Despeckling of SAR Images using Shearlet Transform Based Thresholding

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Abstract:- **The quality of synthetic aperture radar (SAR) images generally suffers from speckle noise, which damages the radiometric resolution of SAR images. A new speckle reduction method is proposed by thresholding the speckled SAR image coefficients in the Shearlet transform domain. The Discrete shearlet Transform (DST) is frequently encountered in wide variety of applications like image processing, image compression, image enhancement. Shearlet transform enables better preservation of significant detail information in despeckled results. The despeckled images based on 2D wavelets typically tend to exhibit artifacts, especially in homogenous regions. Multidirectional representations such as shearlet transform provide nearly the optimal approximation rate for these types of images. Moreover, the classical hard thresholding technique is used to obtain the despeckled images. This despeckling method makes full use of the considerably excellent properties of Shearlets. Experiment results on SAR images demonstrate the efficacy of this method. The proposed method results also compared with contourlet transform and wavelet transform.**

Index Terms—Shearlet transform, SAR image, speckle reduction, thresholding, wavelet transform, contourlet transform.

I. INTRODUCTION

Image restoration is the operation of taking a corrupted/noisy image and estimating the clean original image. Images may suffer with many of problems like additive multiplicative or impulse noise. It is undesirable because it degrades image quality and makes an image unpleasant to see. The several reasons due to which an image can reduce its quality or get corrupted are - motion between camera and object, improper opening of the shutter, atmospheric disturbances, misfocusing etc. Denoising of images is one of the most basic tasks of image processing. With image enhancement noise can effectively be removed by sacrificing some resolution, but this is not acceptable in many applications. Image reconstruction in radio astronomy, radar imaging and tomography is very difficult process.

Noise is the result of image acquisition system whereas image inpainting problems occur when some pixel values are missing. Denoising is a process of extracting useful information of image and to enhance the quality of image which is an enhancement technique to reconstruct a noiseless image which is better than the input image. Denoising is a necessary step to be taken before the image data is analyzed for further use. Because after introducing the noise in image, the important details and features of image are destroyed. It is necessary to apply efficient denoising technique to compensate for such data corruption so the main aim is to produce a noise free image from the noisy data.

The remainder of this paper is organized as follows: The organisation of the report is as follows: Section II describes the different noise models. Section III describes the available despeckling methods. Section IV describes the proposed shearlet transform method and problem formulation. Section V presents the simulation results and quantitative evaluation. Section VI concludes the project.

II. NOISE MODELS

Noise can affect an image by different ways upto different extent depending on type of disturbance. Generally our focus is to remove certain kind of noise. So we identify certain kind of noise and apply different algorithms to remove the noise. The common types of noise that arises in the image are: a) Impulse noise, b) Additive noise, c) Multiplicative noise. Different noises have their own characteristics which make them distinguishable from others [4].

(i). Impulse noise- This term is generally used for salt and pepper noise. They are also called as spike noise, random noise or independent noise. In image at random places black and white dots appears which makes image noisy. Over heated faulty component and dust particles on image acquisition system is the main cause of such noise. Occurrence of such noise is independent of pixel values.

(ii) Additive noise- Gaussian noise comes under the category of additive noise. This noise model follows Gaussian distribution model. The resultant noisy pixel is a sum of original pixel value and randomly distributed

Gaussian noise value. This can be expressed by following equation:

$$w(x, y) = i(x, y) + n(x, y) \qquad (1)$$

(iii). Multiplicative noise- This type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR (Synthetic Aperture Radar) imagery. Speckle noise is a multiplicative noise. The source of this noise is attributed to random interference between the coherent backscattered signals. Fully developed speckle noise has the characteristic of multiplicative noise. Speckle is the result of the diffuse scattering, which occurs when SAR images randomly interferes with the small particles or objects on a scale comparable to the sound wavelength. Speckle noise follows a gamma distribution. It can be given as

$$w(x, y) = i(x, y)\times n(x, y) \qquad (2)$$

III. . DESPECKLING METHODS

It is well known that SAR imaging apparatus have the unique advantage over optical ones that they are capable of acquiring SAR imagery independent of weather and light illumination conditions. However, the quality of a SAR image is generally degraded by speckle noise that results from coherent interference of backscattered radar echoes [7]. This speckle phenomenon dramatically deteriorates the radiometric resolution of SAR images and can thus affect the performance of scene understanding tasks [16].

A variety of speckle reduction methods have been proposed in the existing literature. Generally speaking, these despeckling methods can be categorized into two classes: the spatial domain methods and the transform-domain methods. For the former, speckle reduction is implemented in only one scale, i.e., pixel-level scale [17]. On the contrary, speckle reduction techniques in the latter are developed in a few scales by means of different multiresolution image analysis tools.

However, wavelet representations, whether translation variant version or translation-invariant one, are actually not optimal for all types of signals, specifically for 2-D or higher dimension images. As a result, despeckled images based on 2-D wavelets typically tend to exhibit artifacts, especially in homogenous regions. On the other hand, 2-D separable wavelets can capture only limited directional information by decomposing an image into only three orientations: vertical, horizontal, and diagonal ones [9]. Similar to wavelet, contourlet can decompose the image into different scales. But unlike the wavelet which can only decompose each scale into two directions, contourlet can decompose each scale into any arbitrarily power of two's number of directions and different scales can be decomposed into different number of directions [10].

