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Image Denoising Based on Noise Estimation for Speckle Interference Phase Fringe Image With Neural Convolution Network

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Abstract: The phase fringe image obtained by speckle interferometry often introduces noise due to the influence of illumination conditions, camera equipment, and the working environment. The existence of noise makes the subsequent image analysis and processing complex. With the development of computing power, theartificial neural network is a new denoising method rising in recent years. However, when usinga convolutional neural network for processing, it is challenging to obtain outstanding results due to the lack of sample numbers. Referring to the working principle of a convolutional neural network, this paper improves the denoising convolutional neural network. A learning rate calculation module based on noise estimation is added to the front end of the neural networkso that the neural network can better learn the noise characteristics in the learning process. Good results are obtained when applied to the phase fringe pattern.

1. Introduction

Digital images often produce noise interference in collection, transmission, processing, and storage. Therefore, image denoising to obtain high-quality images is essential to subsequent information extraction [1]. Denoising methods for images can be roughly divided into the following methods: spatial domain filter [2-3], frequency-domain filter [4-6], neural network filter, etc. [7-13]. The spatial domain filter is the earliest filter whose primary purpose is to investigate the spatial distribution relationship between pixels in a single image. Filtering conditions are designed according to prior knowledge and easily affect local pixel distribution. By transforming the spatial distribution of pixels into frequency domain distribution, the frequency domain filter can better grasp the filtering threshold and effect on the whole. However, the area with high-frequency transformation is easily misprocessed in the original image as noise. A neural network filter is a new processing method developed rapidly in recent years. In 2008[14], Viren Jain et al. used a convolutional neural network (CNN) to deal with natural image denoising and obtained similar results to conventional methods (wavelet transform method/Markov random field). This research brings CNN into the eye of researchers in image denoising. Subsequently, it develops different neural network structures such as residual neural network, deep confidence network, and cyclic neural network for image denoising.

The data-driven artificial neural network will be significantly affected by the training set during training and testing, so how to fully use the training set information as much as possible is a crucial issue of research. In this paper, the noise estimation method marks the quality of the training graph. The neural network can fully use the information in the high-quality graph and reduce the use oflow-qualitygraphs during training.

2. Noise estimation based on principal component analysis

A general picture can be represented by

$$Y(X) = S(X) + N(X) \tag{1}$$

Where Y(X) is the noise image, S(X) is the original image, and N(X) is the noise. Noise generally conforms to a Gaussian distribution with a mean of zero and a variance of σ2.

Assume P is the image block W*W represented by a vector, and the covariance matrix composed of L smooth image blocks is as follows.

$$\Sigma I = \frac{1}{L}\Sigma_{i=1}^{L}(P_i - \mu)(P_i - \mu)^T \tag{2}$$

Where Pi represents the subsequenceofthe image block, and μ represents the mean value of the image block matrix.

Set

$$r = \frac{\lambda_{min}}{\sigma^2} \tag{3}$$

Where λmin is the minimum eigenvalue of the covariance matrix I,

The results obtained by analyzing multiple simulation images are shown in Table 1 below

Table 1: R values under different noise levels and number of image blocks

	L(Number of image blocks)					
σ	5000	10000	50000	100000	150000	200000
20	0.823	0.875	0.934	0.945	0.962	0.973
30	0.823	0.875	0.934	0.945	0.962	0.973
40	0.823	0.875	0.934	0.945	0.962	0.973

Table 1 reflects the dependence between different noise levels and the r-value under the number of image blocks. From Table 1, the figure shown in Figure 1 below can be drawn.

