WAVELET DENOISING WITH EDGE DETECTION FOR SPECKLE REDUCTION IN SAR IMAGES

M. Rosa-Zurera, A.M. Móbreces-Álvarez, J.C. Nieto-Borge, M.P. Jarabo-Amores, and D. Mata-Moya

Departamento de Teoría de la Señal y Comunicaciones, Escuela Politécnica Superior, Universidad de Alcalá
Ctra. Madrid-Barcelona, km. 33.600 28805, Alcalá de Henares - Madrid (SPAIN)
email: manuel.rosa@uah.es

ABSTRACT

One of the main problems to resolve in synthetic aperture radar (SAR) images processing is the reduction of speckle noise. This papers describes a method of speckle denoising and enhacement of SAR images in the wavelet domain. Specifically, we apply an edge detection on SAR images in conjunction with soft thresholding method.

One of the principal objectives in a denoising technique is to verify if noise can be smoothed and at the same time maintain sharp edges and shapes. Experimental results over heterogeneous SAR images show that this proposed algorithm is a suitable tecnique for this objective and allow us to improve classification and detection performance for SAR based recognition.

1. INTRODUCTION

A synthetic aperture radar (SAR), is a coherent radar system that generates high resolution remote sensing imagery, using a synthetic antenna installed aboard aircraft or spacecraft.

Unlike conventional radar, SAR uses the platform movement to obtain a larger synthetic antenna, with finer azimuth resolution than the real antenna. During the data acquisition process, the target is illuminated by the antenna beam from different positions along its trajectory, resulting a relatively long synthetic aperture, which yields finer resolution than is possible from a smaller physical antenna. High-resolution synthetic aperture radar is a very effective terrain and sea surface mapping tool.

1.1 Speckle noise

An important feature that degrades SAR images quality is speckle noise, which is due to the coherent nature of the sensor and the signal processing. The total phasor measured by the receiver is the sum of contributions of many elementary scatterers. Statistically, speckle can be regarded as a random walk process as studied Goodman [1].

Applying speckle reduction tecniques is essential before procedures such as automatic target detection and recognition. In the past two decades, many speckle reduction techniques have been developed for removing speckle and retaining edge details in Synthetic Aperture Radar (SAR) images. However, it is still an unresolved probem. Basically, speckle reduction methods fall into two categories: multi-look integration and post-image techniques. Adaptive filtering techniques including Median filter, Lee filter [2] and Kuan filter [3] are among the better denoising post-image algorithms in radar community. Most of them use a defined filter window to estimate the local noise variance of a speckle image and perform the individual unique filtering process. The result is generally a greatly reduced speckle level in areas that are homogeneous, but the image is either over smoothed due to losses in details and edges in heterogeneous areas.

In recent years, wavelet-based denoising algorithm has been studied and applied successfully for speckle removal in SAR images [4, 5]. These methods realize a shrinkage on wavelet coefficients of the SAR image, after a preprocesing etage consisting of a logarithmic transformation. Denoising using wavelet-based algorithm is also known to be more computational efficient than standard speckle filters.

The primary goal of speckle reduction is to remove the speckle without losing much detail contained in an image. To achieve this goal, we will study the application of Donoho and Johnstone's wavelet shrinkage denoising techniques [6] in combination with an edge detector in order to preserve edges and small details in the SAR images.

1.2 Wavelet transform

The wavelet transform descomposes a signal onto a set of basis functions called wavelets, obtained from a single prototype wavelet by dilations and contractions (scalings) as well as shifts.

The wavelet analysis is well localized in time and in frequency, allowing a better representation for non-stationary signals, such as SAR images. The wavelet transform provides an alternative to the clasical Short-Time Fourier Transform, because in contrast to the STFT, which uses a single analysis window, the wavelet transform uses short windows at high frequencies and long windows for low frequencies.

Mallat [7] proposes a multiresolution signal decomposition, implemented by iterating the single stage filter bank shown in Fig 1, where g(k) and h(k) stand for low-pass and high-pass filter, respectively.

