

De-speckling 2D-Discrete Wavelet Transform with Hard Threshold Stage
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ABSTRACT

In this work, a new method is implemented for removing noise from gray scale image that depends on two-dimensional discrete wavelet transform and Threshold stage (hard threshold). This paper represents the algorithm to remove the speckle noise by using logarithm operation. This operation changes the multiplicative noise to additive noise. So that, the removing operation becomes easier. The Matlab program is used to build the Algorithm and measure the PSNR and other measurement criteria as (NMV, NV, NSD, ENL and PSNR) to study the effect of removing noise from corrupted image. The PSNR reaches to 24dB which is very satisfactory result in the reconstructed image, while the maximum value of ENL is $2.23 * 10^6$, and the minimum value of NMV, NV, NSD which is equal to 6.79, $2.67 * 10^{-5}$, $46 * 10^{-4}$ respectively gives a smoother and cleaner image. The universal Threshold is applied in high frequency coefficient (i.e. the LH, HL, and HH-sub band of image) to remove the speckle noise and the low frequency coefficient (LL-sub band of image) is still without any change.

Keyword: speckle noise, discrete wavelet transform, universal Threshold, logarithmic function.

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المخلص

تم في هذا البحث تطبيق طريقة جديدة لإزالة الضوضاء من الصور الرمادية بالاعتماد على التحويل المويجي المقطع الثنائي الأبعاد وعلى حد العتبة (حد العتبة الصلبة والناعمة). يقدم البحث خوارزمية لإزالة الضوضاء الرقراطية باستخدام العلاقة اللوغارتمية. حيث أن هذه العلاقة تغير الضوضاء الضريبية إلى ضوضاء جمعية وهكذا فإن عملية الإزالة ستصبح أكثر سهولة. وقد تم استخدام برنامج الـ Matlab لبناء الخوارزمية وكذلك لقياس الـ PSNR ومعايير قياسية أخرى (NMV, NV, NSD and ENL) من أجل دراسة تأثير عملية إزالة الضوضاء على الصور المتضررة. إن نسبة الخطأ تصل إلى 24 dB وهي نتيجة مرضية للصورة المسترجعة بينما أعلى قيمة لـ ENL هي $2.23 * 10^6$ وأقل قيمة لـ NMV, NV, NSD والتي تصل إلى $6.79, 2.67 * 10^{-5}$, $46 * 10^{-4}$ على التوالي تعطي صورة أكثر نقاوة وحدة. كما تم تطبيق حد العتبة الأحادي (universal threshold) على معاملات التردد العالي (LH, HL, and HH) من أجل إزالة الضوضاء الرقراطية أما معاملات التردد الواطئ فتبقى بدون تغيير.

الكلمة المفتاحية: ضوضاء رقراطية، تحويل مويجي مقطع، العتبة الاحادي، الدالة اللوغارتمية.

1. Introduction:

The digital images are usually corrupted by noise in its acquisition and transmission, so that, the main objective of image de-noising techniques is removing noises while retaining as much as possible of the important signal features. Recently, many challenges have been made to reduce the speckle noise by using wavelet

