Zhejiang Electric Power Co., Ltd., Quzhou, Zhejiang 324000, China
Email: liqs_lqs@hotmail.com

Abstract - In order to solve the problem of low illumination image, dark channel defogging technology is used. The algorithm is similar to the low illumination image and the image with fog. An "S" curve is proposed to optimize the image processing, and the transmission estimation method in the de-fog algorithm is improved. In order to test the feasibility of the algorithm, the comparison method is used to test the performance of the algorithm by changing the type of low-illumination image. The results show that the image information obtained by the improved algorithm in this paper is much larger. Based on the above experiments and evaluation analysis, in terms of subjective evaluation, the algorithm can effectively improve the shortcomings of histogram equalization algorithm and Retinex algorithm, effectively adjust the brightness distribution of images, improve the sharpness and detail information of images, and well adapt to different complex shooting environments. Our algorithm can ensure the visual effect and at the same time, There is also a certain improvement in each evaluation index, and the overall quality of the image has been significantly improved. This study provides an effective solution for low illumination image processing and can be popularized.

Keywords: Dark channel to fog, Design, Low light image.

1. Introduction

Driven by the rapid development of photoelectric technology, image sensors are more and more widely used in low-illumination environments [1].For example, Zhong Yujie, Lei Renfang, Lin Longjun, etc., with typical optical vision sensor technology as the main line, through comprehensive domestic and foreign literature and related reports, from the CCD image sensor, CMOS image sensor, intelligent vision sensor and infrared image sensor research direction, Review and discuss the development status, frontier dynamics, hot issues and trends of optical vision sensor technology in recent years [2]. Another example is Xu Daorun, Liu Yeqi, Yuan Anbo, et al., who designed and developed a four-spectrum time-delay integrated charge-coupled device (TDICCD) image sensor. The device integrates four TDICcds on the same chip and achieves multi-spectrum splitting by plating different narrowband filter films on the corresponding position of the optical window, which promotes the development of image sensors [3]. However, low brightness, lack of contrast and more noise are common problems in low illumination environment, resulting in poor visual quality and clarity of the image, not conducive to subsequent application. Therefore, low-light image enhancement is particularly important in the monitoring and recognition scenes of dark light areas at night [4]. Ji Fanshu studied the low-light image enhancement model based on optimized deep neural network and found that the model could achieve the best exposure in low-light environment [5]. Miao Zuohua, Zhang Li, Xu Houyou, et al. proposed an image enhancement algorithm based on CLAHE-PCA, and tested it through experiments. The results showed that this method could effectively process low-contrast mine roadway images, which was robust and could restore more image details [6]. Sui Tao, Wu Senwei, Jia Hao et al. studied the realization of unpaired low-illumination image enhancement by improving the cyclic generation adversarial network model. The results show that compared with traditional methods, the improved model in this paper has better subjective visual effect and corresponding improvement in objective evaluation indicators, which shows the effectiveness of the improved model [7]. Tang Wan and Liu Xin proposed a method for detecting regions of interest in low-illumination images based on visual attention model. In order to test the feasibility of the method, an empirical study was conducted, and the results showed that the proposed method had better preprocessing effect and lower mismarking and mismarking rates [8]. In this way, the sharpness of the picture is improved, enhance the brightness of the image, highlight the details of the dark part of the image, get key information nodes, which is conducive to computer analysis, and as the pre-processing part of other advanced visual tasks, improve the application scenario of the task, and design the end-to-end intelligent control system. In addition, in the case of poor visual conditions such as snow, rainy days, fog, and night, the complexity of the environment will also make advanced visual tasks extremely challenging. As a result, object missing, detail missing, edge blurring and so on appear, which makes the efficiency of the system limited. It can be seen from the above that low-illumination environment is more common in daily life, and useful information in the photos taken at this time will be covered up, so that people can not directly obtain useful information, affecting the next step of processing. Therefore, low illumination image enhancement technology is very important for people to obtain information in images with poor visual conditions. In order to solve the above problems and enhance the application effect of low-light image enhancement technology, this paper presents an enhancement algorithm based on dark channel fog removal, in order to improve the above bad image problems and improve the visual effect of images.

