Noise Intensity Estimation Method Based on PCA and Weak Textured Block Selection for Neutron Image

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Abstract. Noise intensity estimation has a very important application in image denoising. In image processing, the denoising method can achieve an ideal denoising effect under the assumption that the Gaussian noise intensity in the image is known. But in real denoising applications, especially the neutron image, the noise level is unknown, which will greatly affect the denoising effect of neutron image processing. In this paper, a method which combined the principal component analysis with weak texture block selection is proposed for noise intensity estimation of neutron images. The experimental results show that the proposed method can accurately estimate the Gaussian noise in the neutron image. Compared with the existing noise intensity estimation methods, the qualitative and quantitative results show that the proposed method has higher accuracy and stability.

Keywords: Neutron Image Denoising; Noise Intensity Estimation; Weak Textured Block Selection; Gaussian Noise

1. Introduction
Neutron radiography, as an important nondestructive testing technique, has been widely used in industry, nuclear industry, condensed matter applications [1]. In practical application, the neutron radiography system consists of the neutron source system and the neutron digital imaging system. The imaging quality is highly dependent on the performance of the neutron imaging system. Limited by the intrinsic characteristics of the neutron imaging system and environment, the neutron images are always suffering from the quality degradation such as low contrast, unclear details, noise and blurring, among which the Gaussian noise in the most typical and outstanding one [2, 3]. These phenomena will directly influence the analysis and discrimination of internal structure information of the objects to be measured, and then affect the extensive application of neutron photography in industrial nondestructive testing. Therefore, removal of the Gaussian noise and preservation of the image details are crucial research tasks to improve the quality of neutron images. In image processing, it is assumed that the Gaussian noise intensity in the image is known, as a parameter for denoising, which is not consistent with the reality for the noise intensity in the neutron image is unknown. Under this condition, it is very important to estimate the intensity of Gaussian noise in neutron images accurately.

In recent years, the principal component analysis (PCA) technology has been applied to noise intensity estimation and achieved good results [4, 5]. In PCA, the smooth image blocks were firstly selected and the covariance matrix was constructed. Then the minimum eigenvalue of the covariance matrix was taken and as the result of noise intensity estimated. Generally, the eigenvalues can represent the texture information of the image matrix and the minimum eigenvalue contains the least information about the texture structure of the image matrix, so the minimum eigenvalue is least affected by the texture structure. When the texture in the image block is few enough, it is considered that the image
block is smooth. Further, when the number of image blocks to construct the covariance matrix approaches infinity, the minimum eigenvalue is approximately equal to the true noise variance, that is noise intensity. Under this case, selection the appropriate smooth image block plays a vital role in the noise intensity estimation. In this paper, a new method for selecting weak texture blocks of images is proposed. Combining with the principal component analysis (PCA), the noise intensity of image is estimated. This method can be applied in real neutron images denoising and achieve effective results.

2. Method Description

Assuming that the neutron image is polluted mainly by the additive Gaussian noise, the degradation model is defined as:

\[ Y = S + N \] (1)

where \( Y \) is the noisy image, \( S \) is the original image, and \( N \) is the additive Gaussian noise with variance of \( \sigma^2 \).

2.1. PCA

In the PCA domain, the data variance projected in the direction of the minimum variance is equal to the minimum eigenvalue of the covariance matrix. Therefore, according to formula (1), the following equation can be obtained:

\[ \lambda_{\text{min}}(\Sigma_Y) = \lambda_{\text{min}}(\Sigma_S) + \sigma^2 \] (2)

where \( \Sigma_Y \) is the covariance matrix of the image \( Y \) with noise, \( \Sigma_S \) is the covariance matrix of the image \( S \) without noise and \( \lambda_{\text{min}} \) is the minimum eigenvalue of the covariance matrix [6]. The covariance matrix is calculated as \( \Sigma_Y = \frac{1}{M} \sum_{i=1}^{M} (P_i - \mu)(P_i - \mu)^T \), \( \mu = \frac{1}{M} \sum_{i=1}^{M} P_i \). \( P \) is the image block with size of \( W \times W \) and \( P_i \) represents the i-th image block. \( M \) represents the number of image blocks and \( \mu \) represents the mean value of the \( M \) image block.

2.2. The Image Weak Texture Blocks Selection

Image weak texture block represents the image region with small pixel value change and almost no pixel value mutation. In the image weak texture blocks, the pixel intensity change is mainly caused by noise. For image block that contain rich details and textures, the noise intensity is usually overestimated for the reason that some texture information in the image block is usually regarded as noise. Hence, the appropriate weak texture image block selection is a crucial step for noise intensity estimation.

