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Restoration and Enhancement of Fuzzy Defect Image Based on Neural Network

Zhan-Peng Cui*

College of Information Engineering, Zhengzhou Technology and Business University, Zhengzhou 451400, China
cuizhanpeng@ztbu.edu.cn

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Abstract: In contrast enhancement of fuzzy defect image, details loss and noise expansion are east to occur, which brings difficulties to subsequent image analysis and defect recognition. Therefore, a fuzzy defect image restoration and enhancement method based on neural network is proposed. A double fusion neural network composed of a depth generation network and a discrimination network is designed. The residual of the denoised fuzzy image and the real image is output by the network, which is input into the discrimination network together with the real image, and the difference between the two is judged by the total loss function. To solve the problem of pixel coordinate value of fuzzy defect image, neural network is used to build a fast correction algorithm. Therefore, a fuzzy image restoration and enhancement method based on neural network is proposed to improve the image quality. By reconstructing the resolution of fuzzy defect image, a hierarchical enhancement method of fuzzy defect image region is constructed to achieve fuzzy defect image restoration and enhancement. The results show that the proposed method has high image processing ability in restoration and enhancement of fuzzy defect images. The fitting value of neural network is 0.92, which is significantly higher than that of the other two methods, indicating that the image restoration and enhancement method based on neural network has higher accuracy. Therefore, the restoration and enhancement method of fuzzy defect image based on neural network has a good restoration and enhancement effect, and can effectively meet the actual needs of people for high-quality images.

Keywords: neural network, blurred defect image, image restoration, image enhancement method

1 Introduction

Image is an objective description of everything through color, texture details, shape and other characteristics. Image is rich in various valuable information and is one of the main ways of information transmission as demonstrated [1, 2]. With the continuous advancement of informatization, digital multimedia technology has shown a steady growth trend, and has its application scenarios in all aspects of people's life as demonstrated [3]. It has become an indispensable way of life for people to transmit image information and life dynamics in the social media through smart phones and other mobile terminals. Multimedia and Internet based on images are inseparable from people's life, which greatly meets people's various needs. Image quality directly affects the quality of information communication and people's sensory pleasure in reference [4]. Prabha et al. [5] draw a conclusion that High quality images will give people a pleasant visual feast. On the contrary, blurred images and noise defects will lead to the loss of important information and loss of use value. Quality restoration and contrast enhancement for the image with fuzzy defects can improve the problems of fuzzy defects and excessive noise in the original image, which is conducive to image analysis and defect recognition. Its essence is to selectively strengthen some information in the image so as to suppress other information. Because the fuzzy defect image is very complex, and there is a strong correlation between each level, a little error may lead to incomplete or inaccurate image levels. It is of great significance to restore the fuzzy defect image to the original image through image restoration and enhancement.

Fuzzy defect image restoration and enhancement is a key research hotspot in the field of machine vision. At present, image restoration and enhancement methods rely too much on prior knowledge to restore and enhance fuzzy defect images under the condition of determining fuzzy kernel. With the wide application of neural networks, many scholars have proposed image restoration methods based on convolution neural networks. S.-P. Premnath et al. proposed the application of Jaya based image restoration model in optimization. This method mainly includes three stages: the generation of pixel map, the recognition of noisy pixels and the enhancement of

