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ORIGINAL RESEARCH ARTICLE

Defocused image restoration method based on micro-nano scale

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ABSTRACT

An image adaptive noise reduction enhancement algorithm based on NSCT is proposed to perform image restoration preprocessing on the defocused image obtained under the microscope. Defocused images acquired under micro-nano scale optical microscopy, usually with inconspicuous details, edges and contours, affect the accuracy of subsequent observation tasks. Due to its multi-scale and multi-directionality, the NSCT transform has superior transform functions and can obtain more textures and edges of images. Combined with the characteristics of micro-nanoscale optical defocus images, the NSCT inverse transform is performed on all sub-bands to reconstruct the image. Finally, the experimental results of the standard 500 nm scale grid, conductive probe and triangular probe show that the proposed algorithm has a better image enhancement effect and significantly improves the quality of out-of-focus images.

Keywords: Micro-nano Scale; Defocused Image; NSCT; Image Restoration

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1. Introduction

When observing samples with optical microscope, there is a problem of "Abbe limit" due to the limitation of diffraction limit[1,2]. When the observation scale reaches the micro-nano level, the observed images show fuzzy circular spots no matter how to adjust the focal length. Therefore, the images collected under micro-nano optical microscope have poor resolution, and unclear edges, details and contours not only affect the quality of the image, but also are not conducive to the subsequent observation of "depth" and other information[3].

Traditional image enhancement and preprocessing methods include histogram equalization algorithm[4], Retinex algorithm[5,6], homomorphic filtering algorithm[7], wavelet transform algorithm[8], etc., which have made great progress in recent years[4–8]. However, they have their own advantages and disadvantages, such as serious block effect and relatively complex operation in local equalization algorithm. Global equalization algorithm is also easy to cause color distortion due to over fitting. Retinex algorithm is based on color constancy. Homomorphic filtering algorithm needs to select reasonable filter parameters in frequency domain to realize image enhancement, but it is very difficult to select appropriate parameters.

For the defocus image collected under the microscope, we hope to avoid adding new noise as much as possible and make the enhanced image quality better. Non-subsampled Contourlet transform (NSCT) has superior transformation function due to multi-scale and multi-directional, and can obtain more textures and edges of the image[9,10]. Therefore, this paper chooses NSCT transform. Firstly, the input image is transformed from spatial domain to frequency domain to obtain high-frequency sub-band and low-frequency sub-band; secondly, the low-frequency coefficients are enhanced by anti-sharpening mask algorithm, and the high-frequency coefficients are enhanced by adaptive filtering algorithm[11,12]; thirdly, NSCT is used to inverse transform the image to construct a new image; finally, in order to further enhance the effect of image details, the anti-sharpening mask algorithm is used for image processing.

2. NonsubsampledContourlet transformation (NSCT)

NSCT is conducive to better maintain the image edge information and contour and enhance the translation invariance of the image. It is divided into two processes: multi-scale decomposition and directional filtering. The two processes are independent of each other. **Figure 1** is the overall structure diagram.

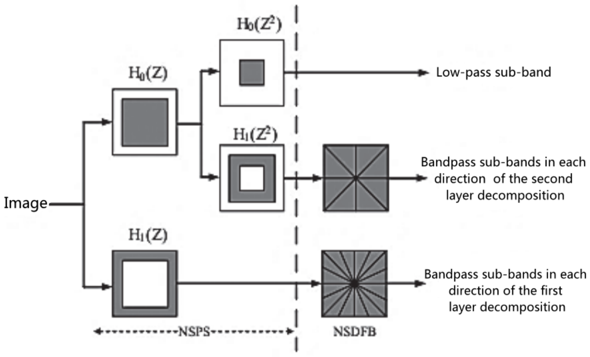

Figure 1. Overall structure diagram.

