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Comparison of Transform Domain based SAR Despeckling Techniques

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Abstract

Objectives: Synthetic Aperture RADAR (SAR) is a satellite imaging technology which is affected by speckle noise having granular pattern. Speckle is multiplicative noise and occurs due to the interference of the signal with the backscattered echoes. **Methods/Analysis:** Speckle degrades the image quality and makes further segmentation and classification of images difficult. Despeckling can be done in spatial and transform domain. In this paper the various transform domain despeckling techniques like wavelet, shearlet, contourlet and curvelet are compared. The results are analyzed using performance parameter like ECF, SSIM and ENL. **Findings:** Comparison of the various methods is done by using synthetic images and real images. ECF and SSIM are used to evaluate synthetic images and ENL is used for real images. In the case of real images the ENL value is highest for curvelet compared to wavelet, shearlet and contourlet. In the case of synthetic images SSIM and ECF value is high for curvelet compared to other methods. ENL value is lowest for shearlet transform whereas SSIM and ECF values are lowest for contourlet transform. From the results, it can be concluded that curvelet outperforms all the other methods. **Novelty/ Improvements:** Transform Domain techniques has got wide spread applications in the field of denoising, segmentation and classification. Using curvelet for despeckling can improve the further segmentation and classification process.

Keywords: ECF, ENL, SAR, SSIM, Speckle

1. Introduction

SAR is all weather day and night satellite imaging technology used for weather forecasting, navigation and guidance, foliage, ground penetration, moving target detection etc. Images captured by this method has got inherently speckle noise in it which appears as granular noise that degrades the quality of the SAR images. Speckle occurs as a result of the interference of echoes backscattered from rough surfaces of the earth. Based on the relative phase, they form dark and bright spots in the image. Speckle noise in SAR makes segmentation, classification and image interpretation difficult. Despeckling can be done in both spatial or transform domain[1]. In Spatial domain filtering a window is moved over each pixel of the image in some order and the central pixel is being replaced by a value calculated mathematically from the other pixels in the window.

This procedure continues until the entire image is being covered. This reduces noise at the cost of introducing smoothing effect in the image. Despeckling in transform domain consist of calculating the transform domain coefficients and carrying out filtering of these coefficients based on a threshold value. A good survey of the existing SAR image despeckling technique is available in[2]. This section compares the effect of despeckling SAR images using various transform domain techniques.

2. Transform Domain Techniques

These method follows the principle that the signal energy is concentrated on few number of transform coefficients, while noise energy will be spread throughout the transform coefficients[3]. The major transform domain

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techniques include wavelet, contourlet, curvelet, shearlet. The basic idea is that the transform domain contains basis elements in different shapes and directions.

2.1 Wavelet Transforms

Wavelets are mathematical functions that segregate the data to small frequency components, and each component is analyzed with a resolution corresponding to its scale[4]. Fourier transform contains only two bases functions-sine and cosine which are not localized. Wavelet transform contains infinite set of complicated localized bases functions called wavelets or mother wavelets. Wavelet transform uses varying window .Here short basis function will be used to isolate discontinuities such as edges and long basis function can be used to get detailed analysis .The discrete wavelet transform is given by the equation

$$\varphi_{(s,l)}(x) = 2^{\frac{-s}{2}}\varphi(2^{-s}x - l) \tag{1}$$

where integer 's' and 'l' represents scale index and location index representing wavelet width and location. Scaling equation for the mother function is given by

$$W(x) = \sum_{k=-1}^{N-2} -1^{k} c_{k+1}\varphi(2x+k) \tag{2}$$

The wavelet coefficients c_k should satisfy the following constraints

$$\sum_{k=0}^{N-1} c_k = 2, \sum_{k=0}^{N-1} c_k c_{k+2l} = 2\delta_{l,0} \tag{3}$$

where δ is the delta function.

Wavelets use basis function that represents spatial location and frequency. Wavelet coefficients are obtained by applying wavelet transform to noisy image and appropriate threshold values are selected in order to remove the noises. Thresholding can be done in two ways. In hard thresholding[5, 6] a threshold value λ is selected and the wavelet coefficients having magnitude lesser than selected threshold is set to zero and rest of the coefficients remains the same. In soft thresholding[7] the weighting factor for all the coefficients with magnitude less than threshold value is set to one and shrinking is performed on other coefficients. Inverse transformation is applied to generate the denoised image.

Wavelets have a basis function which is isotropic and fails to adapt itself to the discontinuities in the geometrical structure. Wavelets perform better in 1D but due to the lack of orientation selectivity, they do not represent higher-dimensional singularities effectively.

