



Despeckling of SAR images using homomorphic subspace technique and wavelet shrinkage

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ABSTRACT: Homomorphic subspace technique and wavelet shrinkage for speckle noise reduction from SAR (synthetic aperture radar) images is proposed. The proposed principle is to apply homomorphic subspace technique to convert multiplicative noise to additive noise and then to decompose the vector space of the noisy image into noise and signal subspaces. The noisy subspace is discarded and the clean image is estimated from the remaining signal subspace using wavelet shrinkage. The performance of the proposed technique is compared with Lee filter, nonlocal mean based speckle filtering, homomorphic butterworth filter and brute force thresholding algorithm.

KEYWORDS Speckle noise, Homomorphic subspace technique, Wavelet shrinkage, Synthetic Aperture Radar (SAR) images.

INTRODUCTION

The synthetic aperture radar (SAR) imaging technique is used to provide high resolution imagery in various weather conditions and used in remote sensing and monitoring applications. Synthetic aperture radar works by transmitting electromagnetic waves towards the target surface (like airborne or spaceborne) and by coherently processing the returned backscattered signals multiple distributed targets [1]. The noisy appearance of the SAR image is because of the coherent processing which produces speckle effect [2]. The speckle occurs in the images as a granular pattern which reduces the image resolution and may hamper the operation of image rendition and analysis. Hence, in SAR imagery system noise filtering becomes an essential part. The main aim of using a despeckle filter is to smooth homogeneous regions while preserving the structural features and textural information [3].

The commonly used filters for speckle noise reduction are Lee filter, homomorphic butterworth filter, brute force threshold algorithm and Non local mean based filter. In Lee filtering following assumptions are made: 1) The SAR speckle noise is modelled as a multiplicative noise. 2) The signal and noise are statistically independent. 3) The variance and sample mean of a pixel are equal to its local variance and local mean computed within a window centred on the pixel of interest.

The performance of this filter depends on the choice of orientation and size of moving window. The Lee filter removes speckle noise in SAR images with an average intensity of the window by computing a linear combination of the center pixel intensity in filter window. Thus the filter achieves a balance between averaging in homogeneous regions and a strict all pass filter in edge contained regions [4]. The Homomorphic butterworth filter has the property of maximally flat frequency response and ripples are not present in the pass band. In stop band it rolls towards the zero. It has monotonically changing magnitude function with frequency. In the process of nonlocal mean based filtering a self-similarity assumption can be exploited to denoise an image. Denoising of image performed by brute force threshold algorithm follows some assumptions: 1) Input wavelet sub band. 2) Find minimum and maximum value of sub band coefficients. 3) Loop through (threshold=minimum to maximum) and execute desired algorithm. 4) Save the results in array for each loop such that $F=[\text{threshold}, \text{result}]$. 5) Select the threshold when loop completed that gives results [5]. These filters have following deficiencies: 1) when SAR image data is small these methods fail. 2) In SAR image highly reflexive point targets are blurred. 3) Image containing dark spotty pixels are not filtered. 4) Back scatter mean preservation in homogeneous areas, ringing impairments and sharpness preservation. The proposed method overcomes the limitations of the techniques described above. In proposed method homomorphic subspace technique is used for additive noise uncorrelated with the signal. However, the speckle noise present in SAR images is multiplicative in nature.



International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 11, November 2015

It is difficult to reduce speckle noise without distorting the image details. So a homomorphic subspace technique takes advantage of logarithmic transformation in order to convert multiplicative noise into additive noise [6][7]. From this the noised image is divided into signal and noise subspaces. The signal subspace is decomposed into sub bands using Haar wavelet and details sub bands which contain most of the noise is eliminated. The speckle denoised image is recovered from the other sub bands [8]. The performance of the proposed method is evaluated using the metrics PSNR, SNR and MSE. A significant improvement in quality of the image when compared to other methods is observed.

