A Novel Method of Neutron Radiography Image Denoising Using Contourlet Transform*

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Abstract A new image transform, namely, the contourlet transform is introduced, which can capture the intrinsic geometrical structure of image. Furthermore, a novel image denoising scheme based on contourlet is presented. Via calculating variance homogeneous measurement (VHM), the locally adaptive window is determined to estimate the shrinkage factor optimally, then the contourlet coefficient is shrunk using the shrinkage factor. The scheme utilizing the correlation of contourlet coefficients in the same subband along the edge or contour of the image, which can get the tradeoff between "noises removing" and "details preserving". In numerical comparisons with various methods, the presented scheme outperforms the traditional contourlet denoising method based on hard-thresholding and Wiener filter in terms of PSNR. Experiments also show that this scheme could not only remove the noises effectively, but also suit for the neutron radiography system.

Keywords Digital neutron radiography; Contourlet transform; Variance homogeneous measurement; Image denoising

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0 Introduction

Neutron radiography is a non-destructive test technology. It has many merits, which X-ray radiography does not have, such as penetrating some dense materials (for example lead, bismuth, uranium) and getting high contrast of light materials enveloped in dense materials; distinguishing isotopes and so on[1]. Many countries show great interests in neutron radiography. There are two methods of neutron radiography: one using films and the other using CCD (named digital neutron radiography). Due to the influence of CCD camera, neutron scatter, control circuit and so forth, the neutron radiography image is generally contaminated by noise. On the other hand, denoising of an image is not only a classical but also a very difficult problem in image processing. Researchers have proposed many kinds of noise removal methods according to the statistical and spectrum distribution properties of noise, which can be classified into two categories: spatial domain denoising approaches and frequency domain denoising approaches. Typically, noise is characterized by high spatial frequencies in an image, and Fourier-based methods, which usually try to suppress high-frequency components, also tend to reduce the edge sharpness. Hence Daubechies and Mallat introduced a new transform namely wavelet[2]. Now wavelet has been widely used in image denoising[3,4]. However, due to the fact that wavelets are blind to the smoothness along the edges, some new transforms have been introduced recently, which possess the main features of wavelets (namely, multiresolution and time-frequency localization) and show a high degree of directionality and anisotropy as well. The curvelet and contourlet are two examples, which developed to sparsely represent natural images. Candes and Donoho used the curvelet transform for image denoising[5]. Minh N Do utilized a double filter banks structure to develop the contourlet transform and used it for some non-linear approximation and denoising experiments[6]. But the original image denosing based on curverlet and contourlet transform, uses a simple hard-thresholding rule for filtering the noisy coefficients. The hard-thresholding rule brings some problems such as killing too many signal coefficients, which might contain useful image information and introduces many visual artifacts.

In order to denoise neutron radiography image effectively and not to generate the severe visual artifacts, a new image denoising approach based on contourlet is presented. It shrinks the noisy contourlet coefficients by the shrinkage factors. The motivation came from the success of the

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shrinkage scheme in a wavelet domain[7]. It is noted that the discrete contourlet provides a tight frame, and the coefficients within subbands can be assumed as independent identically distribution (i. i. d). We generalize shrinkage scheme to contourlet domain. Then, the estimation of the shrinkage factor in a noisy environment became a critical issue. In this paper, we propose a novel scheme, which estimate the shrinkage factor based on the local neighborhood of the coefficient. However, the assumption of i. i. d becomes inaccurate as the size of the neighborhood grows. How to achieve a proper neighborhood region for the shrinkage factor estimation is a challenge. A number of methods based on varying local varying windows have been reported. Chang[8] proposed a spatially adaptive wavelet thresholding with context modeling and varying window. Chen[9] exploit square-shaped neighborhood with fixed size to estimate the shrinkage factor. Cai and Silverman[10] proposed a thresholding scheme by taking the immediate neighbour coefficients into account. We propose a region-based scheme, in which the region centered at the coefficient is partitioned into some disjoint subregions. The proper subregions were selected and merged to determine the locally adaptive window via calculating variance homogeneous measurement (VHM). So the better estimation of the shrinkage factor can be obtained. Experiments show that this method not only keeps the details of image but also yields denoised images with no serious blurring artifacts and better visual quality.