transform as a multi-resolution image processing tool. The wavelet de-noising attempts to remove the noise present in the signal while preserving the signal characteristics, regardless of its frequency content. As the discrete wavelet transform (DWT) corresponds to basis decomposition, it provides a non-redundant and unique representation of the signal. In the past, extensive research has been conducted both the fields of medical imaging and remote sensing for suppressing speckle noise and various algorithms. A number of speckle reduction techniques such as adaptive filters [1] and Rotating Kernel Transformation [2] have been adapted specifically for improving image quality of OCT tomograms. Filtering techniques based on the rotating kernel transform which can produce good contrast enhancement of image features, but they also result in significant edge blurring when strong noise reduction is required [3]. Most of the algorithms are limited in the amount of speckle that can be reduced because of their complexity. Filtering techniques are used as preface action before segmentation and classification. The statistical filter like Wiener filter [4] adopted filtering in the spectral domain, but the classical Wiener filter is not adequate while it is designed primarily for additive noise suppression [5]. To address the multiplicative nature of speckle noise, Jain developed a homomorphic approach, which by obtaining the logarithm of the image, translates the multiplicative noise into additive noise, and consequently applies the Wiener. Adaptive filter takes a moving filter window and estimates the statistical information of all pixels' grey value, such as the local mean and the local variance. The central pixel's output value is dependent on the statistical information. Adaptive filters adapt themselves to the local texture information surrounding a central pixel in order to calculate a new pixel value. Adaptive filters generally incorporate the Kuan filter, Lee filter, Frost filter, and median filter [6]. These filters made their superiority obvious measured up to low pass filters, since they have taken into account the local statistical properties of the image. Adaptive filters present much better than low-pass smoothing filters, in preservation of the image sharpness and details while suppressing the speckle noise [7].

In fact, the thresholding technique is the last approach based on wavelet theory to provide an enhanced approach for eliminating such noise source and ensure better gene expression. Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its basic form, each coefficient is thresholded by comparing against threshold, if the coefficient is smaller than threshold, set to zero; otherwise it is kept or modified. Replacing the small noisy coefficients by zero and inverse wavelet transform on the result may lead to reconstruction with the essential signal characteristics and with less noise. Since the work of Prabakar Puvanathan and Kostadinka Bizheva [8], there has been much research on finding thresholds, however few are specifically designed for images [9], and [10].

The paper is organized as follows: In Section 2, the main features of the wavelet decomposition and noise filtering technique are described. In section 3, the wavelet thresholding is explained briefly. The speckled model is displayed in section 4 and the parameter computation for threshold is given in section 5. The procedure of image denoising is illustrated as in the following chart in section 6. Section 7 contains the different objective assessment parameters which are used to evaluate the performance of the proposed de-speckling technique and all the results are calculated in section 8, finally section 9 concludes this paper.

2. Wavelet Domain Noise Filtering:

The two-dimensional Discrete Wavelet Transform (DWT-2D) corresponds to multiresolution approximation expressions. In practice, multiresolution analysis is carried out by using 4 channel filter banks composed of a low-pass and a high-pass filter and each filter bank is then sampled at a half rate (1/2 down sampling) of the previous frequency. By repeating this procedure, it is possible to obtain wavelet transform of any order. The down sampling procedure keeps the scaling parameter constant (equal to 1/2) throughout successive wavelet transforms so that its benefits are for simple computer implementation. In the case of an image, the filtering is implemented in a separable way by filtering the lines and columns. Note that [11] the DWT of an image consists of four frequency channels for each level of decomposition. For example, for i-level of decomposition we have:

- LL n,i: Noisy Coefficients of Approximation.
- LH n,i: Noisy Coefficients of Vertical Detail,
- HL n,i: Noisy Coefficients of Horizontal Detail, and
- HH n,i: Noisy Coefficients of Diagonal Detail.

The LL part at each scale is decomposed recursively, as illustrated in Fig. 1.

Several properties of the wavelet transform, which make this representation attractive for denoising[12], are

- Multiresolution - image details of different sizes are analyzed at the appropriate resolution scales.
- Sparsity - the majority of the wavelet coefficients are small in magnitude.
- Edge detection - large wavelet coefficients coincide with image edges.
- Edge clustering - the edge coefficients within each-sub band tend to form spatially connected clusters.

