SAR IMAGE DENOISING USING HOMOMORPHIC AND SHEARLET TRANSFORMS

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ABSTRACT

Recently, denoising of Synthetic Aperture Radar (SAR) images has gained particular attention. SAR image is usually affected by speckle noise. In this paper a new method for speckle noise reduction of SAR images using shearlet transform (ST) is introduced. ST could significantly remove the Gaussian noise therefore in the proposed method first, noisy images are converted to a domain which type of noise is Gaussian using homomorphic transform (HT). Second, 2D shearlet is applied to the data. Third, the hard thresholding is used in order to denoise the shearlet coefficients. Finally reconstructed denoised images are obtained by applying the inverse shearlet and homomorphic transforms. The proposed method (ST-HT) is compared with state of art denoising algorithms on SAR images. Obtained results show the superiority of the proposed approach.

***Index Terms*—** Denoising, Synthetic Aperture Radar, Shearlet transform.

1. INTRODUCTION

SAR is a capturing technique to produce a high spatial resolution image from surface of the earth. The SAR image can be captured in all weather conditions. this images are affected by noise a lot therefore denoising is recently considered a lot. The main goal in image denoising is eliminating noise and also preserving the details of the edges well [1]. Speckle is a special phenomenon in lasers, SAR or ultrasound images. Two main reasons for creating speckle noise are: first the the coherent summation of the return scattered signals and second the random interference of electromagnetic signals. In order to estimate the variance of speckle noise recently different methods have been introduced such as Gaussian-Hermite Moments [2] and the other interactive manner [3, 4]. Speckle reduction methods could be classified in two groups: multi-pass single-look and single-pass multi-look. First group capture picture per sweep unlike single-pass multi-look which one picture is taken [5]. Different techniques for denoising SAR image have been investigated such as wavelet [6] and curvelet transforms [7] and speckle reduction techniques based on the nonlocal approach such as local linear minimum mean square error (LLMMSE) [8] and block matching 3D (BM3D) [9] and SURE Approach [10]. In this paper a new despeckling method of SAR images is presented based on homomorphic and shearlet transforms. In this method the variance of speckle noise is also estimated. In order to validate the efficiency of proposed method, it is compared with some of popular denoising method.

The rest of the paper is organized as follows: In section 2 shearlet transform is introduced. In section 3 proposed method is explained. experimental result are shown in section 4. section 5 gives the conclusion.

2. SHEARLET TRANSFORM

The discrete shearlet transform is a particular type of composite wavelet transform. 2D composite wavelet can be defined as [11, 12]:

$$\psi_{j,l,k} = |\det M_{j,l}|^{j/2}\psi(S^l M_{j,l}^j(x-k)) \qquad (j,l \in \mathbb{Z}, k \in \mathbb{Z}^2) \tag{1}$$

which $\psi \in L^2(\mathbb{R}^2)$ is the mother wavelet. $M_{j,l}$ is an anisotropic dilation matrix. S is an invertible shear matrix and $|\det S| = 1$.

$M_{j,l} = \begin{pmatrix} 4 & 0 \\ 0 & 2 \end{pmatrix}$ S= $\begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}$

j shows scale, l represents direction and k depicts shift parameters.

The Fourier transform of (1) is :

$$\Psi_{j,l,k}(w) = \Psi_1(2^{-2j}\omega_1)\Psi_2(2^j \frac{\omega_2}{\omega_1} - l) \times e^{-2\pi i M_{j,l}^{-j} S^{-l} k\omega} \tag{2}$$

Eq.2 shows shear operation effect on frequency domain, where

$$\Psi(\xi) = \Psi(\xi_1, \xi_2) = \Psi_1(\xi_1)\Psi_2(\frac{\xi_2}{\xi_1}) \tag{3}$$

For any $\xi = (\xi_1, \xi_2) \in \mathbb{R}^2, \xi_1 \neq 0$, supp$\Psi_1 \subset [-\frac{1}{2}, -\frac{1}{16}] \cup [\frac{1}{16}, \frac{1}{2}]$, supp$\Psi_2 \subset [-1, 1], \psi_1, \Psi_2 \in C^\infty(\mathbb{R})$
assume that

$$\sum_{j \geqslant 0} |\Psi_1(2^{-2j}\omega)|^2 = 1 \qquad |\omega| \geqslant \frac{1}{8} \tag{4}$$