2.2 Curvelet Transform

Curvelets provide a sparse representation for images with different geometrical structures which is suitable for representing curve discontinuities. Curvelet have multistage, multi orientation, anisotropic, parabolic scaling functions with width ≈ length[2]. Curvelet has a pyramid structure with dyadic scale, location and direction. Curvelets are based on multi scale ridgelets. In order to isolate different scales spatial bandpass filtering operation is being carried out[8]. Curvelets occur variable width, length and anisotrophy.

As shown in [Figure 1], wavelet need more number of coefficients compared to curvelet scheme. To account for edges or singularities along lines and curves, many wavelet coefficients are needed. Also curves are invariant under anisotropic scaling. Therefore we need a more refined scaling concept to handle curved structures.

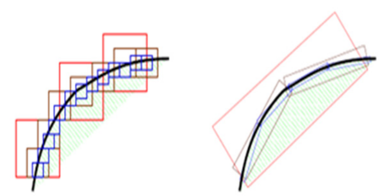


Figure 1. Comparison of wavelet and curvelet coefficients.

[Figure 2] shows a smooth C^2 function along the 2^j scale. Curvelet transform captures the smoothness of the contour of images with several elongated shapes and in different directions. The steps in a curvelet [9] starts with a waveform $\varphi(x) = \varphi(x_1, x_2)$.

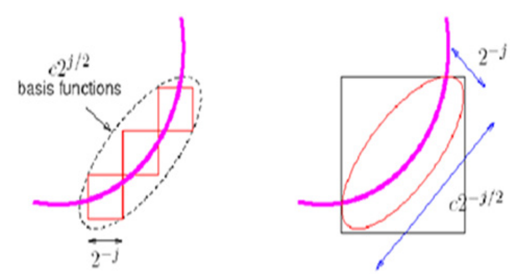


Figure 2. Comparison of wavelet and curvelet schemes.

Where x_1 is oscillatory and x_2 is low pass. Then parabolic rescaling is performed by the equation

$$|D_j|\phi(D_j x) = 2^{3j/4}\phi(2^j x_1, 2^{j/2} x_2)$$
$$where\, D_j = \begin{pmatrix} 2^j & 0 \\ 0 & 2^{j/2} \end{pmatrix}, j \geq 0 \tag{4}$$

Then scale dependent rotation is performed by the equation

$$2^{3j/4}\phi(D_j R_{\theta_{jl}} x), \theta_{jl} = 2\pi . l 2^{-\lfloor j/2 \rfloor} \tag{5}$$

And finally translation over the Cartesian grid 2^{-j} X $2^{-j/2}$ is performed by using the equation

$$2^{3j/4}\phi(D_j R_{\theta_{jl}} x - k), k \in Z^2 \tag{6}$$

The difference between the wavelet tiling and curvelet tiling in frequency domain is as shown in [Figures 3 and 4].

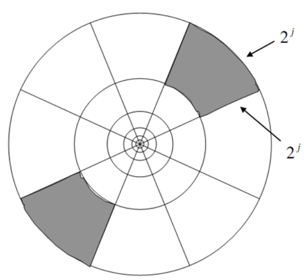


Figure 3. Curvelet tiling.

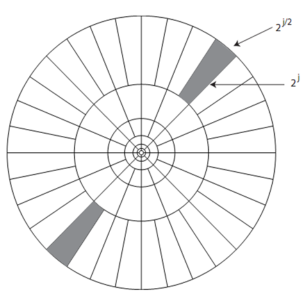


Figure 4. Wavelet tiling.

In curvelet, the image with different sizes can be analyzed by using a single transform. Images of different block sizes can be analyzed using curvelet transform .The curves are partitioned into blocks and ridgelet transform is applied to each block. Ridgelet transform enhances the idea of point-to-point mapping of singularities to point-to-line mappings using the Radon transform[10], which is more effective in handling directions. Curvelet transform is built in continuous domain and multi resolution analysis is not possible.

2.3 Contourlet Transform

Contourlet transform is a multiscale, multi resolution transform proposed by Do and Vetterli[11] in the discrete domain. It exhibits localization, directionality and anisotropic properties. The contourlet transform have basis function at different directions. Here the basis function can appear in different aspect ratio depending on the scale. The basis function is constructed using a double filter bank structure. It consists of a combination of Laplacian Pyramid (LP) introduced by Burt and Adelson[12] and a Pyramid Directional Filter Bank (PDFB) [13]. [Figure 5] shows the LP and DFB filter banks. The multi scale decomposition of signals into bandpass signal is obtained by passing through LP subband and directional information is obtained by passing through DFB. LP introduces oversampling which is avoided by down sampling the lowpass channel. Decoupling multiscale and directional decomposition allows simplicity and flexibility, however it results in some redundancy.