* Corresponding Author

pixels. Firstly, a noisy pixel map is generated from the input image, and then the noisy pixels are identified based on the depth convolution neural network, which is trained by the proposed Jaya bat algorithm. Jaya bat algorithm is developed by combining Jaya optimization algorithm and bat algorithm. Once the noise pixels are identified, the neuro fuzzy system is used to enhance the pixels, but this method consumes a lot of network training time as demonstrated [6]. Zhou et al. [7] proposed lensless image restoration based on depth analysis network and depth denoising prior, combining analysis update with depth denoising, and then gradually improving lensless image quality through several iterations. Its convergence was proved mathematically and verified in the results. In addition, this method is universal in non blind restoration. The solution of the general inverse problem was explained in detail, and five groups of deblurring experiments were carried out as examples. The two experimental results showed that compared with the most advanced methods, the proposed method had achieved excellent performance. This method increases the amount of computation, but is easily limited by the fuzzy kernel. Once the accuracy of the fuzzy kernel is not high, it will directly affect the image restoration effect. Ghulyani et al. [8] proposed a fast roughness minimization image restoration under mixed Poisson Gaussian noise. First, a new iterative method was developed to calculate the approximate solution of PG log likelihood, derive the termination condition of the iterative method, and integrate it into the provable convergence ADMM format. Experiments showed that the performance of this method was better than that of primal dual method in most cases. However, the image restoration process of this method is more complicated, and there is still room to improve the effect of texture detail restoration. Liang et al. [9] proposed a BP neural network fuzzy image restoration method (OBSO-BP) based on brainstorming intelligent optimization algorithm. The brainstorming intelligent algorithm is optimized in both clustering and mutation to solve multimodal high-dimensional function problems, increase the convergence speed of the network, reduce network errors, and improve the quality of image restoration. The experimental results showed that this method could achieve better image restoration effect. Fan [10] proposed a quantum ring symmetry algorithm to improve the quality of fuzzy image reconstruction. First, a quantum ring symmetric model is established to eliminate the computational obstacles. Then, for quantum image and entanglement operations, the maximum entangled state can be used for adaptive fast evolution. Finally, the image reconstruction model is established. The results showed that the reconstructed image is close to the original clear image, and the reconstruction quality is good. Meng et al. [11] proposed paper proposes a novel end-to-end two-stream convolutional neural network for single-image dehazing. This module uses the attention mechanism to construct a unified expression of different types of information and realizes the gradual restoration of the clear image with the semantic information auxiliary spatial information in the dehazing network. It improves the model's ability to discriminate images. The experimental results showed that the model could restore desired visual effects, and it also has good generalization performance in real scenes. Chen [12] designed a lead strip image enhancement algorithm based on histogram equalization and Laplacian. Combining with Laplacian enhancement algorithm and gamma transform function, the multi-enhancement algorithm model is created to enhance the X-ray image features, which to a certain extent achieves the purpose of feature enhancement and restoration of lead strip image. Compared with the existing ordinary enhancement algorithm, the system has better image enhancement effect.

It can be seen from the above contents that the research on restoration and enhancement of fuzzy defect images is rich, but most of the existing image restoration and enhancement methods are complex. At the same time, accurate prediction of fuzzy kernel is required to improve image enhancement effect. Therefore, the research proposes to use neural network to improve the image resolution, build a neural network based fuzzy defect image restoration and enhancement method to process the image, improve the image quality, and better meet the actual needs.

This paper has done some research work in the field of restoration and enhancement of fuzzy defect images, and has made some research achievements. The effect and accuracy of restoration and enhancement of fuzzy defect image using neural network are better than those of traditional image enhancement methods. These results can promote and popularize the application of image restoration and enhancement.

The research content mainly includes four parts. The first part is the overview of the research status of image enhancement methods at home and abroad. In the second part, a fuzzy defect image restoration method based on neural network is proposed. In the first section, a fuzzy defect image restoration strategy based on neural network is proposed. The second section introduces the pixel coordinate extraction method of fuzzy defect image. In the third section, a fast correction algorithm for fuzzy defect image restoration is designed. In the third part, a region enhancement method of fuzzy defect image based on neural network is proposed. In the first section, the resolution of fuzzy defect image is reconstructed using neural network. In the second section, a hierarchical enhancement method of fuzzy defect image region is constructed. The third section realizes restoration and enhancement of fuzzy defect image. In the fourth part, the method proposed in the study is tested and analyzed. The results show that the fuzzy defect image restoration and enhancement method based on neural network has a good effect.

2 Fuzzy Defect Image Restoration Based on Neural Network

2.1 Fuzzy Defect Image Restoration Based on Neural Network

The depth generation network and the discrimination network form a double fusion neural network. Based on the difference between the restored fuzzy defect image and the residual, the fuzzy defect image is mapped to the residual space through the depth generation network, and the recovered image is distinguished by the discrimination network based on the clear image as demonstrated [13]. The specific operation process is as follows: segment the whole fuzzy defect image, divide it into small blocks, and transmit it to the depth generation network by batch. The depth generation network contains 16 convolution layers, which can realize the output of residual blocks as demonstrated [14]. It is accumulated with the transmitted fuzzy defect image block to obtain the recovered image block, which is transmitted to the discrimination network together with the real image block. The discrimination network is used to identify the image, replace the training depth generation network and the discrimination network, and process the loss function of the depth generation network and the discrimination network to make it as small as possible, so as to ensure that the recovered image is difficult to distinguish from the discrimination network, which ensures the accuracy of the discrimination network to the greatest extent. The termination condition of training is that the loss function value does not change anymore, then the restored image blocks are assembled to output the restored image. The structure diagram of double fusion neural network is shown in Fig. 1:

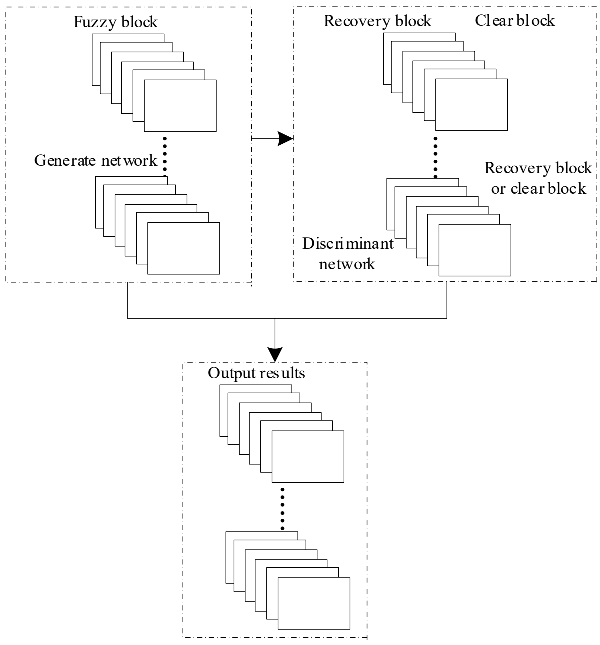


Fig. 1. Structure of double fusion neural network

Deep generation Network. The depth generation network consists of 16 convolution layers, and the convolution kernels of each layer are unified, all of which are 3×3. The residual block is transmitted from the last convolution layer, and the restored image is obtained by merging the residual block and the initial blurred defect image. For size 5×5, the convolution kernel of 7×7 can be split to obtain several 3×3 size. In order to reduce the use of parameters and make the network have high nonlinear mapping performance, the size of each layer of convolution kernel is 3 × 3. The convolution kernel of each layer is of uniform size, which has certain advantages over the depth of the control network. The number of network layers can be reasonably arranged according to the size of the fuzzy kernel, but the increase of the number of network layers will make it lose the gradient. In order to make it not affected by the number of network layers, the residual function is obtained according to the principle of residual network:

$$C_c = A_x + H_x \ . \tag{1}$$

In formula (1), A_x represents the shallow network of the network layer before expansion, H_x represents the expanded network layer, and if $H_x = 0$, it is the representation of identity mapping. When $A_x = y$ still exists after the network layers are expanded, the output image effect will not be affected. Therefore, the depth generation network is regarded as H_x , and the restored image block is y. $H_x = y - x$ represents all convolution layers. After x is transmitted to the depth generation network, its output is the residual of y and x image blocks. This method can find and learn the small differences between them. It is a learning method that fully integrates high-order and low-order features, It can prevent the lack of gradient between deep networks, avoid the loss of fuzzy defect image information, and make the network easier to train.

Discriminant Network. The discriminant method directly learns the decision function or conditional probability distribution, which can not reflect the characteristics of the training data itself. However, it looks for the optimal classification surface between different categories, reflecting the differences between heterogeneous data as demonstrated [15]. The accuracy of learning is often higher when dealing with direct prediction. Because of the direct learning of conditional probability distribution, the data can be abstracted to various degrees, the features can be defined and used, so the learning problem can be simplified. The discriminant network can calculate the state values of the output image and the standard image. The discriminant network can be described as:

$$D_v = \frac{C_{NN} \times G_{HH}}{\alpha \times H_J} \times C_c \ . \tag{2}$$

In formula (2), C_{NN} represents the discrimination network parameter, G_{HH} represents the reward value of the current environment for the current action, α represents the attenuation coefficient, and H_J represents the final state value.

2.2 Extracting Pixel Coordinates of Fuzzy Defect Image

The neural network is used to correct each pixel information of the fuzzy defect image. The principle of pixel correction of multi frame image is to use the equalization sampling theorem to adopt the pixel information of the fuzzy defect image and operate it to extract the fuzzy defect image information. In the projection system of the camera, it is necessary to follow a principle in the projection model of the camera to collect more information into the lens, and its formula is as follows:

$$Q_{AS} = E_d \times \lambda \times D_v \ . \tag{3}$$

In formula (3), Q_{AS} represents the linear distance from any pixel point in the photographic image to the center of the image, E_d indicates the focal length of the camera, λ represents the angle between the light and the optical axis after passing through the camera. Through this projection model, the scene area captured by the camera can be increased. From another point of view, assume that the resolution of the blurred defect image captured by the camera is $F_m \times F_n$, where F_m represents the coordinates of the m pixel in the image in height, and F_n represents the coordinates of the n pixel in the image in width. Thus, the coordinate system of the pixel points and the Cartesian coordinate system can be mutually transformed, and the two can be mutually transformed through formula (4):

$$\begin{cases} F_m = \dfrac{x_i - z_i}{x_i} \\ F_n = \dfrac{y_i - z_i}{y_i} \end{cases} . \quad \textbf{(4)}$$

