



Satellite Image Denoising and Image Improvement using Wavelet Transforms Methods

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Abstract— Mostly images are normally changes to unclear images by the presence of noise, low or high dissimilarity both in the edge area and also in the image area. Speckle noise is generated due to constructive and destructive interference of multiple echoes returned from each pixel. As a result, a granular pattern is produced in the radar image which corrupts significantly the appearance of the image objects. In this work, a satellite image is taken and a known variance of speckle noise is added to this image. In the next step we performed multiscale decomposition in order to calculate coefficients using wavelet transforms methods. The improvement analysis is done by comparing the values based on the assessment parameters. The parameters that are used to evaluate the performance of speckle reduction are MSE(mean square error), RMSE(root means square error), PSNR(peak signal to noise ratio) and SD(standard deviation). These parameters are computed and compared over Bayesshrink filter to evaluate the performance and quality of the image.

Keywords— Satellite Image, Speckle noise, Wavelet Transform methods, Thresholding, SAR, Denoising.

I. INTRODUCTION

Digital images are prone to a variety of types of noise. Noise is the result of errors in the image acquisition process that result in pixel values that do not reflect the true intensities of the real scene. There are several ways that noise can be introduced into an image, depending on how the image is created. For example if the image is scanned from a photograph made on film, the film grain is a source of noise. Noise can also be the result of damage to the film, or be introduced by the scanner itself. If the image is acquired directly in a digital format, the mechanism for gathering the data (such as a CCD detector) can introduce noise. Electronic transmission of image data can introduce noise. Noise is considered to be any measurement that is not part of the phenomena of interest. Noise can be categorized as Image data independent noise and image data dependent noise.

Image denoising[18][19] still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images.

This paper describes different methodologies for noise reduction (or denoising) giving an insight as to which algorithm should be used to find the most reliable estimate of the original image data given its degraded version.[1].

Synthetic aperture radar is a radar technology that is used from satellite technology. It produces high resolution images of earth's surface by using special signal processing techniques. However acquisition of SAR images face certain problems. SAR images contain speckle noise which is based on multiplicative noise Or Rayleigh noise. Speckle noise degrades the appearance and quality of SAR images. Ultimately it reduces the performances of important techniques of image Processing such as detection, segmentation, enhancement and classification. That is why speckle noise should be removed before applying any image processing techniques.[2][15]

II. TYPES OF IMAGES

- 1) *Medical images*: It is part of biological imaging e.g medical photography.
- 2) *Still images*: An image is an artifact that depicts or records visual perception, for example a two-dimensional picture.
- 3) *Satellite images*: Satellite imagery consists of images of Earth or other planets collected by artificial satellites.

III. TYPES OF NOISES

- 1) *Additive and Multiplicative Noises*: Noise is present in an image either in an additive or multiplicative form. An additive noise follows the rule $W(x,y) = s(x,y) + n(x,y)$ while the multiplicative noise satisfies $w(x,y) = s(x,y) * n(x,y)$, where $s(x,y)$ is the original signal, $n(x,y)$ denotes the noise introduced into the signal to produce the corrupted image $w(x,y)$, and (x,y) represents the pixel location. The above image algebra is done at pixel level.
- 2) *Gaussian noise*: Gaussian noise is evenly distributed over the signal. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian

$$F(g) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(g-m)^2/2\sigma^2},$$

distribution, which has a bell shaped probability distribution function, where g represents the gray level, m is the mean or average of the function, and σ is the standard deviation of the noise.[3]

- 3) *Salt and pepper noise*: Salt and pepper noise is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. It has only two possible values, a and b . The probability of each is typically less than 0.1[3].
- 4) *Speckle noise*: Speckle noise[2][15] is a multiplicative noise. This type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR(Synthetic Aperture Radar) imagery. The source of this noise is attributed to random interference between the coherent returns. Fully developed speckle noise has the characteristic of multiplicative noise. Speckle noise follows a gamma distribution and is given as

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!a^\alpha} e^{-\frac{g}{a}},$$

- 5) *Poisson noise*: In probability theory and statistics, the Poisson distribution, is a discrete probability distribution that expresses the probability of a given number of events occurring in a fixed interval of time and/or space if these events occur with a known average rate and independently of the time since the last event.

