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Enhance Bivariate Wavelet-Based Image Denoising with Exploiting Interscale Dependency in SAR

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ABSTRACT:- In this paper we observe how wavelet transforms can be implemented to scale and translate a noise speckle image into a multi-resolution analysis representation. Bivariate shrinkage function used to reduce noise speckle at different resolution levels. These results obtained have shown significant speckle reduction then standard filter methods such as Lee filter, Kuan filter and median filter are among the better denoising algorithms in radar community. In this paper we see the performance of different speckle filters. In recent years, wavelet-based denoising algorithm has been studied and applied successfully for speckle removal in SAR images. Compact support of wavelet basis functions allows wavelet transformation to efficiently represent functions or signals, which have localized features. Then we remove speckle noise using wavelet-based method. Finally we concluded that denoising using wavelet-based algorithm is more efficient than standard speckle filters.

Keywords: Speckle reduction, Synthetic aperture radar (SAR), Complex wavelet.

1. INTRODUCTION

1.1 Context

In the past two decades, many noise reduction techniques have been developed for removing noise and retaining edge details in Satellite and Oceanographic images. Most of the standard algorithms use a defined filter window to estimate the local noise variance of a noise image and perform the individual unique filtering process. The primary goal of noise reduction is to remove the noise without losing much detail contained in an image. To achieve this goal, we make use of a mathematical function known as the wavelet transform to localize an image into different frequency components or useful sub bands and effectively reduce the noise in the sub bands according to the local statistics within the bands. The main advantage of the wavelet transform is that the image fidelity after reconstruction is visually lossless.

1.2 Image Processing

Image processing involves changing the nature of an image in order to either

1. Improve its pictorial information for human interpretation.
2. Render it more suitable for autonomous machine perception.

It is necessary to realize that these two aspects represent two separate but equally important aspects of image processing. A procedure which satisfies condition (1) a procedure which makes an image “look better” may be the very worst procedure for satisfying condition (2). Humans like their images to be sharp, clear and detailed but machines prefer their images to be simple and uncluttered.[15]

1.3 Different Types of Noises

Image denoising involves the manipulation of the image data to produce a visually high quality image. Different noise models including additive and multiplicative types are used. They include Gaussian noise, salt and pepper noise, speckle noise and Brownian noise. Selection of the denoising algorithm is application dependent.

3. Synthetic Aperture Radar (SAR)

Synthetic aperture radar (SAR) is an active microwave sensor that transmits in microwave and detects the wave that is reflected back by the objects. SAR is completely different from passive optical sensors. It enables high-resolution, high contrast observation and accurate determination of topographical features when captured from an airplane or satellite as it makes use of radar waves to gather data about the earth below. SAR systems take the advantage of the long-range propagation characteristics of radar signals and the complex information processing capability of modern digital electronics to provide the high-resolution imagery. [19]

3.1 Image Interpretation

Radar images are composed of many dots, or picture elements. Each pixel (picture element) in the radar image represents the radar backscatter for that area on the ground. Darker areas in the image represent low backscatter and brighter areas represent high backscatter. Bright features mean that a large fraction of the radar energy was reflected back to the radar, while dark features imply that very little energy was reflected. Backscatter for a target area at a particular wavelength will vary for a variety of conditions such as size of the scatters in the target area, moisture content of the target area, polarization of the pulses, and observation angles. Backscatter will also differ when different wavelengths are used. [12]

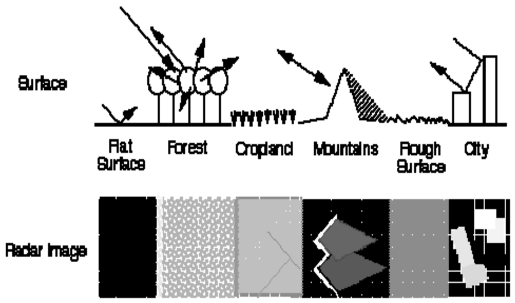

Figure-1: Imaging different types of surface with radar

Backscatter is also sensitive to the target's electrical properties, including water content. Wetter objects will appear bright, and drier targets will appear dark. The exception to this is a smooth body of water, which will act as a flat surface and reflect incoming pulses away from a target; these bodies will appear dark.

