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Reduction of Speckle Noise in SAR Images With Hybrid Wavelet Filter

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Abstract: Images produced by synthetic aperture radar (SAR) are crucial for observing and visualizing situations. However, speckle noise makes it difficult to assess SAR images since it reduces image quality and leads to incorrect interpretation. Multiplicative noise features can be found in speckle noise. For the past few years, experts have concentrated on despeckling or speckle reduction. However, the majority of the current efforts showed a loss of edge information. Since wavelet transform and bivariate shrinkage functions have many advantages, this study is devoted to designing a method for speckle removal. After performing a logarithmic transformation to turn multiplicative noise into additive noise, the suggested approach next applies a Lee filter. Then, a wavelet transform was used to breakdown the filtered image. Prior to applying the median filter, the bivariate shrinkage function was used to estimate each coefficient. The simulation results demonstrate that the suggested approach outperforms previous work and several traditional methods.

Keywords*: Additive White Gaussian Noise (AWGN), Bivariate Shrinkage, Discrete Wavelet Transform (DWT), Speckle Noise, Synthetic Aperture Radar (SAR), Wavelet Filter*.

I. INTRODUCTION

Synthetic aperture radar (SAR) sensors provide a number of advantages over optical remote sensing, the most significant of which is the ability to record throughout the day and throughout the year [1]. The existence of speckle noise, a type of unwanted or undesirable alteration signal-related granular noise, is the main drawback of SAR images [2]. Over the past three decades, a variety of SAR image de-noising approaches have been put forth. To address the problem, a number of researchers average a fixed number of various photographs but value a considerable loss in picture resolution. The additive model produced by the logarithmic transformation that was initially employed to minimise speckle noise is easier to utilize. In order for certain well-known methods for eliminating distortion to also operate with the modified model, additive white Gaussian noise (AWGN) may be used as a model [3]. Such methods usually ignore a few basic speckle features despite how simple they are to use. The zero mean Normal Distribution, or what is commonly referred to as the Gaussian distribution, is not exactly followed by the log-transformed speckle interference. Therefore, the variance needs to be corrected before continuing the process [4]. During the same time period, de-noising inside this initial domain was tackled by extremely sophisticated algorithms based on the multiplicative speckle paradigm. Such studies unequivocally established the necessity of a certain kind of local adaptation to account for the non-stationary of this image. Additional methods for eliminating distortion in the transform domain are becoming available with the development and improvement of such multi-scale analysis framework. After a homomorphic filtering, wavelet shrinkage might be easily added to such altered coefficients. In addition to the spatial domain, wavelet techniques benefit from spatial adaptation while enhancing the image to successfully maintain both image textures and bounds [5]-[8].

Over the past few years, some researchers have worked very hard on SAR to eliminate speckles, and many methods have been created, such as the Lee filter [5], the Kuan filter [6], the Frost filter [7], and the maximum a posteriori (MAP) filter [9]. On the other hand, traditional spatial domain techniques frequently over smooth details like corners and texturing, which can occasionally degrade the spatial quality of images. Such filtering techniques are simple and uncomplicated, but they do not preserve visual characteristics like brightness, strength, edges, borders, etc., and system performance is likely to be affected by the relevant terrain. Consequently, transform domain (mathematical method) filters have been developed recently and have produced excellent results. Examples include the wavelet transform [8], [9], curvelet transform [10], [11], and shearlet transform [12], [13]. Comparatively, while transform domain techniques effectively minimise speckle, they also have the potential to cause pixel distortion and spurious defects, as well as errors in the preservation of back scatter and detailed information in specific places. Despite the image's valuable local or global features, this is primarily due to the transform domain's inherent inefficiency.

This paper suggests a wavelet-based bivariate shrinking technique that significantly reduces speckle in order to produce high resolution SAR images.

Wavelet transformation can effectively define functions or signals with localised features due to the limited support of wavelet basis functions. Then, using a wavelet-based method, we reduce speckle noise. Last but not least, we found that wavelet-based denoising works better than conventional speckle filters.

II. PROBLEM IDENTIFICATION

When compared to Gaussian noise, the multiplicative, non-Gaussian noise found in SAR images is much more challenging to eliminate. The fundamental cause of this is that noise variance varies as intensity changes. This multiplicative noise is described mathematically in eqn. (3).

$$y(i,j) = x(i,j) \cdot n(i,j) \tag{3}$$

Where, $y(i,j)$ = Speckle image, $x(i,j)$ = Original image and $n(i,j)$ = non-gaussian noise

The noise with unknown variance σ^2 is typically believed to be stationary. Eqn.(4) represents the logarithmic transformation of y(i,j) for the purpose of evaluating the additive noise variance.

$$\ln\big(y(i,j)\big) = \ln\big(x(i,j)\big) + \ln\big(n(i,j)\big) \tag{4}$$

After applying ln(y(i,j)) to the discrete wavelet transform (DWT), thresholding is carried out. Then, as seen in Figure 1, the inverse DWT is applied, producing the opposite of the logarithmic operation.