In view of the translation invariance of Laplace filter, the multi-scale nature of NSCT can be guaranteed by using non-subsampled pyramid for image decomposition. NSCT consists of low-pass decomposition filter module $H_0(z)$ and high pass decomposition filter module $H_1(z) = 1 - H_0(z)$, and some low-pass synthetic filtering modules, which are composed of high pass filtering module $G_0(z) = G_1(z) = 1$.

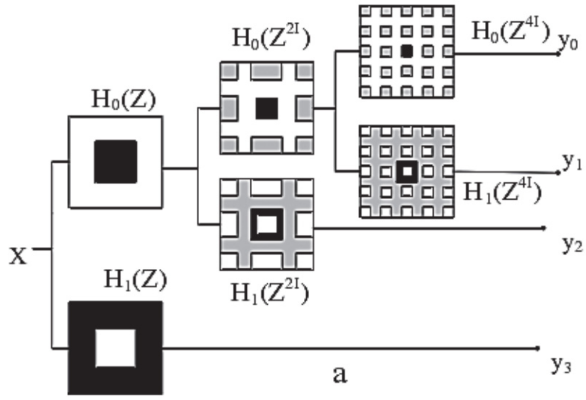

Figure 2. A schematic diagram of the decomposition of three layers of the pyramid.

Figure 2 is the decomposition diagram of three layers of the non-subsampled pyramid, in which the ideal band-pass support region of the low-pass filter decomposed in layer j is $[(\pi/2^J), (\pi/2^J)]^2$, while the ideal band-pass region of the high pass filter is the complement of the low-pass sub-bands $[(-\pi/2^J), (\pi/2^J)]^2/[(-\pi/2^J), (\pi/2^J)]^2$.

Non-subsampling direction filter banks: the filter is based on two channels and decomposes the coefficients into different sub-bands through a tree like structure. The non-subsampling direction filter banks remove the down-sampling module and up-sampling module in the directional filter bank, so that the sampling results at different scales are consistent, and effectively improves the distortion in the sampling process.

3. Micro-nano optical image enhancement algorithm based on NSCT

Due to the multi-scale and multi-directional nature, NSCT has superior transformation function and can effectively improve the image quality. Therefore, we propose a micro-nano optical image enhancement algorithm based on NSCT to preprocess the defocus image obtained under the microscope. Firstly, NSCT decomposes the input image to generate a series of low-frequency and high-frequency components; secondly, the low-frequency coefficients are enhanced by anti-sharpening mask algorithm; adaptive filtering algorithm is used for high-frequency coefficients; finally, all sub-bands are reconstructed by NSCT inverse transform.

3.1 NSCT low-frequency coefficient transformation

The low-frequency coefficients obtained by NSCT decomposition contain some basic information in the image. In this paper, the anti-sharpening mask algorithm is used to enhance it.

$$g(x,y) = f(x,y) + k^{*}(f(x,y) - \overline{f}(x,y)) \quad (1)$$

where, in the formula represent the input image and output image respectively, and K is the adjustment coefficient, taking 2. is the blurred image or approximate image, which can be obtained from equation (2).

$$\overline{f}(x,y) = median\{f(x-i, y-j), (i,j) \in W \quad (2)$$

Where, W is the filter window.

3.2 NSCT high-frequency coefficient conversion

High-frequency coefficients represent detailed information, such as image edges and textures, but also contain a lot of noise. High-frequency coefficient transformation aims to achieve enhancement based on noise reduction. High-frequency coefficients with large values contain image edge details and should be retained. Noise is distributed in NSCT high-frequency coefficients with small values. Threshold noise reduction is to set an appropriate threshold, and noise reduction is performed by comparing the absolute value of NSCT coefficient with the threshold. When the absolute value is greater than the threshold, NSCT coefficient is considered to contain important image information and is retained. When the absolute value of NSCT coefficient decreases or becomes 0 accordingly, it is used to filter noise. By using the coefficient processed by threshold, the NSCT inverse transformation is used to reconstruct the image, so as to eliminate the noise. Threshold de-noising eliminates the noise and retains the image coefficient as much as possible. Therefore, the key of de-noising is to determine the threshold. Less than the threshold is regarded as the noise to be suppressed, and more than the threshold is regarded as the edge information to be enhanced.

$$f_{in}(x,y) = \begin{cases} edges, others \\ noise, p \le T_{1,k} \end{cases} \quad (3)$$

$T_{1,k}$ is the noise threshold in the K direction of the 1 layer, and P is the coefficient value of the subband.

