Low Resolution 3D Image Enhancement Based on Artificial Neural Network

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Abstract. In order to improve the quality of low resolution 3D images, this study proposes a low resolution 3D image enhancement method based on artificial neural network. First of all, the adjustable filter is used to divide the image categories, and the multi-angle mesh model of the machine vision system is constructed. Then, the low resolution image is decomposed into multiple scales by filtering method. The white balance method is used to eliminate the color deviation of low resolution 3D images and realize the color correction of low resolution 3D images. Finally, the atmospheric scattering model is used to de blur the low resolution 3D image. Combining the advantages of color model transformation algorithm and artificial neural network, the low resolution 3D image enhancement algorithm is designed. Experimental results show that this method can improve the quality of low resolution 3D images and enhance the image enhancement effect.

Keywords: Artificial Neural Network · Low Resolution · 3D Image · Image Enhancement · Deblurring

1 Introduction

As a technology in the sub-field of digital signal processing, digital image processing refers to the technology of converting traditional image signals into digital signals and using software or hardware devices to process image information. With the rapid development of modern science and technology, people gradually began to use image data to spread some information, so digital image processing technology came into being [1]. After long-term development, digital image processing technology has been widely used in many fields such as daily life, production, and work, and has driven the progress and development of many related fields [2].

The early digital image processing aims to improve the image quality, but in the actual digital image processing process, the acquisition quality of the acquisition equipment will be reduced due to the impact of the environment. Therefore, it is necessary to carry out some image processing operations to produce clear and high-quality images. Nowadays, with the rapid development of artificial intelligence and deep learning, more

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and more experts and scholars realize that image processing and computer vision will have great influence potential and important position in the future social progress.

Reference [3] proposed a hyperspectral and multispectral image fusion algorithm based on the coupled nonnegative matrix decomposition of the minimum volume constraint of a single object. In the process of unmixing mixed pixels, the algorithm considers the physical meaning of the image and adds the minimum volume constraint of end element simplex. This algorithm can effectively overcome the shortcomings of existing fusion algorithms, and achieve accurate matching of end elements and abundance of hyperspectral and multispectral images. Reference [4] proposed a low illumination image enhancement algorithm using a hybrid implementation strategy of depth learning and image fusion. First, the best exposure component of the image is quickly estimated using the exposure component prediction model, and a moderately exposed image as a whole is obtained under the framework of Retinex model. Then, the low illumination image itself and its overexposure image are used as the correction and supplement image of the moderate exposure image to participate in the fusion. Finally, the local structural fusion and chrominance weighted fusion mechanism are used to fuse the three prepared images to obtain the final enhanced image. Reference [5] proposed an image enhancement algorithm based on illumination adjustment and depth of field difference. This algorithm is based on Retinex theory, uses the dark channel principle to obtain the depth of field, and uses SVD algorithm to cluster the image depth. After sub images are segmented, local haze concentration is estimated according to depth of field, and sub images are enhanced and fused adaptively.

The gray distribution of low resolution images is dense, and there is no obvious boundary between gray levels. Therefore, if you want to improve the visual effect of low resolution images, first convert the images to make them more suitable for human eye observation and equipment processing, so that it is more convenient to observe and extract information. Therefore, it is still important to enhance the useful information of low resolution images obtained under different conditions. Based on the above research background, this paper applies the artificial neural network to the design of low resolution 3D image enhancement methods to improve the quality of low resolution images.

2 Design of Low-Resolution 3D Image Enhancement Method

2.1 Acquisition of Low-Resolution 3D Images

The machine vision system is used to collect low resolution 3D images, and then the adjustable filter wave is used to automatically separate the collected images according to the behavior characteristics. The machine vision system is built to evenly divide the multi angle grid model, and the filtered method is used to multi-scale decompose the processed low resolution 3D images. The specific operations are as follows:

$$x(n) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X(k), n = 0, 1, \cdots, N - 1 \tag{1}$$

Among them, $X(k)$ is the orderly arrangement of the behavioral feature pixels of the machine vision system, and N is the distance feature between the two queues.

