Speckle Reduction in SAR Images by using Homogeneity NeighShrink

Sarungbam Bonny and Yambem Jina Chanu

***Abstract*—Synthetic Aperture Radar (SAR) image suffers from severe artifacts caused by speckle noise which is multiplicative in nature. Some of the adaptive filters such as the Lee filter, the Frost filter and the Kuan filter are the well-known speckle filters. These filters adapt the filter coefficients based on the pixels within a fixed moving window. Though it removes speckle noise well in the homogeneous regions, it leaves noise in the heterogeneous areas to preserve the edges and fine details or smoothes the edges to remove the noise in this area. In order to reduce the speckle noise with the preservation of edges, a new method based on wavelet analysis and adaptive mean filtering is proposed in this paper. A comparative study with other methods show that proposed method is better in preserving edges and fine details while reducing the speckle noise.**

***Index Terms*—Speckle, DWT (Discrete Wavelet Transform), Homogeneity Filter.**

I. INTRODUCTION

Speckle is a form of multiplicative noise which produces fine false structures that decrease contrast and blur the important details [1]. The speckle noise in SAR images reduces the image contrast, resolution and fine details. Thus, it degrades the quality of the SAR images. Therefore, it is necessary to reduce the speckle noise to improve the human interpretation of SAR images.

Adaptive filter such as the Lee filter, the Frost filter and the Kuan filter, the median filter is the well-known speckle filter. The output of the Lee filter is a weighted average based on the local statistics. It performs well in homogeneous region but to preserve the edges, noise in the heterogeneous region remains intact [4],[17],[18],[26],[27]. Kuan filter has the same formation as the Lee filter but modified the weighting function. The weighting function is computed from the estimated noise variation coefficient of the image [5]. In the Frost filter [6], the weighting function decreases with distance from the pixel of interest. The response of these filters varies locally with the coefficient of variation. For low coefficient of variation, the filter output value is the mean of all pixels in the window and for high coefficient of variation; the output value is the value of the input pixel itself. Smoothing of the pixels near edges is excluded as the coefficient of variation is high i.e., near the unity value, thus the noise remains intact\cite{Yu}.

Pierrick Coupe designed a nonlocal (NL)-mean based filter for reducing speckle noise by introducing the Pearson distance\cite{Coupe}. Instead of comparing the pixel's value, the NL-mean filter analyzes the patterns around the pixel. The problem of the spatial domain filter is the removing of the noise near edges. It smoothes the edges to remove the noise near edges otherwise noise will be remaining intact [7]. A trade-off always exists between the denoising and preserving details. Although these spatial filters offer simplicity of implementation, wavelet filters have advantages in preserving many useful details.

Donoho and his co-workers first designed the wavelet denoising scheme by using soft thresholding and hard thresholding [11],[21],[22],[23]. Since then, wavelet transform (WT) has been widely used to recover signals from noisy images. Generally, in the wavelet denoising, both thresholding functions set the wavelet coefficients which are less than threshold value to zero. Hard thresholding function leaves the larger wavelet coefficients unchanged, whereas in soft thresholding, the larger wavelet coefficients shrink towards zero. The threshold value is given by $\sigma\sqrt{2logM}$, where σ is the noise standard deviation and M is the number of samples. It has been shown that this algorithm offers the advantages of smoothness and adaption. Though small wavelet coefficients are mostly noise, it removes too many wavelet coefficients that might contain useful image information. Chen, Bui and Krzyzak designed the neighshrink threshold with the assumption that wavelet transform produces correlated wavelet coefficients [12]. NeighShrink thresholds the wavelet coeffcients according to the magnitude of the square sum of all the wavelet coeffcients within the neighbourhood window. Though these methods work well for additive noise, but not for speckle noise, which is multiplicative in nature.

In this paper, based on wavelet thresholding and spatial filter, a combination of homogeneity filtering and neighshrink method to remove speckle noise is designed. First, pixel intensity is replaced by the mean of homogenous neighbourhood. It removes the noise in the homogeneous region. Then, the wavelet based neighshrink is employed to the output of the homogeneity filtering to remove the noise in the heterogeneous region.

II. SPECKLE MODEL

Speckle noise obeys a negative exponential distribution, therefore, it is multiplicative in nature. Then, the noise image is modeled as follow

$$z_{i,y} = x_{i,j}\, v_{i,j} \qquad (1)$$

Where $z_{i,y}$, $x_{i,j}$ and $v_{i,j}$ denote the noisy image, the noise free image and the noise. The noise $v_{i,j}$ is independent of $x_{i,j}$ and it follows a Rayleigh distribution.