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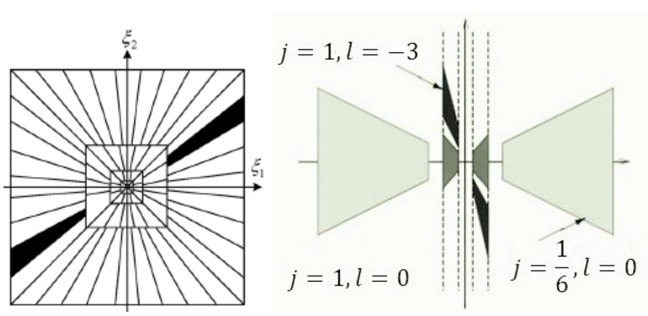
for each $j \geqslant 0$

$$\sum_{l=-2^j}^{2^j-1} |\Psi_2(2^j\omega - l)|^2 = 1 \qquad |\omega| \leqslant 1 \tag{5}$$

which Ψ_1 is the Fourier transform of wavelet function and Ψ_2 is a compactly supported bump function.
In addition to the $\Psi^{(0)}_{j,l,k} : \{j \geqslant 0, -2^j \leqslant l \leqslant 2^j - 1, k \in \mathbb{Z}^2\}$, an other set $\Psi^{(1)}_{j,l,k}$ that $\Psi^{(1)}_{j,l,k} : \{j \geqslant 0, -2^j \leqslant l \leqslant 2^j - 1, k \in \mathbb{Z}^2\}$ is considered.
The two region $D_0 = \{(\xi_1, \xi_2) : |\xi_1| \geqslant \frac{1}{8}, |\frac{\xi_2}{\xi_1}| \leqslant 1\}$ and $D_1 = \{(\xi_1, \xi_2) : |\xi_2| \geqslant \frac{1}{8}, |\frac{\xi_1}{\xi_2}| \leqslant 1\}$ are defined for $\Psi^{(0)}_{j,l,k}(x)$ and $\Psi^{(1)}_{j,l,k}(x)$ respectively. Let $\phi \in L^2(\mathbb{R}^2)$ be such that the set $\{\phi_k(x) = \phi(x - k) : k \in \mathbb{Z}^2\}$ is a tight frame for L^2, where $\{\phi_k, \Psi^{(i)}_{j,l,k} : j \geqslant 0, -2^j \leqslant l \leqslant 2^j - 1, k \in \mathbb{Z}^2, i = 0, 1\}$.
This indicates that the decomposition is invertible and the transformation is numerically well-conditioned. More information about this construction can be found in [13]. Figure 1 shows the tiling frequency domain of shearlet transform for different values of j and l.



(a) (b)

Fig. 1. (a) Shearlet tiling frequency. (b) Frequency domain of shearlet with Different amount of j and l.

3. PROPOSED METHOD

Different algorithms has been introduced for denoising SAR images such as filters [5, 14], wavelet [6], curvelet [7] and shearlet [12] transforms. In this paper a new denoising method for SAR images based on shearlet transform is proposed. A noise model for SAR images can be expressed as follows:

$$y = x + n \times x \tag{6}$$

Eq.6 can be converted to:

$$y = x \times N \qquad (N = n + 1) \tag{7}$$

where N is speckle noise and x is clean image and y is noisy image.
Homomorphic transform is used in order to convert the multiplicative noise to Gaussian additive noise:

$$ln(y) = ln(x) + ln(N) \tag{8}$$

Assume $ln(y) = y'$, so Eq.8 is changed to:

$$y' = x' + N' \tag{9}$$

where N' is an additive Gaussian noise. In order to estimate the variance of Gaussian noise, a blind method based on discrete cosine transform is used [15].
After that, the shearlet transform on logarithm data is applied. Then follow hard thresholding technique is used for denoising shearlet coefficients.

$$f(y) = \begin{cases} y & |y| \geq Tj, l \\ 0 & |y| < Tj, l \end{cases}$$

T is a threshold factor and chosen as $Tj, l = Cj\sigma j, l$ which Cj is a scaling parameter and $\sigma j, l$ is an estimation of the standard deviation of noise and equal to $\sigma = \sqrt{variance}$ which is obtained by [15].
After that the denoised image is obtained using inverse shearlet and homomorphic transforms.

Algorithm 1 DENOISING ALGORITHM (ST-HT)

Input: Noisy image
$y = x \times N$
x =clean image, N =speckle noise
Output: Denoised image $\hat{x}$
1- Apply homomorphic transform (Eq.8).
2- Estimate the variance of Gaussian noise [15].
3- Apply shearlet transform [12].
4- Apply hard thresholding in order to denoise shearlet coefficients.
5- Reconstruct denoised image.