2. Design of Low-Light Image Enhancement Algorithm based on Dark Channel Defogging

2.1 Relationship between Low-light Image and Foggy Image

Low-illumination images refer to images with low local or global light when shooting [12], generally including images with low light or taken at night. The dark area of these images often hides a lot of image details, which brings difficulties to machine vision tasks such as monitoring and target detection. At present, the low-light enhancement field relies on the Retinex theory with low complexity, but its solution of incident light depends on the spatial smoothing characteristics. In some special scenes, the illumination component of the input image cannot be accurately estimated, resulting in the problems of high halo and color saturation in the enhanced low-light image. In addition, image noise enhanced by Retinex theory will be higher, therefore, the focus of research will be on such questions [9-10]. Through the understanding of image de-fogging technology, it is found that the atmospheric scattering model can be effectively solved by improving it.

2.2 Atmospheric Scattering Model

In some specific scenes, reflected light will collide with suspended particles in the atmosphere during transmission, that is, absorption and scattering will occur during the propagation of the optical path, resulting in weakened intensity of reflected light, and excessive atmospheric components will make the pixel of the target object show a low saturation state. In addition, the scattering medium in the atmosphere will produce stronger background light than the target light, so that the effective component of the target object pixel is not enough, resulting in the acquired image showing the edge blur, insufficient detail and other states [11]. In machine vision tasks, the atmospheric scattering model is composed of attenuation model and atmospheric light model.

- ***Attenuation model***

The attenuation model is used to indicate that during the propagation of light [12], with the intervention of suspended particles, the intensity of light is suppressed, that is, the light absorbed by the camera is inconsistent with the intensity of the original propagation light. The specific expression is shown in formula 1.

$$\mathrm{T}(d,\lambda) = T_0(\lambda)e^{-\beta(\lambda)d} \tag{1}$$

Where, $\mathrm{T}(d,\lambda)$ represents the attenuated final light intensity, and $T_0(\lambda)$ represents the input light intensity; $\beta(\lambda)$ represents the atmospheric scattering parameter of the scattering ability of suspended particles in the atmosphere, which is generally a constant. The larger the value, the more light attenuation.

- ***Atmospheric light model***

In the process of light entering the lens, the light will not only produce attenuation, but also absorb the ambient light in the path that is not related to the target scene through scattering. Therefore, the light that finally reaches the observation point includes the initial light after attenuation and the light after refraction of the ambient light [13]. In the final imaging process, the surrounding light will also be refracted through the suspended particles in the air to reach the observation point, the specific expression is shown below.

$$T_a(d,\lambda) = T_\propto(\lambda)\left(1 - e^{-\beta(\lambda)d}\right) \tag{2}$$

Where, $T_a(d,\lambda)$ represents the final light intensity received by the observation point, and d represents the distance between the lens and the light. λ is the wavelength of light; $T_\propto(\lambda)$ represents the total ambient light intensity at positive infinity. It is not difficult to find that as the distance d increases, the more atmospheric light is included in the imaging process.

- ***Fog image imaging model***

According to the above atmospheric scattering model theory, the light intensity finally received by the observation point can be obtained including attenuation model and atmospheric light model, and its mathematical expression is shown as follows:

$$\mathrm{L}(d,\lambda)=T_0(\lambda)e^{-\beta(\lambda)d}+T_\alpha(\lambda)\left(1-e^{-\beta(\lambda)d}\right) \quad (3)$$

At this time, let $\mathrm{L}(d,\lambda)=I(x)$, $T_0(\lambda)=J(x)$,$e^{-\beta(\lambda)d}=t(x)$, then formula 3 can become:

$$I(x)=J(x)t(x)+A\left(1-t(x)\right) \quad (4)$$

Where, $I(x)$ represents the input fog image; $J(x)$ represents the fog-free image that needs to be restored eventually; $t(x)$ stands for transmittance, and its physical significance represents the proportion of atmospheric light attenuated after collision with atmospheric suspended particles in the light absorbed by the detection equipment, with the value range of [0,1]. A represents the atmospheric light value estimated from the fog image. Based on the above theory, it can be seen that A and $t(x)$ are the key to obtain the image without fog. Therefore, in the process of de-fogging the image with fog, A and $t(x)$ need to be obtained by means of prior knowledge or other assumptions, so as to catch the image after de-fogging.