The contents of this paper are as follows. In Section 1, the contourlet transform and some of its advantages are introduced briefly. Next a novel image denoising in contourlet domain using locally adaptive window is presented. Then experimental results will be shown in Section 3. Finally the conclusion and future work are proposed in Section 4.

1 Disctrete contourlet transform

The primary goal of the contourlet construction is to obtain a sparse expansion for typical images that are piecewise smooth away from smooth contours. Two-dimensional wavelets, with tensor product basis functions lack directionality and are only good at catching point discontinuities, but do not capture the geometrical smoothness of the contours[6]. Fig. 1 (a) shows that, it would take many wavelet coefficients to accurately represent even one simple one-dimensional curve. Minh N Do proposed the contourlet transform, which is an improvement over wavelets in terms of this inefficiency. The resulting transform has the multiscale and time-frequency-localization properties of wavelets, but also offers a high degree of directionality and anisotropy. Precisely, contourlet transform involves basis functions that are oriented at any power of two′s number of directions with flexible aspect ratios. With such richness in the choice of basis functions, contourlets can represent any one-dimensional smooth edges with close to optimal efficiency. Fig. 1 (b) shows that compared with wavelets, contourlets can represent a smooth contour with much fewer coefficients.

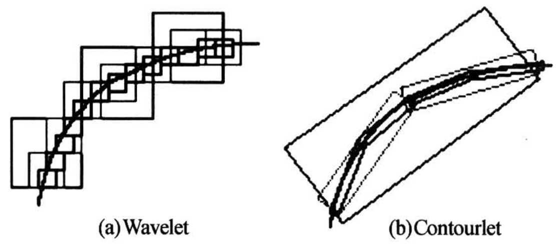

Fig. 1　Wavelet versus contourlet: Represent a smooth contour

Contourlet transform is implemented by the pyramidal directional filter bank (PDFB) that is a cascade of a Laplacian pyramid and a directional filter bank. Laplacian pyramid (LP) is first used to capture the point discontinuities, and then bandpass images from the LP are fed into a directional filter bank (DFB) so that directional information can be captured. The scheme can be iterated on the coarse image. The overall result is an image expansion using basic elements like contour segments, and thus named contourlet.

Fig. 2 illustrates the subspace splitting by contourlet transform. V_l is a subspace, defined on a uniform grid with intervals $2^l \times 2^l$. The difference image in the LP caries the details necessary to increase the resolution from V_l to V_{l-1} on an image approximation. $W_{l,k}^{l_n}$ are the detail directional subspaces, the index l specifies the scale and index k runs to all 2^{l_n} directions . Suppose the family

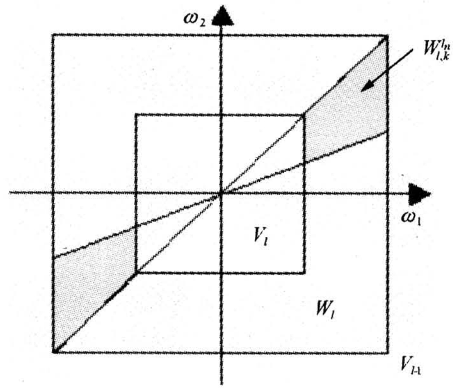

Fig. 2　Subspace splitting by contourlet

$\{\phi_{l,b}\}_{b\in Z^2}$ is an orthonormal basis for an approximation subspace V_l at the scale 2^l; the family $\{\lambda^l_{l,k,b}\}_{b\in Z^2}$ is a tight frame of a detail directional subspace $W^l_{l,k}$. Furthermore, suppose the image $a_0[i,j]$ is $L_2(R^2)$ inner products of a function $f(t)\in L_2(R^2)$ with the scaling functions at a scale J, and $a_0[i,j]$ is decomposed by the discrete contourlet transform into coefficients $\{a_L[i,j], c^{(l)}_{l,k}[i,j]\}$, $l=1,2,\cdots,L$ (in the fine-to-coarse order) and $k=0,1,2,\cdots,2^{ln}-1$. Then

$$a_L[i,j]=\langle f,\phi_{J+L,b}\rangle;\ c^{(l)}_{l,k}[i,j]=\langle f,\lambda^l_{J+l,k,b}\rangle$$