Since the image pixels have the characteristic of neighborhood correlation, the difference signal of adjacent pixels can reflect the degree of correlation between different pixels. In this paper, the central neighborhood correlation is adopted to describe the difference between the central pixel and its neighborhood pixels in an image block. The degree of correlation here is used to judge the smoothness of the image block. The smaller the correlation of the central neighborhood of the image block is, the smaller the volatility of the pixel grayscale in the region is, which means the less texture the image block contains.

Take the 3x3 image block as an example to calculate the correlation of center neighborhood. Calculation the correlation of the block means to calculate the correlation between the center point (pixel value is 5) of the region and the surrounding pixel points. The formula is as follows:

\[ R = \frac{\sum_{t=1}^{8} |f_t(x,y) - f_5(x,y)|}{8} \] (3)

where \( f_t(x,y) \) represents the pixel value of pixel point \( t \) \( (t = 1,2,3,4,6,7,8,9) \) and \( R \) represents the central neighborhood correlation.

The pixel mark diagram is shown in figure 1. Then according to formula (3), the correlation of this image block is calculated as \( R = \frac{20}{8} = 2.5 \).
Figure 1. 3×3 image block pixel point marking diagram

The central neighborhood correlation of each block is calculated and the correlation values of these image blocks are sorted from large to small, represents as \( A = \{R_1, R_2, ..., R_N\} \). Calculate the median value according to formula (4). Let \( B = \{R_1, R_2, ..., R_{md_1}\} \), \( (md_1 < N) \), get \( md_2 \) by formula (4). Then let \( C = \{R_1, R_2, ..., R_{md_2}\} \), \( md_2 < md_1 \) and get \( md_3 \). Looping this operation four times and get \( md_4 \). We set the threshold \( \varepsilon = md_4 \).

\[
md_1 = \begin{cases} 
\frac{R_{(N+1)/2}}{} & N = \text{odd}, \\
\frac{R_{N/2}}{} & \text{otherwise}.
\end{cases}
\]  

(4)

Among all the image blocks, the image blocks the correlation of which is less than the threshold value is regarded as a weak texture block. Then, all the weak texture blocks can be obtained, represented as \( Y = \{Y_1, Y_2, Y_3, ..., Y_n\} \), \( (n < N) \).

2.3. The Noise Intensity Calculation

Once the noise-free block set is known, the noise intensity value can be easily obtained according to formula (2). In practice, the minimum eigenvalue of the covariance matrix of the noise-free block set cannot be obtained. Whereas, the noise-free block has low rank characteristic [7], that means the minimum eigenvalue \( \lambda_{\text{min}}(\Sigma_S) \) of the set \( S \) of noise-free blocks is approximately zero. Then, the formula (2) can be rewritten as formula (5).

\[
\hat{\sigma}_n^2 = \lambda_{\text{min}}(\Sigma_\nu)
\]

(5)

where \( \Sigma_\nu \) is the covariance matrix of the weak texture block and \( \hat{\sigma}_n \) is the estimated noise intensity of the image. The overall framework flow chart of the algorithm is shown in figure 2.

Figure 2. Flow chart of noise intensity estimation

3. Results

All the experiments are tested on a PC configured as Intel processor with 4GB of memory, and the algorithms are encoded in a Windows8 64-bit matlab2016a environment. In this part, several experimental results testing on the simulated images and real neutron images are presented.

3.1. Analog Image Simulation

In this section, the simulated images are tested to evaluate the algorithm in this paper and comparing with the Liu, Immerkær and Amer method [7-9]. The house image with 256×256 pixels and aircraft image with 481×321 shown in figure 3. Different intensity noises are added to the images separately to simulate the images suffered from the different noise pollution. The added and estimated noise intensity values are shown in table 1. From the data in the table, compared with the other methods, the noise intensity estimated by the proposed method has the smaller deviation from the actual value generally. In order to evaluate the performance of these methods, the BM3D [10, 11] denoising method is adopted and the denoised results are used for evaluating the accuracy of noise intensity
estimated by different methods indirectly. We take the aircraft image as an example and add the Gaussian noise with mean 0 and variance 10 into the image. The noisy images is shown in figure 3(c).

In figure 4, from left to right, the images are Immerkær, Amer, Liu and proposed method combined BM3D. In order to avoid the influence of uncertainties caused by subjective evaluation, the general objective evaluation criteria-peak signal-to-noise ratio (PSNR) is adopted to evaluate the denoising image quality. The formula of PSNR is shown in formula (6). All the PSNR values under different noises are shown in table 1.

$$PSNR = 10 \ast \log\left(\frac{(m-1)(n-1)}{MSE}\right)$$

where $MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} ||x(i,j) - y(i,j)||^2$. $m$ and $n$ are the size of the image. $x$ and $y$ are the original and the denoised images. In general, the larger the PSNR is, the less the image distortion is, and the better the denoising effect of the method is [12].