IV. METHODS OF IMAGE IMPROVEMENT

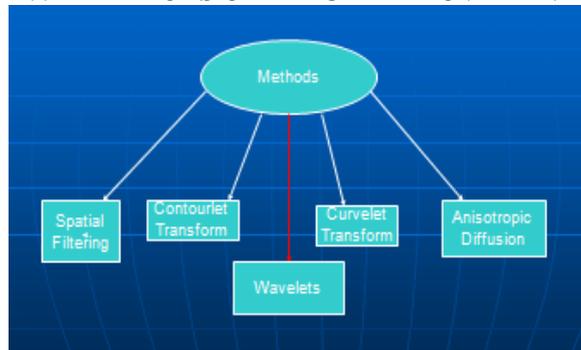


Fig .1 Techniques of denoising

From our experimentation, it has been observed that the filtering approach does not produce considerable denoising for images corrupted with Gaussian noise or speckle noise. Wavelets play a very important role in the removal of the noise.

DWT: Discrete wavelet transform is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency *and* location information (location in time).

Advantages

Wavelets allow complex information such as music, speech, images and patterns to be decomposed into elementary forms at different positions and scales and subsequently reconstructed with high precision [11]. The wavelet representation of a function is a new technique. Wavelet transform of a function is the improved version of Fourier transform. Fourier transform is a powerful tool for analyzing the components of a stationary signal. But it is failed for analyzing the non stationary signal where as wavelet transform allows the components of a non-stationary signal to be analyzed.

In time-frequency analysis of a signal, the classical Fourier transform analysis is inadequate because Fourier transform of a signal does not contain any local information. This is the major drawback of the Fourier transform [4]. The modern applications of wavelet theory as diverse as wave propagation, data compression, signal processing, image processing, pattern recognition, computer graphics, the detection of aircraft and submarines, improvement of CAT scans and some other medical image technology etc.

Two dimensional single level discrete wavelet analysis

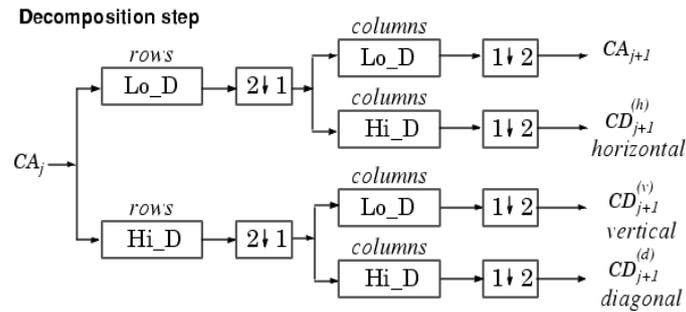
The **dwt2** command performs a single-level two-dimensional wavelet decomposition with respect to either a particular wavelet ('wname', see wfilters for more information) or particular wavelet decomposition filters (Lo_D and Hi_D) you specify[8].

$[cA, cH, cV, cD] = dwt2(X, 'wname')$ computes the approximation coefficients matrix cA and details coefficients matrices cH , cV , and cD (horizontal, vertical, and diagonal, respectively), obtained by wavelet decomposition of the input matrix X . The 'wname' string contains the wavelet name.

Algorithm

For images, there exist an algorithm similar to the one-dimensional case for two-dimensional wavelets and scaling functions obtained from one- dimensional ones by tensorial product. This kind of two-dimensional DWT[10] leads to a decomposition of approximation coefficients at level j in four components: the approximation at level $j + 1$, and the

details in three orientations (horizontal, vertical, and diagonal). The following chart describes the basic decomposition steps for images:



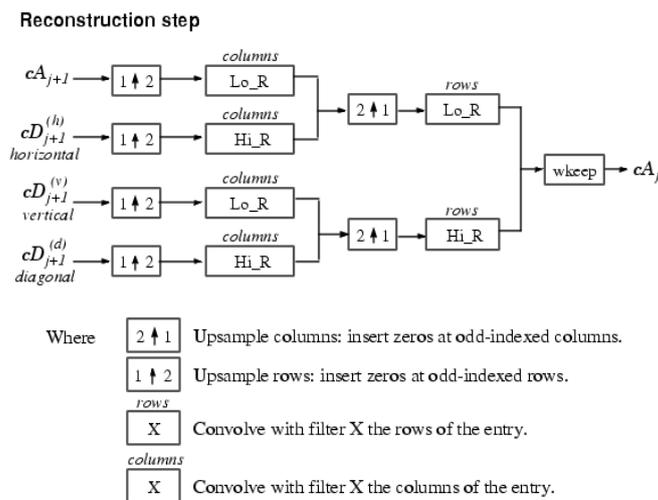
Where $\begin{bmatrix} 2 \downarrow 1 \end{bmatrix}$ Downsample columns: keep the even indexed columns
 $\begin{bmatrix} 1 \downarrow 2 \end{bmatrix}$ Downsample rows: keep the even indexed rows
 $\begin{matrix} rows \\ \boxed{X} \end{matrix}$ Convolve with filter X the rows of the entry
 $\begin{matrix} columns \\ \boxed{X} \end{matrix}$ Convolve with filter X the columns of the entry

Fig. 2 2D single level decomposition step

The `idwt2` command performs a single-level two-dimensional wavelet reconstruction with respect to either a particular wavelet.