As stated above, in the frequency domain, the contourlet transform provides a multiscale and directional decomposition. To decrease artifacts due to the Gibbs-like phenomenon in the DFB stage, we move downsampling and resampling to the end of the synthesis part and to the beginning of the analysis part, using the Nobel identities.

2 A novel image denoising using contourlet

2.1 The noise model in contourlet domain

Suppose the original image $f[i,j]$ is corrupted with additive Gaussian white noise $n[i,j]$

$$a_0[i,j]=f[i,j]+n[i,j] \tag{1}$$

where $n[i,j]\in N(0,\sigma^2)$. Applying the contourlet transform to the noisy image $a_0[i,j]$, the output is the contourlet coefficients $\{a_L[i,j], c^{(l)}_{l,k}[i,j]\}$. Since the Gaussian noise will be nearly averaged out in the low frequency contourlet coefficients, only bandpass directional images need to be thresholded and let lowpass image unchangeably. Note that if both the LP and DFB use orthogonal filters, the discrete contourlet transform provides a tight frame with frame bounds equal to 1, the bandpass directional images $c^{(l)}_{l,k}[i,j]$ can be modeled by

$$c^{(l)}_{l,k}[i,j]=x^{(l)}_{l,k}[i,j]+v^{(l)}_{l,k}[i,j] \tag{2}$$

where $x^{(l)}_{l,k}[i,j]$ and $v^{(l)}_{l,k}[i,j]$ are the expensions of $f[i,j]$ and $n[i,j]$ at specific scale and direction, respectively.

2.2 Restore the noisy contourlet coefficients using shrinkage factor

In this paper, the shrinkage of contourlet coefficients is employed instead of hard-thresholding. The goal is to recover $x^{(l)}_{l,k}[i,j]$ from the noisy observation $c^{(l)}_{l,k}[i,j]$. Suppose the shrinkage factor of $c^{(l)}_{l,k}[i,j]$ is $\xi[i,j]$, the estimator of $x^{(l)}_{l,k}[i,j]$ is

$$x^{(l)}_{l,k}[i,j]=\xi[i,j]\times c^{(l)}_{l,k}[i,j] \tag{3}$$

The performance of a denoising method like (3) is dependent on the quality of the shrinkage factor, $\xi[i,j]$. Chen[9] proposed a low-complexity but powerful scheme to calculate $\xi[i,j]$ in wavelet domain, we generalize the method to contourlet domain. For each coefficient $c^{(l)}_{l,k}[i,j]$, the $\xi[i,j]$ is formed based on a local neighborhood $B[i,j]$. In our previous work, we use a square window $B[i,j]$ which centered at $c^{(l)}_{l,k}[i,j]$ to calculate $\xi[i,j]$. Let

$$A[i,j]=\sum_{c^{(l)}_{l,k}[p,q]\in B[i,j]}\{c^{(l)}_{l,k}[p,q]\}^2 \tag{4}$$

Then we calculate the shrinkage factor $\xi[i,j]$ as

$$\xi[i,j]=\Phi((1-\eta^2/A[i,j])) \tag{5}$$

where $\eta=\sqrt{2\sigma^2\log N}$ is the universal threshold, (σ^2 is the variance of noise and N is the number of coefficients)