3.2 Speckle Filters

There are various speckle reduction filters available to process SAR images. Some give better visual interpretations while others have good noise reduction or smoothing capabilities. The use of each filter depends on the specification for a particular application. In practice, the standard speckle filters such as Median, Statistical Lee, Kuan and Frost are considered to be the best speckle removing algorithms in the radar community. Each of these filters has a unique speckle reduction approach that performs spatial filtering in a square-moving window known as kernel. The filtering is based on the statistical relationship between the central pixel and its surrounding pixels as shown in Figure 2.

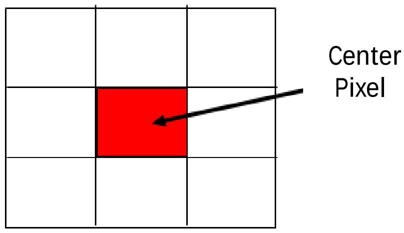

Figure-2: 3.1: 3 x 3 kernel

4. Theory of Wavelet Transform

Wavelet transform has been studied extensively in recent years as a promising tool for image compression and noise reduction. It consists of a set basis functions that can be used to analyze signals in both time and frequency domains simultaneously. This analysis is accomplished by the use of a scalable window to cover the time-frequency plane, providing a convenient means for the analyzing of non-stationary signal that is often found in most applications. [14]

4.1 Fourier versus Wavelet Transform

Short Time Fourier Transform (STFT) is developed by Gabor (1946), to overcome the problem of Fourier transform. It uses a fixed-size window to analyze the non-stationary signal as shown in Figure 3. A small window gives better time resolution and poor frequency resolution, while a large window gives poor time resolution and good frequency resolution. In both cases, the resolution is fixed for high and low frequencies of the signals.

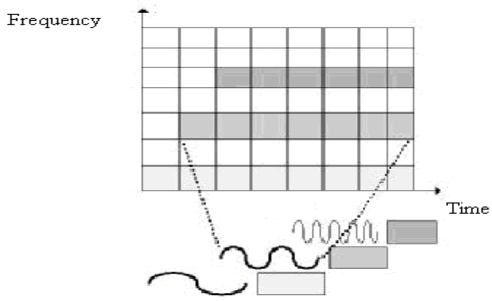

Figure-3: Fourier basis functions, time-frequency coverage of the time-frequency plane.

There is no way to achieve an ideal window size for both time and frequency analysis. Therefore, using STFT will require a compromise between the time and the frequency view of the signal.

4.2 Wavelet Transform

Wavelet analysis adopts a wavelet prototype function known as the mother wavelet given in eqn. (4.2). This mother wavelet in turns generates a set of basis functions known as child wavelets through recursive scaling and translation. The variable *s* reflects the scale or width of a basis function and the variable *t is* the translation that specifies its translated position on the time axis. [10][14]

$$\psi(\tau, s) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \quad (1)$$

In eq. (.1), $\psi\left(\frac{t-\tau}{s}\right)$ is the mother wavelet and the factors $\frac{1}{\sqrt{s}}$ is a normalized factor used to ensure energy across different scale remains the same.

4.3 Wavelet Decomposition

In wavelet analysis, approximations and details are often used for describing the upper and lower portions of the frequency. The approximations are the high magnitude and low frequency components of the signal while the details are represented by the low magnitude and high frequency components.

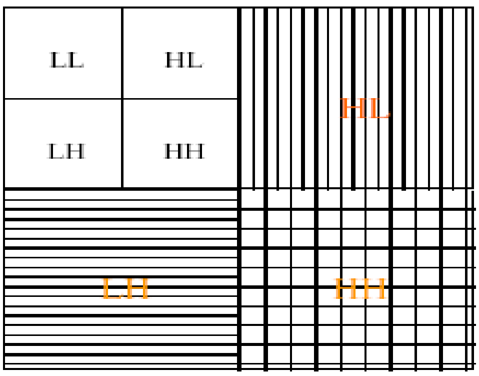

Figure-4: Image representation 2 levels of decomposition

5. Image Denoising

5.1 Denoising Procedure

Given a noisy signal y = x + n where x is the desired signal and n is independent and identically distributed (*i.i.d)* Gaussian noise $N(0,\sigma^2)$, y is first decomposed into a set of wavelet coefficients w = *W*[y] consisting of the desired coefficient θ and noise coefficient n. By applying a suitable threshold value T to the wavelet coefficients, the desired Coefficient θ=T[w] can be obtained; Lastly an inverse transform on the desired coefficient θ will generate the denoise signal x = W^T[θ].[5][6]

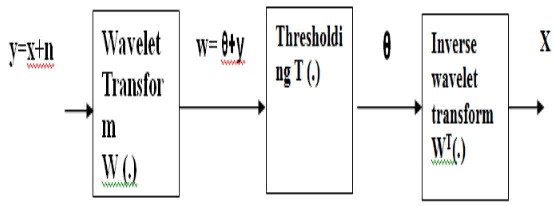

Figure-5: Block diagram for DWT based denoising framework

A similar approach can be applied to a speckle SAR image. The wavelet decomposition process is iterated with successive approximations being decomposed in turn, so that the image is broken down and represented by a small number coarser component in the lower spectral band (LL block) and a large number of detailed components in the higher spectral band (LH, HL and HH blocks).