4. EXPERIMENTAL RESULTS

All the experiments were run in MATLAB R2016a on a laptop with a CORE i7 2.6 GHz CPU and 8GB RAM. The size of test image in Figure 2 is 294×294 which is a part of the ASTER GDEM and is freely distributed on `http://gdem.ersdac.jspacesystems.or.jp/index.jsp` and the size of test image in Figure 3 is 470×470 which is a part of Chile copper mine and is freely distributed on `http://terrasar-x-archive.infoterra.de`.
To evaluate the image quality, the peak signal-to-noise ratio (PSNR) can be used. It estimates the quality of the reconstructed image $\hat{x}$ in comparison to the original one x.
The PSNR in dB is defined as:

$$PSNR_{\text{dB}} = 10 \times \ \log 10 \left(\frac{max^2(x)}{MSE} \right) \tag{10}$$

$$MSE = \frac{1}{I_1 \times I_2} \sum\nolimits_{j=1}^{I_2} \sum\nolimits_{i=1}^{I_1} (x_{ij} - \hat{x}_{ij})^2$$

where (I_1, I_2) is the original image size.
Speckle noise with variance 0.5 is added to both images then different denoising methods are applied to the noisy images. Figures c-g and table 1 show the denoising results.

Table 1. DENOISING RESULTS OF SAR IMAGE

Algorithm	PSNR(dB)1	PSNR(dB)2
Noisy image	16.6996	16.8018
Curvelet method	17.6411	17.1237
Shearlet method	17.4038	17.6314
BM3D	18.3232	18.3964
SURE	19.7611	19.1698
Proposed method	20.0796	19.3311

It can be clearly observed our method (ST-HT) is better than other methods in removing speckle noise and in addition it can preserve the edges well.

5. CONCLUSIONS

In this paper, we introduced a new method for denoising SAR images based on homomorphic and shearlet transforms. First the speckle noise is converted to Gaussian noise and then 2D shearlet transform is used for denoising. The obtained results show the proposed algorithm achieves a significantly better PSNR in comparison with two state of the art algorithms.
In future our aim is to investigate other thresholding techniques in order to improve the efficiency of the proposed method.

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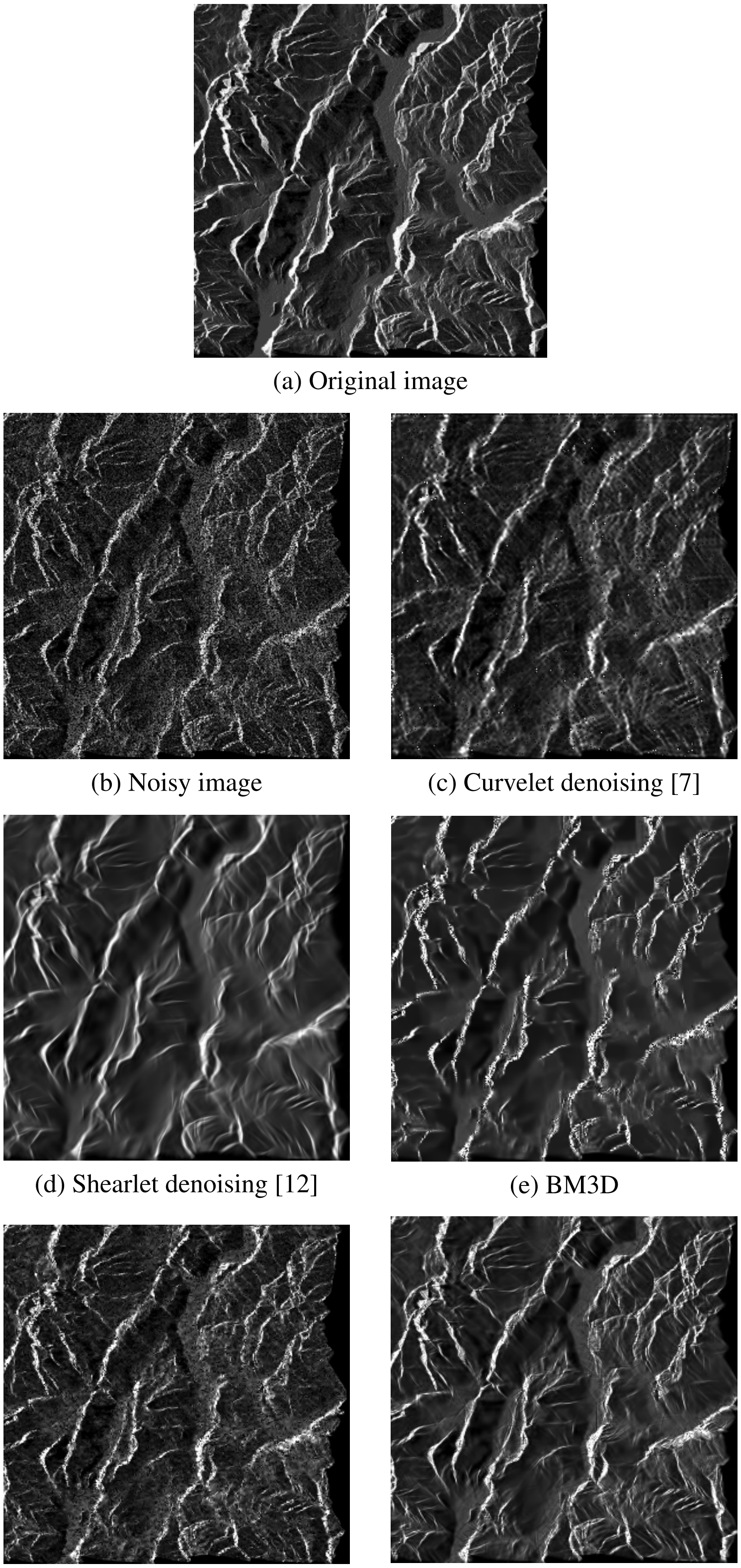