- ***Dark channel prior and bright channel prior***

The three main factors that lead to the low brightness of the dark channel are as follows: First, most of the images will have the corresponding shadow area when shooting; Second, due to the color on the surface of the object, the color value in the black channel is low; Third, the object itself has a darker color, such as dark tree trunks, stones, etc. The process of solving the dark channel is as follows: a pixel in the input non-foggy image is taken as the center point of this region, and the minimum pixel in this region is obtained. Then to solve the minimum value in the RGB three channels, the following formula can be used to represent the above steps:

$$J^{dank}(x)=\min_{y\in\Omega(x)}\left\{\min_{C\in\{R,G,B\}}[J^c(y)]\right\} \quad (5)$$

Where, $J^{dank}(x)$ represents the image dark channel; $\Omega(x)$ represents a local window centered on a pixel point x;In the input image J, the three color channels are represented by $J^c(y)$. Using formula 5, we can get a minimum value close to zero. The basic idea of bright channel prior is similar to that of dark channel prior, which is mainly used to describe the maximum pixel value of a region centered on a certain point in the input image. When the input image is a clear image, the maximum value of this pixel approaches 1. When the input image is a blurred image, the pixels in the channel rarely exceed 1.

$$J^{light}(x)=\min_{y\in\Omega(x)}\left\{\min_{C\in\{R,G,B\}}[J^c(y)]\right\}\rightarrow 255 \quad (6)$$

Where, $J^{light}(x)$ is the image bright channel.

2.3 Relationship between Retinex Model and Atmospheric Scattering Model

Typically, low-light images in Retinex models can be obtained by verifying the product between the enhanced image and the incident component. For the representation of pixel x in the image:

$$\mathrm{L(x)=R(x)T_r(x)} \quad (7)$$

At this time, the three channels of the input image have the same incident component, then the enhanced image $\mathrm{R(x)}$ can be restored by estimating $\mathrm{T_r(x)}$, as shown below:

$$\mathrm{R(x)}=\frac{\mathrm{L(x)}}{\mathrm{T_r(x)}+\varepsilon} \quad (8)$$

In the above formula, in order to prevent the occurrence of zero division problem, a constant ε is added.To facilitate processing, ε is ignored in subsequent calculations. The atmospheric scattering model is used in the inverted image, equation 8 is converted to:

$$1-\mathrm{L(x)}=\left(1-\mathrm{R(x)}\right)\mathrm{T_i(x)}+\mathrm{A}\left(1-\mathrm{T_i(x)}\right) \quad (9)$$

In Formula 9, the atmospheric light value is represented by A, which is estimated by $1-\mathrm{L(x)}$,and $\mathrm{T_r(x)}$ is the transmittance, which is different from $\mathrm{T_i(x)}$. In terms of visual effects, the inversion image is very similar to the fog image, but the inversion image does not look natural, so the above formula is converted as follows:

$$\mathrm{R(x)}=\frac{\mathrm{L(x)-1+A}}{\mathrm{T_i(x)}}+1-\mathrm{A} \quad (10)$$

When $\mathrm{A}=1$ and $\mathrm{T_i(x)=T_r(x)}$, the contra-enhanced image of atmospheric scattering model is equivalent to the low-light image of Retinex model. Let's say we know the value of A, then the formula 10 can be normalized to obtain the following formula:

$$\frac{1-\mathrm{L(x)}}{A}=\frac{\left(1-\mathrm{R(x)}\right)}{A}=\mathrm{T_i(x)}+1-\mathrm{T_i(x)} \quad (11)$$