In this paper, an adaptive filtering algorithm based on BayesShrink is used. The threshold can be calculated by equation (4).

$$T_{1,k} = c\frac{\sigma^2}{\sigma_x^2} \quad (4)$$

Where, c is a constant between 0 and 1, σ^2 is the noise variance, and σ^2_x is the signal variance. The standard deviation of noise can be calculated by equation (5).

$$\sigma = \frac{median(|C_{j,k}|)}{0.6745} \quad (5)$$

Where, $C_{j,k}$ is the high-frequency coefficient of the first layer of the image after NSCT decomposition, i.e., take the median of the absolute value of NSCT coefficients, and calculate the noise standard deviation with 0.6745 as the adjustment coefficient.

$$\sigma_x = \sqrt{max\left(\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} x_{i,j}^2(1,k) - \sigma^2, 0\right)} \quad (6)$$

Where, m and n represent the length and width of the image respectively, and the coefficient located in $X(i, j)$ in the K direction image of layer 1 is $X_{i,j}(1, K)$.

The obtained threshold is used to suppress the noise.

$$x'_{i,j} = \begin{cases} x_{i,j}, x_{i,j} > T_{1,k} \\ 0, x_{i,j} < T_{1,k} \end{cases} \quad (7)$$

Where, $X_{i,j}$ is the coefficient of the high-frequency sub-band of the original image and is the coefficient of the processed image.

The main steps of the algorithm are as follows:

Step 1: NSCT decomposes the defocus image obtained under the microscope to generate a series of low-frequency and high-frequency components;

Step 2: Calculate the low-frequency coefficient obtained by equation (1) to obtain a higher contrast of the image;

Step 3: Adaptive filtering algorithm is used for threshold de-noising of high-frequency coefficients;

Step 4: The image is inversely transformed into the spatial domain by NSCT, and the new image is reconstructed;

Step 5: The reconstructed image is further processed by anti-sharpening mask technology to obtain the optimized clear image.

4. Experimental results and analysis

The experiments are carried out by using the traditional histogram equalization algorithm (HE), Retinex image enhancement algorithm (MSR) and the algorithms proposed in this paper. The experiments are carried out by using the standard nano grid image obtained under the actual optical microscope, the conductive probe and triangular probe sample images collected under the atomic force microscope. **Figure 3**, **Figure 4**, **Figure 5** show the results of preprocessing three kinds of images by three algorithms. Among them, **(a)** is the original image, **(b)** is the image enhanced by histogram equalization algorithm (HE), **(c)** is the image enhanced by Retinex algorithm (MER), and **(d)** is the image enhanced by the algorithm proposed in this paper.

4.1 Subjective evaluation

(1) Standard 500 nm raster image

(2) Conductive probe image

(3) Triangular probe image

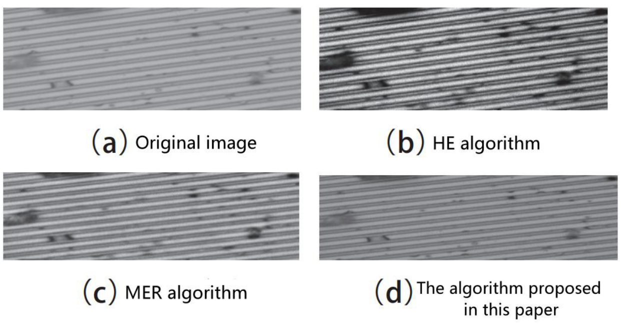

Figure 3. Grid image preprocessing results of three algorithms.