ISPECKLE NOISE MODEL

To explain the mechanism of speckle noise in SAR images, an essential representation of compound speckle noise process model is formulated [9] as

$$I_s(i,r) = I(i,r) + I(i,r) \times S(i,r) \quad (1)$$

Where $I(i,r)$ represents the true value of the original image pixel, $S(i,r)$ denotes the speckle noise pixels introduced into the image to produce speckled (degraded) image pixels $I_s(i,r)$, and “i, r” represents pixel location. The eq. (1) can be reduced into multiplicative form:

$$I_s(i,r) = I(i,r) \times N_s(i,r) \quad (2)$$

Where

$$N_s(i,r) = 1 + S(i,r) \quad (3)$$

Applying homomorphic transformation to the eq. (2) to convert multiplicative form to additive form is given by

$$D(i,r) = F(i,r) \times N(i,r) \quad (4)$$

Where

$$D(i,r) = \log(I_s(i,r)) \quad (5a)$$

$$F(i,r) = \log(I(i,r)) \quad (5b)$$

$$N(i,r) = \log(N_s(i,r)) \quad (5c)$$

Since the original image detected pixel values are factorized into two components as follows:

$$I(i,r) = L(i,r) \times R(i,r) \quad (6)$$

Where $L(i,r)$ is the luminance and $R(i,r)$ is the reflectance of the scene, then the eq. (5b) can be rewritten as

$$F(i,r) = LL(i,r) \times LR(i,r) \quad (7)$$

Where $LL(i,r) = \log(L(i,r)) \quad (8a)$

And $LR(i,r) = \log(R(i,r)) \quad (8b)$



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Thus, eq. (4) can be written as

$$D(i,r)=LL(i,r)+LR(i,r)+N(i,r) \quad (9)$$

Which means that in speckled image each log-transformed pixel $D(i, r)$ consists three additive components. A low frequency one $LL(i, r)$ and two high frequency components $LR(i, r)$ and $N(i, r)$. However, applying any low pass filter on the log transformed speckled image pixel $D(i, r)$ can isolate the high frequency noise component $N(i, r)$, but it will also reduce image quality in the form of blurred signal features due to elimination of high frequency image pixel component $LR(i, r)$. An alternative way is to use haar wavelet in homomorphic filtering. In such filtering, the log transformed image $D(i, r)$ is applied to a homomorphic wavelet shrinkage. Then a proper thresholding high frequency noise components of eq. (9), $N(i, r)$ can be eliminated approximately or even reduced.

III. HOMOMORPHIC WAVELET SHRINKAGE APPROACH

The concept of homomorphic filtering is first to separate the illumination and reflection components of an image and then apply homomorphic filter on these components separately. An image $f(x, y)$ can be expressed in terms of its illumination $i(x, y)$ and reflectance component $r(x, y)$ as,

$$f(x, y) = i(x, y)r(x, y) \quad (10)$$

eq. (10) cannot be used directly in order to operate separately on the frequency components of illumination and reflectance because the fourier transform of the product of two functions is not separable i.e,

$$T[f(x, y)] \neq T[i(x, y)]T[r(x, y)]$$

In order to separate illumination and reflectance component, we define function z such that,

$$\begin{aligned} z(x, y) &= \ln[f(x, y)] \\ z(x, y) &= \ln[i(x, y)r(x, y)] \\ z(x, y) &= \ln i(x, y) + \ln r(x, y) \\ T[z(x, y)] &= T[\ln i(x, y)] + T[\ln r(x, y)] \\ z(u, v) &= I(u, v) + R(u, v) \end{aligned}$$

Where $I(u, v)$ and $R(u, v)$ are the fourier transforms of $\ln i(x, y)$ and $\ln r(x, y)$ respectively.

A homomorphic filter with transfer function $H(u, v)$ is used to process $z(u, v)$, then the response will be,

$$\begin{aligned} S(u, v) &= H(u, v) z(u, v) \\ S(u, v) &= H(u, v)[I(u, v) + R(u, v)] \\ S(u, v) &= H(u, v)I(u, v) + H(u, v)R(u, v) \end{aligned}$$

Then the above eq. in special domain is given as,

$$\begin{aligned} S(x, y) &= T^{-1}[S(u, v)] \\ S(x, y) &= T^{-1}[H(u, v)I(u, v)] + T^{-1}[H(u, v)R(u, v)] \\ S(x, y) &= i'(x, y) + r'(x, y) \end{aligned}$$