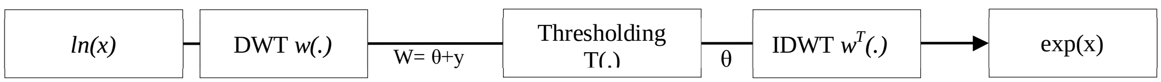

Fig.1 Block diagram for speckle SAR image denoising utilising a logarithmic transformation

III. METHODOLOGY

A. Extension of the symmetrical boundary

On the initial border, the denoising algorithm will use symmetrical extension. In this case, we suggest using symmetrical boundary extension rather than zero padding to increase the image size to 512 pixels by 512 pixels because symmetrical boundary extension does not significantly introduce distortion on the margins. This method involves expanding the original image's four sides before extending the remaining corners.

B. Wavelet Decomposition

The image is divided into wavelets and transformed into 2D filter banks in this step. The image's row and column are subjected to the filter bank. Applying 1D filter bank analysis to each row and column results in the creation of two sub-bands, $N_1/2$ and $N_2/2$. The $N_1/2$ rows and $N_2/2$columns of each sub-band are then subjected to 1D analysis.

C. Denoising Procedure

Threshold selection is used for denoising. To create the HH_k, HL_k, and LH_k sub band areas, a 2D sampled wavelet transform is used. Scale is shown here as k and j is the coarsest scale. Scale is finer when k is less. P(S) represents the parent of sub-band S. Noise variance σ_n^2 is calculated from noisy wavelet coefficients according to the formula in eqn. (5)

$$\sigma_n^2 = \frac{\mathrm{Median}(|y_i|)}{0.6745} \tag{5}$$

Where, y_{1i} is element of sub band HH_1 σ_{y1} and σ_{y2}can be found by :

$$\hat{\sigma}_{y1}^2 = \frac{1}{N_1^2} \sum_{y_{1i} \in s} y_{1i}^2 \tag{6}$$

$$\hat{\sigma}_{y2}^2 = \frac{1}{N_2^2} \sum_{y_{2i} \in p(s)} y_{2i}^2 \tag{7}$$

Where $\sigma_{y1}$and σ_{y2} are Variances of $y_1$andy_2. Using these variances signal variance σ_1&σ_2 can be estimated by applying formula given as:

$$\hat{\sigma}_1 = \sqrt{\hat{\sigma}_{y1}^2 - \hat{\sigma}_n^2} \tag{8}$$

$$\hat{\sigma}_2 = \sqrt{\hat{\sigma}_{y2}^2 - \hat{\sigma}_n^2} \tag{9}$$

Using bivariate shrinkage function-

$$\widehat{w}_1 = \frac{\left(\sqrt{y_1^2 + y_2^2} - \frac{\sqrt{3}\sigma_n^2}{\sigma}\right) + y_1}{\sqrt{y_1^2 + y_2^2}} \tag{10}$$

The algorithm is illustrated as:

1) Evaluate $\sigma_n{}^2$.

2) For each wavelet co-efficient.

a) Calculate σ_1, signal variance.

b) Bivariate shrinkage function is applied on coefficient.

Filter banks are employed during the reconstruction process. The 2D filter bank from N_1 and N_1 is used to merge the sub-bands.

IV. RESULTS AND DISCUSSION

A. Quality Metrics

There are many different assessment metrics that are used to evaluate the effectiveness of speckle reduction systems. The sections that follow discuss several important factors.

Noise Variance: A smaller variance produces a clearer image as more speckles are eliminated. The eqn. (11) provides the variance computation formula.

$$\sigma^2 = \frac{1}{N}\sum_{j=0}^{N-1}(X_j)^2 \tag{11}$$

Mean Square Error (MSE): MSE is measured by computing the difference in error between the original and reconstructed pictures. A higher MSE value indicates improper despeckling. It is calculated mathematically using eqn. (12).

$$MSE = \sqrt[2]{\frac{1}{N}\sum_{j=0}^{N-1}(X_j - \hat{X}_j)} \tag{12}$$

Where, $X_j{}^\wedge$ = reconstructed image, X_j = original image and N = Size of the image.

Equivalent Numbers of Looks (ENL): ENL is a performance metric that can be used to assess the level of speckle noise. Higher scores indicate higher quality. ENL is quantified mathematically as in eqn. (13).

$$ENL = \left(\frac{\mu}{\sigma}\right)^2 \tag{13}$$

Where μ is the mean of the uniform region and σ is the standard deviation of an uniform region.

Peak Signal to Noise Ratio (PSNR): The PSNR is most frequently used as a gauge of reconstruction quality in image compression and de-noising. The PSNR is determined by:

$$PSNR = 10\log\left(\frac{255}{MSE}\right)^2 \tag{14}$$

Therefore, according to equation (14), a greater PSNR value denotes improved image speckle reduction. However, in this case, for the huge speckle reduction MSE is larger.

