A Neural Network-Based Algorithm for Weak Signal Enhancement in Low Illumination Images

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***Abstract*—There is noise interference in low-illumination images, which makes it difficult to extract weak signals. For this reason, this paper proposes a low-illumination image weak signal enhancement algorithm based on neural network. Multi-scale normalization is performed on low-light images, and multi-scale Retinex is used to enhance weak signals in low-light images. On this basis, the GAN artificial neural network is used to detect the weak signal of the weak signal in the image, the normalization of the weak signal of the low-illumination image is completed based on the residual network, the self-encoding parameters of the depth residual are generated, and the weak signal enhancement result of the low-illumination image is output. The experimental results show that the method in this paper has better enhancement effect on low-illumination images and better image denoising effect. When the scale value is large, the low-contrast area of the low-illumination image has a better enhancement effect. The saturated area of the low-light image has a better enhancement effect.**

Keywords—Artificial neural network; GAN neural network; low-light image; weak signal enhancement

I. Introduction

With the advancement and development of science and technology, the methods of image acquisition are becoming more and more abundant, and people's requirements for image quality are getting higher and higher. However, the process of image acquisition will be affected by many factors. Under special lighting conditions, optical imaging equipment may cause uneven exposure of the obtained image, loss of scene details, and unclear recognition of weak and small targets due to uneven lighting. Since the dynamic range of the shooting equipment is limited, if you just adjust the exposure rate of the equipment, it still cannot solve the problem of overexposure or oversaturation in some areas. Under the conditions of lack of light and low visibility such as at night and dusk, the image collected by the image acquisition device not only has dark areas, but also the brightness and contrast of the image will be seriously reduced, making it difficult to distinguish the details of the image or even unable to see any details. The identification and judgment of images and the extraction of information in project management and control have a certain impact. Therefore, it is the current focus in the field of image processing to study and enhance the detail features of low-light images and ultimately improve the overall quality of the image [1].

Image weak signal enhancement is to perform specific processing on a given image, purposefully emphasizing the overall or local characteristics of the image, making the original unclear image clear or emphasizing some interesting features, and expanding the difference between the characteristics of different objects in the image. To meet some special application requirements [2], the difference between them can be suppressed, and the features that are not of interest can be suppressed. Low-illumination images are generally images collected in scenes with insufficient ambient light. The gray levels of such images are concentrated in a lower gray-scale range, and the details of the images are not obvious. In addition, the image will also contain a lot of noise, which seriously affects the image quality. To make the low-illumination image have a better display effect or meet the input requirements of other image processing algorithms, it is necessary to carry out enhancement and noise reduction processing to emphasize the useful information in the image and effectively suppress the interfering information such as noise [2].

Study [3] proposes a low-light image adaptive enhancement algorithm based on maximum difference map decision. First, the concept of a maximum difference map is proposed, and the initial illumination component is roughly estimated by the maximum difference map; then, an alternate guided filtering method is proposed. The algorithm uses alternating guided filtering to correct the initial illumination components to achieve accurate estimation of the illumination components; finally, an adaptive gamma transform for image brightness is designed, which can adaptively adjust the gamma transform parameters according to the acquired illumination components to enhance the image, also eliminates the effects of uneven lighting. Research [4] proposes a recurrent image enhancement network based on generative adversarial networks (GAN). An unsupervised learning method is introduced to estimate the original illumination of low-light images by reducing the loss of cycle consistency and adversarial loss. The image enhancement model formula is used to enhance the brightness of the images collected under insufficient illumination. Finally, the synthetic low-light image data set and the real natural low-light image data set are evaluated qualitatively and quantitatively. Liu Y's team proposed a GAN model that can perceive the lighting details. This model can fine-tune the image lighting effect in the case of high noise and loss of texture details, and use residual dense encoding and decoding strategy to suppress noise. The performance results show that the model is better in the ultra-low light image data set [5]. Jung E's team proposed a multi-frame GAN concept that can enhance stereo vision image sequences under low light conditions. This method is based on the reversible generation of the confrontation

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network, which can transfer the features of bright lighting scenes to the bottom lighting scenes. The research results show that this method has great advantages in visual mileage [6]. Ma Y et al., focusing on the field of medical images, proposed a GAN model that can add terms to the circular structure and illumination constraints of medical images. This model can learn the overall and local details of images. The research results show that this method is better than traditional methods [7]. The above methods are all effective to a certain extent, but it is difficult to ensure the details of the image while realizing the enhancement of the low-illumination image, and the visual perception of the enhanced image still needs to be improved. To this end, this paper proposes a low-light image weak signal enhancement algorithm based on a neural network.

