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SWT based Denoising Technique for SAR Images

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Abstract: Synthetic Aperture Radar (SAR) is a satellite imaging technology. It produces high resolution images and can be used in varied atmospheric conditions. It can be used under all weather conditions. SAR images are generally affected with granular noise termed as speckle noise. Speckle degrades the spatial resolution, contrast of the image, decreases object detectability and causes inconvenience to the SAR image interpreter. Therefore for proper interpretation, it is essential to reduce the speckle noise in SAR images. This paper presents a new speckle noise reduction technique using modelling wa zvelet coefficients. Noiseless and noisy wavelet coefficients are modelled as two-sided generalised Gamma distribution (GΓD) and Gaussian distribution respectively.
Keywords**: *****SAR, speckle, stationary wavelet transform, MoLC***

I. INTRODUCTION

Synthetic Aperture Radar (SAR) has been used for Earth remote sensing for more than 30 years. It is imaging radar mounted on a moving platform. SAR image is usually corrupted by multiplicative speckle noise. It can affect further processing of SAR image. Speckle noise is always present in SAR images. This noise is produced due to the coherent sum of many elementary scatterers in each resolution cell. It gives a grainy appearance to images that make detection more difficult [1]. Signal dependent granular noise is inherent of all active coherent imaging systems that visually degrade the appearance of images [2].In this paper a new despeckling method is proposed by modelling of stationary wavelet transform (SWT) coefficients using two sided GΓD. SWT is applied to overcome the shift variability of discrete wavelet transform. The parameters of the two sided GΓD are estimated using the MoLC method because of its simplicity and applicability. Bayesian MAP estimator is used to estimate the speckle free coefficients with the help of observed data. A prior distribution of noise free wavelet coefficients is firstly chosen then clean coefficients are estimated using the Bayesian estimator.This paper is organized as follows. Section II presents a model of speckle noise. Section III deals with modeling of stationary wavelet coefficients and section IV presents estimation of clean stationary wavelet coefficients using MAP estimation. Section V presents the proposed despeckling method. Section VI shows the experimental results and conclusion is highlighted in Section VII.

II. NOISE MODEL

Speckle is exactly not a noise but is more a granular pattern. The coherent integration of returned scattered energy and that of returned randomly distributed scattered energy causes interference. This ultimately introduces speckle noise. It will record both amplitude and phase values of back scattered radiation [1].In general there are two basic models of noise which are termed as additive noise model and multiplicative noise model. The additive noise is systematic, easily modelled and can be removed easily with lesser efforts. However, multiplicative noise caused by de-phased echoes from scatterers is image dependent. It is complex to model and also difficult to reduce although it contains useful information.Assuming that speckle is fully developed, the corresponding model of SAR image can be expressed as a multiplicative noise [3]:

$$g(x,y)=f(x,y)u(x,y) \tag{1}$$

Here, f(x,y) represents the noise free SAR image, u(x,y) represents the speckle noise term and g(x,y) is the observed noisy image. But additive noise can be easily processed as compared to multiplicative noise. Therefore, multiplicative noise can be transformed to the additive noise using homomorphic filtering. It consists of taking the logarithm of the observed data, so that

$$g'(x,y)=f'(x,y) + u'(x,y) \tag{2}$$

Here g'(x,y), f'(x,y) and u'(x,y) denote the logarithm of the quantities in g(x,y), f(x,y) and u(x,y) respectively.

III.MODELLING OF STATIONARY WAVELET COEFFICIENTS

Two sided GΓD is used for modeling of stationary wavelet coefficients due to its flexibility and goodness of fit [5]. The pdf of GΓD is given by (3).

$$f_x(X) = \frac{\nu}{2\eta\Gamma(\kappa)}\left(\frac{|X|}{\eta}\right)^{\kappa\nu-1}\exp\left[-\left(\frac{|X|}{\eta}\right)^{\nu}\right] \tag{3}$$

Here, Γ (.) is the Gamma function. ν, κ and η denotes the power, shape and scale parameters respectively. The noise free signal is assumed to be two sided GΓD. For parameter estimation MoLC is applied due to its computational efficiency [6].
The first three second kind cumulants of two sided GΓD are given by (4) – (6).

