Speckle Reduction Based on Directional Smoothing of Wavelet Coefficients and De-blurring

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Abstract: This paper represents a two-step approach to improve de-speckling in SAR images. Firstly, Smoothing of the coefficients of the highest wavelet sub-bands is applied on decomposed wavelet coefficients. A Gaussian low pass filter using a tours algorithm has been used to decompose the image. Then, the learning of a Kohonen self organizing map (SOM) is performed directly on the de-noised image to take out the blur. Traditional speckle reduction approaches cause artificial structures, blurred and smoothed image, although intelligent de-blurring technique captured these problems. Quantitative and qualitative comparisons of the results obtained by the new method with the results achieved from the other speckle noise reduction techniques demonstrate its higher performance for speckle reduction in SAR images.

Key words: Directional smoothing, de-blurring, de-noising, wavelets.

INTRODUCTION

In many practical situations, a recorded image presents a noisy and blurred version of an original scene. The image degradation process can be adequately modeled by a linear blur and an additive noise process. Then the degradation model is described by [Tan 01]

\[ g = Df + n \]  

(1)

However, for multiplicative noise, which generally it is called speckle, we propose the follow degradation model

\[ g = Df \cdot s \]  

(2)

Where the vectors \( g, f, n \) and \( s \) represent, respectively, the lexicographically (raster scan) ordered noisy blurred image, the original image, the additive noise, and the multiplicative noise (speckle). The matrix \( D \) is the linear degradation process, and the operator “\( \cdot \)” means element-by-element multiplication. The image de-blurring problem calls for obtaining an estimate of \( f \) given \( g \) and \( D \). For the blind restoration problem, \( D \) is not known [Guo 94].

Speckle noise in SAR images is usually modeled as a purely multiplicative noise process of the form [Don 95]

\[ I_s(r,c) = I(r,c)S(r,c) \]

\[ = I(r,c)[1 + S'(r,c)] \]

\[ = I(r,c) + N(r,c) \]  

(3)

The true radiometric values of the image are represented by \( I \), and the values measured by the radar instrument are represented by \( I_s \). The speckle noise is represented by \( S \). The parameters \( r \) and \( c \) means row and column of the respective pixel of the image. If \( S'(r,c)=S(r,c)-1 \) and \( N(r,c)=I(r,c)S'(r,c) \), we begin with a multiplicative speckle \( S \) and finish with an additive speckle \( N \) [Cha 00], which avoid the log-transform, because the mean of log transformed speckle noise is not equal to zero [Zha 01] and thus requires correction to avoid extra distortion in the restored image.

For single-look SAR images, \( S \) is Raleigh distributed (for amplitude images) or negative exponentially distributed (for intensity images) with a mean of 1. For multi-look SAR images with independent looks, \( S \) has a gamma distribution with a mean of 1. Further details on this noise model are given in [4].

A large number of techniques exist for the de-noising [Arg 02] [Xie 02] [Goo 76] and the de-blurring problems [Sen 02a] [Sen 02b] [Sen 02c]. The image restoration problem is an ill-posed problem.
Therefore, a common ingredient in all restoration approaches is that prior information is used in order to restrict the number of possible solutions (basic idea of regularization). Such prior knowledge can be stochastic (i.e., the original image is a sample of a random field) or deterministic (the high frequency energy of the restored image is bounded) in nature [Fie 87]. Regularization theory is also applied to the blind restoration problem [Sim 97].

In this paper, an original approach is developed toward both the de-noising and the de-blurring problems. Such a (nontraditional) approach for de-noising is based on the work of Mastriani and Giraldez [Mas 06]. They directly apply the Directional Smoothing (DS) filter [Mas 04] in the Bidimensional Discrete Wavelet Transform (DWT-2D) domain to reduce the presence of speckles, because the edges will be protected from blurring while smoothing. While, in order to face blur generated for the de-speckling process, the learning of a Kohonen self-organizing map (SOM) is performed directly on the de-speckled image [Koh 95]. The proposed algorithms differ from the reported results in the literature. Kohonen SOM, for example, is designed from a different point of view than is previously reported in the literature. In the proposed approach, each image to be used for the de-blurring problem contains both the low frequency information of the degraded image (the one which is represented by the degraded edges generated for the de-speckling process) and the corresponding high frequency information of the original image.