II. Research on Weak Signal Enhancement of Low Illumination Image

A. *Multi-Scale Normalization of Low-Light Images*

For low-light images, normalization can reduce the probability of image distortion during the enhancement process and improve the ability to retain details. Through the unified management of image features, the misjudgment rate of target information is reduced and the enhancement efficiency is improved. However, in most cases, the original low-light image contains a large number of isolated discrete pixels, and there is no spatial correlation between these pixels, but the pixels follow the Gaussian distribution, indicating that the data of the original image has a certain influence of noise. To this end, the image is denoised first and then normalized [8].

In this paper, the wavelet transform method is used to denoise the data points in the multi-frequency domain in the image, which helps to deepen the pixel signal characteristics in the image, and can ensure the processing effect of signal noise even in the state of different resolutions. The key to wavelet transformation lies in the selection of the transformed threshold. There are two commonly used thresholds: one is the hard threshold, which is closer to the actual situation and retains the edge information of the image better, but the noise reduction effect for Gaussian white noise is poor. The second is the soft threshold, which has a certain continuity, which can improve the low-light enhancement performance and make the visual expression more natural. In contrast, the latter is more suitable for low-light image processing [9].

By establishing a unified Gaussian frequency division noise reduction model, the original low-light image is used as the input value of the model. In the model, the transform value of each wavelet packet frequency band depends on the frequency band value of the image, and the complex wavelet packet is decomposed. It is assumed that X is the initial value of the image, P is the noise, and Z is the observation image with noise. The expression formula is as follows:

$$Z = X + P \quad (1)$$

If each noise in the image follows the Gaussian distribution of its frequency band, its mean value is 0, and its variance value is σ_k^2. The variance value can be calculated according to statistical values [10].

After determining the frequency band parameters of the image, use the multi-scale method to quickly estimate the noise reduction model, and then use the soft threshold to correct the estimated value ξ to obtain the actual output value e^2. The correction formula is:

$$\begin{aligned} e^2 &= |\xi|^2 / 4 - \sigma_k^2 & |\xi| \geq 4\sigma_k^2 \\ e^2 &= 0 & |\xi| < 4\sigma_k^2 \end{aligned} \quad (2)$$

From the corrected output value, derive the noise value in all frequency bands in the image:

$$\xi = e^2 / \left(e^2 + \sigma_k^2\right) \quad (3)$$

Finally, the estimated value is restored to the original decomposition domain by wavelet packet transform to realize image noise reduction.

Calculate the multiple scale values of the denoised image, and divide the size threshold of the image normalization process according to the scale value. The algorithm framework is as follows.

Given a low-light image of size $p \times q$, where q is the sampling factor, M is the scaling factor of the image, and $m = 1, 2, \cdots, M$. Pixel sampling according to $\frac{p}{q} \times \frac{q}{p}$, pixel point $i \in C$.

The constraint function is:

$$C_{s-1,s}(i, j) = \frac{1}{|N_i|} \qquad \forall j \in N_i \quad (4)$$

In the formula, N_i is the neighborhood of image sampling point i.

Calculate the refraction value W_s^c of the image passing through the light, the radius is r, and the multi-scale value of the image is calculated by $\left(W_s^c, C_{s-1,s}\right)$:

$$W = \begin{bmatrix} W_1^c & & \\ & \ddots & \\ & & W_s^c \end{bmatrix} \quad (5)$$

$$C = \begin{bmatrix} C_{1\square 2} - I_2 & & \\ & \ddots & \\ & & C_{s-1,s} - I_s \end{bmatrix} \quad (6)$$

In the formula, W represents the multi-scale weight. Calculate the image projection value Q:

$$Q = I - AC^T \left(CA^{-1}C^T \right)^{-1} CA \quad (7)$$

In the formula, A represents a multi-scale normalized matrix:

$$A(i,i) = \sum_{i,j=1}^{n} W(i,j) \quad (8)$$

The low-light image is substituted into the matrix, and the final normalized result can be obtained by multiple iterative calculations.