$\mathbf{X} = \text{idwt2}(\mathbf{cA}, \mathbf{cH}, \mathbf{cV}, \mathbf{cD}, \text{'wname'})$ uses the wavelet 'wname' to compute the single-level reconstructed approximation Coefficients matrix X, based on approximation matrix cA and details matrices cH, cV, and cD (horizontal, vertical, and diagonal, respectively).

Algorithm:



Where $\begin{bmatrix} 2 \uparrow 1 \end{bmatrix}$ Upsample columns: insert zeros at odd-indexed columns.
 $\begin{bmatrix} 1 \uparrow 2 \end{bmatrix}$ Upsample rows: insert zeros at odd-indexed rows.
 $\begin{matrix} rows \\ \boxed{X} \end{matrix}$ Convolve with filter X the rows of the entry.
 $\begin{matrix} columns \\ \boxed{X} \end{matrix}$ Convolve with filter X the columns of the entry.

Fig. 3 2D single level reconstruction step

Two dimensional multi level discrete wavelet analysis

wavedec2:

Multilevel 2-D wavelet decomposition

$[C,S] = \text{wavedec2}(X,N,\text{'wname'})$

waverec2 is a two-dimensional wavelet analysis function.

$X = \text{waverec2}(C,S,\text{'wname'})$ performs a multilevel wavelet reconstruction of the matrix X based on the wavelet decomposition structure [C,S]

Bayes Shrink thresholding:

BayesShrink was proposed by Chang, Yu and Vetterli. The goal of this method is to minimize the Bayesian risk, and hence its name, BayesShrink. It uses soft thresholding and is subband-dependent, which means that thresholding is done at each band of resolution in the wavelet decomposition. Like the SureShrink procedure, it is smoothness adaptive. Using this threshold, the wavelet coefficients are thresholded at each band[11].

ALGORITHM DESIGN

The algorithm level design provides a descriptive view of the research work on image denoising.

Using daubechies and biorthogonal wavelet

- Step 1: Read any satellite image using the basic matlab command “uigetfile”.
- Step 2: Choice of adding noise: Speckle or salt & pepper
- Step 3: Choice of noise level : (0.2, 0.3, 0.4, 0.5, 0.6, 0.7) or any variance.
- Step 4: Choice of wavelet type: daubechies or biorthogonal
- Step 5: Choice of thresholding: hard or soft thresholding. Firstly, calculate the default parameters using command“ddencmp”. Secondly, calculate the actual denoising parameters using the command “wdencmp”.
- Step 6: Decompose the image with different levels and then calculate its coefficients i.e approximation and detail coefficients (horizontal, vertical, diagonal) using wavelet.
- Step 7: Choice of decomposition level.
- Step 8: Reconstruct the coefficients and store all of them into temporary register.
- Step 9: Calculate the difference between original image and reconstructed image.
- Step 10: Perform the improvement analysis by parameters MSE, RMSE, PSNR and SD.
- Step 11: Plotting of histogram equalization for all of the images using three wavelets haar, daubechies and biorthogonal.

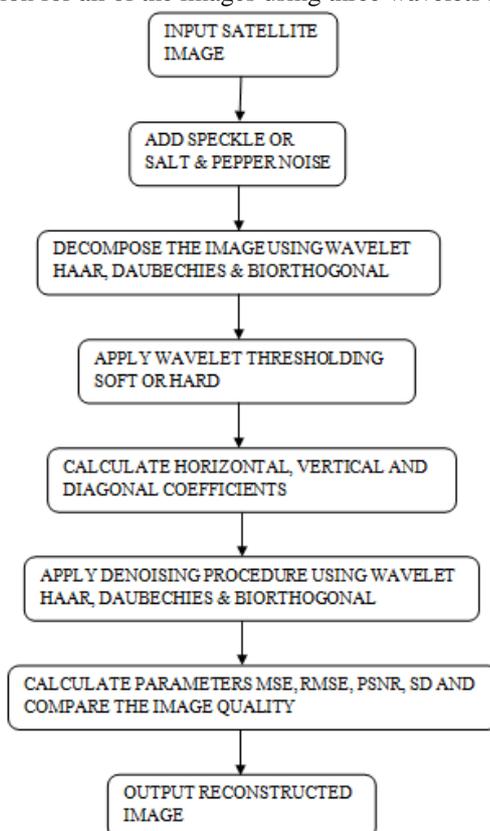


Fig. 4 .Flowchart of image denoising

V. EXPERIMENTAL RESULTS

This table shows the comparison between the three wavelets as shown below. It shows that biorthogonal wavelet is the better in comparison to haar and daubechies on the basis of the parameter PSNR. It is clearly shown from the experimental results that quality of the image is improved by biorthogonal wavelet using various noise levels ranging from (0.02, 0.03, 0.04, 0.05, 0.06, and 0.07).