As can be seen from **Figure 3**, **Figure 4**, **Figure 5**, compared with the original image, the clarity and contrast of the three images processed by HE algorithm are greatly improved, and the overall enhancement effect is better. However, the image processed by this algorithm has more noise, and the processing of the edge details of the image is not ideal. Sometimes there will be local distortion and block phenomenon. For example, the standard 500 nm scale grid image is obviously noisy after being processed by HE algorithm; after the conductive probe and triangular probe are processed by HE algorithm, the probe tip appears local distortion.

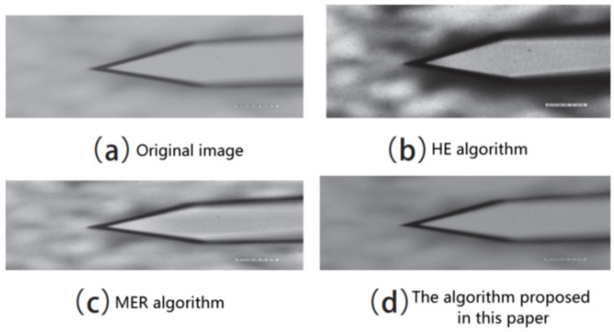

Figure 4. Preprocessing results of three algorithms on conductive probe.

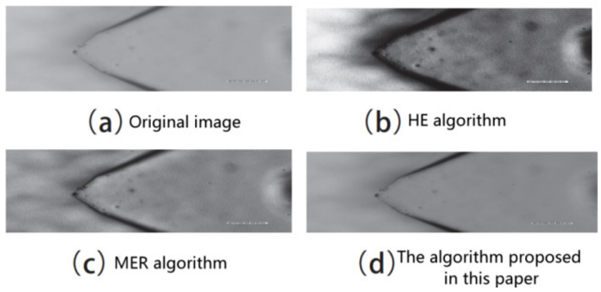

Figure 5. Preprocessing results of three algorithms on triangular probe.

Retinex algorithm decomposes the image into illumination image and reflectance image, and then eliminates or weakens the influence of illumination, so as to achieve the effect of image enhancement. Therefore, compared with the original image, the clarity and contrast of the three kinds of images processed by Retinex algorithm are greatly improved, and the overall enhancement effect is better. However, due to the logarithmic processing, the display range of the bright area of the image is compressed, resulting in the weakening of the details of the image. For example, the details of the edges and corners of the standard 500 nm scale grid, the needles of the conductive probe and the triangular probe are significantly weakened.

Compared with the original image, the sharpness and contrast of the three images processed by the proposed algorithm are improved, and the overall effect is better; moreover, the algorithm adopts an adaptive filtering algorithm for high-frequency coefficients to determine the noise determination threshold suitable for different sub-band coefficients. Therefore, compared with the original image, the noise of the three images processed by the algorithm proposed in this paper is very low.

4.2 Objective evaluation

Sharpness, contrast and peak signal-to-noise ratio are three objective indexes commonly used to measure the effect of image enhancement. These three indexes have been used for objective calculation and evaluation in this paper.

(1) Clarity

It mainly reflects the vein part of the image. The larger is the measured value, the clearer is the representative image, as shown in equation (8).

$$\bar{g} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \sqrt{\frac{(\Delta_m x(i,j))^2 + (\Delta_n x(i,j))^2}{2}} \tag{8}$$

$\Delta_m x(i, j)$, $\Delta_n x(i, j)$ are the difference points of points (i, j) in vertical and horizontal directions.