In formula (4), x_i , y_i and z_i respectively represent the pixel coordinate values in the x-axis direction, y-axis direction and z-axis direction in the actual image. The distance from the pixel point to the center point of the image can be obtained through the distance formula (5):

$$d_{x,y,z} = \sqrt{{x_i}^2 + {y_i}^2 + z_i^2} . \quad \textbf{(5)}$$

In formula (5), $d_{x,y,z}$ represents the distance from any point of the blurred defect image to the center of the image. The projection model can be obtained according to the projection of the blurred defect image, as shown in formula (6):

$$Z_q = \tan\left(\frac{H_k}{K_k}\right) . \quad \textbf{(6)}$$

In formula (6), H_k represents the linear distance between the pixel point k of the blurred defect image and the pixel point of the normal image, and K_k represents the number of pixel points in the blurred defect image. The pixel coordinate value of the blurred defect image can be obtained through formula (7):

$$\begin{cases} X = \lambda_0 + R_1 \\ Y = \lambda_1 + R_1^2 \\ Z = \lambda_2 + R_2^3 \end{cases} . \quad \textbf{(7)}$$

In formula (7), λ_0 represents the correction parameter of the pixel point of the blurred defect image, λ_1 represents the blurred defect parameter of the image, λ_2 represents the incident angle parameter formed by the light and the pixel point after passing through the lens. R_1 , R_1^2 and R_2^3 all represent the radius of the incident angle. Based on the pixel coordinates of the fuzzy defect image, the pixel coordinates of the fuzzy defect image can be extracted from the normal image pixels.

2.3 Design a Fast Correction Algorithm for Fuzzy Defect Image Restoration

In the process of fuzzy defect image processing, due to the large number of pixels, the training and testing time of data set is long. In order to speed up the recovery and correction of fuzzy defect image, a fast correction algorithm based on neural network can be designed for fast correction of image fuzzy defects. It only needs to go through three levels, starting from the pixel input of the input layer, through the correction and summation of the hidden layer, and finally output from the output layer as demonstrated [16]. An activation function is required in the connection weight to process the summation information of offset. The formula is:

$$C_u = \sum_{i=1}^{n} G_{XYZ} \times B_i . \quad \textbf{(8)}$$

In formula (8), C_u represents the weighted sum information of the activation function, G_{XYZ} represents the connection function of pixel points in the x-axis, y-axis and z-axis, which plays a role in suppressing image blur defects in the hidden layer, B_i represents the linear combination bias model parameter of the signal in reference [17]. After the data processing of the above three levels, the functions of the function in the neural network can be divided into two categories, namely, regional linear function and nonlinear function. The relationship formula is:

$$X(x)=\begin{cases}1(x\geq 1)\\ 0(-1<x<1)\\ -1(x\leq -1)\end{cases}, \tag{9}$$

$$F(x)=\begin{cases}-1(x\geq 1)\\ 0(-1<x<1)\\ -1(x\leq -1)\end{cases}. \tag{10}$$

In formulas (9) and (10), $X(x)$ represents the regional linear function and $F(x)$ represents the regional nonlinear function. At this time, through the instructions of these functions, the fuzzy defect image can be quickly corrected, and the input data in the input layer can be transferred to the output layer through the hidden layer. At this time, the fuzzy defect image recovery and fast correction under the neural network can be realized.

3 Region Enhancement Method of Fuzzy Defect Image based on Neural Network

3.1 Reconstruction of Fuzzy Defect Image Resolution Using Neural Network

The neural network is used to construct the numerical imaging model in the fuzzy defect image area. The constructed numerical imaging model can be expressed as:

$$M_x=\frac{(x^2+y^2)}{\pi\omega^2}\times F(x). \tag{11}$$

In formula (11), M_x represents the constructed numerical imaging model, ω represents the range compression parameters in the non significant image area, and x and y represent the pixels in the imaging area respectively. Different from the significant region in the image, there is a compromise processing method of spatial proximity for the pixels in the region. When reconstructing the resolution in the blurred defect image, the image edge details are prone to blur. Therefore, V.-L. Thambawita et al. [18] obtained a different result that guided filtering is used to establish the edge linear constraint relationship among the pixels, forming the linear transfer of the edge pixels. The local window is used to guide the pixels to generate edge gradient, control the pixels to form positive rotation, and control the artifacts generated by the edge of the blurred defect image. After the image edge artifact processing is completed, the image cost caused by forward rotation is calculated by local window function. Using the inverse imaging process of fuzzy defect image, a down sampling numerical model is constructed to minimize the image cost. Kislov et al. [19] obtained that when reconstructing the resolution of the blurred defect image [19], the image reconstruction method is used to set the interpolation function among the image pixels. A pixel is randomly selected and the cubic polynomial is used to build the correlation function between the adjacent pixels of the pixel. Then the back projection method is used to project the pixel interpolation into the above constructed numerical imaging model. The changes of projection parameters during projection processing are shown in Fig. 2:

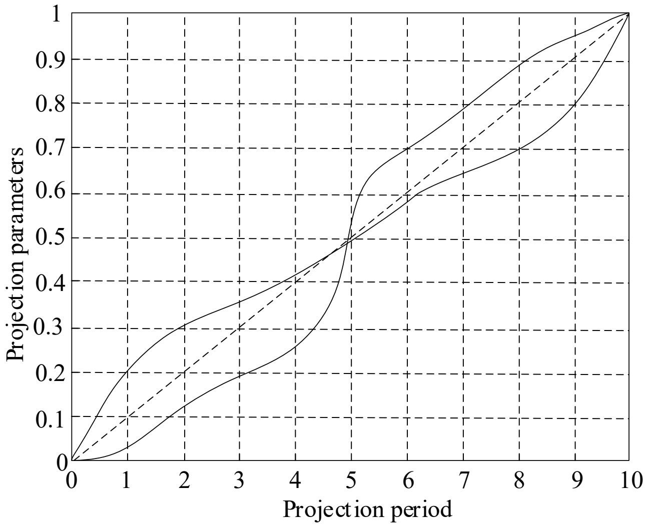


Fig. 2 Change of projection parameters formed

It can be seen from the parameter changes shown in Fig. 2 that the projection parameters are increasing within the calibrated projection period. In order to ensure the resolution accuracy of the reconstructed fuzzy defect image, srcnn model is used to extract the block features of the fuzzy defect image in the region and process them into corresponding high-dimensional vectors. The numerical relationship can be expressed as:

$$F_{12} = \frac{\max(f)}{f_{12}} \times M_x \quad . \tag{12}$$

In formula (12), F_{12} represents the constructed high-dimensional vector, $\max(f)$ represents the preprocessed image block, and f_{12} represents the bicubic preprocessing parameters. There are many pixel structures in the fuzzy defect image. When extracting the illumination component in the region, the multi-scale Gaussian function is used to set adaptive parameters in the image region to correct the empirical parameters in the fuzzy defect image. The correction process can be expressed as:

$$L(x,y) = \frac{L(x,y)'}{L(x,y)''} \quad . \tag{13}$$

In formula (13), $L(x, y)$ represents the formed correction function, $L(x, y)'$ represents the region extracted by bilateral filtering, and $L(x, y)''$ represents the light source point function in the blurred defect image. The empirical parameters in the obtained corrected blurred defect image are fused into the constructed numerical imaging model to reconstruct the resolution in the blurred defect image. From formula (13), it can be seen that the deviation value in the correction process is related to the pixel factor, and the pixel points of the image can be converged. Under the condition of multi frame images, the above formula is used to converge the pixel points. When the pixel points of the modified multi frame images are more similar to the original images, the results are better. Therefore, the application of neural network to the super-resolution reconstruction technology can effectively rotate the fuzzy defect image to change the image information, so that its internal structure does not change. The reconstructed super-resolution technology is used to modify the pixels of multi frame images, which effectively improves the accuracy of high-frequency information in the process of image enhancement. After the resolution reconstruction of the fuzzy defect image, the regional layered enhancement method is constructed, and finally the design of the enhancement method is completed.

3.2 Construction of Region Hierarchical Enhancement Method for Fuzzy Defect Image

When constructing the layered enhancement method for the fuzzy defect image region, the resolution of the reconstructed fuzzy defect image is taken as the processing object, and the region difference formed by the above guidance function processing is defined. The difference value relationship can be expressed as:

$$C_{zc} = \frac{A_\alpha + B_\beta}{L(x,y)} \times O_P \ . \tag{14}$$

In formula (14), C_{zc} represents the calculated difference, A_α and B_β represent the adjustable parameters of reconstructed pixels, and O_p represents the output pixel function. According to the calculated difference value, same detail parameters are set in the guidance area, and the numerical relationship of the set parameters can be expressed as:

$$W_{Jk} = \frac{N_k \times R_D}{\phi} \times C_{zc} \ . \tag{15}$$

In formula (15), N_k represents the variance in the local window, R_D represents the total number of pixels in the non significant area, and ϕ represents the total number of guided filtering times. A Gaussian smoothing process is constructed in the region. By changing the edge contrast in the image region, the intensity parameters in the image region are continuously adjusted to control the halo formed in the region. A dynamic processing process is set to form a detail highlighting effect within the image processing range, and an illuminance value relationship is built between the region and the image background brightness:

$$y_u(x,y) = \frac{L_{op}}{\theta} + W_{Jk} \ . \tag{16}$$

In formula (16), $y_u(x, y)$ represents the numerical relationship between area visibility and background brightness, L_{op} represents the background illumination of low illumination area, and θ represents parameters. Under the above illuminance numerical relationship, the background illuminance parameter is taken as the enhancement object, and an image subtraction model is used to construct a numerical enhancement process. The numerical relationship can be expressed as:

$$E_1 = \frac{R_{fg} - D_c}{m_u} \times y_u\left(x,y\right) \ . \tag{17}$$

In formula (17), R_{fg} represents the construction of a numerical enhancement function, D_c represents the image reflection component of the region, and m_u represents the control factor of the region. In order to avoid excessive enhancement in the region, the reflection image is used to set a numerical region in the control factor to control the excessive enhancement of the region by the enhancement method. Based on the above process, the fuzzy defect image region layered enhancement method is finally completed.