When $L_n(x) = \frac{1-L(x)}{A}, R_n(x) = \frac{(1-R(x))}{A}$, then formula 11 can be converted to:

$$L_n(x) = R_n(x)T_i(x) + 1 - T_i(x) \quad (12)$$

Sorting can obtain:

$$1 - L_n(x) = (1 - R_n(x))T_i(x) \quad (13)$$

Where, $1 - L_n(x)$ represents the normalized inverted image. Let $L_{n,i}(x) = 1 - L_n(x)$, $R_{n,i}(x) = 1 - R_n(x)$, then the above formula can be converted to:

$$L_{n,i}(x) = R_{n,i}(x)T_i(x) \quad (14)$$

$L(x)$ and $R(x)$ in formula 14 are replaced by the inversion images $L_{n,i}(x)$ and $R_{n,i}(x)$ of the normalized inversion image, at this point, the transmittance $T_i(x)$ of the inverted image is replaced by the incident light in Retinex. Therefore, equation 14 can be viewed as an alternation with the Retinex model. When $A = 1$, 7 is equivalent to 14. When $T_i(x)$ can be accurately estimated, $R_{n,i}(x) = L_{n,i}(x)/T_i(x)$. Since $R_{n,i}(x) = 1 - R_n(x) = 1 - (1 - R(x))/A$, the following formula can be obtained:

$$R(x) = A(R_{n,i}(x) - 1) + 1 \quad (15)$$

Among them, $R(x)$ can be obtained by estimating the incident component $T_r(x)$. According to the above formula, for the image normalized after low-illumination inversion, $T_i(x)$ and A can be substituted for the solution of the incident component in Retinex model. $T_i(x)$ can be estimated in two ways, one is to calculate the transmittance according to $T_r(x)$; The second is to calculate the transmittance according to the atmospheric scattering model. To sum up, the atmospheric scattering model will be used in the inversion image in this paper. $A \neq 1$, $T_i(x) \neq T_r(x)$. The ambiguity of atmospheric light scattering model is eliminated by converting the low-illumination inversion image into gray level image and using the inversion image to enhance the low-illumination image.

2.4 Improve the Low-light Image Enhancement Algorithm based on Dark Channel Defogging

Because A is the key parameter for calculating transmittance, and there are other factors in the process of obtaining atmospheric light, so it is impossible to estimate the transmission accurately. According to the similarity characteristics described above, an improved method of obtaining transmittance based on saturation stretching is proposed. The dark channel is used to solve the atmospheric light value, which effectively reduces the algorithm complexity and realizes the enhancement of low illumination image.

- ***Improved transmission estimation method***

In the estimation of pixel-level projection maps, saturation is used to achieve this, and the corresponding expression is derived as follows:

$$\min_c L_n(x) = \min_c R_n(x)T_i(x) + 1 - T_i(x) \quad (16)$$

Where, c represents three color channels of image R, G and B; $\min_c L_n(x)$ is the minimum value of the three color channels; For the input low-illumination inversion image A, when the minimum value of the RGB three channels is the same, then formula 15 can be transformed into:

$$T_i(x) = \frac{1-\min_c L_n(x)}{1-\min_c R_n(x)} \approx \frac{1-\frac{1}{A}+\max_c L(x)}{1-\frac{1}{A}+\max_c R(x)} \quad (17)$$

Among them, $\max_c R(x)$ is A bright channel in the image, which plays an important role in solving $T_i(x)$. In the past, $\max_c R(x)$ was solved by calculating the maximum pixel value in the local window. If the value of $\max_c R(x)$ is close to 1, it means that the main content is to estimate the pixel transmission graph, so it is difficult to estimate $\max_c R(x)$. For this reason, a new transmission estimation method is proposed, which uses the saturation degree component in HSV space to solve the projection plot of low illumination inversion image. Let $S_K(x)$ represent the saturation component of HSV at the pixel point in the input color image, the specific expression is as follows:

$$S_K(x) = 1 - \frac{\min_c K(x)}{\max_c K(x)} \quad (18)$$

By combining the saturation in the $L_n(x)$ and $R_n(x)$ components, a solution projection is obtained, as shown below:

$$T_i(x) = \frac{1-\min_c L_n(x)}{1-\min_c R_n(x)} = \frac{1-\max_c L_n(x)(1-S_{L_n}(x))}{1-\max_c R_n(x)(1-S_{r_n}(x))} \quad (19)$$

Since the $\min_c L(x)$ and $\max_c L(x)$ values of low-light images are both low, the values of many saturation components of low-light images tend to 0.