B. Weak Signal Enhancement of Low-Light Images based on Multi-Scale Retinex

1) Low-light sub-image segmentation based on LIP model: In image processing, general arithmetic operations are not suitable for some actual image processing work, and the result obtained by directly adding (or multiplying) two images has a certain gap with the human visual effect, and will produce “hyper-interval value” problem, the LIP model provides a new arithmetic construct that defines new vector operations such as addition, subtraction, multiplication, etc. The gray values of the images applied with this model are all in the (0, M) interval, so as to avoid the problem of exceeding the interval value, which is also consistent with the saturation characteristics of the human visual system [11].

In order to make the enhancement effect of the proposed method more obvious, when the low-illumination image is denoised, it is decomposed in two dimensions according to the background intensity and gradient information.

Let $I(x,y)$ be the background intensity, which is obtained by calculating the weighted mean of the pixels in the field, as shown in the following formula:

$$I(x,y) = m \otimes n \left(2 \otimes \sum_{L}^{m} f(x,y) \right) \quad (9)$$

In the formula, the set of neighborhood pixels in the four directions of the pixel to be processed is L; the weights are m and n; the set of domain pixels on the diagonal of the pixel to be processed is L'.

If the gradient $G(x,y)$ of the pixel value of the low-light image is used as the information transition rate, the maximum difference value of the low-light image pixel needs to be defined. The calculation method is as follows:

$$Id = \left[\max(f(x,y)) \Theta \min(f(x,y)) \right] \quad (10)$$

Let I_i be the threshold of the background intensity; G_i be the threshold of the gradient, and use the following formula to divide the low-light image into regions:

$$\begin{cases} I_1 = a * Id; I_2 = b * Id; I_3 = c * Id \\ GG_1 = 0.01\beta \max(GG(x,y)I(x,y)) \\ GG_2 = GG_1 I_2 \\ GG_3 = GG_1 I_3 \end{cases} \quad (11)$$

Pixels in saturated regions of low-light images satisfy the following equation:

$$\begin{cases} I(x,y) \geq I_3 \\ \begin{cases} GG(x,y) \\ I(x,y) \end{cases} \geq GG_3 \end{cases} \quad (12)$$

Pixels in the de Vries region of a low-light image satisfy the following equation:

$$\begin{cases} I_2(x,y) \geq I(x,y) \geq I_1 \\ \begin{cases} GG(x,y) \\ I(x,y) \end{cases} \geq GG_2 \end{cases} \quad (13)$$

Pixels in the Weber region of a low-light image satisfy the following equation:

$$\begin{cases} I_3(x,y) \geq I(x,y) \geq I_2 \\ \begin{cases} GG(x,y) \\ I(x,y) \end{cases} \geq GG_1 \end{cases} \quad (14)$$

The proposed method decomposes the low-illumination image into several sub-images and then merges the remaining pixels into the low-contrast area uniformly, which completes the division of each area of the low-illumination image and realizes the purpose of image enhancement for different sub-images [12].

2) Local multi-scale Retinex algorithm: The Retinex theory believes that an image can be divided into incident components and reflection components. First, the low-illumination image is segmented by the area division method of the above LIP model. Then, according to the illumination characteristics of each sub-image after segmentation, Retinex of different scales σ is used to highlight the advantages of Gaussian functions of different scales are enhanced, and the specific process of the method is shown in Fig. 1.

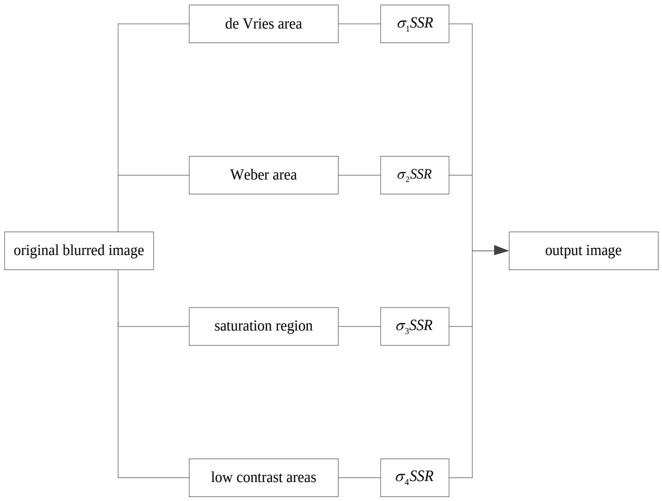


Fig. 1. Local multi-scale Retinex algorithm process

The pixels in the low-contrast area are filtered using Gaussian template $F_1(x,y)$ with scale σ_1.