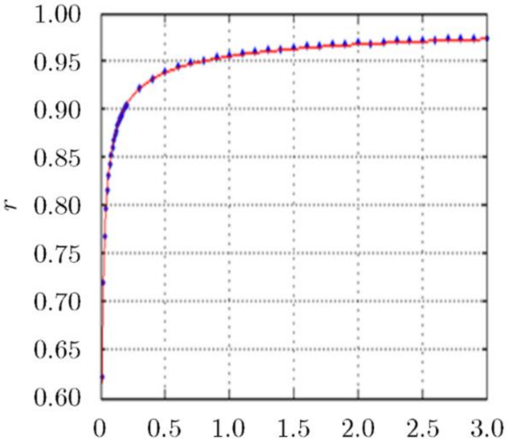

Figure 1: Relationship between the number of image blocks and R-value

As shown in Figure 1, the horizontal axis is the number of image blocks L, and the vertical axis is straight R. It can be seen from the image that R and L meet certain nonlinear distribution rules, and the analysis of the above data shows that R and L meet the regression equation as follows

$$r = aL^b + 1 \tag{4}$$

Plug in the data to solve a= -9.6357, b= -0.4589

Therefore, the estimate of the mean-variance of the image noise is

$$\hat{\sigma} = \sqrt{\frac{\lambda_{min}}{-9.6357L^{-0.4589} + 1}} \tag{5}$$

3. Network construction

In this paper, PyTorch is used to build the network. After many tests, the specific structure of the network is shown in Figure 2 below. The network consists of nine layers. The first layer consists of Conv and ReLu activation function, the second to eighth layer consists of Conv plus Batch Normalization plus ReLu activation function, and the ninth layer consists of Conv. The input image is pre-cropped to 420×512, and the data is enhanced by rotation/flip. Convolutional kernels of 5×5 size are used in all convolutional layers, and the acquisition of the learning rate depends on the learning rate calculation module. The atlas used in training is a simulation at different noise levels, with about 1000 images divided into a training set and verification set in a ratio of 7 to 3.

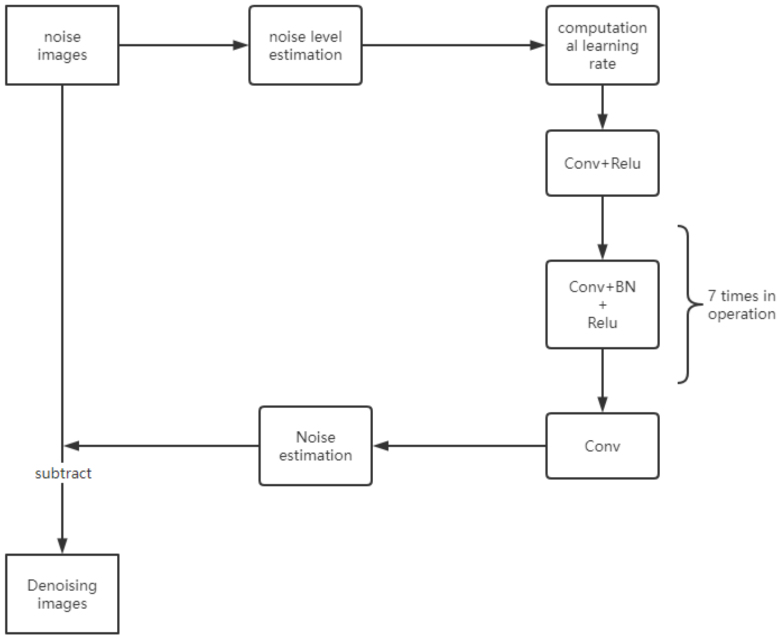

Figure 2: Neural network structure in this paper

The learning rate is obtained through the following steps.

1) randomly select 100 noise images from the training atlas.

2) Estimate the noise level of 100 images.

3) Generate normal distribution according to the noise level of 100 images.

4) When the network obtains new image input, estimate its noise level and find its percentile position in the accumulative normal distribution in the above steps.

5) The following formula calculates the learning rate

Learning rate =0.002×F (α)

Where F(X) function is the cumulative normal distribution obtained from the noise level estimation of 100 images, and the α is the percentile of the noise level estimation of the new input image in the cumulative normal distribution.