The sign operator $\Phi(X)$ is defined as follows

$$\begin{cases}\Phi(X)=X, X\geqslant 0\\ \Phi(X)=0, X<0\end{cases} \tag{6}$$

Note that this thresholding rule is a modification to the classical soft-thresholding rule. And the size of window $B[i,j]$ has influence on the performance of denoising with our method. The larger the window, the relatively smaller the threshold is. If the size of window is too large, it is meaningless for keeping the edge of image, a lot of noise will be treated as signal due to the too small threshold value. Furthermore, the proposed method depend on the assumption that the coefficients are locally independent and identically distribution (i. i. d). However, the locally i. i. d assumption becomes inaccurate as the size of the neighborhood grows. This suggests the existence of a proper neighborhood region for the shrinkage factor estimation of each contourlet coefficient. This paper proposed a new method to determine a reasonable window in order to yield better estimators.

2.3 Shrinkage factor estimate using locally adaptive window

Our scheme is based on region partition[11]. Assuming that there is a big region $N[i,j]$ centered at $c^{(l)}_{l,k}[i,j]$, $N[i,j]$ is partitioned into subregions $r_0[i,j],\cdots,r_{Q-1}[i,j]$, where $r_m[i,j]\cap r_n[i,j]=\phi(m\neq n)$, and $\bigcup r_m[i,j]=(m=0,\cdots,Q-1)$. Only subregion $r_0[i,j]$ includes $c^{(l)}_{l,k}[i,j]$. Locally adaptive window is determined by calculating variance homogeneous measurement (*VHM*). For each coefficient $c^{(l)}_{l,k}[i,j]$, $VHM_m(i,j)$ is defined as the absolute difference in variance of the subregions between 0 and m, or

$$VHM_m(i,j)=|\sigma_m^2-\sigma_0^2| \tag{7}$$

where $m=0,\cdots,Q-1$; and $\sigma_m^2[i,j]$ is the local variance of $r_m[i,j]$. Since the local mean of contourlet coefficients is very small, $\sigma_m^2[i,j]$ is approximately calculated by

$$\sigma_m^2[i,j]=\frac{1}{M}\sum_{[k,p]\in r_m[i,j]}(c^{(l)}_{l,k}[k,p])^2 \tag{8}$$

where M is the number of coefficients in $r_m[i,j]$. $VHM_m(i,j)$ indicates whether the variance $\sigma_m^2[i,j]$ is homogeneous with $\sigma_0^2[i,j]$. In our experiment, we utilize a square shaped region $N[i,j]$ centered at $c_{l,k}^{(l_j)}[i,j]$ and square shaped subregion for low complexity. We use 9×9 $N[i,j]$, and eight 3×3 subregions(not include $r_0[i,j]$). We select four subregions, which VHM are the smallest, and merge them with $r_0[i,j]$ to determine locally adaptive window $B[i,j]$, and then the shrinkage factor is obtained by (5).

2.4 Denoising algorithm

Image denoising is achieved by employing (3) with the shrinkage factor ξ. The steps of image denoising are summarized as follows.

1) Transforming the noisy image into the contourlet domain via the 2-D discrete contourlet transform.

2) For every specifically scale and direction cotourlet coefficients determines locally adaptive window $B[i,j]$.

3) Calculate shrinkage factor $\xi[i,j]$ via employ (5), in order to determine universal threshold η the noise variance σ^2 needs to be estimated first. In some situations, it may be possible to measure σ^2 based on information other than the corrupted image. In digital neutron radiography image denoising, it is estimated from the corresponding cotourlet coefficients set $\{c_{l,k}^{(l_j)}[i,j]\}$ by the robust median estimator, which also used in[8]

$$\sigma=\frac{\text{Median}(|Y_{m,n}|)}{0.6745} \tag{9}$$

where $Y_{m,n}\in\{c_{l,k}^{(l_j)}[i,j]\}$

4) Within the specifically scale and direction subband, for every cotourlet coefficients $c_{l,k}^{(l_j)}[i,j]$, estimates the coefficients via a shrinkage rule (3).