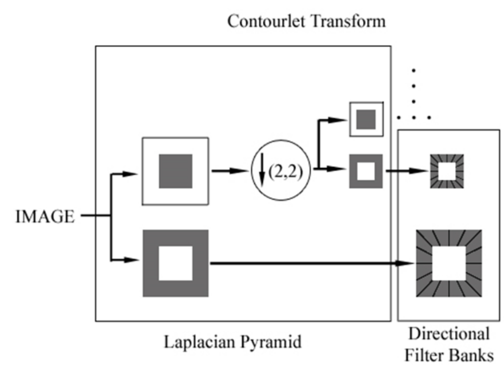


Figure 5. LP and DFB Banks.

The contourlets are directional extensions of wavelet transforms[14]. As the first step in despeckling the contourlet coefficients are obtained by applying contourlet transform. Number of levels of Laplacian pyramidal decomposition is carried out. Later speckle is reduced by thresholding and coefficient variance in each band is estimated and scaled. Finally contourlet coefficient shrinkage is performed by setting all coefficients that are less than a fixed multiple of the scaled variance to zero value. The Contourlet transform captures the smoothness of the contour of images with different elongated shapes but have less clear directional features compared to curvelets resulting in artifacts during denoising and compression.

2.4 Shearlet Transform

Shearlets are non adaptive method where the shearing functions are controlled by Shearing matrix. Shearlets are constructed by parabolic scaling, shearing and translation of basis functions. Wavelets are isotropic objects and are not capable of accommodating anisotropic features such as edges in images. Shearlets are a natural extension of wavelets to accommodate the anisotropic features. Ridgelets are supported by directional ridges satisfying the parabolic scaling law, *length² ≈ width*. A shearlet frame can be defined as follows[15].

For $c \in R^+, \psi^1_0, \ldots, \psi^L_0, \psi^1_1, \ldots, \psi^L_1 \in L^2(R^2)$ and $\varphi \in L^2(R^2)$, we define

$$\psi^0_c = \{\psi^{i,0}_{jkm} : j,k \in Z, m \in Z^2, i = 1, \ldots\ldots L\} \quad 7)$$

$$\psi^1_c = \{\psi^{i,1}_{jkm} : j,k \in Z, m \in Z^2, i = 1, \ldots\ldots L\} \quad (8)$$

and

$$\psi^2_c = \{T_{cm}\varphi : m \in Z^2\} \quad (9)$$

$$\bigcup\{\psi^{i,0}_{jkm} : j \geq 0, -2^j \leq k \leq 2^j, m \in Z^2, i = 1, \ldots\ldots L\} \quad (10)$$

$$\bigcup\{\psi^{i,1}_{jkm} : j \geq 0, -2^j \leq k \leq 2^j, m \in Z^2, i = 1, \ldots\ldots L\}] \quad (11)$$

where $\psi^{i,l}_{jkm} = D_{A_l^{-j} B_l^{-k}} T_{cm} \psi^i_l$ (12)

For $l = 0, 1$, $m \in \mathbb{Z}^2$, $i = 1, \ldots\ldots L$ and $j, k \in \mathbb{Z}$

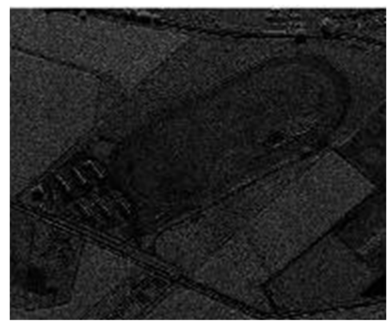
If ψ^p_c is a frame for $L^2(R^2)$, then we call function $\psi^{i,l}_{jkm}$ in the system ψ^p_c shearlets.

The shearing matrices are used to control the directionality of the shearlet transform which has merit of preserving the discrete setting.

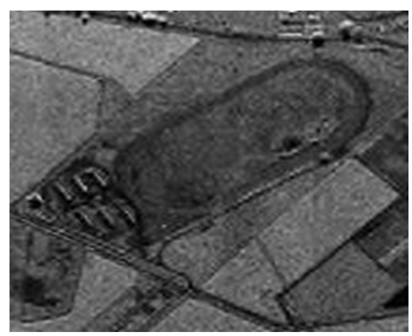
3. Result Analysis

The results are analyzed using Matlab toolkit. Here we take into account both synthetic and real images. The results are analyzed using performance parameter like ECF (Edge Correlation Factor), SSIM (Structural Similarity) and ENL (Equivalent No. of Looks). Real images itself contain noise and only the ENL value can be used to compare the results. ECF and SSIM are used to evaluate synthetic images since they take into account the noise free original image and the denoised image.