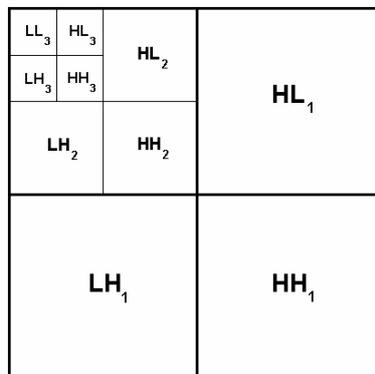


Fig.1 Data Preparation of the Image. Recursive Decomposition of LL parts

3. Wavelet Thresholding:

All the wavelet filters use wavelet thresholding operation for denoising .Speckle noise is a high-frequency component of the image and appears in wavelet coefficients. One widespread method exploited for speckle reduction is wavelet thresholding procedure. The basic procedure for all thresholding method is as follows [12] :

- Calculate the DWT of the image.
- Threshold the wavelet coefficients. (Threshold may be universal or sub band adaptive) .
- Compute the IDWT to get the de-noised image. As shown in Fig. 2.

There are two thresholding functions frequently used, i.e. a hard threshold, a soft threshold.

The hard-thresholding is described as follows [11], [13]:

$$\begin{cases} x-T, & \text{if } x \geq T \\ X+T, & \text{if } x \leq -T \\ 0, & \text{if } |x| < T \end{cases} \quad 103$$

$$Y_T(x) = \dots(1)$$

Where is $Y_T(x)$ a wavelet coefficient, T is the threshold. The hard-thresholding in Fig.3. The soft-thresholding function is described as follows

$$Y_T(x) = \begin{cases} x, & \text{if } |x| > T \\ 0, & \text{if } |x| \leq T \end{cases} \dots(2)$$

The soft-thresholding rule is chosen over hard-thresholding. The soft thresholding can be represented [13] as shown in Fig.4.

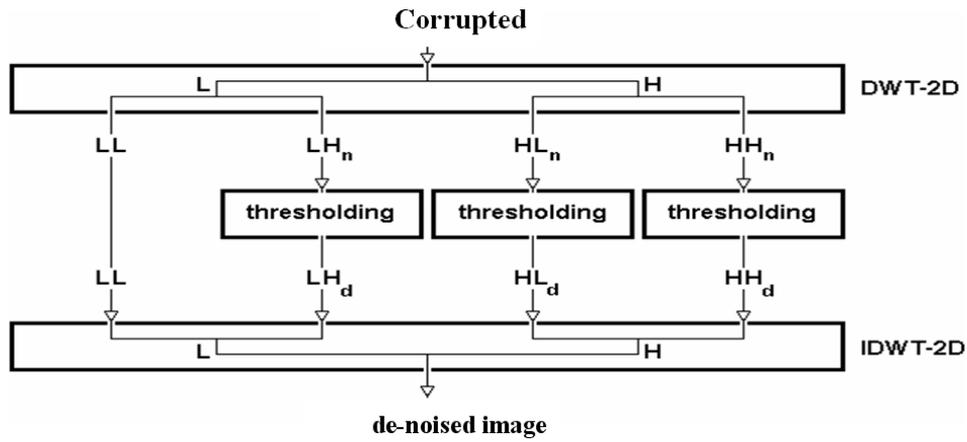


Fig.2 The Proposed Algorithm.

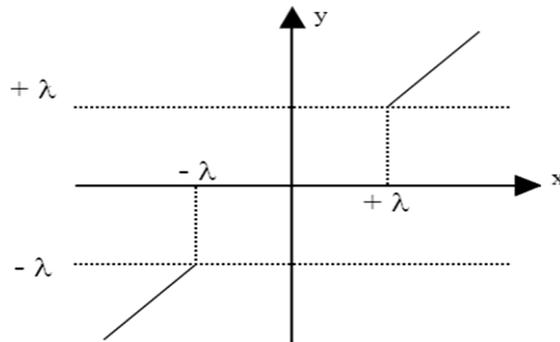


Fig.3 The Hard-thresholding Scheme.