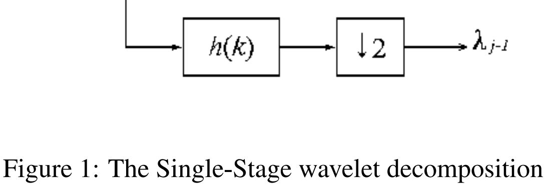

Figure 1: The Single-Stage wavelet decomposition

1.2.1 *Wavelet transform in images*

Multiresolution representations are very effective for analizing the information content [illegible] the information into a set of details appearing at different resolutions.

In order to apply wavelet decomposition to two-dimensional signals as images, separably wavelets can be used, so that the solution corresponds to a separable two-dimensional filter bank with subsampling by 2 in each dimension. At each level of decomposition, four images are obtained: an approximation and three detail images corresponding to vertical, horizontal and diagonal details as is shown in Fig. 2. The energy of the image is concentrated in the approximation coefficients, while detail coefficients have values near to cero.

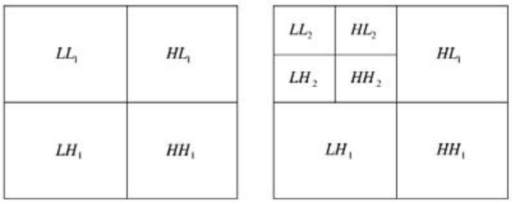

Figure 2: Two-dimensional Wavelet decomposition.

2. WAVELET COEFFICIENT SHRINKAGE

This methods are based on the principle that the noise will dominate the wavelet coefficients at finer scales and only few large coefficients will represent the relevant information of the image. Thus, thresholding the noisy wavelet coefficients should remove most of the noise and preserve large coefficients.

The denoising is done only on the detail wavelet coefficients of LH, HL, and HH, which capture the horizontal, vertical and diagonal features in the images, respectively.

2.1 Noise model and preprocessing stage

In an image contamined with aditive Gaussian noise the basic model for each pixel is as follows:

$$s(x,y) = f(x,y) + \sigma \cdot e(x,y) \tag{1}$$

where f(x,y) is the unoised image, σ is the noise level and e(x,y) is N(0,1) noise.

As speckle noise is propotional to the received signal it is generally modeled as a multiplicative noise:

$$s = f \cdot e \tag{2}$$

where f is the desired texture information and e is the multiplicative noise. Logarithmic transformation of a SAR image converts the multiplicative noise model to an additive noise model:

$$ln(s) = ln(f) + ln(e) \tag{3}$$

Our goal is to extract f and reduce the noise e. We will first apply a logarithmic transformation to the image data, and, after the denoising technique, the corresponding exponential transformation will be done.

2.2 Denoising technique

The denoising techique is based on the three following major steps:

1. Decomposition: First, we perform the wavelet decomposition. We thus obtain at each decomposition level the wavelet coefficients associated with the vertical, horizontal and diagonal details. The level is selected depending on the image as a compromise between the information to preserve and the noise reduction.

2. Threshold t selection and soft thresholding: For each decomposition level (1 to N) and for each detail subband, a threshold t is selected.
   This papers focus on soft-thresholding technique which consists in putting to zero all detail wavelet coefficients of amplitude smaller than t, reducing the amplitude of the other coefficients by the quantity t:

$$f(x) = \begin{cases} x - t & \text{if } x > t \\ 0 & \text{if } |x| \leq t \\ x + t & \text{if } x < -t \end{cases} \tag{4}$$

3. Reconstruction: After the wavelet coefficient shrinkage, the wavelet reconstruction is performed with the aproximation coefficients at level N and the modified detail coefficients from level 1 to N.

3. EDGE DETECTION IN THE WAVELET DOMAIN

One of the desired features of the speckle filters is to preserve the edges. That is, the sharpness and the position of an edge should be maintained after filtering. Wavelet shrinkage denoising scheme tends to kill too many wavelet coefficients that might contain useful image information. Therefore, we apply an edge detector to clasify pixeles in the detail images of each subspaces as edges coefficients or non-edges coefficients, so thay only the amplitude of non-edge coefficients will be shrunk by using a soft thresholding scheme.