Published on October 30, 2016.
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III. PROPOSED METHOD

The proposed method consists of homogeneity adaptive spatial filter and wavelet thresholding based on neighshrink. First, homogeneity spatial adaptive filter is applied on the noisy SAR image. Then, wavelet thresholding is performed on the output of the adaptive filter. The proposed filter is shown in

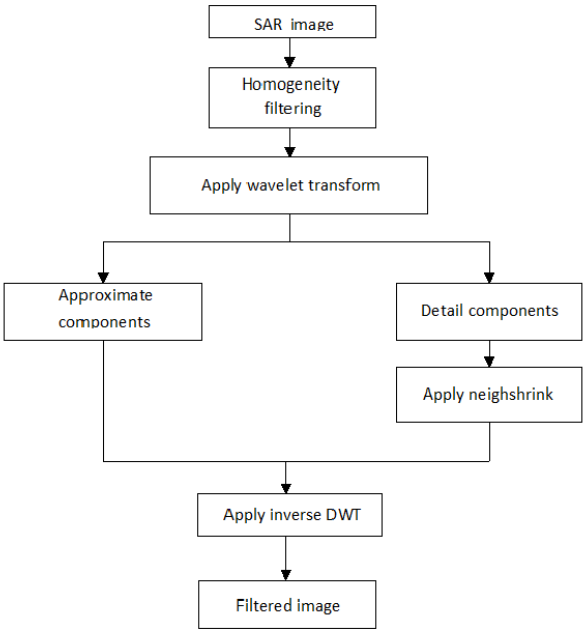

Fig. 1 A block diagram of the proposed method.

A. *Homogeneity Spatial Filter*

It is used to remove the speckle noise in the homogeneous region with preserving edges and fine details in the heterogeneous region by using the Lee filter which is based on minimum mean square (MMSE). It is given by the equation

$$\hat{x}_{i,j} = \bar{z}_{i,j} + K(z_{i,j} - \bar{z}_{i,j}) \qquad (2)$$

Where $\bar{z}_{i,j}$ is the mean value of a square window $W_{i,j}$ of odd length which centered at the pixel $z_{i,j}$ and K is given as

$$K = \frac{var(x)}{\bar{x}^2\sigma_v^2 + var(x)} \qquad (3)$$

$var(x)$ Is computed by

$$var(x) = \frac{var(z) + \bar{z}^2}{\sigma_v^2 + \bar{v}^2} - \bar{x}^2 \qquad (4)$$

Here, the quantities $\bar{z}$ and $Var(z)$ are approximated by the local mean and local variance of the noisy image [18]. When $K = 0$ i.e., in the homogeneous region, the value of the filter output is equal to the mean of the window i.e., $\hat{x}_{i,j} = \bar{z}_{i,j}$ and $K = 1$, the value of the filter output is the pixel itself i.e., $\hat{x}_{i,j} = z_{i,j}$.

B. *Wavelet Filter*

This filter is applied on the previous stage output to remove the noise in the heterogeneous region which is not removed in the homogeneity filtering. A 2D discrete wavelet transform is performed on the output of the adaptive spatial filter. Then, it is divided into approximate sub-band and detail sub-bands. Detail sub-bands consist of three bands namely LH, HL and HH. Thresholding operation will be performed on the coefficients of the detail components as they contain high frequency components while leaving the coefficients of the approximate component unchanged. The

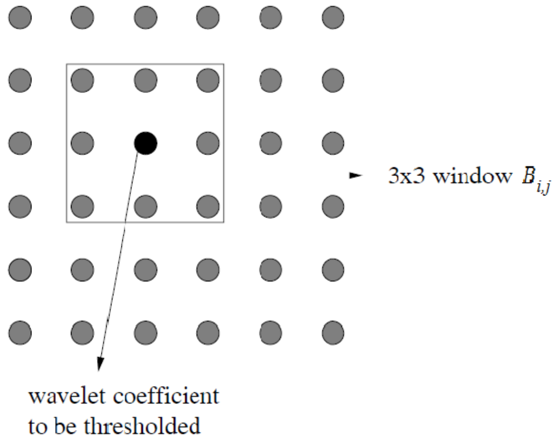

Fig. 2 A 3×3 window $B_{i,j}$.