3.3 Implementation of Restoration and Enhancement of Fuzzy Defect Image

The restoration and enhancement prediction of the fuzzy defect image is to rotate the image information, correct the pixel points, and obtain different image information. Then, the fuzzy defect image information results are averaged and summed to obtain the improved super-resolution image information. There will be great differences in the accuracy of image information after super-resolution reconstruction with an image information after rotation, pixel correction and other operations.

Based on the super-resolution technology of reconstruction, combined with the strong linear analysis and simulation ability of neural network, the fuzzy defect image information in multiple frames is restored and enhanced, so as to realize the research of fuzzy defect image restoration and enhancement methods and algorithms. The main steps are as follows:

Step1: The restoration and enhancement method of multi frame super-resolution fuzzy defect image is predicted by the original low resolution image as the reference image.

Step2: Referring to multi frame super-resolution images, the original low resolution pixels with (M_1, M_2) rows and columns are selected. The image of (N_1, N_2) multi frame image super-resolution pixels is predicted as S_1 , and it is set as the iterative original value.

Step3: Predict other original low resolution pixel points ψ_i ($i \in 1, ..., M - 1$), subject to the reference multi frame super-resolution image ψ_0 .

Step4: The original low resolution image information is used to construct multi frame super-resolution images by visual communication design method, and the correction function of pixels is calculated.

Step5: According to the reconstructed super-resolution technology, the k time multi frame super-resolution image correction process is simulated. The predicted value of the original low resolution image sequence is $\psi_i^{'}$, ($i \in 0, ..., M - 1$), and the deviation between the predicted value and the actual value is ε_i ($i \in 0, ..., M - 1$).

Step6: Combined with the prediction rule conditions, the kth multi frame super-resolution image ξ^k is reconstructed by using the deviation value ε_i , and the $k + 1$ multi frame super-resolution image is finally obtained.

Step7: Whether the final multi frame super-resolution image meets the requirements is determined. If it is not, repeat step 5 and step6.

To sum up, by modifying the pixels of multi frame images, the enhancement prediction of multi frame images is carried out, and the research on Fuzzy defect image restoration and enhancement method based on neural network is realized.

4 Experimental Analysis

In order to verify the effectiveness of the fuzzy defect image restoration and enhancement method based on neural network, simulation experiments were carried out on a computer. In the simulation experiment, MATLAB is used as an experimental tool and implemented on a PC with Intel Celeron dual core processor (2.5GHz) and 2GB memory. The images in the experiment come from the network digital image database, from which several images are randomly selected as experimental objects. During the experimental test, the specific parameter settings are shown in Table 1.

Table 1. Experimental parameters

Parameter name	Parameter size	Parameter name	Parameter size
Initial point cloud coordinates	(x_0, y_0)	Pixel coordinates	(x_1, y_1)
Processor model	Iner(R)Core(TM)i5-7400	Development platform	Windows10
Sparse constraint	3	Operating frequency	3.30 GHz
Processor size	3.00GHz	Processor bits	64 bit

The experimental scheme of this experiment is constructed by using the preset image of the experimental object. In this experiment, the verification process of the application effect of fuzzy defect image restoration and enhancement method based on neural network is roughly divided into two parts, and the specific settings are as follows:

(1) Subjective assessment process

The proposed method, the pre selected reference [6] method and reference [7] method are used to restore and enhance the image. After obtaining the image restoration and enhancement results, the blurred defect image is visually evaluated to preliminarily determine the use effect of different methods, which is one of the evaluation contents of the effect of restoration and enhancement methods.

(2) Objective assessment process

In order to make a more comprehensive analysis of the application effect of the research method, the method in this paper and the methods in the comparison reference [6] and reference [7] selected in the experiment are used to process the images in the database as a whole, and the overall recovery and enhancement effect of the processing results are compared.

Based on the statistical analysis of the denoising performance of the fuzzy defect image of the three methods, the analysis is carried out from the visual angle of the image to further verify the performance of the method in this paper. The original image is shown in Fig. 3. Compared with the literature method, the fuzzy defect image restoration performance of this method is further verified. The experimental results are shown in Fig. 4.