1. Directional Smoothing of Coefficients in Wavelet Domain (SmoothShrink)

Since Sveinsson et al. [Sve 96] directly apply the Enhanced-Lee filter in the Bi-dimensional Discrete Wavelet Transform (DWT-2D) domain to reduce the presence of speckles. We use the DS [Mas 04], because the edges will be protected from blurring while smoothing. The experimental results demonstrate that DS is better than Enhanced-Lee filter in all the carried out experiments. Therefore, we begin decomposing the speckled SAR image into four wavelet subbands: Coefficients of Approximation (CA), and speckled coefficients of Diagonal Detail (CDDs), Vertical Detail (CVDs), and Horizontal Detail (CHDs), respectively. We apply DS within each high subband, and reconstruct a SAR image from the modified wavelet coefficients, that is to say, despeckled coefficients of Diagonal Detail (CDDd), Vertical Detail (CVDd), and Horizontal Detail (CHDd), respectively, as shown in Figure 1, where: IDWT-2D is the inverse of DWT-2D. Based on Equation (1) SmoothShrink does not need log-transform [Str 00].

1.1. Theory of Directional Smoothing

To protect the edges from blurring while smoothing, a directional averaging filter must be applied. Spatial averages \( d(r,c:Θ) \) are calculated in several directions as

\[
d(r,c:Θ) = \frac{1}{N_{Θ}} \sum_{k,l} \sum x(r-k,c-l)
\]

(4)

And a direction \( Θ^* \) is found such that \( |x(r,c)-d(r,c:Θ^*)| \) is minimum, where \( x \) is the respective detail sub-band. Then

\[
d(r,c) = d(r,c:Θ^*)
\]

(5)

Gives the desired result for the suitably chosen window \( W; N_Θ \) is the number of directions, and \( k \) and \( l \) depends on the size of such windows (kernel) [Mas 05].

Figure 1. Smoothing of Coefficients in wavelet domain (SmoothShrink).

The DS filter has a speckle reduction approach that performs spatial filtering in a square-moving window defined as kernel, and is based on the statistical relationship between the central pixel and its surrounding pixels as shown in Figure 2.

Figure 2. 3-by-3 filter window on a sub-band (CHD, CVD, and CDD)

The size of the filter window can range from 3-by-3 to 33-by-33, with an odd number of cells in both
directions. A larger filter window means that a larger area of the image will be used for calculation and requires more computation time depending on the complexity of the filter’s algorithm. If the size of filter window is too large, the important details will be lost due to over smoothing. On the other hand, if the size of the filter window is too small, speckle reduction may not be very effective. In practice, a 3-by-3 or a 7-by-7 filter window usually yields good results in the cases under study [Yu 02].

DS performs the filtering based on either local statistical data given in the filter window to determine the noise variance within the filter window, or estimating the local noise variance using the effective equivalent number of looks (ENL) of the image under study. The estimated noise variance is then used to determine the amount of smoothing needed for each sub-image. The noise variance obtained from the local filter window is more applicable if the backscatter of an area is constant (flat and homogeneous) [Foi 07].

Most simple nonlinear thresholding rules for wavelet based de-noising assume that the wavelet coefficients are independent [Mas 04] [Yu 02] [Mas 04]. However, wavelet coefficients of natural images have significant dependencies. In this paper, we will consider the dependencies between the coefficients and their neighbors in detail. The Smooth Shrink do not assume the independence of wavelet coefficients, because, It is based on the DS algorithm, which keeps in mind the incidence of the neighboring elements by

\[ \| x - w^{(i)} \| = \min_{j} \| x - w_{ij}^{(k)} \| \] (6)