(2) Contrast

It represents the overall contrast intensity of the image. Generally, the greater is the contrast, the better is the image enhancement effect. The contrast calculation formula is:

$$Con = \frac{VAR}{\left[\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - \mu_x)^2\right]^{\frac{1}{4}}} \tag{9}$$

Where, μ_x represents the average value of gray scale, M and N represent the number of pixels in image rows and columns. VAR is the variance of image, and the calculation formula is:

$$VAR = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - \mu_x)^2 \tag{10}$$

(3) Peak signal-to-noise ratio

According to the ratio of maximum signal power and noise power, the greater is the PSNR, the better is the image enhancement effect. The calculation formula of PSNR is:

$$PSNR = 10 \times 1g \frac{L \times L}{MSE} \tag{11}$$

Where, L is the gray level range, usually 255, and MSE is the mean square error, which can be calculated by equation (12).

$$MSE = \frac{\sum_{0<j<N} \sum_{0<i<M} (f_{ij-o_{ij}})^2}{M \times N} \tag{12}$$

Where, f_{ij} and O_{ij} are the gray values of the input image and the output image at points (i, j), and M and N represent the number of pixels in the rows and columns of the image.

Table 1, **Table 2** and **Table 3** respectively show the objective evaluation indexes of the images of standard nano grid, triangular probe and conductive

Table 1. Comparison of objective evaluation indexes of three algorithms for raster image processing

Evaluating indicators	Original image	HE algorithm	Retinex algorithm	Textual algorithm
Clarity	3.63	21.02	13.65	5.71
Contrast	10.92	64.65	41.98	14.56
Peak signal-to-noise ratio	—	10.84	15.79	20.49

Table 2. Comparison of objective evaluation indexes of three algorithms for processing conductive probe images

Evaluating indicators	Original image	HE algorithm	Retinex algorithm	Textual algorithm
Clarity	3.68	19.03	12.11	5.16
Contrast	20.35	64.50	29.64	26.76
Peak signal-to-noise ratio	—	10.68	15.12	17.67

Table 3. Comparison of objective evaluation indexes of three algorithms for processing triangular probe images

Evaluating indicators	Original image	HE algorithm	Ritinex algorithm	Textual algorithm
Clarity	3.71	25.32	17.52	5.91
Contrast	13.39	64.63	28.80	15.51
Peak signal-to-noise ratio	—	9.88	14.94	18.67

probe in atomic force microscope processed by three algorithms.

(1) Standard 500 nm scale grid

(2) Conductive probe

(3) Triangular probe

From **Table 1** to **Table 3**, it can be seen that the clarity of different defocused images processed by HE algorithm and Retinex algorithm is relatively high. Although the clarity of defocused images processed by the algorithm proposed in this paper is not very high, it also improves the clarity of different defocused images to a certain extent and can effectively improve the image quality.

The contrast of different defocused images processed by HE algorithm and Retinex algorithm is relatively high. Although the contrast of defocused images processed by the algorithm proposed in this paper is not very high, it also improves the contrast of different defocused images to a certain extent and can effectively improve the image quality.

It can be seen from the peak signal-to-noise ratio data that compared with HE algorithm and Retinex algorithm, the proposed algorithm has the largest peak signal-to-noise ratio, the most information retained, the least distortion and better visual effect.

Therefore, through the comparative experiments of standard nano-grid images obtained under the actual optical microscope, triangular probe and conductive probe sample images collected under the atomic force microscope, it can be seen that the image enhancement effect of the proposed algorithm is relatively better than that of histogram equalization algorithm (HE) and Retinex algorithm (MER), and can effectively improve the image quality.

5. Conclusion

The out of focus images collected under micro-nano optical microscope are not very clear in detail, edge and contour. Combined with NSCT image transformation method, which has multi-scale and multi-directional, and superior transformation function, more texture and edge of the image can be obtained. At the same time, an adaptive noise reduction and enhancement algorithm of micro-nano optical image based on NSCT is proposed to restore the defocus image obtained under the microscope. The experimental results of standard nano-grid images, triangular probe images and conductive probe images show that the enhanced image effect of the algorithm proposed in this paper is better than histogram equalization algorithm (HE) and multi-scale Retinex algorithm, which not only improves the quality of defocused images, but is also conducive to the depth information recovery of subsequent defocused images.

Conflict of interest

No conflict of interest was reported by the author.

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