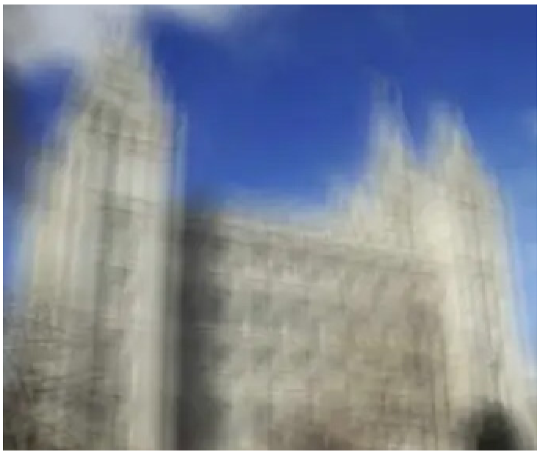
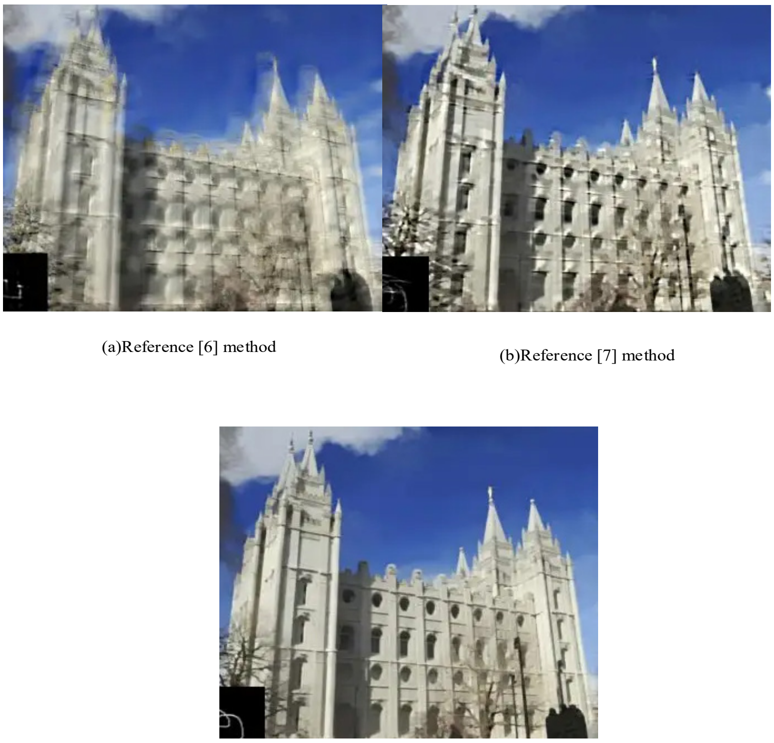


Fig. 3. Original image



(a)Reference [6] method

(b)Reference [7] method

(c)Paper method

Fig. 4. Restoration effect of blurred defect image under different methods

It can be seen from Fig. 4 that the image restoration effect of the reference [6] method is poor, the image quality is poor, the image definition and texture details are fuzzy, and the image content cannot be recognized normally. Compared with the other two methods, the effect of image restoration using this method is poor. The image restored by the reference [7] method has significantly improved in texture detail and image definition, which shows that this method is superior to the reference [6] method, but there is still room for improvement in the contrast of the fuzzy defect image. The images restored by the two reference methods are distorted to varying degrees. The image restored by this method shows the best effect in terms of color, contrast, image brightness and texture details. The results show that this method can achieve the restoration of fuzzy defect image, and the effect is remarkable.

In order to further verify the effectiveness of this method, the fuzzy defect image enhancement effect is compared. Fig. 5 shows the original image, and Fig. 6 shows the effect of reference [6] method, reference [7] method and the proposed method after fuzzy defect image contrast enhancement.

Fig. 5. Original image

(a)Reference [6] method

(b)Reference [7] method

(c)Paper method

Fig. 6. Enhancement effect of fuzzy defect image under different methods

It can be seen from Fig. 6 that there are small defects in the original image, the overall gray value of the image is low, and the light and dark partitions are obvious. The details in the image cannot be obtained, and the lines and image contours are relatively vague. After contrast enhancement, the image defects of the method in reference [6] are blurred, basically covered up, and the shading is improper. Image information cannot be accurately extracted. Under the reference [7] method, the processing effect of light and dark areas is poor, and the overall gray value of the image is low. The shading effect of this method is good, the gray value of the image has been significantly improved, and the effect of fuzzy defect image enhancement is good. From the above analysis, compared with the traditional methods 6 and 7, the proposed method has good effect in image restoration and image enhancement. The method proposed in this paper solves the problem of low image pixel coordinates and image resolution through the dual fusion neural network composed of depth generation network and discrimination network. On the basis of traditional methods, it reduces the dependence on fuzzy kernel and improves image quality.