Fortunately, multidirectional representations such as shearlets [1, 12] provide nearly the optimal approximation rate for these types of images. Moreover, the number of orientations at different scales can be specified flexibly to make a tradeoff between the despeckling effectiveness and the despeckling efficiency.

Compared with other multidirectional representations, such as contourlets [3], shearlets are more powerful in capturing the geometry of images and optimally more efficient in representing images containing edges. Taking into account the richer detail information in most SAR images, we propose to exploit the Shearlet tranform to despeckle this type of images for which detail preservation is vitally important for subsequent image interpretation and understanding tasks.

Generally the SAR images are affected by speckle noise. For despeckling, a new speckle reduction method in shearlet transform domain based thresholding is developed. The Discrete shearlet Transform (DST) is basis of this method. The Discrete shearlet Transform frequently encountered in wide variety of applications like image processing, image compression, image enhancement. Shearlets are a multiscale framework which allows to efficiently encode anisotropic features in multivariate problem classes. Shearlet transform enables better preservation of significant detail information in despeckled results [9]. Synthetic Aperture Radar (SAR) is a form of radar which is used to create images of an object, such as a landscape. Compared with the wavelet transform, Shearlet transform is more suitable for image restoration applications where detail preservation is highly demanding. The Shearlet basis functions can be more compactly supported in the frequency domain. Thus, finer image detail information can be well captured by this type of basis functions, which is in favor of better detail preservation of despeckled results [2]-[5].

IV. PROPOSED METHOD

Image restoration is a challenging work to design a edge/texture-preserving image denoising scheme. Nonsubsampled shearlet transform (NSST) is an effective multi-scale and multi-direction analysis method, it not only can exactly compute the shearlet coefficients based on a multiresolution analysis, but also can provide nearly optimal approximation for a piecewise smooth function [11]. Both continuous and discrete shearlet transform is available. The discrete shearlet transform is the basis of this method. An important advantage of the shearlet transform over the contourlet transform is that there are no restrictions on the number of directions for the shearing. In addition, in the shearlet approach, there are no constraints on the size of the supports for the shearing, unlike the construction of the directional filter banks.

The shearlet transform has two important parameters such as decomposition direction and decomposition size. The shearlet transform can perform three important functions such as scaling, shearing, translation.The discrete shearlet transform consists of two main procedures: the Laplacian pyramid decomposition procedure and the directional filtering. The below block diagram illustrates the succession of Laplacian pyramid and directional filtering. The general class of linear transform decomposes an image into various components by multiplication with a set of transform functions. Some examples are the Discrete Fourier and Discrete Cosine Transforms, the Singular Value Decomposition, and finally, the Wavelet Transform, of which the Laplacian Pyramid and other subband transforms are simple ancestors [13].

A. Laplacian Pyramid Decomposition and Directional Filtering

A directional filter is an edge detector that can be used to compute the first derivatives of an image. The first derivatives (or slopes) are most evident when a large change occurs between adjacent pixel values. The total number of subbands coefficients is the same as that of the original image, and these coefficients can be used to reconstruct the original image without any errors (like aliasing, amplitude and phase distortions). In signal processing, a filter bank is an array of band-pass filters that separates the input signal into multiple components, each one carrying a single frequency sub-band of the original signal [3].

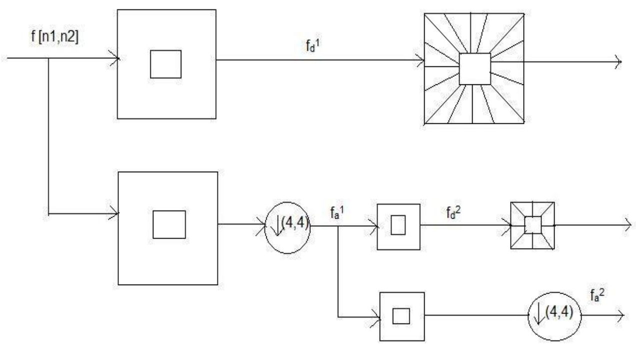

Fig.1 The Two Level Discrete Shearlet Decomposition of an Image.

A filter bank consists of an analysis stage and a synthesis stage. Each stage consists of a set of filters in parallel. The filter bank design is the design of the filters in the analysis and synthesis stages. The analysis filters divide the signal into overlapping or non-overlapping subbands depending on the application requirements. The synthesis filters should be designed to reconstruct the input signal back from the subbands when the outputs of these filters are combined together [13].