First, the incident component of the image in this area is estimated, and then the reflection component is discarded to complete the enhancement of the low-contrast area in the low-illumination image, as shown in formulas (15) and (16):

$$F_1(x,y)=2\frac{1}{\pi}\sigma_1\exp(-\frac{x^2+y^2}{2\sigma_1^2}) \tag{15}$$

$$R_1(x,y)=\lg S_1(x,y)-\lg\left[S_1(x,y)*'F_1(x,y)\right] \tag{16}$$

In the formula, the Gaussian function with a scale of σ_1 is $F_1(x,y)$; the pixel in the low-contrast area is $S_1(x,y)$, and the processing result of the low-contrast area in the original image is $R_1(x,y)$.

Use Gaussian filters of different scales to estimate the incident components of the remaining de Vries area, Weber area, and saturation area, and complete the enhancement of each area according to the above calculation method. The calculation method is as shown in formulas (17) and (18). Show:

$$F_K(x,y)=2\frac{1}{\pi}\sigma_K\exp(-\frac{x^2+y^2}{2\sigma_K^2}) \tag{17}$$

$$R_K(x,y)=\lg S_K(x,y)-\lg\left[S_K(x,y)*F_K(x,y)\right] \tag{18}$$

Through the above calculation, three sub-images $R_2(x,y)$、$R_3(x,y)$、$R_4(x,y)$ are obtained in the same way for the other three regions, and the sub-images $R_1(x,y)$、$R_2(x,y)$、$R_3(x,y)$、$R_4(x,y)$ are combined together to obtain the final enhancement effect.

Because the pixel contrast in the low-contrast area of the low-illumination image is low, choosing a relatively small σ -value can better highlight the details of the image and achieve an enhanced effect. Among them, σ_1、σ_2、σ_3、σ_4 are different scales selected in the four regions decomposed in the low-illumination image by using the Gaussian function.

The de Vries region represents the low-light region of the low-light image, the Weber region represents the medium-light region of the low-light image, and the saturated region represents the high-light region of the low-light image. Therefore, the scale can be selected according to the rule of $\sigma_2<\sigma_3<\sigma_4$. At the same time, through the improved multi-scale Retinex algorithm, the proposed method satisfies the enhancement requirements for different specific pixel regions in low-illumination images, so that low-illumination images can obtain better color fidelity and detail enhancement effects.

III. Improved Algorithm for Weak Signal Enhancement of Low-Light Images based on Neural Network

A. *Weak Signal Detection of Weak Signal in Image based on Artificial Neural Network*

Before designing the low-light image weak signal enhancement algorithm, extract the weak signal of the image, apply the mathematical model and other techniques to plan the image edge data into a set of multi-dimensional data structure [13], and then use the random process of the data and the feedback in the artificial neural network. The mechanism divides the weak signal of the image into functional regions and non-functional regions [14], and its noise function expression is as follows:

$$g(y)=\frac{1}{\sqrt{2\pi}}\exp\left(\frac{(y-\mu)}{2}\right) \tag{19}$$

In the formula, y represents the gray value of the noisy edge image, and μ represents the expected value of the image edge noise on the gray value. The formation of Rayleigh noise is mainly caused by other elements in the edge data collection environment during the image generation process, and the noise is relatively high. The complex data edge environment, and then the formation of noise, the function representation is as follows:

$$g(y)=\frac{2}{b}(y-a)\exp\left[-\frac{(y-a)^2}{b}\right],y\geq a \tag{20}$$

In the formula, a represents the high probability complex factor existing in the weak signal data environment of the image, and b represents the correlation between the weak signal data of the image and the original data of the image edge. In order to observe the influence of different noises on the image edge more intuitively, this paper extracts the noise data of the original image edge, and then the Matlab software is used for model simulation processing. The obtained weak signal detection processing results of different types of images are as follows:

The application of artificial neural network technology to extract image weak signal edge noise data requires the application of various types of algorithms and filtering techniques [15-17]. As the feedback object and data extraction library of artificial neural network, the filtering algorithm formula used in this paper is as follows

$$f(x,y)=\frac{1}{M\times N}\sum_{M,N\in R} f(m,n) \tag{21}$$

In the formula, M and N respectively represent the average noise wave value of different types in the image weak signal edge data, which can produce a certain degree of defense against the image edge noise data, and complete the image edge noise without losing the original image clarity. Data detail processing and extraction will not affect the post-processing of images such as missing data.

After filtering and classifying the relevant data in the weak signal of the image by applying filtering technology, two parts of noise coefficients are generated, which respectively exist in the image edge database with different noise frequencies. Initialize the data information at the edge of weak signal. The specific change expression is as follows:

$$w_{j,k}^{n}=\begin{cases} w_{j,k} & \left|w_{j,k}\right|\geq\lambda \\ 0 & \left|w_{j,k}\right|<\lambda \end{cases} \tag{22}$$

In the formula, λ represents the image edge noise threshold, and $w_{j,k}$ represents the noise coefficient in the neural network. To accurately extract the noise coefficient, the data connection state in the artificial neural network has been in a continuous mode, resulting in obvious threshold division and easy to make other noise factors. Reshape the details of the weak signal edge of the image.

B. Create a Normalized Processing Structure for Weak Signals in Low-Light Images

GAN technology is actually a low-light image weak signal confrontation processing program, which mainly processes the weak signals of low-light images one by one according to the corresponding steps. First, we need to prepare a low-light image weak signal discriminator and a generator. The discriminator mainly makes a corresponding judgment on whether the weak signal of the low-illumination image belongs to the real data distribution, and calculates the respective probability values of the data input and output. The generator captures relevant data and indirectly forms a similar data distribution. Calculate the objective function of the GAN. Calculated as follows:

$$G\left\{F(a,b)\right\}=E\left[Lg(1+\sqrt{5})\right] \tag{23}$$

In the formula, G represents the value of the objective function, F represents the set range of the function, a represents the maximum value of the function, b represents the minimum value of the function, and E represents the corresponding separation function of the GAN objective function. Through calculation, its objective function is obtained. Then, a model is generated using the objective function and balanced optimization is performed on it. In a specific low-light image weak signal processing environment, use SRGAN to build a GAN network architecture processing structure, as shown in Fig. 2:

Fig. 2 shows the related process of the low-light image weak signal processing structure of the created GAN network. After that, a normalized processing relationship is established between the weak signal loss function of the low-illumination image obtained in the model and the adversarial function, as shown in the following formula:

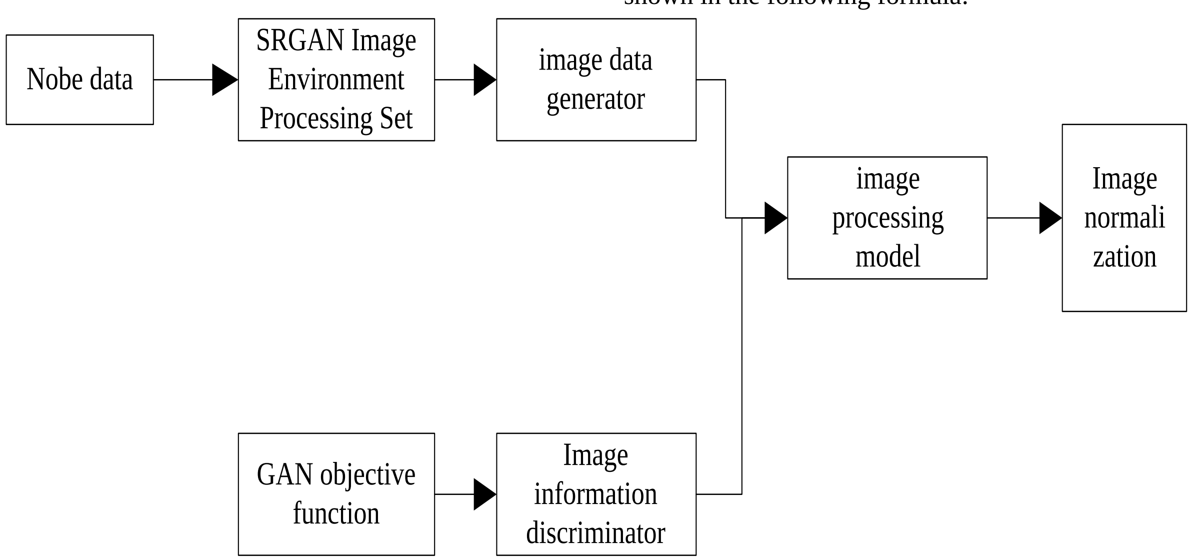


Fig. 2. GAN network low-light image weak signal processing architecture

$$Y = B - C + r \quad (24)$$

In the formula, Y represents the relationship between the loss function and the adversarial function, B represents the directional processing distance, C represents the target processing distance, and r represents the error distance. After the processing relationship is established, the weak signal of the low-illumination image is imported into the processing system, and the generator is used to first obtain the data information corresponding to the weak signal of the low-illumination image, and then a convolution layer of the weak signal of the low-illumination image is established to improve its resolution. Subsequently, the convolutional layer is activated using the ReLU activation layer in the discriminator, and then 10 residual network modules are constructed through the processing steps, and these modules are skip-connected. At this time, the connection surfaces of each layer are superimposed on each other and continue to be superimposed under the action of the convolution layer. Such a low-light image weak signal processing mode can prevent the low-level low-light image weak signal features from being generated. loss, and expand the size, length, width, and area of weak signals in low-light images. In general, it can be expanded to about four times the weak signal of the original low-light image, and finally, a picture with four times the resolution is obtained. Then, the discriminator is used again to superimpose the weak signal of the low-illumination image processed above by using the processing path again to superimpose the connection surface. This time, multiple convolution structures need to be repeated, and their lengths are separated into two types, one and two, using different processing types used to process low-light images, weak signals, and pictures in different formats. Subsequently, the image scale was changed to 1/16 in the original image processing system. Adjust the number of channels to 612, activate the discrimination result, output the result in another system dimension, and set the sigmoid function to perform the final processing on the weak signal of the low-light image, to use the related technology of GAN to create a low-light image. Normalized processing structure for weak signals.

C. *Low-Light Image Weak Signal Enhancement Algorithm based on Residual Network*

After the normalization of the weak signal of the low-illumination image is completed, next, a low-illumination residual network is constructed to enhance the weak signal of the low-illumination image. First, the auto-encoding parameters of the depth residual are generated. Auto coding is a neural network control value that uses a backpropagation algorithm to process data information. It compresses the weak signal of a low-light image to an editable size, hides its spatial representation, and then outputs it through the representation. Next, the low-light processing coefficient of the residual processing model is established in a low-light processing environment. The calculation formula is as follows:

$$X = (\alpha + \beta) - \frac{1}{l} \quad (25)$$

In the formula, X represents the low-light processing coefficient of the model, represents the processing distance, represents the straight-line processing distance of the model, and one represents the number of inertial protons. Through the above calculation, the low-light processing coefficient is obtained. On this basis, next, the total iteration value of the discrimination of the weak signal of the low-light image is calculated. The calculation formula is as follows:

$$K = \frac{\Delta i}{\Delta j} - \frac{1}{v} \quad (26)$$

In the formula, K represents the total iterative value of discrimination for weak signal processing of low-illumination images, i represents the total distance of calculation iterations, j represents the number of iterations, and v represents the objective function. After obtaining the iterative value of the weak signal processing of the low-illumination image, next, the processing system is used to establish an enhancement relationship between the weak signal of the original low-illumination image and the weak signal of the target low-illumination image to enhance its versatility.