threshold value which is used here for removing noise is the neighshrink. In the neighshrink, for every wavelet coefficient $d_{i,j}$, a square neighboring window $B_{i,j}$ around the wavelet coefficient is chosen. The size of the window should be 3×3, 5×5, 7×7 etc. The Fig. 2 illustrates a 3×3 window $B_{i,j}$ centered at the wavelet coefficient to be thresholded $d_{i,j}$. The wavelet coefficient $d_{i,j}$ is thresholded by the following formula

$$d'_{i,j} = d_{i,j}\beta_{i,j} \qquad (5)$$

and $\beta_{i,j}$ is the shrinkage factor and it is given by

$$\beta_{i,j} = \left(1 - \lambda^2/S^2_{i,j}\right)_+ \qquad (6)$$

and
$$S^2_{i,j} = \sum_{l,m \in B_{i,j}} d_{l,m} \qquad (7)$$

the + sign at the end of eqn (5) means to keep only the positive value and set it to zero when the value is negative. i.e.,

$$d_{i,j} = \begin{cases} d_{i,j}\beta_{i,j} & if \;\; \beta_{i,j} > 0 \\ 0, & otherwise \end{cases}$$

The λ in eqn (5) is the universal threshold and it is given by $\lambda = \sigma\sqrt{2logM}$ where σ is the standard deviation and M is the number of samples. The σ is calculated by

$$\sigma = \frac{median(|HH|)}{0.6745} \qquad (8)$$

The wavelet denoising algorithm is as follows:

1. Perform the 2D DWT on the output of the homogeneity filter.
2. Apply the neighshrink on the wavelet coefficients of the detail components by using the eqn (4).
3. Perform the inverse 2D DWT to obtain the denoised image.

IV. EXPERIMENTAL RESULTS

Experiments are conducted on the SAR image with size of 500 × 500 and compare with other methods such as Lee, Kuan, Frost, bayesshrink and neighshrink. By using matlab, speckle noised images were created by adding speckle to the synthetic SAR image with variance of 0.02, 0.04, 0.06, 0.08 and 0.1. To evaluate the performance of the proposed method, the PSNR and SSIM values of the proposed method and the existing method are calculated based on the original, noised and despeckled images. The parameter Peak Signal to Noise Ratio (PSNR) is computed by

$$PSNR = \frac{10\log(L^2)}{\frac{1}{NM}\sum_{k=1}^{N}\sum_{l=1}^{M}\left[x_{k,l} - g_{k,l}\right]} \qquad (9)$$

where, N and M are the number of the rows and columns of the image. x and g are the original and output images respectively. It is used as quality measurement. The Structure Similarity Index (SSIM) computes the amount of estimated structural similitude of images with noise free images and its value ranges in [0, 1] with unity when the output image is same with the original image. The SSIM is computed by

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (10)$$

where, μ and σ are the mean and the standard deviation of pixels in a local window respectively. The subscripts x and y denote the original and filtered image respectively. σ_{xy} is the covariance of x and y. C_1 and C_2 are the constant.. The table I and table II provides the PSNR and SSIM values. The experimental results show that the proposed method reduces the speckle noise with much preserving edges and fine details compare to other existing methods. The noise free SAR image, noised image of variance 0.08 and output images of different filters and the proposed one are shown in the Fig. 8.

V. CONCLUSION

In this paper, a homogeneity neighshrink approach for reducing the speckle noise with preserving edges in SAR images is presented. It is based on the combination of spatial adaptive filter and wavelet transform filter. The spatial filter which is used here is the Lee filter, suitably designed to remove noise near edges. First, spatial adaptive filter i.e., Lee filter is performed on the noised image. Then, a 2D DWT is performed on the output of the Lee filter. Neighshrink thresholding is applied on the coefficients of the detail sub-bands (LH, HL and HH). Finally, inverse 2D DWT is performed on the wavelet de-composition to produce the filtered image. The results of the proposed method in terms of PSNR and SSIM show superior performance in comparison with the conventional speckle filters such as Lee, Frost, Kuan and wavelet filters in reducing speckle noise with preserving edges and fine details.