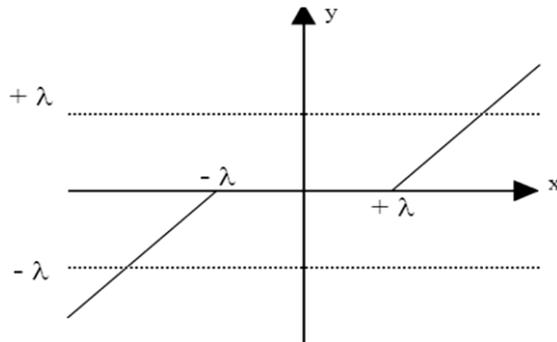


Fig.4 The Soft-thresholding Scheme.

4. Speckle Model :

To explain the mechanism of speckle noise in ultrasound and SAR images, an essential multiplicative/additive compound noise process model is formulized as [14]

$$\text{Image_speckled}(r,c) = \text{Image}(r,c) + \text{Image}(r,c) \times \text{Speckle}(r,c) \quad \dots(3)$$

“r and, c” represent the pixel location. The model in equation (3) can then be reduced to the following multiplicative form:

$$\text{Image_speckled}(r,c) = \text{Image} \times \text{Noise}(r,c) \quad \dots(4)$$

where

$$\text{Noise}(r,c) = 1 + \text{Speckle}(r,c) \quad \dots(5)$$

Applying homomorphic transformation, the log-transform of eq. (4) yields an additive speckle model of the type given by

$$\begin{aligned} \text{Log}[\text{Image_speckled}(r,c)] &= \text{Log}[\text{Image} \times \text{Noise}(r,c)] \\ \text{Log_Image_speckled}(r,c) &= \text{Log_Image}(r,c) + \text{log_Noise}(r,c) \quad \dots(6) \end{aligned}$$

Since the original image detected pixel values can be factorized into two components (luminance and reflectance of the scene) as in the following equation:

$$\text{Image}(r,c) = \text{Luminance}(r,c) \times \text{Reflectance}(r,c) \quad \dots(7)$$

By taking the logarithmic transformation from equation (7), then produces as follows:

$$\text{Log_Image}(r,c) = \text{Log_Luminance}(r,c) + \text{log_Reflectance}(r,c) \quad \dots(8)$$

Thus, eq. (6) can then be rewritten as

$$\begin{aligned} \text{Log_Image_speckled}(r,c) &= \text{Log_Luminance}(r,c) + \text{Log_Relectance}(r,c) \\ &\quad + \text{Log_Noise}(r,c) \quad \dots(9) \end{aligned}$$

which means that each log-transformed pixel in the speckled image consists of three additive components; A low frequency one ($\text{Log_Luminance}(r,c)$) and two high frequency components ($\text{Log_Relectance}(r,c)$ and $\text{Log_Noise}(r,c)$). However, applying any low pass filtering (LPF) on the log-transformed speckled image pixel ($\text{Log_Image_speckled}(r,c)$) can isolate the high frequency noise component ($\text{Log_Noise}(r,c)$), but it will also blur many important signal features due to elimination of high frequency image pixel component ($\text{Log_Relectance}(r,c)$). An alternative way is to use wavelet thresholding in the homomorphic framework. In such a frame, the log-transformed image (i.e. $\text{Log_Image_speckled}(r,c)$) is applied to a 2-D discrete wavelet transform (DWT). Then, by a proper thresholding, the high frequency noise components can approximately be eliminated or even reduced, leaving the high frequency image component together with low frequency to act as inputs to a 2-D inverse discrete wavelet transform (IDWT), forming the final restored image. This technique provides better reductions in the speckle noise as compared with that of the spatial-domain filters.