All the neurons within a certain neighborhood around the leader participate in the weight-update process. Considering random initial values for \( w_{ij}^{(0)} \), \( i (0 \leq i \leq n) \), this learning process can be described by the following iterative procedure:

\[ w_{ij}^{(k+1)} = w_{ij}^{(k)} + H_{ij}^{(k)} (x_{ij} - w_{ij}^{(k)}) \] (7)

The lateral interactions among topographically close elements are modeled by the application of a neighborhood function or a smoothing Kernel defined over the winning neuron [Foi 07]. This Kernel can be written in terms of the Gaussian function

\[ H_{ij}^{(k)} = \alpha(k) \exp(-d(i,i) / \sigma^{2}) \] (8)

Where \( d(l, i) = ||l - i|| \) is the distance between the node \( l \) and \( i \) in the array \( a^{(b)}(t) \) is the learning-rate factor and \( \sigma^{(k)} \) defines the width of the Kernel at the iteration \( k \). For the convergence, it is necessary that \( H_{ij}^{(k)} \rightarrow 0 \) when \( k \rightarrow T \), where \( T \) is the total number of step of the process [21]. Therefore, for the first step, \( \alpha^{(0)} \) should start with a value that is close to unity, thereafter decrease-sing monotonically [21]. To achieve this task, we use

\[ \alpha^{(k)} = \alpha^{(0)} (1 - \frac{k}{T}) \] (9)

Moreover, as learning proceeds, the size of the Neighborhood should be diminished until it encompasses only a single unit. So, we applied for the width of the Kernel the monotonically decreasing function:

\[ \sigma^{(k)} = \sigma^{(0)} \frac{\sigma^{(T-k)}}{\sigma^{(T-k)}} \] (10)

The ordering of the map occurs during the first steps, while the remaining steps are only needed for the fine adjustment of the weight values.

The learning process is performed directly on the real image to be de-blurred. An input vector is filled with the grey levels of the pixels of the image (see Figure 3). Therefore, each neuron has rows-by-columns weights allowing locating it in the input space. At each step, the weights are modified according to Equation (7). Experiments have shown that this training strategy provides as good results as an ordered image scanning process while spending less processing time.

The de-blurring task consists in using the Equation (7) over the image. For each iteration, the corresponding input vector \( x \) is compared with all the

\[ \| x - w_{ij}^{(k)} \| = \min_{j} \| x - w_{ij}^{(k)} \| \] (6)

Owing to its self-organizing properties, the SOM is able to reduce the representation space. Such a reduction of the representation space is the result of the neighborhood function or a smoothing Kernel defined over the winning neuron [Foi 07]. This Kernel can be written in terms of the Gaussian function

\[ H_{ij}^{(k)} = \alpha(k) \exp(-d(i,i) / \sigma^{2}) \] (8)

Where \( d(l, i) = ||l - i|| \) is the distance between the node \( l \) and \( i \) in the array \( a^{(b)}(t) \) is the learning-rate factor and \( \sigma^{(k)} \) defines the width of the Kernel at the iteration \( k \). For the convergence, it is necessary that \( H_{ij}^{(k)} \rightarrow 0 \) when \( k \rightarrow T \), where \( T \) is the total number of step of the process [21]. Therefore, for the first step, \( \alpha^{(0)} \) should start with a value that is close to unity, thereafter decrease-sing monotonically [21]. To achieve this task, we use

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neurons using Equation (6). The winning neuron, the one which leads to the smallest distance, gives the class of the winner pixel in which iteration. However, before any de-blurring task, we have to calibrate the map in order to associate the label mean or edges to each neuron.

Assuming that the input vector $x_0 = (0,\ldots,0)^t$ should represent an image setting on an identical mean value, it is very useful to define the distance graph representing the Euclidean distance in the rows-by-columns-dimensional space between the point $x_0$ and all the neurons. Such a graph is given in Figure 3 and Figure 4 respectively before and after learning for a 512-by-512-neuron network.