In general a signal has its energy concentrated in a small number of coefficients, while noise has its energy spread across over a large number of coefficients. Hence, through suitable thresholding or wavelet shrinkage of the higher spectral bands components (where the noise predominantly lies) we can greatly reduce or remove the noise speckle of the image in a wavelet domain.

Since the noise characteristics can be different in each higher spectral block, each block will have to be thresholded separately according to its local noise variance. Finally, the thresholded coefficients are used in a wavelet reconstruction process to retrieve the speckle-reduced image with little loss of detail.

5.2 Thresholding Techniques

According to wavelet analysis, one of the most effective ways to remove speckle without smearing out the sharp edge features of an ideal image is to threshold only the high frequency components while preserving most of the sharp features in the image. The approach is to shrink the detailed coefficients (high frequency components) whose amplitudes are smaller than a certain statistical threshold value to zero while retaining the smoother detailed coefficients to reconstruct the ideal image without much loss in its details. This process is sometimes called wavelet shrinkage since the detailed coefficients are shrunk towards zero.

There are three schemes to shrink the wavelet coefficients, namely the “keep-or-kill” hard

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thresholding, "shrink-or-kill" soft thresholding introduced by Donoho *et al.* (1995) and third is semi-soft or firm thresholding from Bruce and Gao (1997). Shrinking of the wavelet coefficient is most efficient if the coefficients are sparse that is the majority of the coefficients are zero and a minority of coefficients with greater magnitude can represent the image.

The criterions of each scheme are described as follows: given λ denotes the threshold limit, X denotes the input wavelet coefficients and Y denotes the output wavelet coefficients after thresholding.

6. Wavelet Decomposition

To use the wavelet transform for image processing we must implement a 2D version of the analysis and synthesis filter banks. In the 2D case, the 1D analysis filter bank is first applied to the columns or rows of the image and then applied to the other dimension as described in decomposition procedure. If the image has N1 rows and N2 columns, then after applying the 1D analysis filter bank to each column we have two subband images, each having N1/2 rows and N2 columns; after applying the 1D analysis filter bank to each row of both of the two sub band images, we have four subband images, each having N1/2 rows and N2/2 columns.[4]

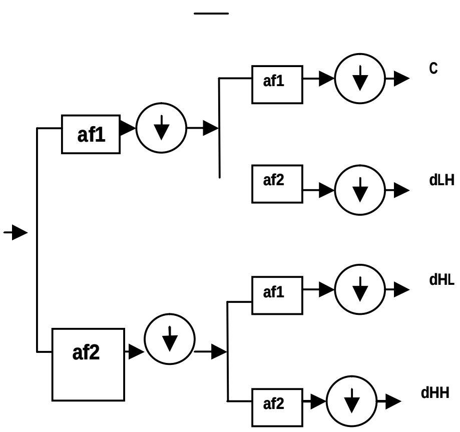


Figure-6: One stage in multi-resolution wavelet decomposition of an image

6.1 Perform Denoising

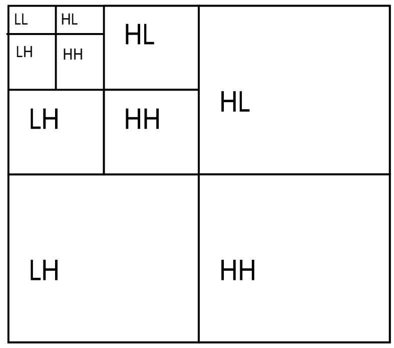


Figure-9: Sub band regions of critically sampled wavelet transform.

Denoising is performed by proper threshold selection. The algorithm for thresholding is described below.