The approach attempts to look for the neighborhood area of a coefficient, in the detail images of the wavelet decomposition, using a 3x3 moving window as is shown in Fig. 3, and considering spatial relationship on the coefficients belonging to an edge. The reason is that a wavelet coefficient representing an edge will probably have wavelet coefficients of similar amplitude representing the same edge at its neighbours.

For this goal, the absolute local average of the coefficients in the moving window is calculated. Suppose $d_{(i,j)}$ is wavelet coefficients of the detail subbands at (i,j) coordinate and consider a neighbouring window $W_{(i,j)}$ around it. The local average value is then calculated:

$$A = \frac{1}{N-1} \sum_{(k,l) \in W_{(i,j)}} |d_{(k,l)}| \tag{5}$$

If the absolute value of the central pixel, is similar to the local average A, this will result to an unchanged coefficient. However, a value distant from the local average is identified as an isolated or non-edge c [illegible] le by the sotf thresholding function 4. The criterion used to identify an non-edge coefficient is the following:

$$A \cdot \lambda < |d_{(i,j)}| < A \cdot \gamma \qquad (6)$$

where A is the local average of the coefficients in the moving window, $d_{(i,j)}$ is the center coefficient of the window and λ and γ are two adjustable parameters. In this paper, the values used are: $\lambda = 1.7$, $\gamma = 0.7$.

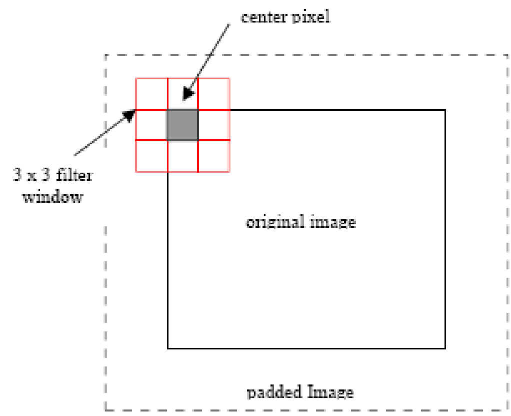

Figure 3: Window analysis for edge detection

4. RESULTS

The algorithm explained before was applied over some heterogeneous SAR images to evaluate the efficiency of the proposed method. In this paper we consider two images shown in Figs. 4 and 5.

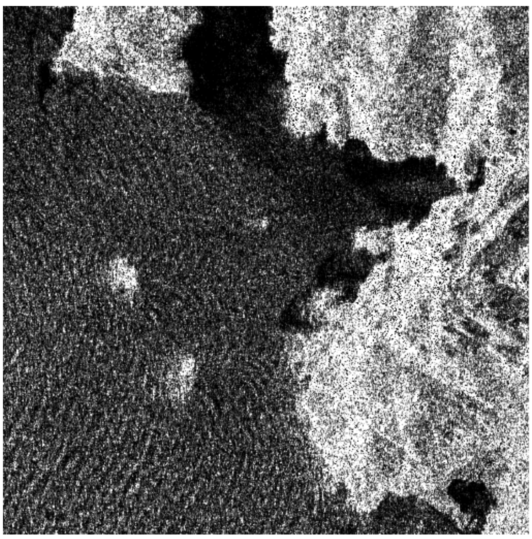

Figure 4: Original SAR image

Fig. 4 is an Envisat's ASAR (from ESA) image of the Spanish Coast, acquired in November 2002 to study the stricken Prestige tanker disaster. Two homogeneous areas, sea and land, with different speckle parameters (radar cross section from land is larger than from sea) are well different. Coastline is also very irregular. An efficient

Figure 5: Original SAR image

despeckling method must preserve these irregular edges, for future detection and classification tasks. Other details like the wave field shown in the sea should also be maintained.

