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DESPECKLING OF SAR IMAGES USING SHIFT INVARIANT SHEARLET TRANSFORM

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Abstract:To suppress speckle noise effectively in remote sensing image processing. The optimal solution of image denoising based on sparse representation does not have one –to- one mapping of the original signal space. In this paper, we propose a novel synthetic aperture radar (SAR) image denoising via sparse representation in shearlet domain. First, a speckle noise is added to an input image. Second, a shearlet transform is applied to the noised SAR image. Third, a new optimal denoising model is constructed using sparse representation model. Finally, shearlet is combined with DTCWT to solve the optimal denoising model to obtain the denoised image. The experimental results show that the proposed model not only effectively suppresses the speckle noise and improves the peak signal-to-noise ratio of denoising SAR image, but also obviously improves the visual effect of the SAR image, especially by enhancing the texture of the SAR image.

Index Terms-SAR image denoising, sparse representation, shearlet transform, DTDWT.

1. Introduction

SYNTHETIC aperture radar (SAR) image denoising is one of the key problems in remote sensing image processing , the basis of remote sensing image postprocessing,which is a controversial and yet meaningful question for research. Speckle suppressing has two main categories:multiview smooth processing during the imaging process and image filtering after the imaging process[1],[2]. The first method,which played an important role in image denoising in the early days, is more direct and has good denoising effect, but it seriously influences the spatial resolution of the position image. After 1980, denoising algorithms based on filtering techniques after imaging had been widely adopted in speckle suppression.Hence,it has become the main trend in the image denoising field.

With wide application of the wavelet transform. The most direct way is dealing the image directly with the wavelet transform. the most direct way is dealing the image directly with the wavelet transform,which yields signal compositions at different scales;from these compositions denoised images can be reconstructed effectively in which high frequency components caused by speckle noise is removed, In an effort to seek better denoising methods, many scholars so far have been studying the influence of speckle on wavelet co-efficient. Compared with Fourier analysis,wavelet has bearer time-frequency characteristics and can preserve image edges to some extent while removing the speckle, for which it has gained extensive attention quickly. Although the wavelet transform has good effect of non-linear approximation for 1-D piecewise smooth functions, it comes with some notable adverse effects as well. The wavelet support intervals are of different sizes of squares. With the resolution getting smaller, the wavelet transform can only use spots to approach a singular curve and thus cannot optimally represent high-dimensional functions with line or surface that contains singularity, which means 2_D wavelet are unable to represent high-dimensional functions more sparsely. Besides, the 2-D

Wavelet has only limited directions, which imposes significant restrictions on its effectiveness in capturing the direction information.

To address the above limitations, scholars worldwide have proposed many kinds of multiscale geometric transformations, The most widely used trasnsforms in SAR image denoising are dual-tree complex wavelet transforms DTCWT), contourlet,and curvelet transform [3]–[6]. However, DTCWT is not the most optimal sparse representation and contourlet is not shift invariant. Besides, the mathematical theory of contourlet is imperfect. Curvelet is not generated from the action of a finite family of operators on a single function. It leads to not conform to the multiresolution framework and has many challenges when discretizing [7]. Thus, these transforms in image denoising can make the image edge fuzzy, produce

artificial images, and so on.In an attempt to overcome these disadvantages, Glenn and his colleagues [7] construct Shearlet through the affine system with synthetic expansion character. It has flexible direction selectivity like curvelet but is easier and more flexible to achieve [7], [8]. In fact, the debut of Shearlet immediately attracts considerable attention from many scholars and it is used in general image denoising quickly. For example, the image denoising in Shearlet domain based on hard threshold in [8], the image denoising in Shearlet domain based on total variation in [9], and the image denoising algorithm

via wiener filtering in the Shearlet domain in [10]. The algorithm in [11] puts forward the method combining the Shearlet transform with the Bayesian statistical theory, while in [12], the bivariate model is generalized in wavelet domain to Shearlet domain. The in-depth Shearlet approach is widely applied to SAR image denoising. The multiplicative noise is changed to additive noise before image denoising under normal circumstances, and then the denoising algorithm in Shearlet domain is used to deal with the noisy image. For example, a self-adaptive SAR image denoising in Shearlet domain is put forward in [13]. To avoid the shift variability in Shearlet domain, Hou *et al.* [14] propose SAR image despeckling based on the non