| Table 1. Estimate of noise intensity and PSNR (dB) value of denoised image. |
| --- |
| Image | Method | Estimated results and PSNRs of different noises |
| | | 1 | 5 | 10 | 20 | 50 | 60 | 90 |
| House | Immerkær | 2.09 | 5.43 | 10.43 | 20.70 | 51.34 | 61.54 | 91.82 |
| | Amer | 1.47 | 5.50 | 9.84 | 19.02 | 47.12 | 57.93 | 81.82 |
| | Liu | 1.20 | 4.85 | 9.94 | 19.44 | 48.66 | 58.76 | 86.47 |
| | Our | 1.69 | 5.07 | 10.02 | 19.90 | 49.63 | 59.41 | 89.34 |
| Aircraft | Immerkær | 1.52 | 5.29 | 10.26 | 20.43 | 50.88 | 60.99 | 91.10 |
| | Amer | 1.36 | 5.65 | 9.74 | 18.66 | 45.50 | 53.71 | 80.24 |
| | Liu | 1.05 | 4.96 | 9.89 | 19.64 | 49.47 | 59.20 | 88.80 |
| | Our | 1.47 | 5.06 | 9.98 | 19.86 | 49.67 | 59.77 | 89.62 |
| House | Immerkær | 46.32 | 39.73 | 36.68 | 33.73 | 29.65 | 28.72 | 26.43 |
| | Amer | 48.29 | 39.68 | 36.72 | 33.67 | 29.57 | 28.59 | 25.87 |
| | Liu | 48.87 | 39.84 | 36.69 | 33.80 | 29.61 | 28.59 | 26.32 |
| | our | 47.72 | 39.84 | 36.72 | 33.81 | 29.66 | 28.73 | 26.49 |
| Aircraft | Immerkær | 49.32 | 41.70 | 38.17 | 34.48 | 29.75 | 28.90 | 26.75 |
| | Amer | 49.83 | 41.69 | 38.18 | 34.42 | 29.33 | 28.31 | 25.98 |
| | Liu | 50.47 | 41.70 | 38.18 | 34.45 | 29.84 | 28.93 | 26.87 |
| | our | 49.44 | 41.75 | 38.18 | 34.49 | 29.86 | 29.03 | 26.91 |

Figure 3. (a) House image, (b) Aircraft image; (c) Noisy image of Aircraft.

Figure 4. Denoised images and local images.
3.2. Neutron Image Tests

In this section, the performance of the proposed method is measured by testing on two real neutron images presented in figure 5(a). The two images are gun and termination resistor [13, 14]. In order to evaluate the availability of the proposed method in neutron images noise intensity estimation, the estimated results are used as the input parameters for BM3D denoising. The denoising results are shown in figure 5, in which from left to right, are original image and results by Immerkær, Amer, Liu and the proposed method combined with BM3D. From the denoising results, the noise intensity estimated by the proposed method is more accurate than the other methods. The zoomed fragments extracted from the right part of the termination resistor can further illustrate the robust and high accuracy of the proposed method.

In order to quantitatively evaluate the performance of different methods, the blind image quality index (BIQI) is used to evaluate the quality of denoised images. The formula of BIQI is shown in formula (7).

\[
BIQI = \sum_{i=1}^{5} p_i q_i
\]

(7)

where \( p_i \) represents the probability of the five sets of distortions usually appearing in the degraded image and \( q_i \) is the quality scores from each of the five sets of distortions [15]. After normalization and negate operation, the value of BIQI is in the range 0 to 1. The higher the value BIQI is, the better the image quality will be. The results of noise estimation of neutron images and the value of unreferenced evaluation index as shown in table 2.

| Method | Image and estimated value | BIQI values |
|--------|---------------------------|-------------|
|        | Gun | Termination resistor | Gun | Termination resistor |
| Immerkær | 2.09 | 2.64 | 0.72 | 0.92 |
| Amer    | 2.82 | 0.45 | 0.87 | 0.75 |
| Liu     | 0.52 | 0.51 | 0.61 | 0.75 |
| Our     | 3.74 | 4.64 | 0.98 | 0.99 |

Figure 5. Original image, denoised images and local images.

From table 2 can see that the image quality of the proposed method combined with BM3D is better than the compared methods. Combine figure 5, the proposed method is more accurate and stable in noise intensity estimation than the other methods.
4. Conclusion
The Gaussian noise intensity estimation is an important task in neutron image denoising. In real image denoising processing, the denoising method can achieve excellent result under the circumstance that the noise intensity is known or setting the optimal noise parameter manually. In this paper, a Gaussian noise intensity estimation method that combining the principal component analysis and weak texture block selection is proposed. Experimental results show that the proposed method can effectively estimate the noise intensity of the neutron image accurate and stable, which is helpful for the neutron image reprocessing.

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