The change gradient value of the low-resolution 3D image represents the quality of the image. The smaller the change gradient value, the higher the quality of the low-resolution 3D image. The change gradient value of the low-resolution 3D image can be calculated by the following formula:

$$\tilde{g} = \frac{1}{M \times N} \sum_{i=0}^{M} \sum_{j=0}^{N} f(i, j) \tag{2}$$

In the above formula, M is the total number of rows of low resolution 3D images; N is the total number of columns of low resolution 3D images, and $f(i, j)$ is the contrast value of low resolution 3D images.

The entropy value of the low resolution 3D image refers to the effect of the low resolution 3D image after enhancement processing. The higher the entropy value, the more information can be extracted from the image. The entropy value of the image is calculated as follows:

$$J = \sum_{m=0}^{m} \rho(m) \tag{3}$$

In the above formula, $\rho(m)$ is a single pixel of a low-resolution 3D image.

The filtering method is used to separate the features of the collected low-resolution 3D images [6], and the low-resolution 3D image data extracted by the machine vision system is collected and analyzed. The low-resolution 3D image acquisition and analysis process is as follows:

$$x(k+1) = \frac{f(x)}{V(k)} + O_{x,y} \tag{4}$$

Among them, $O_{x,y}$ represents the grid model coordinates of the low resolution 3D image acquired by the machine vision system, $f(x)$ represents the grid model of the original image, and $V(k)$ represents the characteristics of the low resolution 3D image.

Multi angle template matching is performed according to the contrast difference of the collected image to obtain the intersected low resolution 3D image feature unit:

$$\begin{cases} e = \dfrac{1}{|\nabla u|}\left(\dfrac{\partial u}{\partial y} i - \dfrac{\partial u}{\partial x} j\right) \\ f = \dfrac{1}{|\nabla u|}\left(\dfrac{\partial u}{\partial x} i + \dfrac{\partial u}{\partial y} j\right) \end{cases} \tag{5}$$

Among them, ∇u represents the multi-angle matching template.

By adjusting the contrast and feature correction, the contrast deviation equation of the low-resolution 3D image is obtained as:

$$\frac{I(x, y; t)}{\partial t} = \frac{I(x, y; t)}{\partial \xi^2} + c^2 \frac{I(x, y; t)}{\partial \eta^2} \tag{6}$$

where, ξ represents the adjusted contrast, and η represents the characteristic correction value.

The enhanced low resolution 3D image is processed by multi-scale optimization through the machine vision system to obtain the information space characteristics of the low resolution 3D image as follows:

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} \xi \\ \eta \end{bmatrix} \tag{7}$$

Set the matching value of the enhanced image model to K, the height of the enhanced image to be H, and read the pixel decomposition spectral information of the enhanced image to obtain the high pixel information feature c. The calculation formula is as follows:

$$c = \sqrt{\exp\left[-\frac{1}{K}|\nabla u(x, y; t)|\right]} \tag{8}$$

When $|\nabla u(x, y; t)|$ reaches the maximum value, the contrast space feature value of the low resolution 3D image is mapped through the high pixel information feature. Set $|\nabla u(x, y; t)| = 0$ to decompose the 2D data of the enhanced image through the machine vision machine. Output formula is obtained according to the image information feature decomposition of direction f:

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix} \begin{bmatrix} p \\ q \end{bmatrix} \tag{9}$$

According to the above process, the acquisition of a low-resolution three-dimensional image is realized.

2.2 Correcting the Color of Low-Resolution 3D Images

The absorption of light by the medium leads to the decline of the color of low resolution 3D images. Because red light and orange light have been completely absorbed under strong light, generally, the acquired low resolution 3D images show a blue-green tone. In order to eliminate the color deviation of low resolution 3D images, it is necessary to correct the color of low resolution 3D images.