5) Obtaining the denoised image via the inverse contourlet transform on the shrunk contourlet coefficients.

3 Experimental results

In order to evaluate the performance of proposed method, we perform our experiments on the well-known images Barbara (512×512) and a digital neutron radiography image. For comparison, we also implement Wiener filter and contourlet-based hard-thresholding method. We use a 5×5 neighbourhood of each pixel in the image for Wiener filter. The universal threshold is applied to hard-thresholding. For the contourlet transform, in the LP stage we use the "9-7" filters, in the DFB stage we use the "23-45" biorthogonal quincunx filters and modulate them to obtain the biorthogonal fan filters. In order to make the contourlet expansion satisfy the parabolic scaling, we enforce that the number of directions 2^{ln} is doubled at every other finer scale. Fig. 3 illustrates one actual neutron radiography image, which acquires from a Research Nuclear Reactor by CCD. We can see the neutron radiography image is corrupted by noise severely. The denoised image processed by the Wiener filter, hard-thresholding method and proposed method is also illustrated in Fig. 3. Fig. 4 displays a "zoom-in" comparison of the denoised when applying Wiener filter, hard-thresholding method and proposed method on the part of the image. From Fig 4, we can see Wiener filter can't restrain noise effectively, hard-

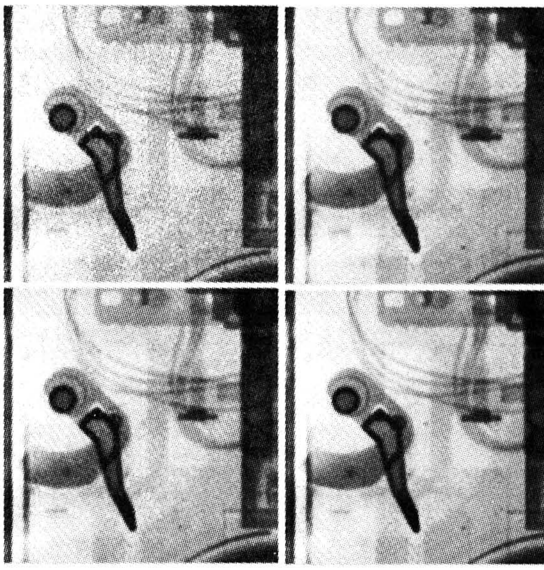

Fig. 3 Neutron radiography image (top left) and filtered images using wiener filter (top right), Contourlet-based hard-thresholding (bottom left), Proposed method(bottom right)

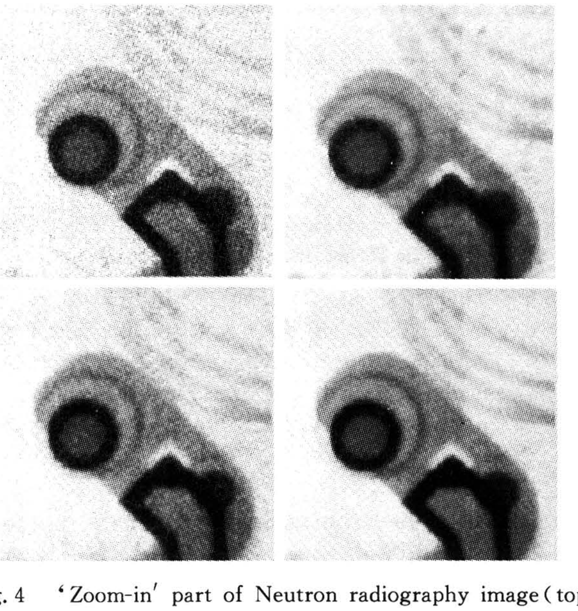

Fig. 4 'Zoom-in' part of Neutron radiography image (top left) and filtered using Wiener filter (top right), contourlet-based hard-thresholding (bottom left), Proposed method(bottom right) thresholding method can' t protect details and introduces many visual artifacts, the proposed method is shown to be more effective in recovering smooth contours.