$$k_1 = \log\eta + \frac{\phi_o(\kappa)}{\nu} \tag{4}$$

$$k_2 = \frac{\phi_o(1,\kappa)}{\nu^2} \tag{5}$$

$$k_3 = \frac{\phi_o(2,\kappa)}{\nu^3} \tag{6}$$

Here, $\phi_o(z)$ is digamma function and $\phi_o(n,z)$ is the polygamma function. These first three log cumulants can be estimated empirically from observed data [7].Parameters η, κ, ν can be estimated by substituting the values of estimated log cumulants in (4), (5) and (6). These parameters are calculated for the observed coefficient Y denoted by η_y, κ_y and ν_y. Now the parameters for noise free coefficients i.e. η_x, κ_x, ν_x are calculated with the help of 2nd, 4th and 6th absolute central moments.According to the formula for qth order absolute central moment of two sided GΓD model,

$$m_q = E\left[|X|^q\right] = \eta^q\left[\Gamma\left(\kappa + q/\nu\right)/\Gamma\left(\kappa\right)\right] \tag{7}$$

Hence, m_2^y, m_4^y and m_6^y can be calculated with the help of parameters η_y, κ_y and ν_y. The 2nd, 4th and 6th absolute central moments for the noise free coefficients can be calculated as-

$$m_2^x = m_2^y - \sigma_N^2 \tag{8}$$

$$m_4^x = m_4^y - 6m_2^x\sigma_N^2 - 3\sigma_N^4 \tag{9}$$

$$m_6^x = m_6^y - 15m_4^x\sigma_N^2 - 15m_2^x 3\sigma_N^4 - 15\sigma_N^6 \tag{10}$$

The parameters of clean image coefficients are calculated using the moments of noise free coefficients given in (8), (9) and (10).

IV. BAYESIAN MAP ESTIMATION

Bayesian MAP estimator is used for estimating the clean SWT coefficient from the noisy coefficients. It is defined using (11).

$$\hat{X} = \arg\max_X\left[f\left(X/Y\right)\right] \tag{11}$$

From Bayes rule, (11) can be written as

$$\begin{aligned}\hat{X} &= \arg\max_X\left[f\left(Y/X\right)f\left(X\right)\right]\\ &= \arg\max_X\left[f_N\left(Y-X\right)f_X\left(X\right)\right]\end{aligned} \tag{12}$$

In (12), $f_X(X)$ is the assumed prior distribution of noise free coefficients and $f_N(.)$ is the probability density function of noise which is assumed to be Gaussian (logarithmic transform of multiplicative noise) is given by

$$f_N\left(N\right) = \frac{1}{\sqrt{2\pi}\sigma_N}\exp\left(-\frac{N^2}{2\sigma_N^2}\right) \tag{13}$$

Here, σ_N is the noise standard deviation and can be estimated using [8]. Equation (12) can be written as (14).

$$\hat{X} = \arg\max_X\left[\mathrm{Ln}\left(f_N\left(Y-X\right)\right) + \mathrm{Ln}\left(f_X\left(X\right)\right)\right] \tag{14}$$

The clean coefficients are estimated by substituting the value of $f_N(.)$ from (13) and $f_X(.)$ from (3).

$$\hat{X}_{G\Gamma D} = \mathrm{sign}\left(Y\right)\max\left(0, |Y| - \sigma_N^2\left|\frac{\frac{\nu|Y|^{\nu-1}\mathrm{sign}(Y)}{\eta^{\nu}}}{-\frac{(\kappa\nu-1)}{Y}}\right|\right) \tag{15}$$

Equation (15) gives the clean coefficients of the stationary wavelet transform. It will help in restoring the despeckled SAR image.

V. PROPOSED METHOD

The proposed method is based on the modeling of detailed band SWT coefficients obtained after applying stationary wavelet transform on log transformed image. Fig. 1 shows the flow chart of the proposed method. The proposed despeckling technique uses a three level decomposition of SWT. From the prior knowledge of the clean SWT coefficients, the detailed band coefficients are modeled using a two sided GΓD distribution and speckle noise is modeled using zero mean Gaussian distribution. The corresponding parameters of distribution are needed to be estimated from empirical data. The parameters η, κ and ν are obtained from MoLC method based on Mellin transform using the observed data. The parameters of the noise free image are obtained using the absolute central moments. Then clean image coefficients are obtained from empirical data using MAP estimator based on Bayes rule. Finally, denoised image is obtained by applying exponential operator on inverse stationary wavelet transformed coefficient.