NIQE_diff: The Natural Image Quality Evaluator (NIQE) is a performance metric used to gauge the quality of images. The NIQE-diff is used to determine the quality difference between an original image and a denoised or reconstructed image. It is assessed mathematically according to Equation (15):

$$NIQE\_diff = NIQE(Original_{img}) - NIQE(Denoised_{img}) \tag{15}$$

B. Result Analysis

The standard photos for the 8-bit grey level (Lena, Boat, Cameraman, Airplane, Man, Peppers, and House) were used as the reference images in this study.

Speckle noise was added to each image to test the effectiveness of the image noise reduction technique.

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These photos demonstrated the traits of multiplicative noise that followed the Rayleigh distribution. All image processing was carried out in MATLAB (R2020).

The suggested algorithm is contrasted to conventional filtering approaches as Gaussian, Frost, SRAD, Bitonic filters, K-SVD and Pre processing Filter, and Discrete Wavelet Transform-Based Noise Reduction Technique algorithm to assess the efficacy of speckle noise reduction. Fig. 3 presents some of the test findings for the suggested methodology. The suggested wavelet-based bivariate shrinking methodology is compared with other techniques in Tables I and II. Bivariate Shrinkage Function provides the lowest noise variance among common filter techniques.

Original Image Noisy Image Denoised Image

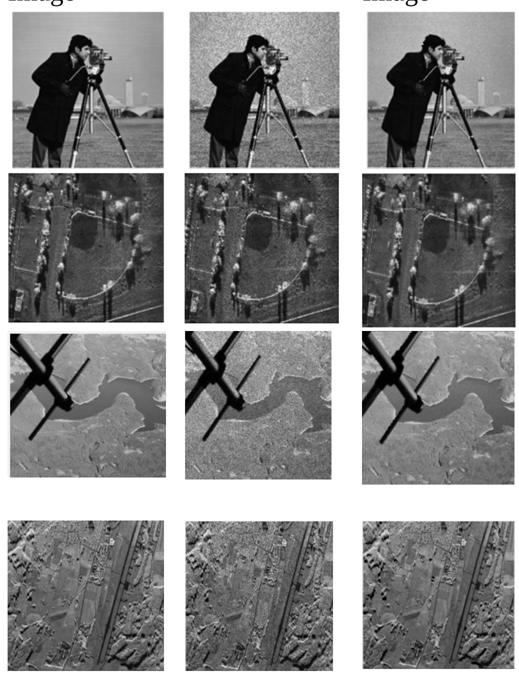

Fig. 3. The test images (left) original, (centre) under noise and (right) after filtration

Table 1. Comparative Performance Analysis

Image (size)	Measure	Noisy	Gaussian	K-SVD	Frost	SRAD	Bitonic	Previous	Proposed
Lena (512 x 512)	RMSE	30.31	13.49	15.18	17.40	11.85	13.31	8.18	7.50
	PSNR (dB)	18.50	25.53	24.51	23.32	26.65	25.65	29.88	29.90
	SSIM	0.27	0.70	0.56	0.45	0.72	0.75	0.81	0.82
Boat (512 x 512)	RMSE	31.66	13.86	16.37	19.54	11.20	14.53	10.93	9.5
	PSNR (dB)	18.12	25.30	23.85	22.31	27.15	24.89	27.36	28.2
	SSIM	0.32	0.65	0.53	0.43	0.70	0.64	0.72	0.85
Cameraman (256 x 256)	RMSE	31.05	19.14	18.21	19.96	12.20	18.77	11.84	9.36
	PSNR (dB)	18.29	22.49	22.92	22.13	26.41	22.66	26.66	27.54
	SSIM	0.41	0.61	0.50	0.47	0.70	0.69	0.77	0.79
House (256 x 256)	RMSE	33.05	13.90	18.09	19.52	10.28	12.15	9.37	9.24
	PSNR (dB)	17.75	25.27	22.98	22.32	27.89	26.44	28.69	28.75

	SSIM	0.24	0.64	0.53	0.37	0.68	0.73	0.77	0.80
Man (1024x1024)	RMSE	24.68	10.81	13.53	15.03	8.83	11.76	8.63	7.69
	PSNR (dB)	20.28	27.45	25.50	24.59	29.21	26.72	29.41	29.80
	SSIM	0.47	0.73	0.62	0.58	0.77	0.70	0.79	0.90

Table 2. ENL Comparative Analysis

Measure	Noisy	Gaussian	K-SVD	Frost	SRAD	Bitonic	Previous	Proposed
ENL	31.41	163.82	340.33	88.80	156.74	260.18	246.17	357.35
	50.49	96.03	255.18	106.57	159.14	213.23	210.88	328.59

V. CONCLUSION

In this study, the wavelet transform is used to scale the image, eliminate speckle noise, and create a multi-resolution representation. The paper uses a bivariate shrinkage function in combination with wavelet decomposition at various noise variance levels to achieve this. The outcome is assessed based on various performance metrics and contrasted with some already in use strategies. Results allow for the development of more efficient approach. Future research can expand on this work by using dual tree complex wavelet transforms to denoise and de-blur multiple resolution images.

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