![Figure 3. The distance graph between the 100 neurons of the SOM before learning.](image)

![Figure 4. The distance graph between neurons obtained after learning.](image)

Both figures show that the maximal distance between two successive cells is smaller after learning than before. We show only 100 of 512x512 neurons around the winner. We can deduce that, after learning, neurons that are topologically close in the array are close in the input space too. As a matter of fact, neurons that are physical neighbors should respond to a similar input vectors [Koh 95].

3. Assessment Parameters

In this work, the assessment parameters that are used to evaluate the performance of speckle reduction are Noise Variance, Mean Square Difference, Noise Mean Value, Noise Standard Deviation, Equivalent Number of Looks, Deflection Ratio, and Pratt’s figure of Merit [Mas 06] [Mas 05] [Foi 07].

3.1. Noise Mean Value (NMV), Noise Variance (NV), and Noise Standard Deviation (NSD)

NV determines the contents of the speckle in the image. A lower variance gives a “cleaner” image as more speckle is reduced, although, it not necessarily depends on the intensity. The formulas for the NMV, NV and NSD calculation are

\[ \text{NMV} = \frac{1}{R \times C} \sum_{r=0}^{R-1} \sum_{c=0}^{C-1} I_d(r,c) \]

\[ \text{NV} = \frac{1}{R \times C} \sum_{r=0}^{R-1} \sum_{c=0}^{C-1} (I_d(r,c) - \text{NMV})^2 \]

\[ \text{NSD} = \sqrt{\text{NV}} \]

Where $R$-by-$C$ pixels is the size of the de-speckled image ($I_d$). On the other hand, the estimated noise variance is used to determine the amount of smoothing needed for each case for all filters [Mas 04].

3.2 Mean Square Difference (MSD)

MSD indicates average difference of the pixels throughout the image where $I_d$ is the de-noised image, and $I_s$ is the original image (with speckle), (see Figure 3). A lower MSD indicates a smaller difference between the original (with speckle) and de-noised image. This means that there is a significant filter performance. Nevertheless, it is necessary to be very careful with the edges. The formula for the MSD calculation is

\[ \text{MSD} = \frac{1}{R \times C} \sum_{r=0}^{R-1} \sum_{c=0}^{C-1} (I_d(r,c) - I_s(r,c))^2 \]

3.3 Equivalent Numbers of Looks (ENL)

Another good approach of estimating the speckle noise level in a SAR image is to measure the ENL over a uniform image region [Sim 97]. A 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 also tradeoff the accuracy of the readings. Due to the difficulty in identifying uniform areas in the image, we propose to divide the image into smaller areas of 25x25 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

\[ \text{ENL} = \frac{\text{NMV}^2}{\text{NSD}^2} \]

The significance of obtaining both MSD and ENL measurements in this work is to analyze the performance of the filter on the overall region as well as in smaller uniform regions.
3.4 Deflection Ratio (DR)

A fourth performance estimator that we use in this work is the DR proposed [Gue 94]. The formula for the deflection calculation is

\[
DR = \frac{1}{R \times C} \sum_{r=1}^{R} \sum_{c=1}^{C} \frac{I_d(r,c) - NMV}{NSD}
\]

(16)

The ratio DR should be higher at pixels with stronger reflector points and lower elsewhere. In [Gue 94], this ratio is used to measure the performance between different wavelet shrinkage techniques. In this paper, we apply the ratio approach to all techniques after de-speckling in the same way [Yu 02].

3.5 Pratt’s figure of merit (FOM)

To compare edge preservation performances of different speckle reduction schemes, we adopt the Pratt’s figure of merit. [Str 00] defined by

\[
FOM = \frac{1}{\max\{N, N_{dea}\}} \sum_{i=1}^{k} \frac{1}{1 + d_i^2 \alpha}
\]

(17)

Where \(N\) and \(N_{dea}\) are the number of detected and ideal edge pixels, respectively, \(d_i\) is the Euclidean distance between the \(i_{th}\) detected edge pixel and the nearest ideal edge pixel, and \(\alpha\) is a constant typically set to 1/9. FOM ranges between 0 and 1, with unity for ideal edge detection [Moh 08].