To study the dependency of the proposed method on the noise level we generated a set of noisy image (the PSNR of the noise image range from 11.88 dB to 26.93 dB) for Barbara. We then compared the three different methods used in our experiments. This series of experiments are summarized in Table. 1 and Fig 5. From Table. 1 we can see that the proposed method outperforms hard-thresholding method and Wiener filter for all cases. Hard-thresholding does not have any denoising power when the noise level is low. Under such a condition, hard-thresholding produces even worse results than the original noisy image. However the proposed method performs very well in this case. Fig. 5 displays the PSNR after filtering with different methods versus PSNR of noise image before filtering.

Tble. 1 PSNR before and after filtering the noisy image with different methods (Barbara + Gaussian White Noise)

Noisy image	Wiener	Hard thresholding	Proposed method
26.93	27.28	23.65	27.78
21.25	23.55	21.23	24.61
17.84	21.42	20.21	22.74
15.56	20.01	19.68	21.52
13.86	18.95	19.23	20.63
12.45	17.97	18.95	20.04
11.88	17.50	18.89	19.85

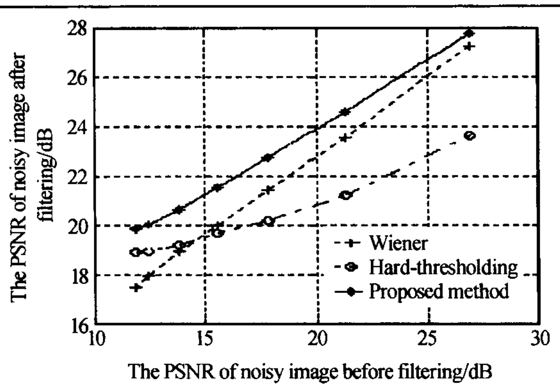

Fig. 5 The PSNR after filtering with different methods versus PSNR of noise image before filtering for Barbara. The three methods based on the Proposed method, Wiener and the Hard-thresholding are represented with a solid, dashed and dashdot line

5 Conclusion

A novel neutron radiography image denosing method based on contourlet transform was proposed. The shrinkage scheme was generalized to contourlet domain. Most of the visual artifacts due to thresholding contourlet coefficients via hard-thresholding rule could be eliminated by this scheme. A new approach for determining the locally adaptive window using a region-based scheme was presented to get optimal shrinkage factor. Because this approach used variance homogeneous measurement(VHM), the denoising method became an efficient algorithm for removing noise in neutron radiography image. Experimental results show that the proposed denoising method outperforms hard-thresholding method and Wiener filter both in terms of visual effects and PSNR values. In this work, we confined ourselves to square shaped region and square shaped subregion for low complexity. The future work should be concentrated on how to utilizing the correlation of contourlet coefficients across scales, directions and locations. A more sophisticated scheme by using statistical modeling may achieve further improvements.

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一种新颖的Contourlet域中子辐射图像降噪方法

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摘 要 由于受CCD相机、中子散射及控制电路等因素的影响,数字中子照相系统所获图像常被噪音污染,抑制噪音对于提高数字中子照相系统图像质量具有重要意义.利用多尺度几何分析能捕获图像几何结构的特性,提出一种新颖的基于contourlet变换的图像去噪方法.通过计算方差一致性测度(VHM),确定局部自适应窗口,从而最优估计contourlet系数的阈值萎缩因子,对contourlet系数进行萎缩,实现降噪功能.该方法将阈值去噪法与基于子带相关的图像去噪法相结合,充分利用在同一方向子带中沿边缘或轮廓contourlet系数的相关性,它能实现"去噪"和"保留信号"之间的平衡.实验结果表明,该方法在峰值信噪比指标上优于传统的contourlet系数硬阈值处理方法及维纳滤波方法,能有效地抑制图像噪音,同时适合于中子辐射图像的处理.

关键词 数字中子照相;contourlet变换;方差一致性测度;图像降噪

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