The color correction of low-resolution 3D images is very mature. There are various white balance methods such as Gray Word method, max-RGB method, Shades of Gray method and Gray Edge method. The principle is to correct the color deviation of the image according to the color temperature of the image. [7]. The application scenarios of these methods are generally ordinary color casts, and the processing results for severe color casts are not ideal.

The white balance method in this paper is proposed based on the max-RGB method, and the Shadesofgray method. The mathematical formula is as follows:

$$I_{wb}(x) = \frac{I(x)}{\chi \times \delta} \tag{10}$$

where, $I_{wb}(x)$ represents the color corrected image, $I(x)$ represents the original low resolution 3D image, χ represents the constant, and δ represents the illumination color.

The white balance method in this paper adds a gain factor in the process of solving the illumination color, which can be expressed as:

$$\chi\delta = \max_x I(x) \times \int I(x)^{\frac{1}{p}} + \phi \tag{11}$$

Among them, $\max_x I(x)$ represents the maximum value of each color channel of the original low-resolution 3D image, and the value of ϕ varies in the range of [0, 0.5]. The closer the value of ϕ approaches 0, the brighter the processed image will be. On the contrary, the greater the value of ϕ, the lower the brightness.

The white balance method proposed in this paper effectively eliminates the color deviation of low resolution 3D images, and obtains more natural color correction images. However, the color correction image still has low contrast and blurring. In order to get a better enhanced image, the image scene depth model is used to de blur the color correction image.

2.3 Deblurring of Low-Resolution 3D Images

From the perspective of scattering, the low-resolution 3D image is very similar to the atmospheric foggy image, both of which are affected by the scattering of suspended particles, and both will have the phenomenon of contrast reduction and detail blurring. Therefore, people often apply the atmospheric scattering model to the low-resolution environment, and use this model to eliminate image blur and improve its contrast. On the basis of removing the color deviation of the low-resolution 3D image, this paper also uses the atmospheric scattering model to deblur the low-resolution 3D image [8], and believes that the color correction step is complete for the color compensation of the low-resolution 3D image. At this time, the color correction map can be regarded as an atmospheric foggy image for further processing.

The deblurring process of low resolution 3D images is shown in Fig. 1.

As shown in Fig. 1, based on the color correction map, two important parameters in the atmospheric scattering model are solved: transmittance map $e(x)$ and atmospheric spectrum G, and then the atmospheric scattering model is used to deblur the low-resolution 3D image. In this paper, the solution of the transmittance map $e(x)$ is different from the dark channel prior method. In this paper, the scene depth artificial neural network model is used to estimate the scene depth of the color correction map, and the scene depth map $g(x)$ is obtained, while the scene depth map $g(x)$ and the transmittance map are obtained. There is an exponential relationship between $e(x)$, so the scene depth map $g(x)$ is transformed into a transmittance map $e(x)$. Finally, combining color correction map $I_{wb}(x)$, atmospheric light G and transmittance map $e(x)$, we can get the deblurring map of low resolution 3D image.

The color correction image of the low resolution 3D image is treated as a fogged image, that is, the color correction step completely compensates the color fading of the low resolution 3D image [9]. In this paper, the atmospheric scattering model is used in the image deblurring process. The mathematical expression of the atmospheric scattering model is as follows:

$$I(x) = Y(x)e(x) + G(1 - e(x)) \tag{12}$$

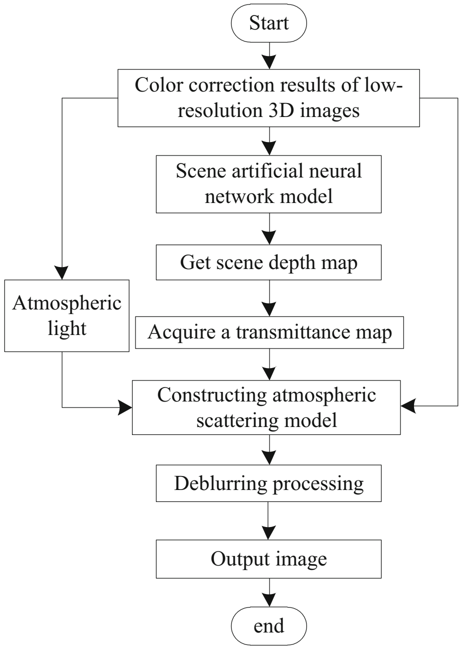

Fig. 1. Deblurring process of low-resolution 3D images

Among them, $Y(x)$ represents the fog-free image, and $I(x)$ represents the foggy image. After image conversion, you can get:

$$Y(x) = \frac{I(x) - G}{e(x)} + G \tag{13}$$

In the low resolution application scenario, the above model can be expressed as:

$$I_{ab}(x) = \frac{I_{wb}(x) - G}{e(x)} + G \tag{14}$$

In the formula, $I_{ab}(x)$ represents the deblurring map. It can be seen from the above formula that the atmospheric light G and the transmittance map $e(x)$ can be estimated, and the deblurring map can be obtained. For the atmospheric light G, this paper obtains the average value of the three channels of the color correction map R, G and B. For the transmittance map $e(x)$, this paper uses the scene deep artificial neural network model to estimate it.

Considering the exponential relationship between the transmittance map A $e(x)$ and the scene depth map $g(x)$, it is shown as follows:

$$e(x) = e^{-\beta g(x)} \tag{15}$$

where β is the atmospheric scattering coefficient.

Considering the difficulty in estimating the value of the atmospheric scattering coefficient β, the maximum visible scene depth $l_{\max}$ is introduced. When the visible scene depth reaches the maximum, the transmittance will reach the minimum $t_{\min}$, the mathematical expression is as follows:

$$t_{\min} = e^{-\beta l_{\max}} \tag{16}$$

According to formula (15) and formula (16), the following formula for calculating transmissivity diagram $e(x)$ is obtained:

$$e(x) = (t_{\min})^{\frac{g(x)}{l_{\max}}} \tag{17}$$

In the formula, $t_{\min}$ represents the minimum transmittance. After comparison, this paper assumes that $t_{\min}$ is 0.2. The above derivation transforms the problem of estimating the transmittance map into the problem of estimating the scene depth map. Obviously, the estimation of the scene depth map becomes a key step in the deblurring process of low-resolution 3D images. In this paper, the scene depth artificial neural network model is used to estimate the scene depth map corresponding to the color correction map.

2.4 Design Low-Resolution 3D Image Enhancement Algorithm Based on Artificial Neural Network

In view of the defects of the current low resolution 3D image enhancement algorithm, such as excessive enhancement or unnatural effects, artifacts and strong saturation, this paper combines the advantages of color model transformation algorithm and artificial neural network [10] to enhance the low resolution 3D image. The processing flow of low resolution 3D image enhancement algorithm is shown in Fig. 2.

For low-resolution 3D images, the expression for converting from RGB color space to HSI color space is as follows:

$$\theta = \cos^{-1}\left\{\frac{[(R-G)+(R-B)]/2}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right\} \tag{18}$$

$$H = \begin{cases} \theta & B \le G \\ 360-\theta & B > G \end{cases} \tag{19}$$

$$S = 1 - \frac{3 \cdot \min(R, G, B)}{R+G+B} \tag{20}$$

$$I = \frac{R+G+B}{3} \tag{21}$$

For HSI space of low resolution 3D images, the values of each color component are $0^{\circ} \le H \le 360^{\circ}$, $1 \le S \le 1$, and $1 \le I \le 1$. Because the hue H is different, the conversion from HSI color space to RGB color space needs to change according to the change of H.. For RG sector ($0^{\circ} \le H < 120^{\circ}$), the conversion formula is:

$$R = I\left[1 + \frac{S\cos H}{\cos\left(60^{\circ} - \mathrm{H}\right)}\right] \tag{22}$$