In the neural network, the number of input parameters is 256*12*12, and the total number of output parameters is 256. The parameters are the maximum value for the normal operation of training parameters. In order to avoid over fitting, the interaction between nodes can be reduced by the method of random neglect, and parameter training can be carried out in the connection layer. Through the methods of reference [6], reference [7] and this paper, the numerical results of observed fitting degree in the continuous iteration process can be obtained, as shown in Fig. 7.

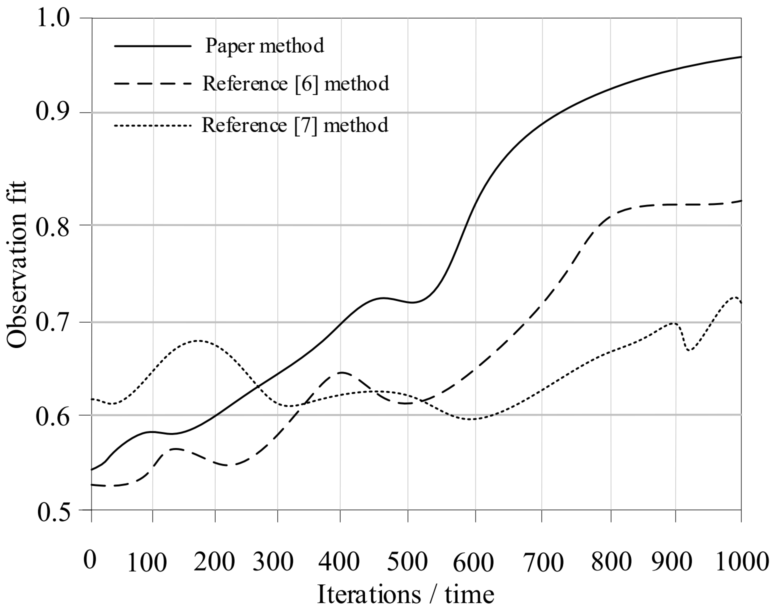


Fig. 7. Comparison results of observation Fitting Correction

It can be seen from Fig. 7 that in the observed fit data, the fluctuations of the three image enhancement methods are relatively large. Among them, the initial value of Reference [6] method is 0.54, the initial value of Paper method is 0.55, and the initial value of Reference [7] method is 0.62, which is significantly higher than the other two methods. However, after iteration, the fit of this method has not been significantly improved. In the data of observation fitting degree, the data obtained by the neural network algorithm is 0.96 after 1000 iterations, and the observation fitting degrees of the other two comparison methods are 0.83 and 0.72 respectively. The fitting degree of neural network algorithm is 0.13 and 0.25 higher than that of the other two methods, respectively. The closer the observation fit is to 1, the more accurate the result of the correction parameter is. Therefore, among the three methods, the accuracy of the observation fit correction parameter of this method is the highest.

To sum up, the proposed neural network based fuzzy defect image restoration and enhancement method is significantly better than the other two methods in restoring the quality of fuzzy defect image. At the same time, the fitting value of neural network is 0.92, which is significantly higher than the fitting value of the other two methods, indicating that the image restoration and enhancement method based on neural network has a higher accuracy. Therefore, the fuzzy defect image restoration and enhancement method based on neural network has a good restoration and enhancement effect, which can effectively meet the actual needs of people for high-quality images.

5 Conclusion and Prospect

5.1 Conclusion

(1) The results show that this method can achieve the restoration of fuzzy defect image, and the effect is remarkable.

(2) The shading effect of this method is good, the gray value of the image is significantly improved, and the effect of fuzzy defect image enhancement is good.

(3) The accuracy of observation fitting correction parameters of this method is high.

5.2 Prospect

This paper has done some research work in the application field of fuzzy defect image restoration and enhancement, and has made some research results. The results can promote the application of image restoration and enhancement. Due to the limitations of their own knowledge and ability, this research still has some shortcomings that need to be improved. The specific contents are as follows:

(1) In addition to improving the adverse conditions and performance of the collected images, it is also necessary to further study and develop effective image deblurring methods and image mosaic methods to improve the applicability and real-time performance of the methods.

(2) Image acquisition can be stored by CF card and other storage devices. Wireless transmission of image data is considered to transmit the fuzzy defect image collected in real time to the computer for more effective processing on the computer, so as to make the fuzzy defect image recovery and enhancement more real-time and accurate.

(3) The stability and accuracy of the method have an important impact on the subsequent image processing methods. It can be further optimized in the further research. On the one hand, the volume and weight of the device can be reduced, including the image sensor of the system, and more portable devices can be selected. on the other hand, it is necessary to improve the stability of the system positioning device, reduce the positioning error, and make the processing system more stable and accurate.

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