TABLE I: PSNR VALUES FOR DIFFERENT NOISE VARIANCE

σ^2	0.02	0.04	0.06	0.08	0.10
Noise	29.41	26.39	24.63	23.39	22.42
Lee	31.77	29.75	28.60	27.77	27.23
Kuan	28.77	28.37	28.01	27.67	27.32
Frost	28.21	28.15	28.04	27.96	27.86
Bayes	31.34	29.11	27.76	26.79	26.02
Neigh	30.58	28.91	27.81	27.01	26.29
Proposed	31.56	30.08	29.07	28.37	27.89

TABLE I: SSIM VALUES FOR DIFFERENT NOISE VARIANCE

σ^2	0.02	0.04	0.06	0.08	0.10
Noise	0.9974	0.9949	0.9924	0.9899	0.9875
Lee	0.9985	0.9976	0.9969	0.9963	0.9957
Kuan	0.9970	0.9967	0.9965	0.9962	0.9959
Frost	0.9966	0.9966	0.9965	0.9964	0.9963
Bayes	0.9983	0.9972	0.9962	0.9953	0.9944
Neigh	0.9971	0.9962	0.9953	0.9944	0.9936
Proposed	0.9985	0.9978	0.9973	0.9968	0.9964

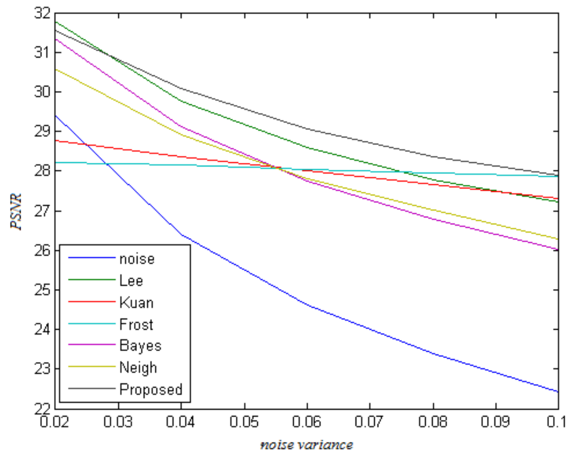

Fig. 3 PSNR values of different filters and noised image.

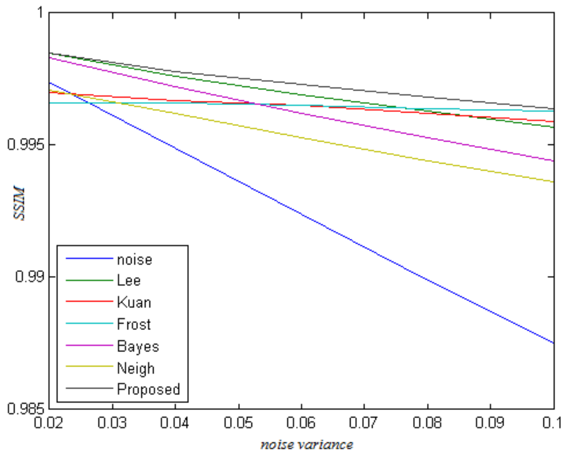

Fig. 4 SSIM values of different filters and noised images.

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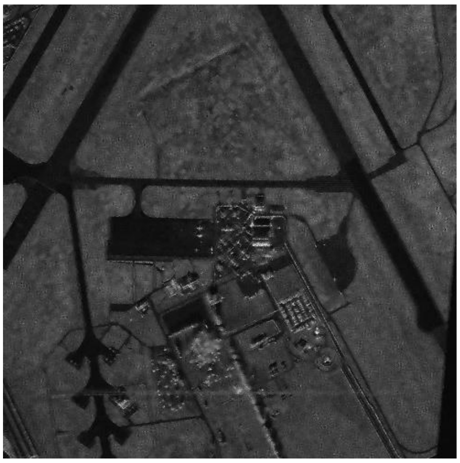

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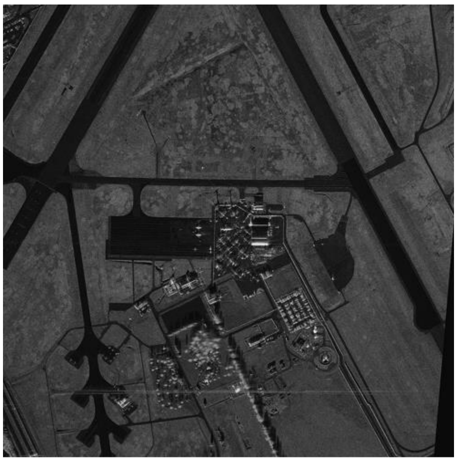