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subsampled Shearlet transform to attain good effects. Liu *et al.* [15] use the statistical characters of the speckle noise in Shearlet domain, which utilizes the context-based mode to shrink coefficients and get the effect of the image denoising, whereas in [16] is given a new SAR image denoising method based on generalized nonlocal means in nonsubsample Shearlet domain. These algorithms can achieve good effects of image noising, but they all are SAR image denoising based on the statistical property of speckle noise in Shearlet domain. Somehow, this limits the effects of image denoising. Recently, the development of sparse representation theory has a great influence on image denoising and the image denoising based on the sparse coding theory has a good effect [17], [18]. Many scholars have made some improvement on it. Ji and Zhang [19] combine the sparse coding with contourlet transform to denoise the image, and Dupé [20] apply it to remove the Poisson noise in the image. However, all of these methods need an optimal complete sparse dictionary.Moreover, the structure of the dictionary is complicated and time-consuming. Thus, a new wavelet denoising framework based on sparse representation is proposed in [21]. In this method, image denoising problem is turned to an optimal model that can be solved by steepest descent method. Besides, it has been proven that the optimal solution is a unique and unbiased estimation of the real solution. These offer very fast implementation with appealing effects. However, in [21], steepest descent method is used to solve the optimal model in the denoising method, which imposes another restriction on measurement matrix and obviously complicates construction of the measurement matrix. From the analysis above, it is evident that 2-D discrete wavelet transform does not lend itself to optimal sparse representation. Sparse image decomposition, in fact, can be achieved by replacing wavelet transform with Shearlet, which has optimal representation of the image as in [22], and uses the conjugate gradient algorithm to solve the optimal model. As a result, it can reduce the restriction on the measurement matrix, as the improved method has the same unbiased estimation as the original method and the optimal solution is the smallest in the local. In addition to the better convergence of the conjugate gradient algorithm than that of the steepest descent algorithm, it has quadratic convergence, which offers significant computational efficiency as the optimal model can be obtained with limited steps. What is more, there can be some improvements of the denoising method in Shearlet domain based on sparse representation in [22]: the threshold selection, the solution of the noise variance, and the solution selection of the iterative initial value. It puts forward the image denoising model via sparse representation in Shearlet domain based on Bayesian, which provides good effects.As the in-depth development of the image denoising method in transform domain, especially for the shift invariant phenomenon, there are some new disadvantages of the image denoising in transform domain. At the beginning, in order to overcome the shift variant of wavelet transform, cycle spinning is introduced. However, at the same time, this can also lead to artificial texture as in [23]. The research in [24] finds that this method does not have a one-to-one mapping of the original signal space, which means this method may lead to signal distortion. Reference [24] proposes a new denoising method iteration cycle spinning method, which is similar to one-to-one mapping. However, when faced with the total variation and the threshold algorithm based on the cycle spinning problems, it puts forward the continuous cycle spinning in [25] and [26] and completes the denoising method in wavelet domain theoretically.Besides, Kazerouni *et al.* [26] further point out that the optimal solution (denoised image) of denoising model via sparse representation based on the redundant dictionary cannot be one-to-one mapping of the original signal space, because the coefficients of signal which are decomposed by redundant dictionary are not unique. Shearlet also has redundancy, so the denoising method in Shearlet domain via sparse representation in [22] also has the same disadvantage. Therefore, in this paper, to overcome this disadvantage, we propose a new SAR image denoising via sparse representation in Shearlet domain, based on continuous cycle spinning and change SAR image denoising to solving the optimal problem.

II. SPARSE REPRESENTATION DENOISING MODEL BASED ON SHEARLET

A. Shearlet Transform

As the wavelet is not the most optimal representation of the image, the curvelet is difficult to disperse, and the contourlet does not conform to the Multi Resolution Analysis (MRA) theory, Shearlet is proposed to overcome these shortcomings. The Shearlet has the same image approximation order as the curvelet, but its implementation is simpler and more flexible. For a 2-D signal, the affine transform systems of the Shearlet function are

$$AAB(\psi) = \{\psi_{j,l,k}(\boldsymbol{x}) = |\det \mathbf{A}|^{j/2}\psi(\mathbf{B}^l\mathbf{A}^j\boldsymbol{x} - \boldsymbol{k}) : j, l \in Z, \boldsymbol{k} \in Z^2$$

where $\psi \in L^2(R^2)$, $\boldsymbol{A}$, $\boldsymbol{B}$ is 2-D invertible matrices and $|\det \boldsymbol{B}| = 1$. Let $\mathbf{A} = \mathbf{A}_0$,be the anisotropic dilation matrix and $\mathbf{B} = \mathbf{B}_0$, be the shear matrix. Then we can get one group of wavelet functions

$$\{\psi^{(0)}_{j,l,k}(\boldsymbol{x}) = 2^{3j/2}\,\psi^{(0)}(\mathbf{B}_0^l\mathbf{A}_0^j\boldsymbol{x} - \boldsymbol{k}) : j \geq 0, -2^j \leq l \leq 2^j - 1, \boldsymbol{k} \in Z^2\}. \quad (2)$$

we can get another group of wavelet function

$$\{\psi^{(1)}_{j,l,k}(\boldsymbol{x}) = 2^{3j/2}\,\psi^{(1)}(\mathbf{B}_1^l\mathbf{A}_1^j\boldsymbol{x} - \boldsymbol{k}) : j \geq 0, -2^j \leq l \leq 2^j - 1, \boldsymbol{k} \in Z^2\}. \quad (3)$$