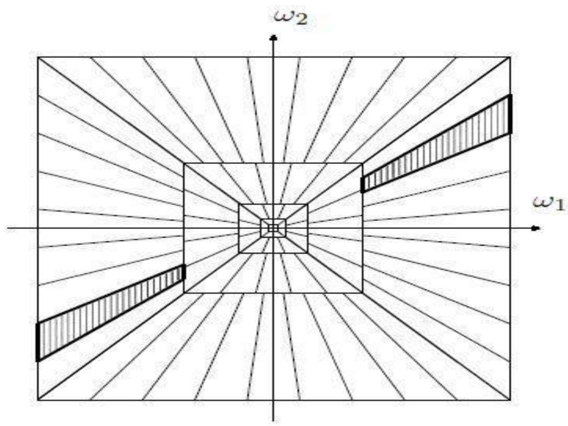

Fig.2 Tiling of Frequency Plane R induced by Shearlets.

B. Problem Formulation

Let $S_o^j(m,n)$ be the original Shearlet coefficient in the location(m,n) in a detail subband $O \in \{O_1^j, O_2^j \,........ O_k^j\}$ at scale j. Then $\hat{S}_o^j(m,n)$ is the despeckled shearlet coefficient. The goal of this method is to obtain the despeckled Shearlet coefficient $\hat{S}_o^j(m,n)$ corresponding to the location (m, n) by adjusting the original coefficient for the speckled pixel.Here, the classical hard thresholding technique is used to obtain the estimated speckle-free coefficient:

$$\hat{S}_o^j(m,n) = \begin{cases} S_o^j(m,n) & \text{if } S_o^j(m,n) > t_o^j \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

where t_0^j denotes the thresholding value specified for the speckled Shearlet coefficients in the detail subband O at scale j.

Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images. The most important thresholding techniques are of two types such as hard thresholding and soft thresholding. In the present work, classical hard thresholding is used. In hard thresholding all coefficients whose magnitude is greater than the selected threshold value t_0^j remains same and the others whose magnitude is smaller than t_0^j are set to zero. In soft thresholding, the coefficients whose magnitude is greater than the selected threshold value are shrunk towards zero by an amount of threshold t_0^j and others set to zero. The only difference between the hard and soft thresholding procedures is in the choice of the nonlinear transform on coefficients.

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C. Proposed Speckle Reduction Algorithm

1) Transfer the multiplicative speckle noise into additive noise through the logarithmic operation.
2) According to the forward DST, decompose the SAR image into *J* scales, for each scale, a few subband images are generated according to the number of orientations.
3) For each speckled Shearlet coefficient $S_o^j(m,n)$ in the detail subband *o* at scale *j*, estimate the corresponding speckle-free coefficient $\hat{S}_o^j(m,n)$ using Eqn (3).
4) Apply the inverse DST followed by the exponential operation to obtain the despeckled image.

V. PERFORMANCE EVALUATION AND SIMULATION RESULTS

This work has been implemented using MATLAB as a simulation tool. The proposed method is tested on image, "SAR_Image.JPG" of size 512 X 512. The simulation results are taken at various noise densities and Peak Signal to Noise Ratio and Mean Square Error also calculated. Comparison results on previous despeckling methods such as wavelet, contourlet with shearlet transform are determined.

A. Mean Square Error (MSE)

MSE measures the quality change between the original and processed images in an M x N window. The MSE is widely used to quantify image quality .It is used together with other quality metrics and visual perception.

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B. Peak Signal to Noise Ratio (PSNR)

PSNR value of a denoised image with respect to the original image denotes the closeness of the denoised image to the original image. For higher PSNR value, the denoised image is closer to the original image.

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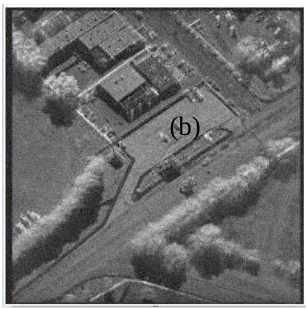

(b)

(c)

(d)

(e)

Fig.3 Despeckled Results for SAR image (a) Original Image (b) Noisy Image (c) Restored Image using Contourlet based hard thresholding (d) Restored Image using Wavelet based hard thresholding (e) Restored Image using Shearlet based hard thresholding.

Table.1. Performance Comparison

	Noisy Image	Restored Image using Contourlets	Restored Image using Wavelets	Restored Image using Shearlet
PSNR(dB)	28.1359	29.8904	32.2378	35.5169
MSE	99.88322	45.0934	23.9821	18.2552

VI. CONCLUSION AND FUTURE WORK

To validate the performance of this DST-based hard thresholding method, SAR images of size 512x512 are utilized to conduct the despeckling tasks. For performance comparison, wavelet transform and contourlet transform are considered. For speckle reduction performance, qualitative evaluation can be straightforwardly made by visual inspection, especially for the evaluation of detail preservation performance. To make a quantitative performance evaluation, the Peak Signal to Noise Ratio and Mean Square Error for SAR images are calculated.

An efficient method for speckle reduction in SAR images is developed using hard thresholding technique in the discrete Shearlet transform domain.This despeckling method makes full use of the considerably excellent properties of Shearlets in capturing the geometry of images as well as in optimally representing images containing edges. Experimental results on real SAR images demonstrate the efficacy of this method. For high efficiency, this will be implemented using advanced filtering techniques or VLSI technology in future.

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