Figure-9 illustrates the sub band regions of the two-dimensional (2-D) critically sampled wavelet transform. For convenience, let us label the sub bands HH_k, HL_k, and LH_k, where k is the scale, and j is the coarsest scale. The smaller k is, the finer the scale is. Let us also define subband P (S). P (S) is the subband of the parents of the coefficients of the subband S. For example, if S is HH_1, then P (S) is HH_2, or if S is HL_2, then P (S) is HL_3.
σ_n^2 = Median ($|y_i|$) / 0.6745 y_i element of sub band HH1

$$\hat{\sigma}_{y1}^{2} = \frac{1}{N_1^2}\sum_{y1i\in s} y_{1i}^2 \quad (2)$$

σ_{y1} and σ_{y2} can be found by :

$$\hat{\sigma}_1 = \sqrt{(\hat{\sigma} y_1^{2} - \hat{\sigma}_n^{2})_+} \quad (3)$$

Where σ y_1 and σ y_2 are Variances of y_1 and y_2. Using these variances signal ariance σ_1 & σ_2 can be estimated by applying formula given as:

$$\hat{\sigma}_2 = \sqrt{(\hat{\sigma} y_2^{2} - \hat{\sigma}_n^{2})_+}. \quad (4)$$

$$\hat{\sigma}_{y1}^{2} = \frac{1}{N_1^2}\sum_{y1i\in s} y_{1i}^2 \quad (5)$$

Using bivariate shrinkage function

$$\hat{w}_1 = \frac{(\sqrt{y_1^2 + y_2^2} - \sqrt{3}\frac{\sigma_n^2}{\sigma}) + .y_1}{\sqrt{y_1^2 + y_2^2}} \quad (6)$$

Each coefficient is estimated briefly, the threshold algorithm is summarized as follows:

1. Calculate the noise variance.
2. For each wavelet coefficient,
   a. Calculate signal variance,
   b. Estimate each coefficient using the bivariate shrinkage function

6.2 Wavelet Reconstruction

Analysis filter bank used in decomposition process. In reconstruction process synthesis filter banks is used. The 2D synthesis filter bank combines the four subband images obtain in decomposition obtain original image of size N1 by N2.

7. TEST

Various Assessment parameters are used to evaluate the performance of speckle reduction methods. Some important parameters are described below.

7.1 Noise Variance

Noise variance determines the contents of the speckle in the image. A lower variance gives a cleaner image as more speckles are reduced. The formula for calculating the variance is given in eqn (7.1).

$$\sigma^2 = 1/N \sum_{j=0}^{N-1} (X_j)^2 \quad (7)$$

7.2 Mean Square Error (MSE)

MSE indicates average error of the pixels throughout the image. In our work, a definition of a higher MSE does not indicate that the denoised image suffers more errors instead it refers to a greater difference between the original and denoised image. This means that there is a significant speckle reduction. The formula for the MSE calculation is given in eqn (7).

$$MSE = 1/N \sum_{j=0}^{N-1} (X_j - \overline{X}_j)^2 \quad (7)$$

where Xj is the reconstructed image, Xj is the original image and N is the size of the image.

7.3 Equivalent Numbers of Looks (ENL)

Another good approach of estimating the speckle noise level in a SAR image is to measure the equivalent numbers of looks (ENL) over a uniform image region. A larger the value of ENL usually corresponds to a better quantitative performance. The value of ENL also depends on the size of the tested region, theoretically a larger region will produces a higher ENL value than over a smaller region but it also tradeoff the accuracy of the readings. Due to the difficulty in identifying uniform areas in the image, we proposed to breakdown the image into smaller areas of 25 x 25 pixels, obtain the ENL for each of these smaller areas and finally take the average of these ENL values. The formula for the ENL calculation is given in eqn (8).

$$ENL = \left(\frac{\mu}{\sigma}\right)^2 \quad (8)$$

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

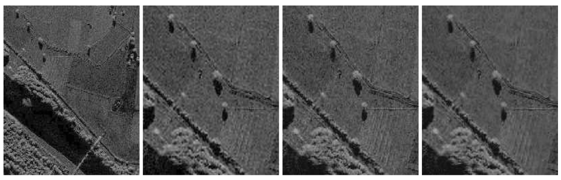
7.4 Peak Signal to Noise Ratio (PSNR)

The PSNR is most commonly used as a measure of quality of reconstruction in image compression and image denoising etc. The PSNR is given by

PSNR=10 log (255/MSE) ----------- (9)

In general greater the value of PSNR represents better the speckle reduction of images. But in this particular case MSE is greater for significant speckle reduction. So according to equation 9. PSNR will be less in case of better speckle reduction.