Network training was performed on an NVIDIA GTX 1660Ti, CPU Core I5 9400F @2.90Ghz, 16Gb ram computer, Python 3.6, CUDA 10.4.

4. Training results

We compare the proposed method with traditional image processing methods and get good results. The comparison methods include enhanced phase space filter (CED), Windowed Fourier transform (WFF), and convolutional neural network (CNN). The indicators for comparison are peak signal-to-noise ratio (PSNR), mean absolute error (MAF), and comparison in running time. The results are shown in Table 2 below.

Table 2: Comparison of different methods

	CED	WFF	CNN	Paper
PSNR (dB)	12.22	15.13	24.52	26.41
MAP	42.944	30.863	8.645	7.652
Run time(s)	2.29	222.17	0.81	1.35

As shown in Table 2, the deep learning approach in terms of peak signal-to-noise ratio and the average absolute error too much good than traditional methods, the method based on vector improvement compared to the more general convolution neural network can learn the noise distribution image, so the general convolution neural network training than after effect is better. In terms of running time, the method in this paper adds a module to calculate the learning rate, so the running time of each picture is longer than that of the general convolutional neural network. It can be considered to remove this module after the completion of training in the future, and the time should be improved.

Figure 3 compares this paper with other methods in phase image denoising and skeleton line extraction. The upper part of the image is the phase fringe image, and the lower part of the image is the skeleton line extracted.

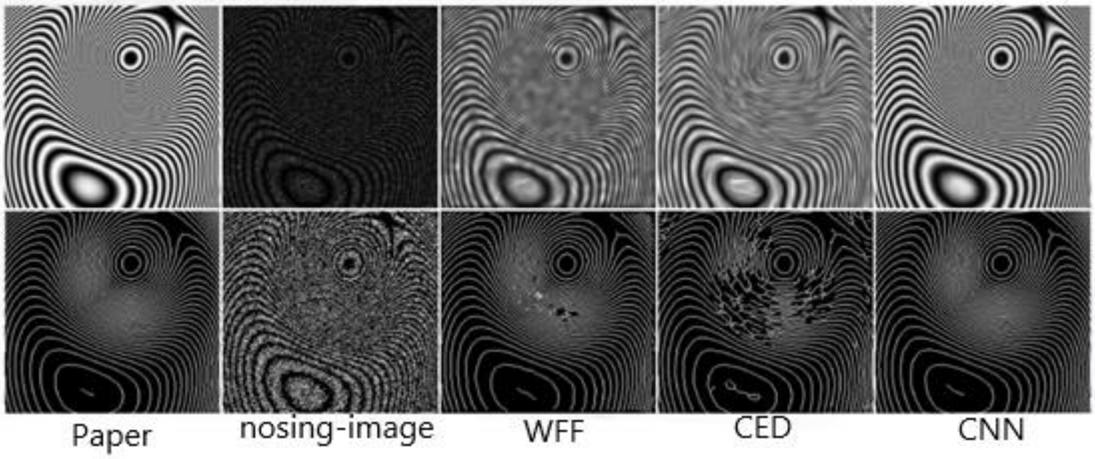

Figure 3: Comparison of different methods

As seen in Figure 3, the traditional methods have ambiguity and artifact problems to varying degrees. The images using the CED method are very chaotic in the high-frequency region after processing, and there are a lot of fractures in skeleton line extraction. Although the image processed by the WFF method can reduce the fracture actual of the skeleton line, it has the problem of low blur/cost high-frequency region, making it challenging to obtain transparent phase distribution from the image. In this paper and the CNN method, noise is better removed, and skeleton lines are well preserved, which provides help for different phase information acquisition.

5. Conclusion

This paper proposes a phase-striping algorithm based on an estimation-based convolutional neural network. Compared with traditional denoising methods, the denoising method in this paper has a better effect, shorter time, and better real-time performance. After the training, it has a specific migration ability, which can be extended to other phase fringe image denoising, such as holographic phase interferogram.

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