However, the saturation component value of low-illumination inversion images is concentrated in the interval close to 0, so an "S" type function is proposed to adjust the saturation component, as shown below:

$$S(x,y) = aI(x,y)^{\gamma} + (1-a)I(x,y)^{\frac{1}{\gamma}} \tag{20}$$

The saturation component of an unprocessed image is represented by $I(x,y)$The saturation component after enhanced treatment is represented by $S(x,y)$; a and γ represent the function values used to adjust the trend of the image curve. Different values will show different curves, the details are shown in the following figure:

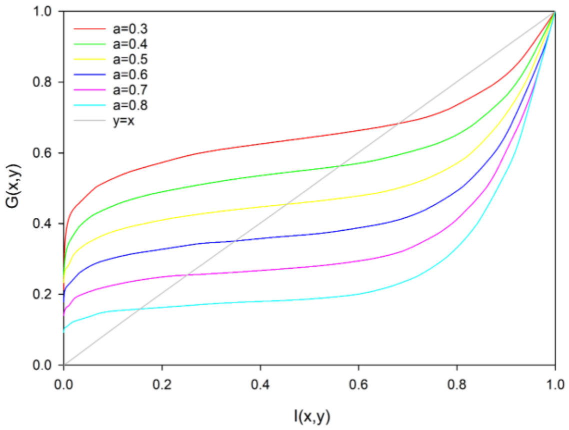


Figure 1: Function curves of different γ

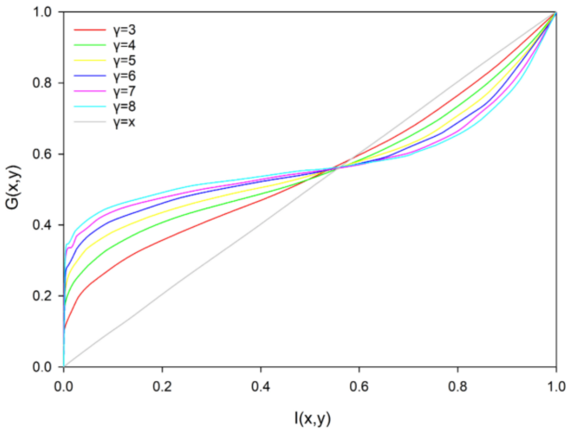


Figure 2: Function curves of different a

It is not difficult to find that the line shape is basically presented in an "S" shape. The γ coefficient has a great influence on the transformation rate of the curve. When $0 \leq x \leq 0.55$, the overall trend of the curve is convex function, indicating the improvement of the image value. When $0.55 \leq x \leq 1$, the curve extends upward with a concave function trend, indicating the suppression of image pixels. With the increase of coefficient γ, the adjustment effect of image pixel value is more obvious.

Coefficient a is used to control the intersection position of line $y = x$ and function curve. With the increase of a, the intersection position gradually increases with line $y = x$, the convex function interval decreases, and the concave function interval becomes larger, which means that the improvement range of input image pixels is large, but the suppression range is small. Since the saturation of different images is different, the use of fixed γ coefficient will have certain restrictions on the image, and the brightness of different images varies correspondingly with the bright channel. Therefore, this chapter proposes a selection method based on the bright channel prior to adapt to different images corresponding to different pixel enhancement and suppression intervals. First, the bright channel of the reversed image is obtained, and the γ-coefficient is clarified after the minimum value is known. The specific expression is shown in formula 20.

$$\gamma_{light} = \min_{c}\left(\max_{y\in\Omega(x)}\left(\max_{c} L(x)\right)\right) \tag{21}$$

The saturation component of the final stretch can be obtained by finishing, as shown below.

$$S_{R_n}(x,y) = aS_V(x,y)^{\gamma_{light}} + (1-a)S_V(x,y)^{\frac{1}{\gamma_{light}}} \tag{22}$$