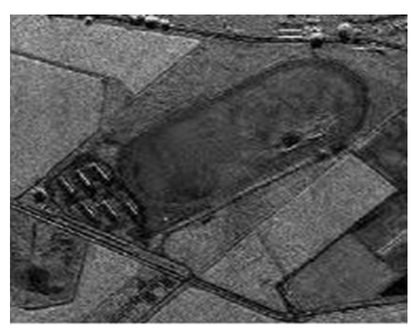
From [Figure 6], we can conclude that curvelet transform outperforms all the other methods. The details are preserved and the granular patterns are removed from the image. The edges are more precise and accurate. [Table 1] shows the ENL value for each method. Higher the ENL value, the better the image clarity. From the [Table 1] it can be concluded that shearlet transform is not suitable for multiplicative speckle noise removal. The maximum ENL value is obtained for curvelet and the output also confirms the same.



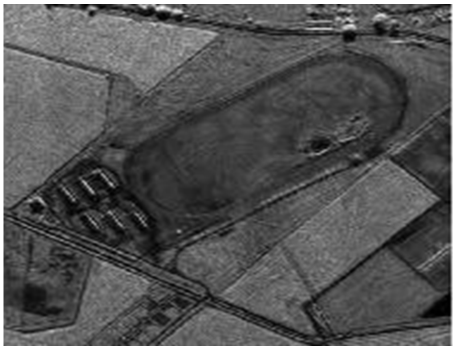
(a)



(b)



(c)



(d)

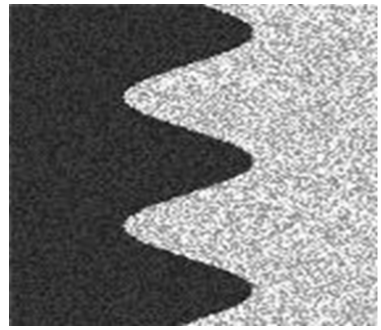
Figure 6. The output for Real Image (Horse Track Image) **(a)** Shearlet **(b)** Wavelet **(c)** Contourlet **(d)** Curvelet.

Table 1. ENL value corresponding to each method

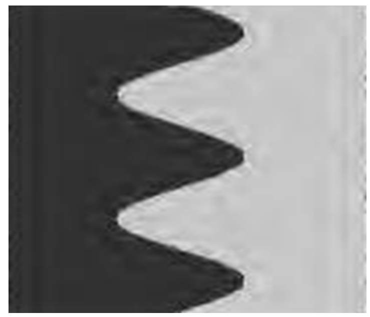
Method	ENL
Shearlet	7.44
Wavelet	46.7
Contourlet	35.61
Curvelet	47.54

[Figure 7] shows the result of various transform method on synthetic images. Here we generate an image and add multiplicative noise into it. ECF value will be close to unity for a better quality image. Higher the SSIM, better will be the result. [Table 2] shows the ECF and SSIM value for various transforms. The result shows that shearlet is having minimum value for ECF and SSIM and curvelet is having the maximum value. So the curvelet method is found to preserve clear edge separation and clarity of the image.

(a)



(b)



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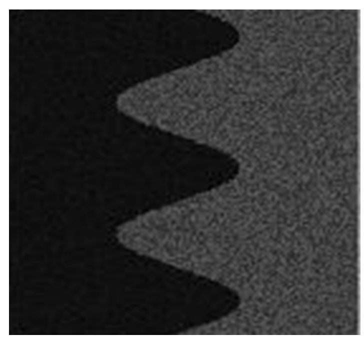
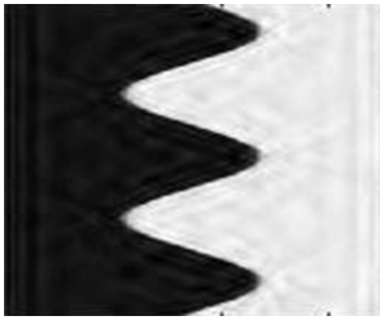


(d)

(e)



(f)

Figure 7. Output images for **(a)** Original **(b)** Noisy **(c)** Shearlet **(d)** Wavelet **(e)** Contourlet **(f)** Curvelet.

Table 2. ECF and SSIM value corresponding to each method

Method	ECF	SSIM
Shearlet	0.183	0.3379
Wavelet	0.6896	0.7335
Contourlet	0.1094	0.2253
Curvelet	0.7581	0.9150

4. Conclusion

In this paper we compared the various transforms domain techniques which play an important role in denoising images. Here the performance of four major transform domain techniques like wavelet, shearlet, contourlet and curvelet are compared. The effect of these methods in removing particularly speckle noise is being analyzed. Speckle is multiplicative in nature and is difficult to remove. SAR images and Ultrasound images usually encounter speckle noise. Isotropic basis function of wavelets makes them inefficient to adapt to discontinuities in the geometrical structure. The results verified using MATLAB show that shearlets are not appropriate for despeckling and curvelets give comparatively good results .The results are also visually verified using ENL, EC Fan SSIM measures in both synthetic and real images.

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