4. Experimental Results

Here, besides our approach, we present a set of experimental results using one ERS SAR Precision Image (PRI) standard of Buenos Aires area. For statistical filters employed along, i.e., Median, Lee, Kuan, Gamma-Map, Enhanced Lee, Frost, Enhanced Frost [Mas 04] [Str 00] Wiener [Yu 02], DS [Mas 04] [Mas 05] and Enhanced DS (EDS) [Mas 06], we use a homomorphic speckle reduction scheme [Mas 05], with 3-by-3, 5-by-5 and 7-by-7 kernel windows. Besides, for Lee, Enhanced Lee, Kuan, Gamma-Map, Frost and Enhanced Frost filters the damping factor is set to 1/Yu 02] [Foi 07]. On the other hand, the statistical filters used inside SmoothShrink method were DS and EDS (improvements were not noticed with other statistical filters).

Figure 5(a) [Ava 08] shows a noisy image used in the experiment from remote sensing satellite ERS-2, with a 242-by-242 (pixels) by 65536 (gray levels); and the filtered images, processed by using VisuShrink (Hard-Thresholding), BayesShrink, OracleShrink, SURE-Shrink, and SmoothShrink techniques respectively, see Table 1. All the thresholding techniques used Daubechies 15 wavelet basis and 1 level of decomposition (improvements were not noticed with other basis of wavelets) [Yu 02] [Mas 06] [Foi 07]. Besides, Figure 5 summarizes the edge preservation performance of the Smooth Shrink technique vs. the rest of the shrinkage techniques with a considerably acceptable computational complexity.

![Figure 5](image)

Table 1 shows the assessment parameters vs. 19 filters for Figure 5(a), where En-Lee means Enhanced Lee Filter, En-Frost means Enhanced Frost Filter, Non-log SWT means Non-logarithmic Stationary Wavelet Transform Shrinkage [6] and Non-log DWT means Non-logarithmic DWT Shrinkage [Mas 06].

We compute and compare the NMV and NSD over six different homogeneous regions in our SAR image, before and after filtering, for all filters. The Smooth Shrink and de-blurring has obtained the best mean preservation and variance reduction, as shown in Table 1. Since a successful speckle reducing filter will not significantly affect the mean intensity within a homogeneous region, Smooth Shrink and de-blurring demonstrated to be the best in this sense too. The quantitative results of Table 1 show that the Smooth Shrink technique can eliminate speckle without distorting useful image information and without destroying the important image edges. In fact, the Smooth Shrink outperformed the conventional and non conventional speckle reducing filters in terms of edge preservation measured by Pratt’s figure of merit [Foi 07] [Mas 06], as shown in Table 1.
5. Conclusion

Direct smoothing of wavelet coefficient causes artificial structure, blurred and smoothed in image. By using SOM neural de-blurring algorithm, final image becomes more acceptable. Proportional to applying DWT, 15% improvement in edge prevention is received by new approach.

Although the SOM-based de-blurring, 1) did not use the traditional Gaussian neighborhood function as a property for the algorithm, 2) the learning-rate factor is constant along iterations, and 3) the width of the Kernel is constant along iterations, the results are better than the results of such well-known methods as de-blurring.

The drawback of this approach is complexity and time consuming. In one computer, our method long-time is 5 times as of DWT.

Further improvements to de-noising algorithm may be achieved using knowledge-based information such as image texture or PDF of radar cross section (RCS). Integrating these different kinds of information may be performed using Neural Networks. Finally, the natural extension of this work is in medical applications, as well as in micro arrays de-noising.

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Table 1. Assessment Parameters vs. Filters for Figure. 5(a).

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<th>Filter</th>
<th>MSD</th>
<th>NSD</th>
<th>ENL</th>
<th>DR</th>
<th>FOM</th>
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<td>11.093</td>
<td>2.558e</td>
<td>0.302</td>
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REFERENCES