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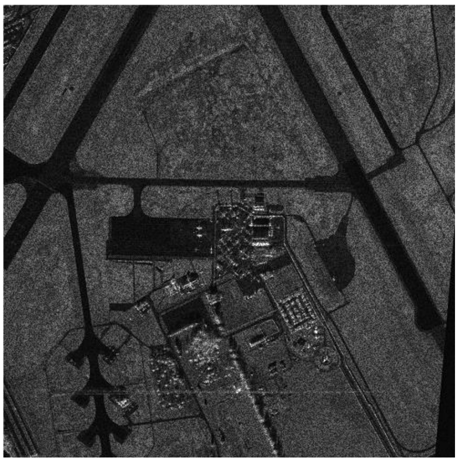

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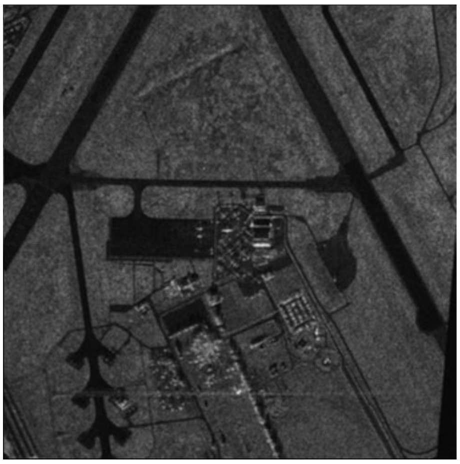

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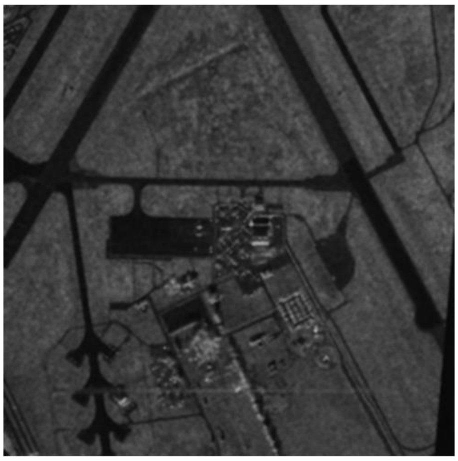

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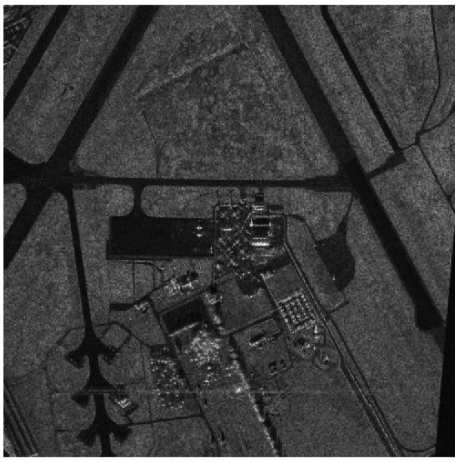

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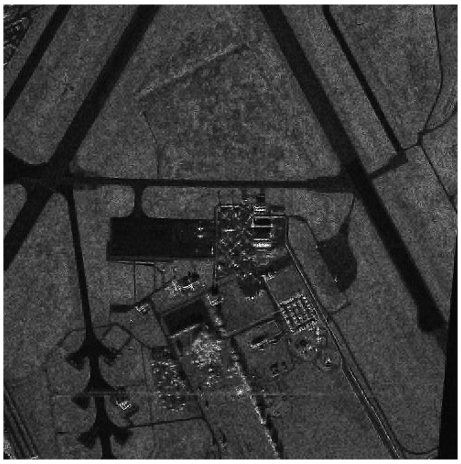

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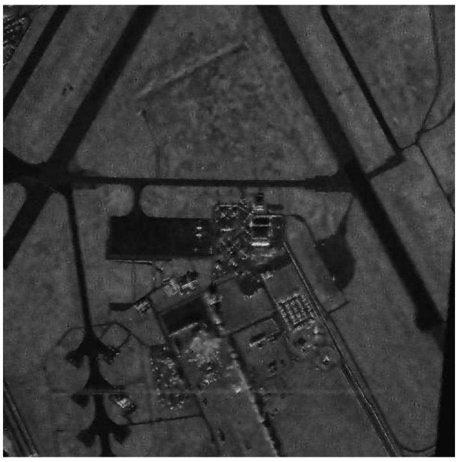

(h)

Fig. 5 SAR images (a) noise free SAR image (b) speckle noise image with varaince 0.08 (c) Lee filter image (d) Kuan filter Image (e) Frost filter (f) BayesShrink image (g) NeighShrink image (h) Proposed method image