Some of the parameters used are:

- The analysis was performed with the db4 wavelet.
- Up to 5 levels of decomposition were applied.
- The threshold $\boldsymbol{t}$ used for the soft thresholding method is known as universal threshold and it is given by:

$$t = \sigma\sqrt{2ln(M)} \qquad (7)$$

  where σ is the square root of the local noise variance in each subband of a speckle image after decomposition. The estimated local noise variance is usually obtained by averaging the squares of the wavelet coefficients or it is set to one. M is the block size in the wavelet domain.

The processed images are shown in Fig.6 and Fig.7. We observe a significant speckle reduction in the homogeneous areas of the SAR images, while the edges and small details are considerably well preserved.

On the other hand, figures 8 and 9 show the results of processing the same images with only the soft-thresholding method, without applying the proposed method for edge detection in the wavelet domain. As expected, the details of the images have been smoothed and appear less well-defined than in the images obtained with the proposed method. For example, you can observe the wave field in the sea area of both images. The waves are not defined in the image obtained without applying the proposed edge detection method.

4.1 Quantitative quality measures

In this paper, the assessment parameters that are used to evaluate the performance of speckle reduction are Noise Variance, Mean Square Error and Equivalent Number of Looks. These all statistical measurements are performed over some homogeneous areas of the SAR image.

- Noise Variance (NV): Noise variance determines the contents of the speckle in the image. A lower variance gives a *cleaner* image.

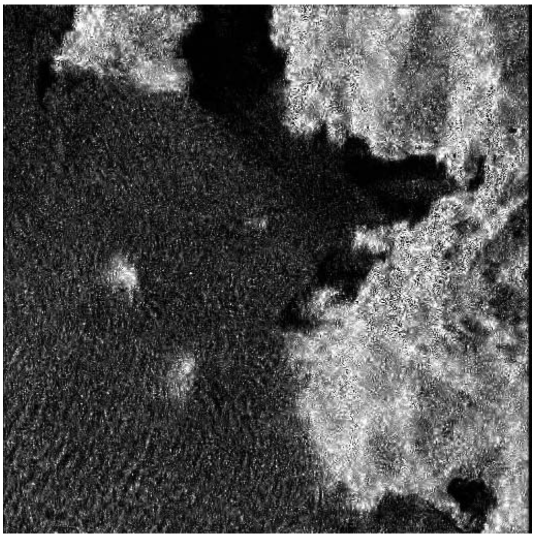

Figure 6: Processed SAR image with the proposed method, 4 levels of decomposition

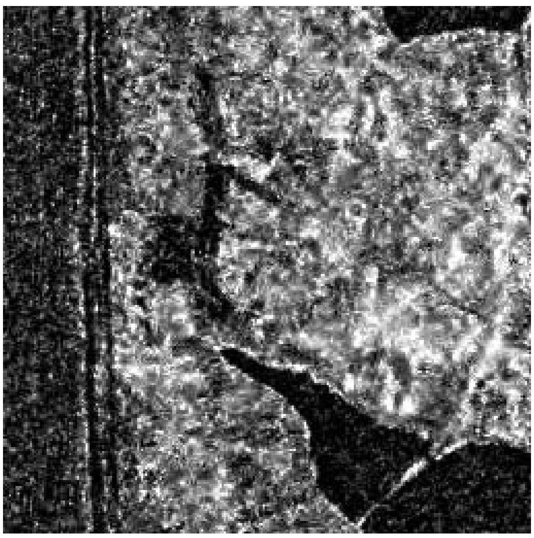

Figure 7: Processed SAR image with the proposed method, 2 levels of decomposition

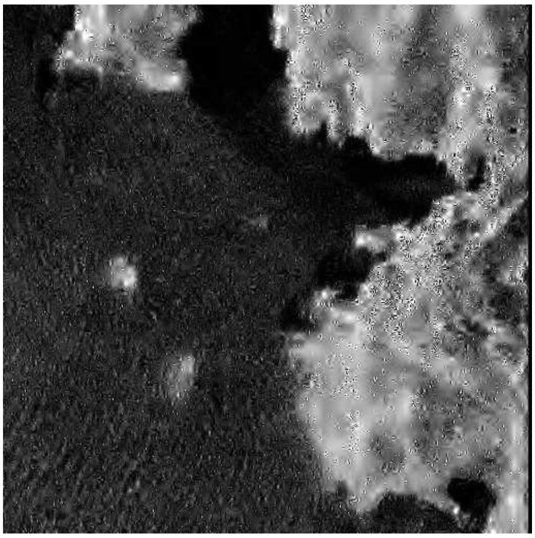

Figure 8: Processed SAR image with sotf-thresholding method, 4 levels of decomposition