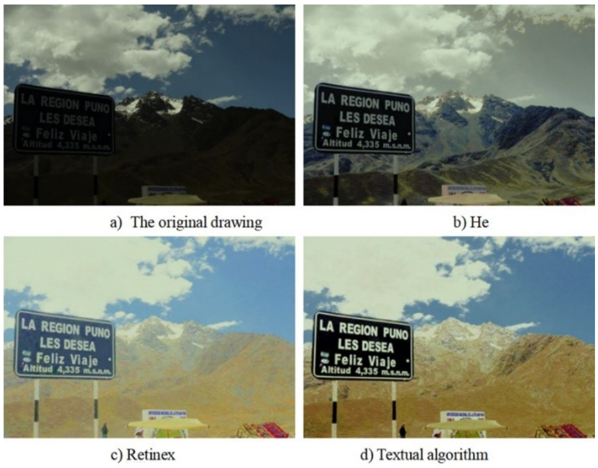
In summary, the non-uniform characteristics of low illumination images can be realized, and the reasonable saturation stretching can be achieved, so that the transmission of different low illumination images can be better solved.

3. Analysis of Experimental Results

Then, images from different datasets were selected for testing and comparison. By comparing the original image, histogram equalization (He) algorithm, Retinex algorithm and the algorithm in this paper, the enhanced images were comprehensively analyzed by combining subjective and objective evaluation. The results of low image processing show the effectiveness of the algorithm.

3.1 Subjective Experimental Analysis

In this experiment, several low-light images in different scenes were selected. The original image 3 was the low-light image with a large bright sky background; The original image 4 is a low-light backlight image; The original image 5 is a night low light image. The corresponding algorithms are compared from the aspects of brightness, contrast, detail information and clarity of enhanced images.



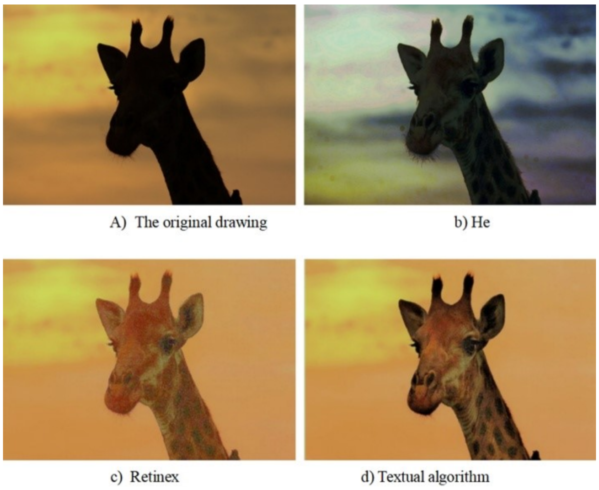


Figure 4: Comparison of low-illumination images

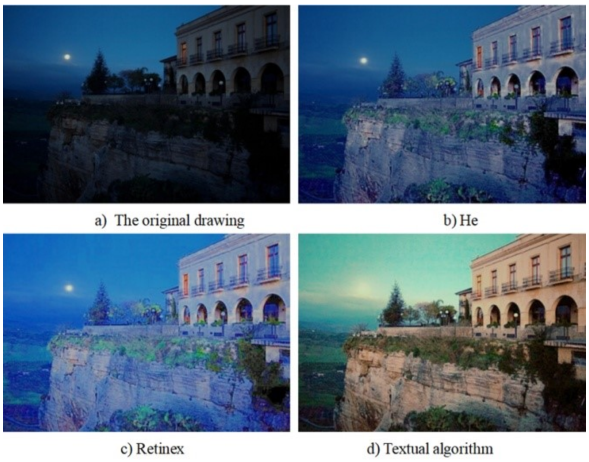


Figure 5: Comparison of low-illumination images

Figure 3 (a) represents a low-light image with the sky (high brightness) as the background. It is not difficult to see this in Figure 3(b), compared with the original image, after He algorithm intervention, the image brightness is improved to some extent,at the same time, the details in the shadow are also enlarged to a certain extent. However,the background tone has changed, and some color distortion problems have appeared.