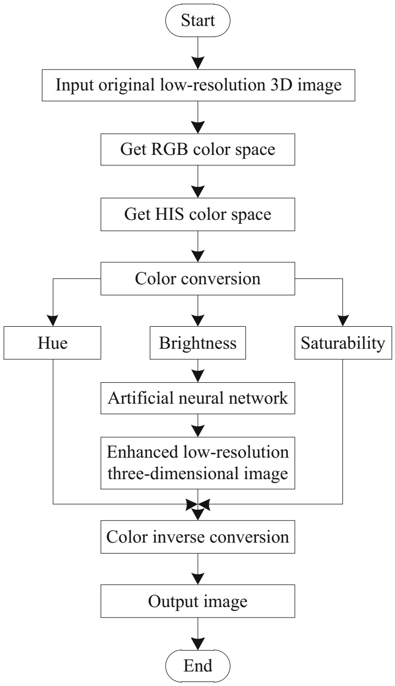

Fig. 2. Flow chart of low-resolution 3D image enhancement algorithm

$$G = 3I - (R + B) \tag{23}$$

$$B = I(1 - S) \tag{24}$$

The artificial neural network in this section performs a zero-padding operation before the color space conversion to ensure that the size of the image remains unchanged during the transmission of the artificial neural network. The specific steps are:

Step1: Input layer and output layer. The input layer obtains the luminance component of the low-resolution 3D image, and the output is the luminance component enhanced by the artificial neural network.

Step2: Feature extraction. In order to learn the relationship between the low resolution 3D image and its illumination map, firstly, the overlapped pixel blocks are extracted from the low resolution 3D image, and each pixel is represented by a high-dimensional vector through m_1 filters, whose mathematical expression is as follows:

$$F_1(p) = \max(0, \partial_1 \times p + \ell_1) \tag{25}$$

where p is the input image patch of size $m \times m$, and ∂_1 and ℓ_1 are the weights and biases of the kernel function in the artificial neural network. The size of ∂_1 is $m_1 \times f_1 \times f_1$, where f_1 is the size of a single kernel function, and m_1 is the number of kernel functions. ℓ_1 is an m_1-dimensional vector, each element of which is associated with a filter, and "x" represents the convolution operation. $\max(0, x)$ is a rectified linear unit used to speed up training convergence and improve network performance.

Step3: Feature enhancement. Inspired by the use of feature enhancement layers in reducing compression artifacts, feature enhancement layers are used to map "noise" features to a relatively "clean" feature space, because low resolution 3D images are usually affected by noise. It is expressed as:

$$F_2(p) = \max(0, \partial_2 \times F_1(p) + \ell_2) \tag{26}$$

Step4: Nonlinear mapping. Nonlinear mapping is to map each high-dimensional vector to another high-dimensional vector, i.e. convert $F_2(p)$ to $F_3(p)$:

$$F_3(p) = \max(0, \partial_3 \times F_2(p) + \ell_3) \tag{27}$$

where, ∂_3 contains m_3 filters of size $m_3 \times f_3 \times f_3$, and ℓ_3 is an m_3 dimensional vector.

Step5: Image reconstruction. A convolutional layer is designed to aggregate image patches to generate the learned 3D image, $F_3(p)$ is transformed into $F_4(p)$, the expression is:

$$F_4(p) = \partial_4 \times F_3(p) + \ell_4 \tag{28}$$

where, ∂_4 contains m_4 filters of size $m_4 \times f_4 \times f_4$, and ℓ_4 is an m_4 dimensional vector.

These unknown artificial neural network parameters $\Omega = \{\partial_1, \partial_2, \partial_3, \partial_4, \ell_1, \ell_2, \ell_3, \ell_4\}$ are achieved through supervised learning to minimize the mean squared error loss function. Minimizing the mean squared error loss function is expressed as:

$$L(\Omega) = \frac{1}{N}\sum_{i=1}^{n} \|F(P_i; \Omega) - W_i\|^2 \tag{29}$$

Among them, N is the number of image blocks in the artificial neural network training batch, P_i is the low-resolution 3D image block, W_i is the low-resolution 3D image block corresponding to P_i, and $F(\cdot)$ is the learned mapping function.