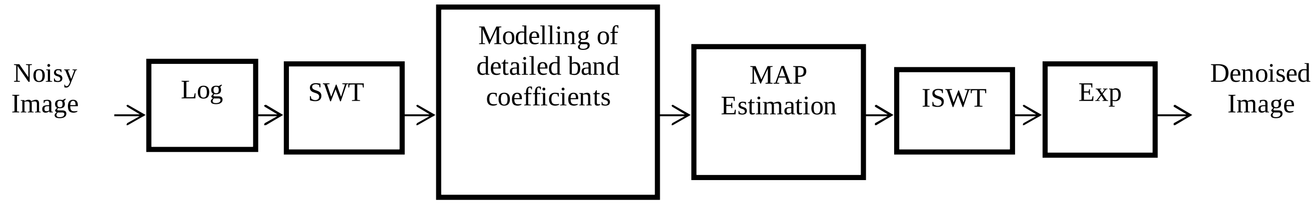

Fig. 1 Flowchart for Proposed Method

VI. EXPERIMENTAL RESULTS

Experiments are carried out on both synthetic image and real SAR images. A 512 x 512 Lena image is used as a synthetic image. The noisy image is obtained by introducing speckle noise from MATLAB. The real image is a portion of Ka-band image of a golf course clubhouse at Kirtland AFB obtained from Sandia Laboratories [9]. PSNR and ENL parameters are used for performance evaluation of synthetic Lena image and real SAR image respectively. The PSNR is defined as the ratio of maximum possible power of a signal to the power of the noise that deteriorates the exactness of a signal [2]. It is defined using (16).

$$\mathrm{PSNR} = 20\log_{10}\left(\frac{\max_X}{\sqrt{\mathrm{MSE}}}\right) \tag{16}$$

ENL is calculated in the homogenous areas as the ratio of squared mean to the variance in that region [10].

$$\mathrm{ENL} = \frac{\mu^2}{\sigma^2} \tag{17}$$

Here, μ and σ^2 are the mean and variance respectively over the homogenous region. A large ENL value corresponds to better speckle suppression.

The results obtained for proposed method are compared with other existing modeling based methods viz. Wiener filter [11], VISU Shrink [12] and modelling of stationary wavelet coefficients using Cauchy distribution [13]. Table 1 shows the PSNR values obtained for synthetic Lena image. PSNR values are calculated at noise variances, 0.1, 0.15 and 0.2. A significant improvement is seen in PSNR values at 0.1, 0.15 and 0.2 oise variances. Table 2 shows the ENL values obtained for real SAR image. ENL values for the real image are evaluated over two homogenous regions, abbreviated as region 1 and region 2 (highlighted in red in Fig. 3(a). The ENL values obtained for the proposed method is higher than EN value obtained for real original SAR image.

TABLE I. PSNR VALUES FOR SYNTHETIC IMAGES

	Noise Variance		
	0.1	0.15	0.2
Speckled Image	16.0024	14.3828	13.2530
Wiener [11]	23.9181	22.4395	21.4598
VISU Shrink [12]	23.5336	22.2220	21.1598
SWT_Cauchy [13]	22.3722	17.9184	16.6447
Proposed Method	25.2875	24.6390	23.4410

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TABLE II. ENL VALUES FOR REAL SAR IMAGE

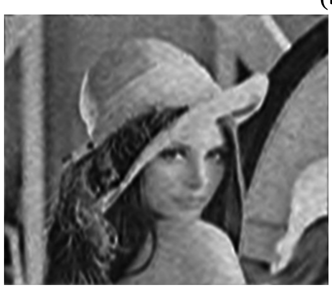
	Region 1	Region 2
Before despeckling	92.638	86.8384
Wiener [11]	94.489	88.5989
Visu Shrink [12]	305.0579	286.6438
SWT_Cauchy [13]	382.3235	285.9522
Proposed Method	451.7821	326.5924

The proposed method has better results in terms of PSNR as well as ENL in comparison to three existing methods for both synthetic and real images. High PSNR value obtained shows the strong despeckling capability and high ENL value shows the better visual quality of reconstructed image obtained using proposed method.Fig. 2(a) shows the corrupted image by speckle noise with 0.1 noise variance. Fig. 2(b) shows the despeckled image obtained by Wiener filter. Fig. 2(c) shows the denoised image obtained by VISU Shrink.Fig. 2(d) shows the despeckled image obtained by modeling of wavelet coefficients using Cauchy distribution and Fig. 2(e) shows the image obtained by proposed method. It can be clearly seen that quality of the denoised image obtained using proposed method is superior to the denoised images obtained using existing methods.

Fig 3(a) shows the real speckled SAR image. Fig. 3(b) – 3(e) shows the despeckled SAR images obtained using Wiener filter, VISU Shrink, SWT_Cauchy and proposed method respectively. In Fig. 3(b) – (d) scratches are found in the homogenous regions and edges are also not preserved properly.In Fig 3(e) edges and boundaries are very well preserved showing the effectiveness of the proposed method over other methods. Also, proposed method shows good despeckling capability in homogenous areas yielding highest ENL value.


(a)

(b)

(c)

(d)

(e)

Fig. 2 Results of various despeckling method for Lena image (a) Noisy image; (b) Wiener; (c) VISU Shrink; (d) SWT_Cauchy; (e) Proposed method.