NOISE	SAR IMAGE											
	HAAR				DAUBECHIES				BIORTHOAGONAL			
	MSE	RMSE	PSNR	SD	MSE	RMSE	PSNR	SD	MSE	RMSE	PSNR	SD
0.02	1.55	1.24	46.23	0.96	0.09	0.3	58.73	0.38	0.09	0.29	58.82	0.37
0.03	1.71	1.31	45.79	1.05	0.09	0.31	58.42	0.38	0.09	0.3	58.54	0.38
0.04	1.85	1.36	45.46	1.12	0.1	0.31	58.2	0.39	0.1	0.31	58.24	0.39
0.05	1.97	1.4	45.19	1.18	0.1	0.32	58.05	0.39	0.1	0.32	58.07	0.39
0.06	2.08	1.44	44.94	1.23	0.1	0.32	57.92	0.39	0.1	0.32	57.94	0.39
0.07	2.19	1.48	44.73	1.27	0.11	0.33	57.81	0.39	0.11	0.33	57.83	0.39

I. Comparison between wavelets on various parameters

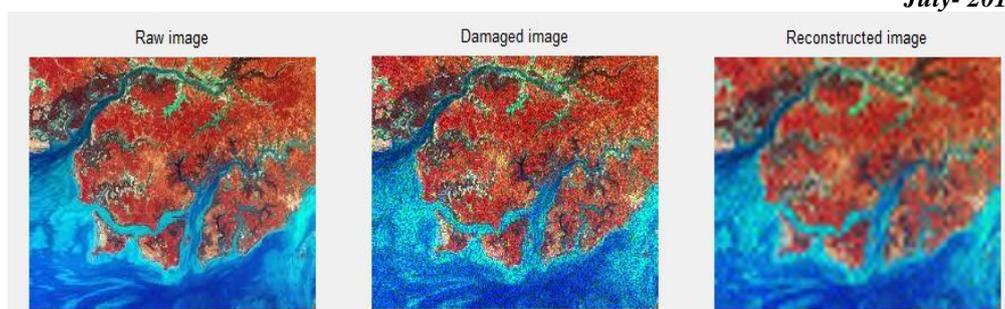


Fig .5 Original Image degraded by speckle noise and reconstructed Image

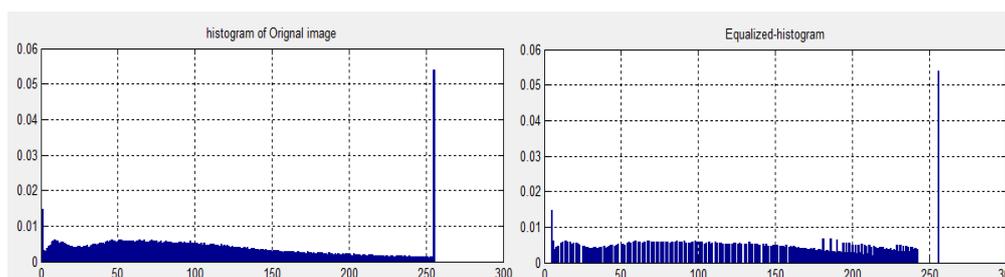


Fig. 6 Graphical representation of Original image and reconstructed image using histogram

VI. CONCLUSION

From the exhaustive experiments, conducted with the developed image denoising software (i) for different noise parameters and (ii) for different levels of DWT decomposition using soft thresholding technique, the following conclusions are derived: (i) The highest PSNR (dB) is obtained for first level of DWT decomposition (SNR1) for most of the Speckle noise added images, (ii) Further, it is observed that the SNR obtained for higher level of DWT decomposition is lesser than SNR1 or SNR2 and for the fourth level of DWT decomposition, severe blurring occurs, irrespective of images and noise parameters and (iii) Moreover, it is interested to note that for images corrupted with lesser noise densities, single level of DWT decomposition is sufficient; while for images corrupted with higher noise densities, second level of DWT decomposition is required, irrespective of images.

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