Therefore, the Shearlet transform of f can be defined as

$$SH_\psi = (f, \psi^{(d)}_{j,l,\boldsymbol{k}}) \quad (4)$$

where $j \geq 0$, $l = -2^j \sim 2^j - 1$, $\boldsymbol{k} \in Z^2$, $d = 0, 1$. $\hat{\psi}^{(d)}_{j,l,\boldsymbol{k}}$ is supported with a pair of trapezoids, oriented along lines of slope $l2^{-j}$, and the size is about $2^{2j} \times 2^j$. There is a discrete form of the Shearlet in [8], and in this paper we use the shift invariant Shearlet transform of it to achieve SAR image denoising based on sparse representation. The proposed discrete form is cascading Shearlet transform with no sampling Laplace transform. Because of the high redundancy, the sparse representation of the image can achieve a better effect so that it is preferred in image denoising.

B. Denoising Model Based on Sparse Representation

Assuming the noise model of SAR image is as follows:

$$F = R \cdot N \quad (5)$$

where F is the observed signal, R is the desired de-noised image, and N is the speckle noise. To allow for better progress of the image denoising, we do not turn the

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multiplicative noise in (5) to the additive noise by the popular homomorphic filtering. On the contrary, we use the following equation to turn the noise to the additive noise of zero mean:

$$F = R + R(N - 1) \quad (6)$$

where $N - 1$ is the random variable of zero mean. In this way, $R(N - 1)$ is also the random variable of zero mean and it can be seen as the additive noise. To make the descriptions more convenient, we use the following to represent the additive noise model:

$$f(\boldsymbol{k}) = s(\boldsymbol{k}) + n(\boldsymbol{k}) \quad (7)$$

where $f(\boldsymbol{k})$ and $s(\boldsymbol{k})$, respectively, denote the obser- ved signal and the noise-free signal, and $n(\boldsymbol{k})$ is the random noise. For most natural images without noise, their Shearlet coefficients are sparse [7]. That is to say, most values of the Shearlet coefficients are very small, even close to zero. Nevertheless, if the natural image is contained by noise, the sparseness of its She- armlet coefficients will be greatly reduced so that the goal of the image denoising turns to how to recover the sparsity of Shearlet coefficients. In other words, the denoising process can be translated to the optim- ization problem of recovering the sparsity of Shearlet coefficients [22].Therefore, let the above Shearlet coefficients be $wl, j,\boldsymbol{k}$, where l is the different direct- ions decomposed by Shearlet, j is the different scales, and $\boldsymbol{k}$ is the different locations. For convenience, $\boldsymbol{W}$ denotes Shearlet coefficient matrix at some scale and some direction (the size of $N \times N$). Let $\_M \times N$ (M is smaller than N) be the random measurement matrix in sparse representation and _ should satisfy the uniform uncertainty principle. [20]. Suppose $\boldsymbol{y} = \mathrm{l}\boldsymbol{\phi W}$ and we can get the matrix $\hat{}\boldsymbol{w}$ with the optimal sparse coefficients by solving the following problem:

$$\boldsymbol{w}\hat{} = \mathrm{argmin}\ z\ \|z\|0 \text{ s.t. } \|\boldsymbol{y}\text{-}\boldsymbol{\phi}z\|2 \le \varepsilon. \quad (8)$$

To facilitate implementation of the algorithm, we can substitute
(8) with (9) to obtain the solution

$$\hat{}\boldsymbol{w} = \mathrm{argmin}\ z(\|\ \boldsymbol{y} - \boldsymbol{\phi}z\|22 + \gamma\ \|z\|0) \quad (9)$$

where $\|\ \|0$ denotes $L0$ norm, which is the number of the non zero elements. Although it is an N-P problem in mathematics,we can get the optimal solution under certain conditions by orthogonal matching pursuit (OMP), the steepest descent algorithm, or conjugate gradient algorithm. As seen in [22], the conjugate gradient method is used to get the optimal solution of (9).

III.DUAL TREE DISCRETE WAVELET TRANSFORM(DTDWT)

The dual-tree DWT exhibits less shift varian- ce and more directional selectivity than the critically sampled DWT with only a 2^dredundancy factor for d-dimensional data. The redundancy in the dual-tree DWT is significantly less than the redundancy in the undecimated (stationary) DWT.This example illustra- tes the approximate shift invariance of the dual-tree DWT, the selective orientation of the dual-tree analy- zing wavelets in 2D and 3D, and the use of the dual-tree complex wavelet transform in image and volume denoising.