The image after Retinex enhancement is shown in Figure 3 (c). It is not difficult to find that the brightness of the image after processing is improved, but the exposure is too high, so that the original details cannot be reflected. Figure 3 (d) shows the image enhanced by the algorithm in this paper. It can be seen that the enhanced image performs well in terms of brightness and saturation. Figure 4 (a) is a low-illumination backlight image. Figure 4 (b) shows the image enhanced by He algorithm. Compared to the original, the overall enhancement effect of the image enhanced by He algorithm is not good; In Figure 4 (c), the detail of the giraffe is significantly improved, and the overall color of the image is rich, but the image contrast is not high; In Figure 4 (d), the details of the giraffe's chin and neck are significantly enhanced. The enhanced image is not as bright as that in Figure (c), However, in brightness, figure (b) is relatively low, and the overall image is clear and natural. 5 (a) is a low-illumination image at night. Figure 5 (b) is the result of the enhanced histogram equalization algorithm. It is not difficult to find that the brightness after enhanced treatment has been improved to a certain extent, but the overall color of the enhanced image is blue; Figure 5 (c) shows the enhanced image after Retinex algorithm. The enhanced image can obviously observe the details of the shadow part of the original image. Compared with Figure (b), the brightness of figure (c) is higher, but the overall blueness of the image still exists. Figure 5 (d) has a high contrast. Compared with the previous two algorithms, the enhanced image color of the proposed algorithm is more consistent with human observation and has a good visual effect. As can be seen from the above pictures, it shows that the image can show a considerable visual effect after the algorithm enhancement processing. The method of obtaining the final transmittance through adaptive stretch saturation can effectively adapt to images with different brightness, and has a good restoration of the color of the image. It can bring people more comfortable visual enjoyment.

3.2 Objective Experimental Analysis

In addition to subjective evaluation, comprehensive analysis will be carried out in combination with objective evaluation indicators. We will conduct comprehensive analysis and evaluation of images from four aspects: average gradient, contrast, NRSS and PSNR. The higher the value of the above four evaluation indicators is, image optimization. The experimental results are as follows.

Table 1. Image 3 Detection results under different algorithms

Method	Mean gradient	Contrast	NRSS	PSNR
Master drawing	2.6123	45.4258	0.2594	
He	6.0541	153.9419	0.3153	27.3451
Retinex	4.9562	126.4265	0.3046	27.8652
Textual algorithm	7.5142	331.6584	0.3547	27.8726

Table 2. Image 4 Detection results under different algorithms

Method	Mean gradient	Contrast	NRSS	PSNR
Master drawing	2.2548	19.9456	0.2546	
He	4.9546	72.8462	0.3365	27.8314
Retinex	5.9326	163.5433	0.2751	28.1545
Textual algorithm	5.3695	146.2245	0.2658	28.2644

Table 3. Image 5 Detection results under different algorithms

Method	Mean gradient	Contrast	NRSS	PSNR
Master drawing	9.3452	346.1523	0.4832	
He	12.8432	327.6542	0.6582	28.4251
Retinex	10.5426	225.4921	0.6626	28.2351
Textual algorithm	17.6542	588.1412	0.6686	28.2644

As can be seen from Table 1, for the low-light image with a large bright sky background, after He algorithm enhanced processing, the average gradient increased by 131.75% compared with the original image, the contrast has increased by 238.88%, and the NRSS has increased by 21.54%, showing a high improvement in all aspects. Compared with Retinex algorithm, after enhanced image, in contrast, there are obvious improvements in all aspects. Compared with He, PSNR is improved, but the improvement in average gradient, contrast and NRSS is not as good as that of histogram equalization algorithm. The results of the algorithm in this chapter are all optimal on the selected image quality evaluation index, it is thought that the algorithm can enhance the low illumination image and improve the bad condition of image. As can be seen from Table 2, for low-illumination backlight images, the enhanced algorithm in this paper improves the four objective evaluation indexes to varying degrees, including 138.13% increase in average gradient, 633.11% increase in contrast, and 4.39% increase in NRSS. The average gradient, contrast and NRSS are slightly lower than Retinex algorithm, but it still has the best performance in PSNR, which is improved compared with histogram equalization algorithm and Retinex algorithm.