(a) Original image

(b) Noisy image

(c) Curvelet denoising [7]

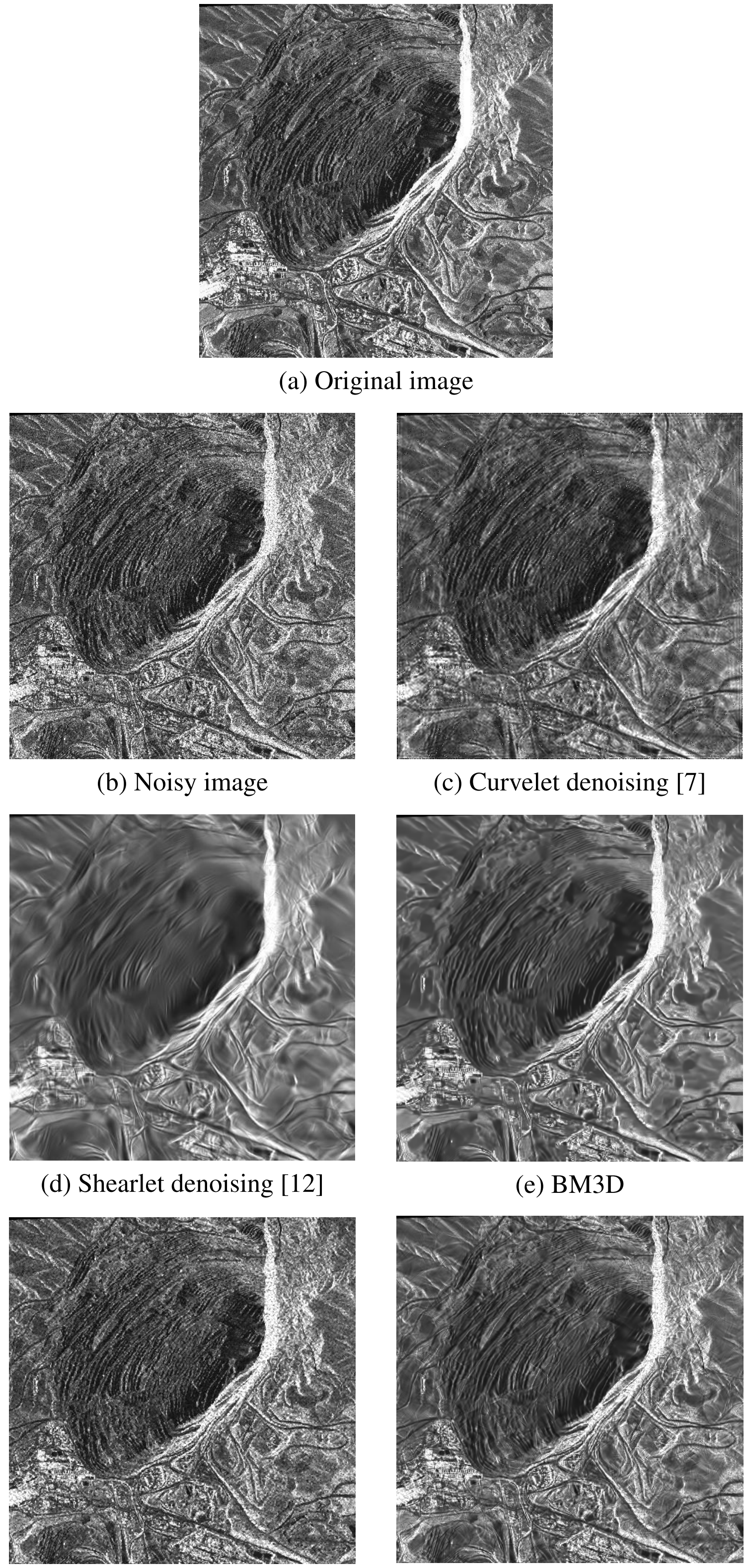
(d) Shearlet denoising [12]

(e) BM3D

(f) SURE [10]

(g) ST-HT

Fig. 2. SAR image denoising results.



(a) Original image

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(c) Curvelet denoising [7]

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(f) SURE [10]

(g) ST-HT

Fig. 3. SAR image denoising results.