5. Parameter Computation for Threshold :

In general, a small threshold value will leave behind all the noisy coefficients and subsequently the resultant de-noised image may still being noisy. On the other hand, a large threshold value makes more number of coefficients as zero which directs to smooth the signal that destroys details and the resultant image may cause blur and artifacts. So, optimum threshold value should be found out, which is adaptive to different sub-band characteristics. Thus, the present work consists of the estimating

appropriate threshold by analyzing the statistical parameters of the wavelet coefficients. Our threshold is based on Universal thresholding function. In the original work of Donoho et. al [12], the proposed universal threshold has been derived, as shown in equation (3).

$$\lambda = \sigma_n \sqrt{\text{Log}2N} \quad \dots(10)$$

which depends on the image size (N) and the noise of the standard deviation σ_n . It is easy to implement over smooth the images. This is due to the fact that is based on a Universal threshold and not sub-band adaptive unlike the other schemes. Threshold does not depend on the content of the image; rather it depends on the size of image. Based on this, we proposed our threshold by estimating a parameter weighted variance (λ).

The parameter noise variances (σ_n) needs to be estimated first. It may be possible to measures (σ_n) based on information other than the corrupted image and it is estimated from the sub band high frequencies by the robust median estimator,

$$\sigma_n = \frac{\text{median}(|W_{i,j}|)}{0.6745} \quad \dots(11)$$

which $W_{i,j}$ is a high frequencies coefficients of wavelet decomposition.

6. Image De-noising Procedure:

This section depicts the image-denoising algorithm, which achieves near optimal soft or hard thresholding in the wavelet domain for recovering original signal from the noisy one. The wavelet transform employs Daubechies' least asymmetric compactly supported wavelet with four vanishing moments with four scales of orthogonal decomposition. It has the following steps. As shown in Fig.6.

- Transform the multiplicative noise model into an additive one by taking the logarithm of the original speckled data.
- Perform the DWT of the noisy image up to 2 levels (L=2) to obtain seven sub-bands, which are named as LL1, HH1, LH1, HL1, HH2, LH2, HL2 and LL2.
- Obtain noise variance (σ_n) using equation (11) for each high frequencies sub-bands, i.e. applying equation (11) into HH1, LH1, HL1, HH2, LH2 and HL2.
- Calculate the universal threshold of signal λ depending on equation (10).
- Threshold all high frequencies sub band coefficients(HFSC) using hard thresholding by applying the threshold value obtained depends on Fig.3 as shown in Fig.5.