As can be seen from the results in Table 3, after image enhancement, the contrast has been significantly improved, but overall, the advantages of the proposed algorithm are more prominent, which increases by 69.90% compared with the original image, indicating the effectiveness of the algorithm in this chapter. In terms of average gradient, it is improved by 88.91% compared with the original image, 51.48% compared with the histogram equalization algorithm, and 76.10% compared with the Retinex algorithm, which is the best in both NRSS and PSNR. It can be seen from the above table that compared with other methods, the improved algorithm proposed in this chapter can obtain much more image information. Based on the above experiments and evaluation analysis, in terms of subjective evaluation, the proposed algorithm can make up for the shortcomings of He and Retinex algorithms and make the image more clearly visible, effectively adjust the brightness distribution of images, improve the sharpness and detail information of images, and well adapt to different complex shooting environments. Our algorithm can ensure the visual effect and at the same time. There is also a certain improvement in each evaluation index, and the overall quality of the image has been significantly improved.

4. Conclusions

In this chapter, we propose a method to improve low illumination image by using dark channel defogging method. First, according to the similarity between images taken in foggy weather and low light conditions, the possibility of image enhancement by using the defogging principle in low light conditions is illustrated. Meanwhile, the relationship between Retinex theory and the defogging theory in foggy day is analyzed. According to the relationship, a method to estimate image transmission by stretching image saturation inversion is proposed. for the characteristic difference between low illumination map, in order to obtain more flexibility in transmittance, a scheme is proposed to stretch the saturation channel of low-illuminance inversion images by combining the minimum value of the bright channel of the inversion image to improve the image quality, and then the overall image frame is explained and realized. Finally, according to the empirical results, the feasibility of the proposed algorithm is confirmed by comparing He with Retinex.

Funding

This study was supported by Research on optical fiber mirror visual detection technology of switchgear (5211QZ240004).

References

[1] Xu J, Wang X, Wang T, et al. "Research progress of optical vision sensor technology," Journal of Image and Graphics, 2023, 28 (06): 1630-1661.

[2] Zhong Y, Lei R, Lin L, et al. "Application of laser annealing in back-illuminated CCD image sensor," Semiconductor Optoelectronics, 2023, 44 (02): 241-244.

[3] Xu D, Liu Y, Yuan A, et al. "Design and fabrication of four-spectrum TDICCD image sensor," Semiconductor Opto-Electronics, 2022, 43 (03): 547-551.

[4] Song W, Chen Q, Liu Y, et al. "Underwater low-illumination image enhancement based on color correction and brightness estimation," Sensors & Microsystems, 2024, 43 (08): 30-34.

[5] Ji F. "Low illumination image enhancement technology based on optimized deep neural network," China High-Tech, 2024, (13): 27-29.

[6] Miao Z, Zhang L, Xu H, et al. "Mine low illumination image enhancement based on CLAHE - PCA study," Journal of Metal Mine, 2024, (6): 165-172.

[7] Sui T, Wu S, Jia H, et al. "Low illumination image enhancement based on improved cycle generation adversarial network," Science Technology and Engineering, 2024, 24 (14): 591-5919.

[8] Tang W, Liu X. "Region of interest detection in low illumination image of visual attention model," Computer Simulation, 2024, 41 (05): 242-245+337.

[9] Zhang Y, Zhou B, Wang J. "Implementation of ZYNQ for multi-scale Retinex low-illumination image enhancement," Fire Control & Command Control, 2023, 48 (07): 156-162.

[10] Zhang B, Sun Y, Wang Q, et al. "Retinex low-illumination image enhancement algorithm based on HSV space," Journal of Tianjin Normal University (Natural Science Edition), 2023, 43 (06): 69-74.

[11] Liu C, Qi P. "Fog removal and enhancement of video image based on atmospheric scattering model and correlation frame compensation," Journal of Information Engineering University, 2024, 25 (02): 167-174.

[12] Shi J, Zhong Y, Zheng X, et al. "Low illumination image enhancement based on light scattering attenuation model," Optical Precision Engineering, 2023, 31 (08): 1244-1255.

[13] Lin S, Zha Z. "Based on the inhomogeneous atmospheric correction model of light image to fog at night," Journal of Beijing university of aeronautics and astronautics, 1-16 [2024-10-31].