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Where,

$$i'(x, y) = T^{-1}[H(u, v)I(u, v)]$$

$$r'(x, y) = T^{-1}[H(u, v)R(u, v)]$$

Since $z(x, y)$ was formed by taking logarithm of $f(x, y)$, the inverse operation would give the enhanced image $g(x, y)$ i.e

$$g(x, y) = \exp[S(x, y)]$$

$$g(x, y) = \exp[i'(x, y) + r'(x, y)]$$

$$g(x, y) = \exp[i'(x, y)]\exp[r'(x, y)]$$

$$g(x, y) = i_0(x, y)r_0(x, y)$$

Where,

$$i_0(x, y) = \exp[i'(x, y)]$$

$$r_0(x, y) = \exp[r'(x, y)]$$

$i_0(x, y)$ and $r_0(x, y)$ are the illumination and reflectance components of the output image.

Homomorphic filter is used for image enhancement. It simultaneously normalizes the brightness of the image and increase contrast. Homomorphic filter is used to convert multiplicative noise into additive noise present in SAR images [7]. Then a user defined filter (wavelet thresholding and shrinkage) is used and finally exponent operation is done.

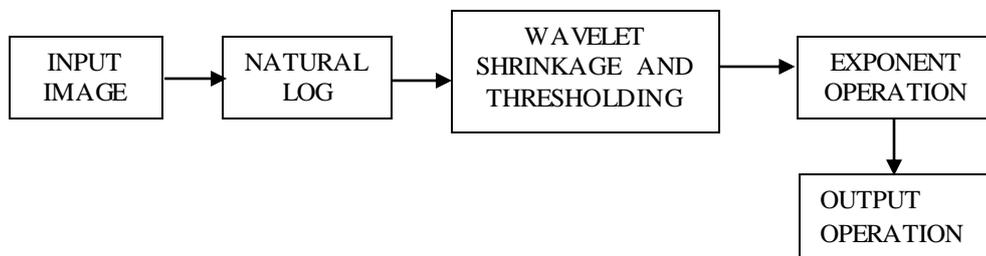


Fig. 1 Homomorphic Filtering

Wavelet shrinkage and thresholding is used to view or process digital image multiple resolution fig.2 shows wavelet shrinkage and thresholding of an image.

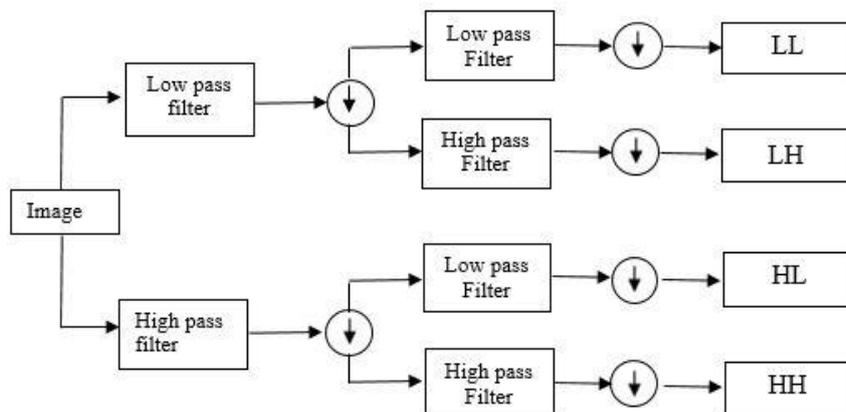


Fig 2. Wavelet shrinkage and Thresholding



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In fig.2 after filtering the image with a pair of quadrature mirror filters alternately along rows and columns, down sampling by a factor of two in each direction. In wavelet shrinkage process the image decomposed into four sub bands low-low (LL), low-high (LH), high-low (HL), and high-high (HH). LL coefficients are called approximation coefficients. HL, LH and HH coefficients are called vertical, horizontal and diagonal detail coefficients, respectively. The LL sub band further decomposed into another level of decomposition. From the original image four new images are created for each level decomposition. Downsampling not used to obtain an equal number of coefficients at each resolution scale but it increases the computational cost significantly and causes storing and transmitting the double of information with the decomposed signal.