To sum up, a low resolution 3D image enhancement algorithm is designed by using color model transformation algorithm and artificial neural network to achieve low resolution 3D image enhancement.

3 Experimental Analysis

3.1 Experimental Environment

The software environment of this experiment is Windows 10 operating system, the CPU processor is Intel Core i7–3770 8-core processor, the memory is 48 GB, the graphics card is NVIDIA GeForce GTX 1080, and the video memory is 8 GB. The experiment is mainly based on the artificial neural network framework Tensorflow, version 1.5. CUDA version is 9.0 and cuDNN version is 7.0.

3.2 Training Method

The input of the artificial neural network is a low resolution 3D image, and the output is a corresponding normal 3D image. The training data is transferred to the artificial neural network in batch as a unit for training. The width and height of the input and output are consistent. The input size is m × n, and the output size is m × n.

The optimizer uses the gradient descent method with momentum, the momentum coefficient is 0.9, the initial learning rate is 0.001, and the learning rate decays to 10% of the original every 20 epochs. The loss functions of the decomposition network, the low-resolution map augmentation network, and the emissivity map refinement network are minimized using the optimizer Adam.

3.3 Experimental Comparison

The enhancement algorithm based on the minimum volume constraint of a single object and the enhancement algorithm based on the combination of depth learning and image fusion are compared to complete the performance verification together with the method in this paper.

3.4 Image Enhancement

Take the low resolution 3D image as the research object, as shown in Fig. 3. Three methods are used to enhance them, and the results shown in Fig. 4 are obtained.

Fig. 3. Low-resolution 3D image

According to the results in Fig. 4, compared with the two comparison methods, the method in this paper has a better enhancement effect on low resolution 3D images and can improve the quality of low resolution 3D images.

Fig. 4. Image enhancement experiment results

3.5 Performance Test

3.5.1 Experimental Indicators

In the experimental test, the signal-to-noise ratio, structural similarity and enhancement time are used as the indicators for evaluating the low-resolution 3D image enhancement method. The calculation formula is:

$$\phi = 10 \times \lg \frac{255^2}{\|d - g\|_2^2} \tag{30}$$

$$S = \frac{4\chi_d \chi_g \chi_{dg}}{\left(\chi_d^2 + \chi_g^2\right)\left(\delta_d^2 + \delta_g^2\right)} \tag{31}$$

Among them, ϕ is the signal-to-noise ratio index of the image, the common unit is dB, S is the structural similarity index, the common unit is %, d is the initial depth of the low-resolution 3D image, g is the enhanced depth of the low-resolution 3D image, χ represents the enhanced depth mean, and δ represents the enhanced depth variance.

3.5.2 Analysis of Results

In the experiment, 300 3D images with resolution were enhanced. Due to the space limitation, 12 images were selected from them for analysis.

The SNR test results of three low resolution 3D image enhancement methods are shown in Table 1.

From the results in Table 1, it can be seen that the signal-to-noise ratio indicators obtained by the two comparison methods in the experimental test process are relatively close, but far lower than those obtained by the method in the paper. The average signal-to-noise ratio obtained by the method in this paper is 31.49 dB, because the method in this paper can make the image converge in space by correcting the color in the low resolution 3D image, so it has better enhancement effect.