(a)

(b)

(c)

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(d) (e)

Fig. 3 Results of various despeckling methods for real SARimage (a) SAR image; (b) Wiener; (c) VISU Shrink; (d) SWT_Cauchy; (e) Proposed method

VII. CONCLUSION

In this paper, a new despeckling method based on stationary wavelet transform is proposed. A Bayesian MAP estimator is used to estimate the clean coefficients of SWT. The SWT coefficients of the noise free image and of the speckle noise is modeled as two sided GΓD and zero mean Gaussian distribution respectively. PSNR and ENL values obtained using proposed method shows the effectiveness of this method over other existing methods.

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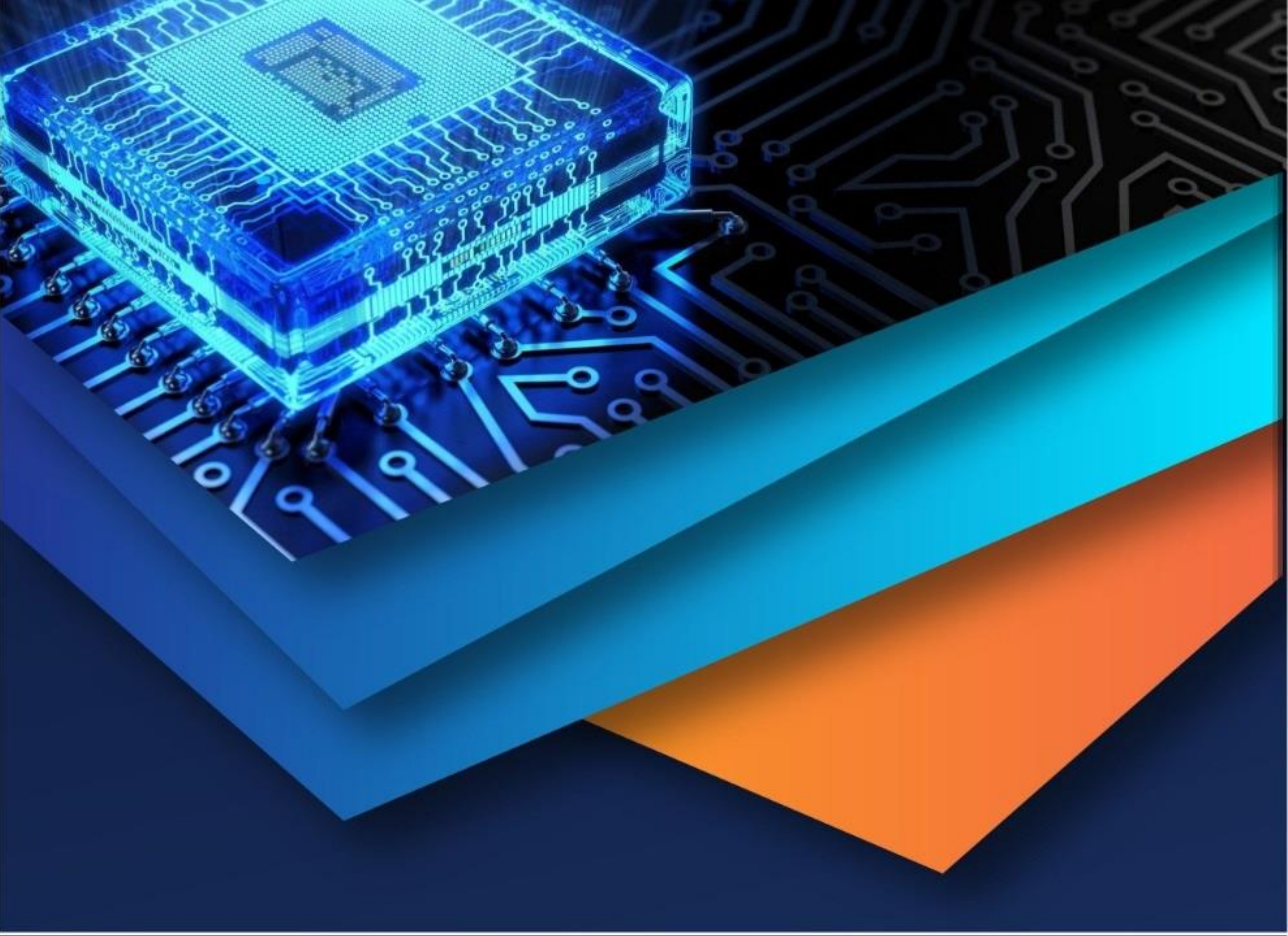

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