Near Shift Invariance of the Dual-Tree DWT

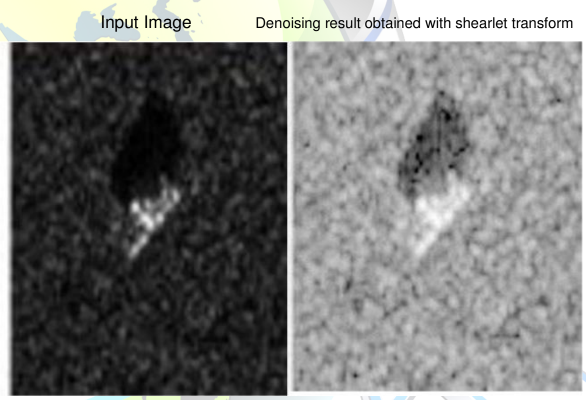
The DWT suffers from shift variance, meaning that small shifts in the input signal or image can cause significant changes in the distribution of signal/image energy across scales in the DWT coefficients. The DT-CWT is approximately shift invariant.

To demonstrate this on a test signal, construct two shifted discrete-time impulses 128 samples in length. One signal has the unit impulse at sample 60, while the other signal has the unit impulse at sample 64. Both signals clearly have unit energy (ℓ^2 norm).

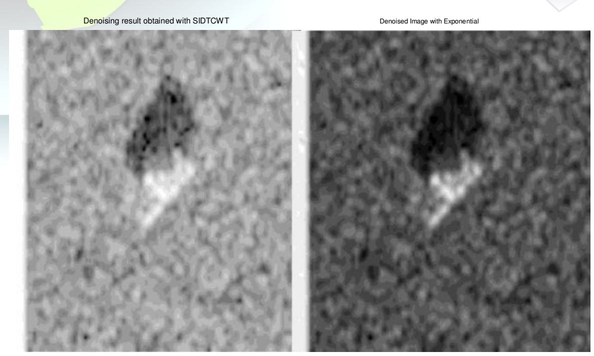
VI.Result and Analysis

Fig.1(a)Input image,(b)Shearlet Image

(c)Shearlet and DTCWT,(d)Output image



(a)Input image (b)Shearlet image



(C)shearlet and DTCWT (d) output image

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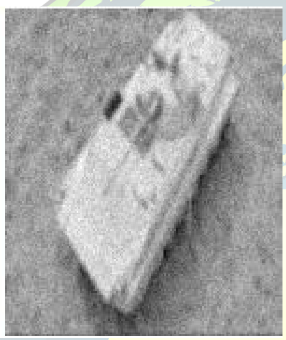
Denoising method	PSNR	ENL	SSI	SD	EPI	MSE
Shearlet	11.6455	26.8398	0.2638	0.3003	0.8565	4.8673e+03
DWT	11.6453	27.2247	0.2586	0.2982	0.8568	4.4869e+03
Shearlet+ DTCWT	12.0812	8.7459	0.3111	1.6766	0.9659	4.0584e+03

Table 1:Performance parameters

Fig.2(a)Input image ,(b)Shearlet image ,(c)Shearlet and DTCWT ,(d)Output image



(a)Input image (b)Shearlet image

Denoising result obtained with SIDTCWT

Denoised Image with Exponential

(c)Shearlet and DTCWT (d)Output image

Denoising method	PSNR	ENL	SSI	SD	EPI	MSE
Shearlet	4.7889	481.4912	0.0982	0.0882	0.9848	2.1757e+04
DWT	4.7887	535.9390	0.0931	0.0931	0.9458	2.1757e+04
Shearlet+ DTCWT	5.1790	124.6210	0.3342	0.7764	0.9159	1.9888e+04

Table 2:Performance parameters

V.Conclusion

First, in this paper we look back into the history of SAR image denoising, the structure of multiscale geometric transformation-Shearlet, and its frequency response. Then we briefly review the denoising model based on sparse representation and its shortcomings. Combining with the dual tree complex wavelet transform, we put forward a new Shearlet domain SAR image denoising via sparse representation based on directional sensitivity. The experimental results show that the proposed method has better denoising effects.The proposed method greatly reduces the directional selectivity and makes the process easy and overcome the drawbacks of processing of geometric image features like ridges and edges. However, the proposed method does not consider, the visual effects of images as the value of equivalent number of looks has reduced in this proposed method. As the future work, the proposed method may benefit from increased visual effects of images. In addition, we will also try to accelerate the speed of iteration.

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