8.RESULTS



(a) Speckled image (b) Despeckled image

Figure-7: Denoising using Filter

9. Comparison Chart

Table-1: Statistical Measurement of Different Filters

STATISTICAL MEASURE-MENT	Lee Filter	Median Filter	Kuan Filter	Frost Filter	Bivariate Shrinkage Function
Noise Variance	.0348	.0381	.0354	.0382	.0316
Equivalent Numbers of Looks (ENL)	6.7300	6.1446	6.5799	6.0533	6.9848
MSE	. .0132	.0127	.0029	.0163	.0353
PSNR	85.740	86.0755	99.162	83.86	77.17

Noise variance is lowest in Bivariate Shrinkage Function in comparison to other standard filter method. Equivalent number of Looks is maximum in Bivariate shrinkage function which measure smoothness of the image. Mean square error is maximum in Bivariate method. That means greater difference between the original and denoised image. This means that there is a significant speckle reduction.

The denoised images and results from Table-1 have shown conclusively that wavelet based bivariate shrinkage technique provides significant speckle reduction as compared to speckle filters. [7]

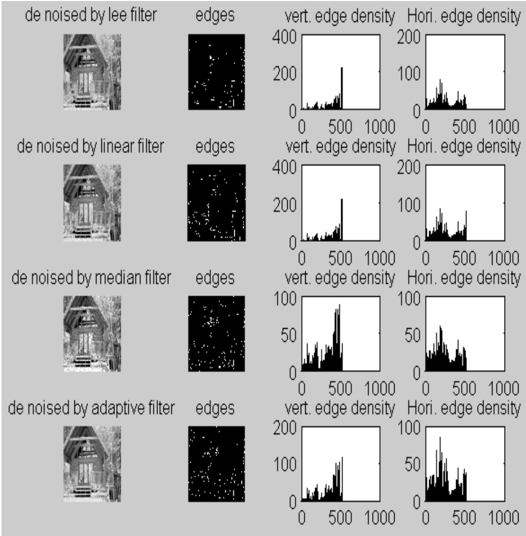


Figure8: By Different Filters

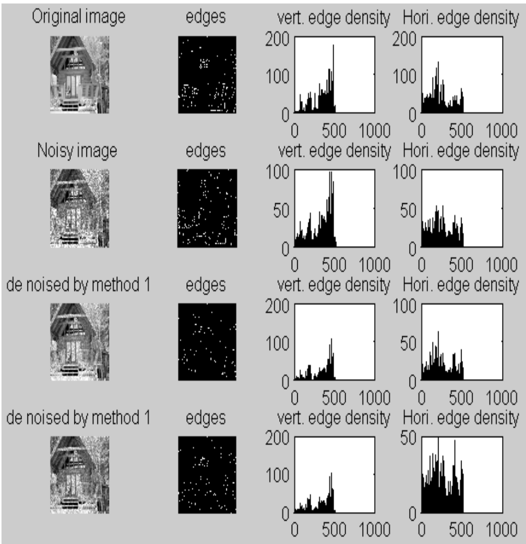


Figure-9. By Wavelet Transformation

10. Conclusions

1) Same analysis can be applied to dual tree complex wavelet transform.The dual tree complex wavelet transform incorporate good properties of fourier transform in wavelet transform. As the name implies 2 wavelet tree are used one generating real part of complex wavelet coefficient tree and other generating imaginary part. This transform provide good basis for multiresolution image denoising and de-blurring.[11]

2) Bivariate distributions are proposed for wavelet coefficients of natural images in order to characterize the dependencies between a coefficient and its parent. That is more efficient then classical soft thresholding approach. Other simple bivariate shrinkage functions can also be developed, for example, a bivariate hard Threshold with a circular or ellipsoidal deadzone.

3) We obtained these results by observing the dependencies between only coefficients and their parents. It is expected that the results can be further improved if the other dependencies between a coefficient and its other neighbors are exploited. The quality of the noise removal can be improved by careful choice of the wavelet mother function and parameters for the probability distribution functions. In addition, joint statistical properties of the pixel and its spatial neighbors and sub-band neighbors can be taken into consideration to improve the result.

4) Multivariate probability distribution functions are also developed for wavelet coefficients of natural images to exploit the dependencies between the coefficients. These are extensions of the bivariate probability distribution functions proposed in this thesis. Based on this new multivariate shrinkage rule, we can develop a high performance image denoising application which exploits inter and intrascale dependencies.

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