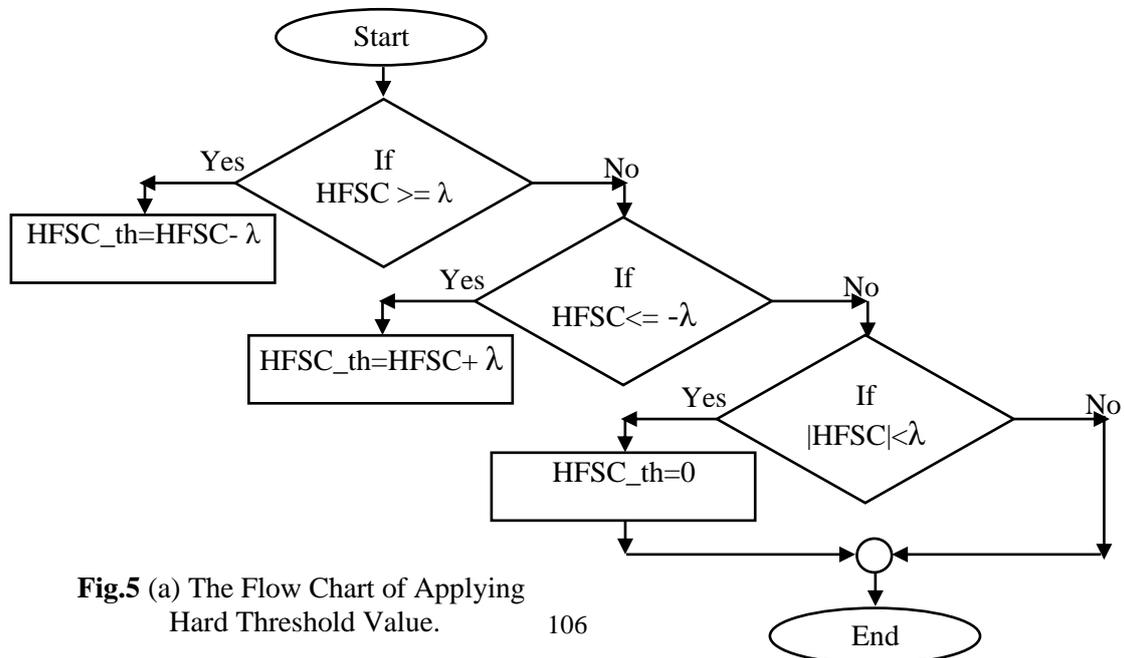


Fig.5 (a) The Flow Chart of Applying Hard Threshold Value.