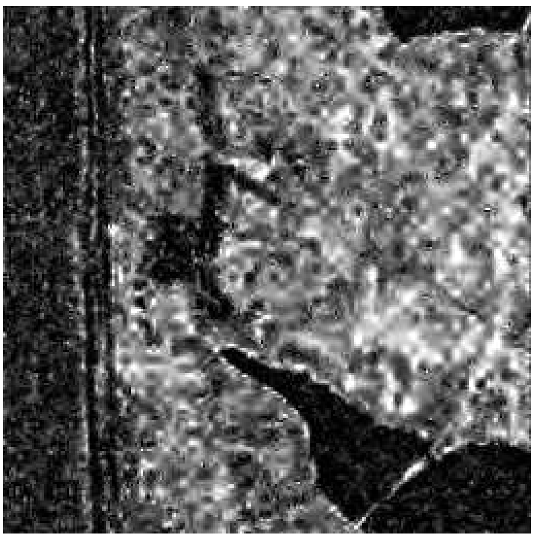

Figure 9: Processed SAR image with soft-thresholding method, 2 levels of decomposition

	NV	MSE	ENL
Original Image Fig.4	0.7335	-	1.3634
Processed image N=1	0.71246	0.3997	1.4036
Processed image N=2	0.5916	0.41321	1.6904
Processed image N=3	0.5264	0.3962	1.8999
Processed image N=4	0.5102	0.3908	1.9604
Processed image N=5	0.5102	0.38924	1.9588

Table 1: Quantitative quality measures for a sea homogeneous area

	NV	MSE	ENL
Original Image Fig.4	0.2659	-	3.7614
Processed image N=1	0.2336	0.1268	4.2814
Processed image N=2	0.2033	0.1467	4.918
Processed image N=3	0.1880	0.1509	5.3171
Processed image N=4	0.1794	0.1525	5.5742
Processed image N=5	0.17661	0.1538	5.6622

Table 2: Quantitative quality measures for a land homogeneous area

- Mean Square Error (MSE): MSE indicates average error of the pixels throughout the image. In this aplication it refers to a greater difference between the original and denoised image.
- 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 results of the proposed technique with different parameters are discussed in this subsection. The following tables show the influence of the level of decomposition in the results. The measurements were performed over homogeneous areas from sea and land textures of the Fig.4.

As shown in the Tables 1 and 2, an increase in the number of decomposition levels will contribute to a greater reduction of speckle. The images, however, will suffer degradation as the removal of more noisy coefficients causes over smoothing. Therefore, a compromise solution has to be found between the information to preserve and the noise reduction.

5. CONCLUSION

In this paper, we study SAR image despeckling by incorporating an edge detector to the well known wavelet shrinkage method. We can learn from the experimental results that our proposed algorithm can retain more edge information, showing a reliable speckle reduction and preservation of edges and detail information.

Edge preservation is fundamental in many applications. Unfortunately, traditional algorithms for speckle noise reduction usually give rise to over smoothed images due to losses in details and edges in heterogeneous areas. The proposed algorithm tries to avoid this problem.

Another important result is the fact that an increase in the number of decomposition levels will contribute to a greater reduction of speckle, but with an increase in the smoothing of the image. So, there is a trade-off between speckle reduction and smoothing when despeckling algorithms are applied in the wavelet domain. Finally, we present an algorithm which combines soft-thresholding and edge detection in the wavelet domain for speckle noise reduction maintaining the main details of the image.

6. ACKNOWLEDGMENT

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