The cyclic residual neural network is used to enhance the weak signal of the low-light image. First, optical color analysis needs to be performed on the low-light image that needs to be processed, and the color that cannot be edited is recorded. Then, use the residual neural network technology to amplify the weak signal of the low-light image to a size that can be processed, separate the color replacement factors in the low-light image, and adjust the color of the low-light image to a single mode, and turn on the intelligent color in the system processing. Adjustment function, a kind of original low-light image weak signal, restores the color and increases the control parameters of its saturation so that the low-light image weak signal overall is more three-dimensional. Then, set the residual coefficients that satisfy the weak signal enhancement processing of low-illumination images in the system, add auxiliary graphics processing programs, and change the processing mode of the system to multiple-simultaneous loop processing. Then, in the low-light and low-light image processing environment, the corresponding low-light image weak signals and photos are enhanced at various levels, to complete the low-light image weak signal enhancement processing by the cyclic residual neural network.

IV. Experimental Analysis

A. *Experimental Conditions*

To verify the effectiveness of the low-light image weak signal enhancement algorithm based on a neural network, a simulation comparison experiment was carried out. Select the images in the Joint Video Stitching and Stabilization from Moving Camer (http://www.liushuaicheng.org/TIP/VideoStitching2016/index.html) dataset, and the schematic diagram of the low-light image is shown in Fig. 3.

Fig. 3. Schematic diagram of low-light image

TABLE I. GAN NEURAL NETWORK PARAMETERS

Index	Parameter
The number of network layers	3
The number of iterations	94
The weight of the first layer	0.5
The offset term	0.7
The learning rate	0.001

The parameters of the GAN neural network are set as shown in Table I.

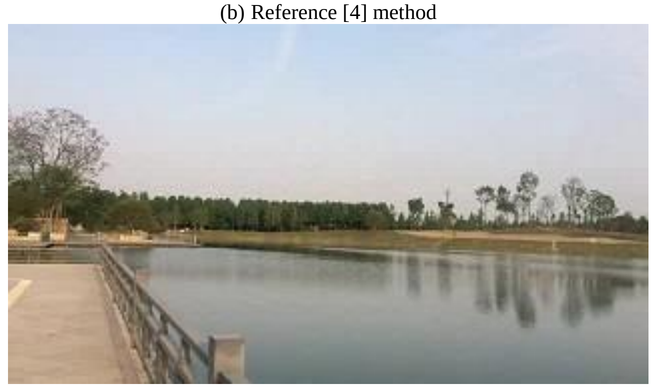
Under the above experimental conditions, the method of studies [3] and [4] are used as experimental comparison methods to test the effectiveness of the low-light image weak signal enhancement algorithm.

B. Analysis of Experimental Results

Fig. 4 is a low-illumination image enhancement effect diagram obtained by applying the method of study [3], the method of research [4] and the method of this paper to the low-illumination image enhancement operation.

(a) Reference [3] method

(b) Reference [4] method



(c) This paper method

Fig. 4. Low-light image enhancement effect diagram

As can be seen from the above figure, the original low-illumination image is dark in brightness and the blurring phenomenon is serious. The enhancement effect of the method in studies [3] and [4] is poor, while the low-illumination image enhanced by the method in this paper has low brightness and sharpness. It shows that the application of this method can realize the enhancement of low-light images, and the enhancement effect is better, which can better meet the needs of practical work.

Clarity and information entropy are two important indicators that reflect the enhancement effect of weak signals in low-light images. Table II shows the values of sharpness and information entropy at different scales obtained by performing sub-image enhancement operations on saturated areas of weak signals and low-contrast areas of low-illumination images using the method in this paper.

TABLE III. CLARITY AND INFORMATION ENTROPY AT DIFFERENT SCALES

Scale value	low contrast area		saturation area	
	sharpness	information entropy	sharpness	information entropy
0.6	20.52	6.21	23.63	8.63
1.2	21.52	6.59	22.52	8.52
1.8	22.03	7.03	22.02	8.01
2.4	22.96	7.42	21.96	7.56
3.0	23.65	7.86	21.56	6.98
3.6	24.52	7.99	20.32	6.23
4.2	25.63	8.09	19.56	5.56
4.8	26.66	8.33	18.96	4.98
5.4	27.33	8.86	18.23	4.88
6.0	27.86	9.01	17.63	4.35

It can be seen from Table II that with the increase of the scale value, the sharpness and information entropy value of the low-contrast area of the low-illumination image both show an increasing trend. When the value is 0.6, it is increased by 34%; the sharpness and information entropy of the saturated area of the low-light image shows a decreasing trend with the increase of the scale. When the scale value increases from 0.6 to 6.0, the sharpness of the image decreases by 25%. Description: When the value of the scale is large, the low-contrast area of the low-light image has a better enhancement effect, and when the value of the scale is small, the saturated area of the low-light image has a better enhancement effect. Therefore, when applying the method in this paper to perform image enhancement on low-illumination images, large-scale and small-scale combined operations should be performed in the low-contrast and saturated regions of the low-illumination image to achieve better image enhancement effects.