The Speckle noise corresponds to a high frequency component of the SAR image and appears in wavelet coefficients. Thus the wavelet shrinkage is widely used in denoising SAR images. Homomorphic wavelet shrinkage technique involves five steps: 1) apply logarithmic transform to the SAR image. 2) Calculate discrete wavelet transform. 3) process the coefficients of the wavelet. 4) Compute inverse discrete wavelet transform to obtain the reconstructed image

IV. EVALUATION METRICS

Some common measurements that are needed to evaluate the performance of speckle reduction filters for ultrasound images are listed below

A. Mean Square Error

It indicates that how different the images being compared are. It is given by:

$$MSE = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} [I(m, n) - \bar{I}(m, n)]$$

Where $I(m, n)$ is original image, $\bar{I}(m, n)$ is filtered image, M is number of rows, N is number of columns. Therefore lower value is the closer the estimated image to the original image.

B. Signal to Noise Ratio

It shows the relationship between the real image and estimated image. This ratio indicates how strong the noise corrupted the original image. It is given by:

$$SNR = 10 \log_{10} \frac{\frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I^2(m, n)}{MSE}$$

Where I is the original image, M is number of rows, N is number of columns. Here higher the value indicates an improvement.

C. Peak Signal to Noise Ratio

In PSNR we are interested in signal peak. This is more content specific than pure SNR. Here we say how high intensity regions of the image come through the noise and paying much less attention to low intensity regions. It is given by:

$$PSNR = 10 \log_{10} \frac{(2^B - 1)^2}{MSE}$$

Where B is number of bits used for representing each pixel, MSE is mean squared error. Here higher the value indicates an improvement.

V. EXPERIMENTAL RESULTS AND DISCUSSION

To evaluate the performance of the proposed method, a clean SAR image with speckle noise added at variance level of 0.2 is taken as the input. MSE, SNR and PSNR of the denoised image using homomorphic wavelet shrinkage is compared to that of lee filter, nonlocal mean based speckle filtering, homomorphic butterworth filter and brute force thresholding algorithm.

The original image, speckled image and their corresponding histograms are shown in the figure below

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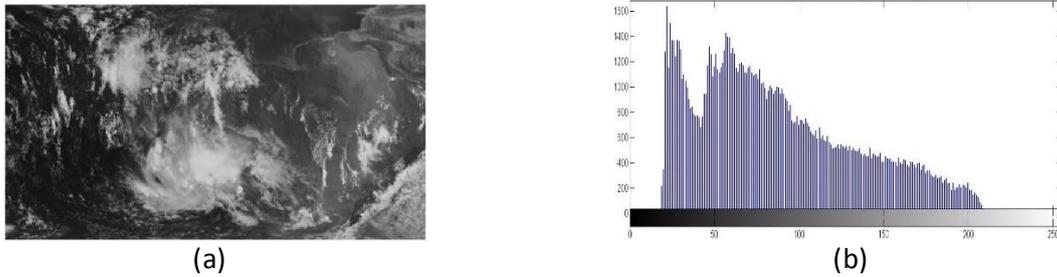


Fig 3. (a) Original image. (b) Histogram of original image.

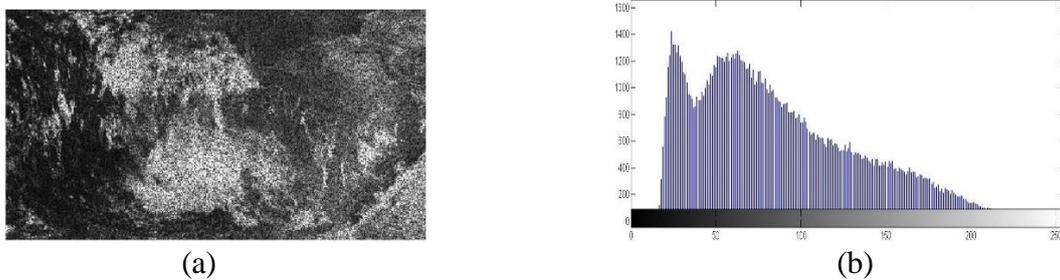


Fig 4. (c) Noisy image. (d) Histogram of noisy image.