Table 1. Test results of signal-to-noise ratio of low-resolution 3D images

Image number	Low-resolution 3D image SNR/dB		
	An Enhancement Method Based on the Minimum Volume Constraint of Simplex	Enhancement method based on deep learning and image fusion hybrid	Method in the text
4.1.01	32.38	32.56	35.79
4.1.03	32.16	32.45	35.69
4.1.04	31.09	31.50	37.02
4.1.05	29.91	30.59	34.73
4.1.06	25.71	26.19	27.75
4.1.08	32.04	32.31	36.13
4.2.03	23.76	23.88	24.56
4.2.05	29.62	30.27	31.62
5.1.10	23.78	24.09	27.08
5.1.11	29.20	29.87	34.80
5.1.12	27.11	27.50	30.53
5.1.13	18.66	18.80	22.22
Average value	27.95	28.33	31.49

The structure similarity test results of three low resolution 3D image enhancement methods are shown in Table 2.

From the results in Table 2, it can be seen that in the structural similarity index test, the results obtained by the three low-resolution 3D image enhancement methods are relatively close, but the method in this paper is obtained in the 4.2.05th and 5.1.10th images. The enhancement effect is better because the method in this paper improves the resolution of the low-resolution 3D image by deblurring the low-resolution 3D image, so that the low-resolution 3D image obtained by this algorithm has a better enhancement effect.

Based on the above test results, in order to further verify the effectiveness of the method in this paper in terms of image enhancement time, experimental analysis was conducted and the experimental results as shown in Fig. 5 were obtained.

It can be seen from the results in Fig. 5 that as the low resolution 3D images become larger and larger, the enhancement time of the three enhancement methods for the low resolution 3D images is gradually increasing. However, compared with the two comparison methods, the time required for the image enhancement process of the methods in this paper is the shortest, which proves that they can effectively improve the enhancement speed of the low resolution 3D images.

Table 2. Structural similarity test results

Image number	Structural similarity/%		
	An Enhancement Method Based on the Minimum Volume Constraint of Simplex	Enhancement method based on deep learning and image fusion hybrid	Method in the text
4.1.01	0.97	0.96	0.95
4.1.03	0.95	0.98	0.94
4.1.04	0.90	0.95	0.97
4.1.05	0.97	0.96	0.94
4.1.06	0.95	0.97	0.96
4.1.08	0.90	0.90	0.97
4.2.03	0.86	0.88	0.85
4.2.05	0.93	0.97	0.98
5.1.10	0.98	0.95	0.98
5.1.11	0.98	0.90	0.96
5.1.12	0.93	0.94	0.94
5.1.13	0.90	0.92	0.97
Average value	0.935	0.94	0.95

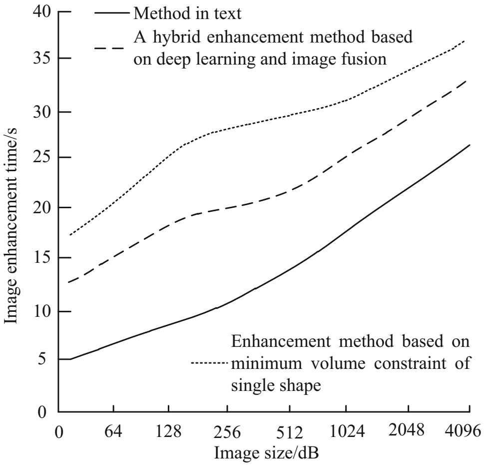

Fig. 5. Image enhancement time test results

4 Conclusion

In this paper, artificial neural network is applied to the design of low-resolution 3D image enhancement method. In the process of research, this paper classifies the image characteristics intelligently by using the adjustable filter, and establishes the multi-angle mesh model of the machine vision system. On this basis, the low-resolution image is decomposed by multi-scale, and the color deviation is eliminated, and the image quality is improved by color correction. Finally, the atmospheric scattering model is used to complete the image deblurring processing, and the self-learning function of the artificial neural network and the ability to find the optimal solution at high speed are used to effectively enhance the low-resolution 3D image.

Experimental results show that this method can improve the quality of low resolution 3D image and has better performance. However, there are still many deficiencies in this research. In the future research, we hope to introduce clustering algorithm to classify low resolution 3D images, and further improve the image enhancement performance.

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