Fig. 5 shows the sharpness curves under different signal-to-noise ratios obtained by applying the method in this paper, the method in study [3] and [4] to perform weak signal multi-scale enhancement operations on low-illumination images respectively. In Fig. 5, with the increase of the signal-to-noise ratio, the sharpness curves of the three methods all show an upward trend, but the sharpness curves of the method in this paper are higher than those of the methods in researches [3] and [4] from the beginning, and with the increase of the signal-to-noise ratio, the sharpness curve obtained by applying the method in this paper to perform the image enhancement operation on the low-illumination image has an obvious upward trend. Increased by 50% and 65%. Prove: Applying the method in this paper to perform image enhancement operations on low-light images can obtain higher image clarity, and the advantages of low-light image enhancement are more obvious.

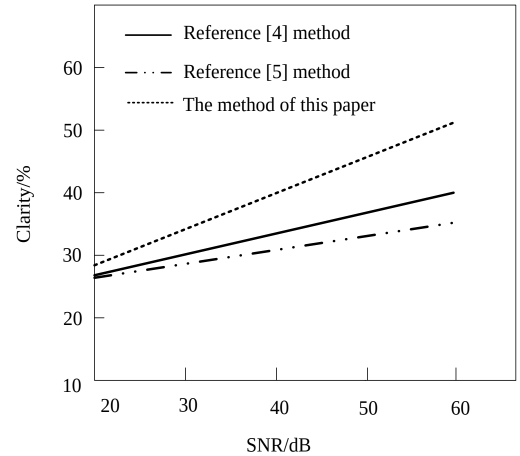


Fig. 5. Comparison of sharpness curves

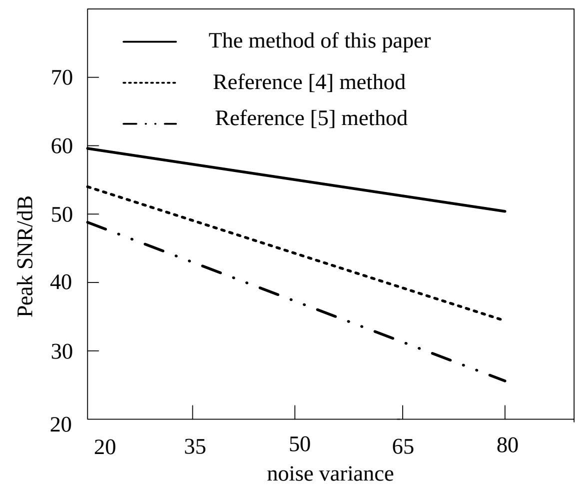


Fig. 6. Peak signal-to-noise ratio curves of different methods

In order to verify the advantages of the method in this paper in denoising low-illumination images, the peak signal-to-noise ratio curves under different noise variances obtained by applying three methods to perform denoising operations on low-illumination images are shown in Fig. 6.

Analysis of Fig. 6 shows that the peak signal-to-noise ratio curves obtained by applying the three methods to perform denoising operations on low-illumination images all gradually decrease with the increase of noise variance, but the peak signal-to-noise ratio curves obtained by applying the method decrease from one to one. In the beginning, it is higher than the methods of [3] and [4], and with the increase of noise variance, the downward trend of the curve is very insignificant. Experiments show that the method in this paper is used to perform denoising operation on low-illumination images, and the denoising effect is better than the methods in [3] and [4], and it has more advantages in denoising low-illumination images.

V. CONCLUSION

This paper proposes a low-light image weak signal enhancement algorithm based on a neural network. The experimental results show that the method in this paper has a better enhancement effect on low-light images. When the scale value is large, the low-contrast area of the low-light image has a better enhancement effect. When the scale value is small, the saturation area of the low-light image has a better effect. It has a better enhancement effect, and the image-denoising effect of this method is better.

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