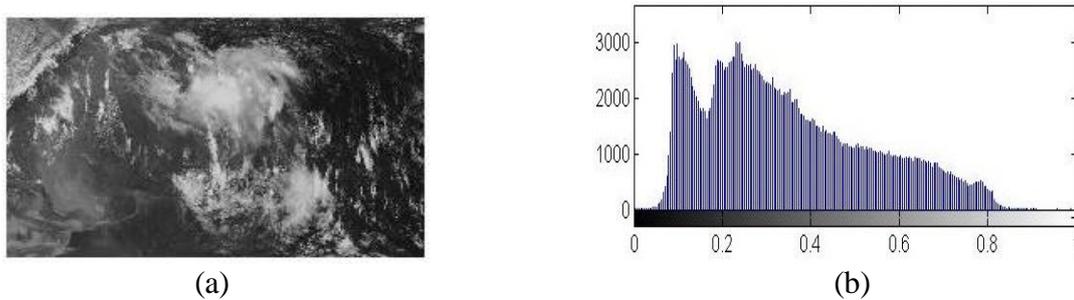


Fig 5. (a) Filtered image using single level decomposition(HH band eliminated). (b) Its Histogram

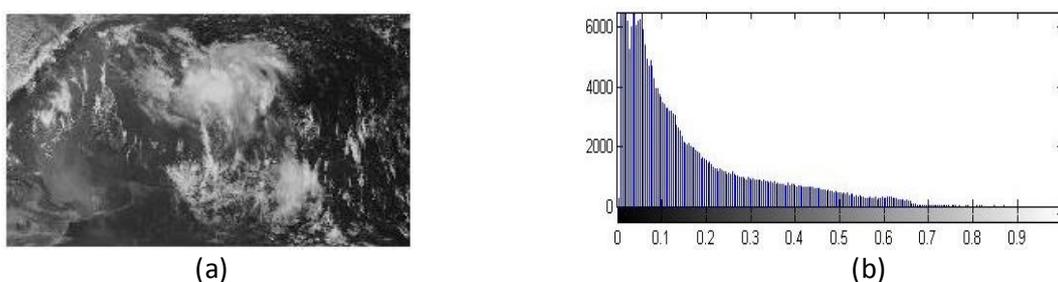


Fig 6. (a) Filtered image using double level decomposition(HH band eliminated). (b) Its Histogram

Both single and double level decomposition of the speckled SAR image is carried out. Firstly the denoised image is restored from the sub bands of the single level decomposition by eliminating the HH band. Secondly denoising is done by reconstructing the image from subbands of double level decomposition by eliminating the LL-HH band. The metrics



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MSE, SNR and PSNR for the image restored using single level decomposition coefficients only (band eliminated HH) is better than that of image restored from two level decomposition coefficients (band eliminated LL-HH).

Three parameters MSE, SNR and PSNR considered for comparing the results of proposed method with existing methods in the literature. These are shown in Table 1.

Table I: Computed Performance Metrics of Various Filters

Filter	MSE	SNR	PSNR
Noisy	99.3338	30.1205	31.1786
Homomorphic butterworth	0.1421	64.3121	65.2092
Lee	0.0150	70.1211	73.1203
Nonlocal mean	0.0185	68.7211	69.5507
Brute force thresholding	0.0501	67.3210	69.2401
Homomorphic wavelet shrinkage	0.0079	79.1882	83.6429

VI. CONCLUSION

The homomorphic subspace technique and wavelet shrinkage denoising for SAR images has been presented and tested. The proposed technique is based on reduced rank subspace model to estimate the clean image from the corrupted one with speckle noise. The capability of proposed homomorphic subspace technique and wavelet shrinkage in efficiently representing SAR images has been discussed and verified.

Next, the performance of the homomorphic subspace technique and wavelet shrinkage has been tested and compared with lee filter, nonlocal mean based speckle filtering, homomorphic butterworth filter and brute force thresholding algorithm. The results indicates less blur, less artifacts and better preservation of radiometric edges of the targets. The results show moderate noise reduction by proposed homomorphic subspace technique and wavelet shrinkage filter. Moreover, the capability of the algorithms in preserving and cleaning is tested. Finally, The results show better performance by homomorphic subspace technique and wavelet shrinkage comparison to lee filter, nonlocal mean based speckle filtering, homomorphic butterworth filter and brute force thresholding algorithm.

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