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if (HFSC >= λ)
    HFSC_th = HFSC - λ;
elseif (HFSC <= -λ)
    HFSC_th = HFSC + λ;
elseif (abs ( HFSC) < λ)
    HFSC_th = 0;

```

Fig.5 (b) the Instructions of Represent Hard Threshold Value.

- Perform the inverse DWT to reconstruct the de-noised image.
- Take Exponent.

7. Performance Evaluation :

The performance of the wavelet thresholding method that has been proposed in this paper is investigated with simulations. Denoising is carried out for Synthetic Aperture Radar (SAR) images with Speckle noise of variance $\sigma_n = 0.02$ using standard wavelet filters and median filter. Different objective assessment parameters are used to evaluate the performance of the proposed de-speckling technique. These parameters are Noise Mean Value (NMV), Noise Variance (NV), Noise Standard Deviation (NSD), and Equivalent Number of Looks (ENL), [4],[5],[10]-[12]. NV determines the contents of the speckle in the image. A lower variance gives a “smoother and cleaner” image as more speckles are removed, although, it is not necessarily to depend on the intensity. The formulas for calculating NMV, NV and NSD are given by the following equations [14] :

$$NMV = \frac{\sum_{r,c} I_d(r,c)}{R * C} \quad \dots(12)$$

$$NV = \frac{\sum_{r,c} [I_d(r,c) - NMV]^2}{R * C}, \quad \dots(13)$$

and

$$NSD = \sqrt{NV} \quad \dots(14)$$

ENL is another good approach of estimating the speckle noise level in an image over a uniform region. Larger 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 produce a higher ENL value than over a smaller region but it is also trade-off the accuracy of the readings [14].

For objective evaluation, the Peak signal to noise ratio (PSNR) of each de-noised image has been calculated by using Peak Signal to Noise Ratio (PSNR), which is defined as [12]:

$$PSNR = 10 \log_{10} \frac{255}{MSE} \quad \dots(15)$$

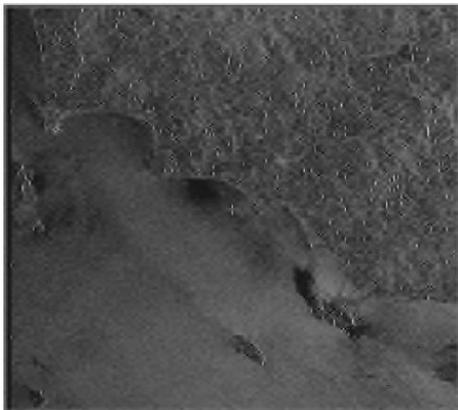
$$MSE = \frac{1}{M * N} \sum_{i=1}^M \sum_{j=1}^N (X(i, j) - Y(i, j))^2 \quad \dots(16)$$

8. Experiment Results :

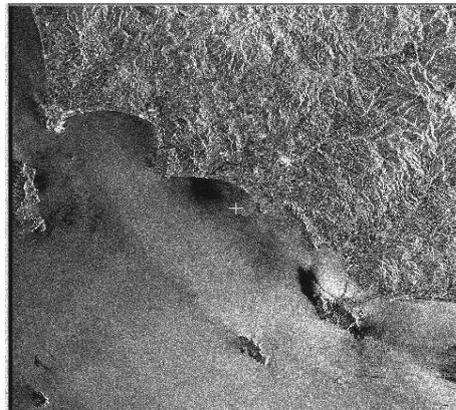
Table 1 shows the objective assessment parameters for different images shown in Fig.7. The quantitative results of Table 1 again highlights the ability of the proposed technique to eliminate speckle, preserving the useful image information, since it has a good NMV preservation and gives the best variance reduction (NSD). The proposed technique also outperforms the others in terms of ENL. Larger ENL value usually corresponds to a better quantitative performance.

Table 1. The Objective Assessment Parameters for SAR Images

Images 256*256	Objective Assessment Parameters				
	PSNR (dB)	NMV	NV	NSD	ENL
Sar_sea	24.136	6.79	2.67*10 ⁻⁵	46*10 ⁻⁴	2.23*10 ⁶
Terrasar_sar	24	6.6499	6.08*10 ⁻⁵	78*10 ⁻⁴	7.27*10 ⁵
Srvr	24.094	7.4066	1.05*10 ⁻⁵	32*10 ⁻⁴	5.2*10 ⁶



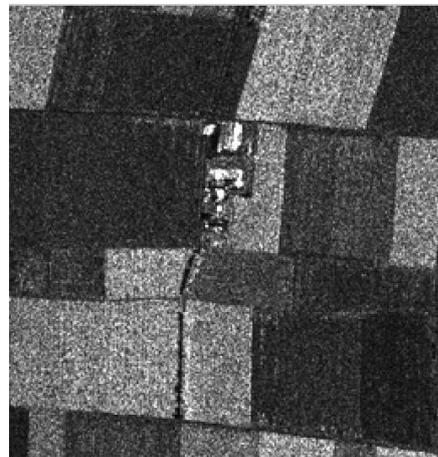
Anti-speckled sar_sea image



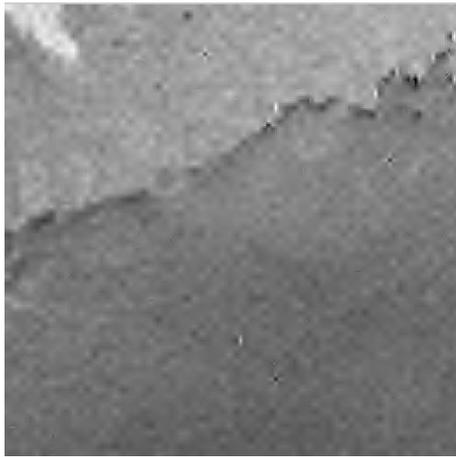
The corrupted sar_sea image



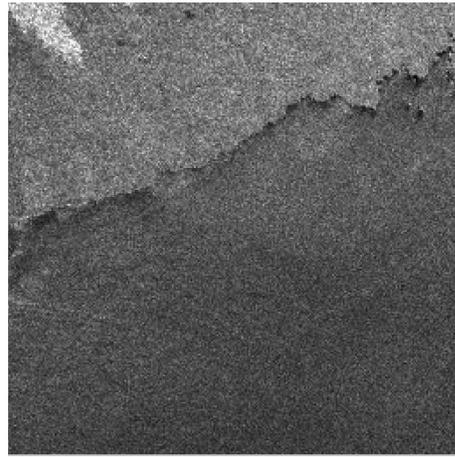
Anti-speckled terrasartxsx-sar image



The corrupted terrasartxsx-sar image



Anti-speckled srvr image



The corrupted srvr image

Fig.7. The Corrupted and the Anti-speckled Images.

9. Conclusion:

In this work, we have introduced a relatively simple method of hard threshold and 2D discrete wavelet transform to remove a speckle noise from different SAR (sar_sea, terrasartxsx-sar and srvr) images. The evaluation of the results supports the conclusion that the proposed method yields significantly to the improved visual quality as well as better PSNR (reach to 24dB). The objective assessment parameters of such technique highlights its superiority, good NMV preservation and best variance reduction (lowest NSD value) show the ability to eliminate the speckle noise. A better quantitative performance is also expected as ENL value is the highest as shown in Table.1.

REFERENCES

- [1] Syed Musharaf Ali, Muhammad Younus Javed, and Naveed Sarfraz Khattak, “Wavelet-Based Despeckling of Synthetic Aperture Radar Images Using Adaptive and Mean Filters”, *World Academy of Science, Engineering and Technology* 31, 2007.
- [2] J. Rogowska and M.E. Brezinski, “Evaluation of the adaptive speckle suppression filter for coronary optical coherence tomography imaging”, *IEEE Trans. Med. Imaging*, 19, 1261–6 (2000).
- [3] D.C. Adler, T.H. Ko, and J.G. Fujimoto, “Speckle reduction in optical coherence tomography images by use of a spatially adaptive wavelet filter”, *Opt. Lett.*, 29, 2878–80 (2004).
- [4] R. Sivakumar, D. Nedumaran, “Comparative study of Speckle Noise Reduction of Ultrasound B-scan Images in Matrix Laboratory Environment”, *International Journal of Computer Applications (0975–8887) Volume 10– No.9, November, 2010.*
- [5] Javier Portilla, Vasily Strela, Martin J. Wainwright and Eero P. Simoncelli, “Adaptive Wiener Denoising using a Gaussian Scale Mixture Model in the wavelet Domain”, *Proceedings of the 8th International Conference of Image Processing Greece. Thessaloniki, 2001.*
- [6] Aliaa A.A. Youssif A.A. Darwish A.M.M. Madbouly, “Adaptive Algorithm for Image Denoising Based on Curvelet Threshold”, *IJCSNS International Journal of Computer Science and Network Security, VOL.10 No.1, January 2010.*
- [7] T. Ratha Jeyalakshmi and K. Ramar, “A Modified Method for Speckle Noise Removal in Ultrasound Medical Images”, *International Journal of Computer and Electrical Engineering, Vol. 2, No. 1, February, 2010, 1793-8163.*
- [8] Prabakar Puvanathan and Kostadinka Bizheva, “Speckle reduction algorithm for optical coherence tomography based on Interval Type II Fuzzy Set”, *Coherence Domain Optical Methods and Optical Coherence Tomography in Biomedicine XI (BO111) BIOS 2008.*
- [9] K. Thangavel, R. Manavalan, I. Laurence Aroquiaraj, “Removal of Speckle Noise from Ultrasound Medical Image based on Special Filters: Comparative Study”, *ICGST-GVIP Journal, ISSN 1687-398X, Volume (9), Issue (III), June 2009.*
- [10] S.G. Chang, B. Yu, and M. Vetterli, “Adaptive wavelet thresholding for image denoising and compression”, *IEEE Transactions on Image Processing*, vol. 9, no. 9, pp.1532-1546, September 2000.
- [11] Mario Mastroiani, “Systholic Boolean Orthonormalizer Network in Wavelet Domain for Microarray Denoising”, *International Journal of Signal Processing Volume 2 Number 4, 2005.*
- [12] S. Sudha, G.R. Suresh and R. Sukanesh, “Speckle Noise Reduction in Ultrasound Images by Wavelet Thresholding based on Weighted Variance”, *International Journal of Computer Theory and Engineering, Vol. 1, No. 1, April 2009, 1793- 8201.*

- [13] A.i Pizurica, Bartomeu Coll and J.M. Morel, “On Image De-noising Methods”, Centre de Mathematiques et de Leurs Application, CNRS et Ecole Normale Superieure de Cachan , N. 2004-15.
- [14] M. Mastriani, “New Wavelet-Based Super resolution Algorithm for Speckle reduction in SAR Images”, International Journal of computer science, Vol.1, No.4, pp.291-298, 2007.