WAVELET BASED SPECKLE REDUCTION WITH APPLICATION TO SAR BASED ATD/R

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ABSTRACT

This paper introduces a novel speckle reduction method based on thresholding the wavelet coefficients of the logarithmically transformed image. The method is computational efficient and can significantly reduce the speckle while preserving the resolution of the original image. Both soft and hard thresholding schemes are studied and the results are compared. When fully polarimetric SAR images are available, we proposal several approcahes to combine the data from different polorizations to achieve even better performance. Wavelet processed imagery is shown to provide better detection performance for synthetic-aperture radar (SAR) based automatic target detection/recognition (ATD/R) problem.

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1. INTRODUCTION

Speckle results from the need to create the image with coherent radiation. Speckle phenomena can be found in SAR, acoustic imagery, and laser range data. A fully developed speckle pattern appears chaotic and unordered. Thus when image detail is important, speckle can be considered as noise that causes degradation of the image. Therefore, speckle reduction is important in several applications of coherent imaging.

In this paper, we study the minimization of speckle effects when we already have a digitized speckled image. Dewaele *et al.* [4] compared several speckle reduction techniques, including Lee's statistical filter, the sigma filter, and Crimmins' geometric filter. These methods achieve moderate speckle reduction, but smooth out sharp features in the image. Novak [10] derived a polarimetric whitening (PWF) filter for fully polarimetric SAR data. However, this method does not utilize spatial correlation – only the correlation across polarizations is used.

We propose a novel speckle reduction method based on thresholding the wavelet coefficients of the logarithmically transformed image. This method can provide significant speckle reduction and target-to-clutter improvement while preserving the resolution of the original SAR imagery. Thus it can be used as a pre-processing step to imporve the performance of automatic target detection and recognition algorithms based on SAR images.

Brief overviews of the basic statistical properties of the speckle noise, and the wavelet shrinkage method for denoising data are given in section 2. Section 3 presents our method of speckle reduction for single polarization SAR image. Both soft and hard thresholding schemes are studied and the results are compared. When fully polarimetric SAR images are available, we can combine the PWF and the wavelet shrinkage method to achieve even better performance. Several approaches to combine these methods are discussed in section 4. The speckle reduction techniques are applied to actual fully polarimetric, high-resolution SAR data gathered by the Lincoln Laboratory MMW airborne sensor. We compare the resulting target and clutter statistics, and show significant improvements.

2. PRELIMINARIES

2.1. Statistical Properties of the Speckle Noise

The statistical properties of the speckle noise were studied by Goodman [6]. He shows that when the imaging system has a resolution cell that is small in relation to the spatial detail in the object, and the speckle-degraded image has been sampled coarsely enough that the degradation at any pixel can be assumed to be independent of the degradation at all other pixels, coherent speckle noise can be modeled as multiplicative noise. Also, the real and imaginary parts of the complex speckle noise are independent, have zero mean, and are identically distributed Gaussian random variables. Arsenault [1] shows that when the image intensity is integrated with a finite aperture and logarithmically transformed, the speckle noise is approximately Gaussian additive noise, and it tends to a normal probability much faster than the intensity distribution. Thus we have

$$\tilde{y}(m,n) = \tilde{x}(m,n) + \tilde{e}(m,n) \qquad (1)$$

where $\tilde{y} = ln(|y|)$, and y is the observed complex SAR imaginary. x is the desired texture information, but it is contaminated by the speckle noise e. If an integrating aperture is used, and if we assume that the size of the aperture is small enough to retain texture detail, then $\tilde{e}$ is close to Gaussian distributed. The goal for speckle reduction is equivalent to finding the best estimate of x.

2.2. De-noising via Wavelet Shrinkage

Recently Donoho [5] has proposed a wavelet thresholding procedure for optimum recovering functions from additive

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Gaussian noisy data. Let

$$y_i = f(t_i) + \sigma z_i, \qquad i = 1, \ldots, n \tag{2}$$

where f is the unknown function of interest, the t_i are equispaced points on the unit interval, and z_i are i.i.d. Gaussian white noise having zero mean and unit variance. By the 1960's it was known that it is not possible to get estimates which work well for *any* function f. Donoho and Johnstone [5] have developed the following wavelet shrinkage method: Suppose we have N data points of the form 2 and that σ is known.

1. Apply a wavelet transform to the data, obtaining N wavelet coefficients $(w_{j,k})$.
2. Set a threshold $t_n = \sqrt{2\log(n)}\sigma/\sqrt{n}$, and apply the soft threshold nonlinearity $\hat{w} = sgn(w)(|w| - t)_+$ with the threshold value $t = t_n$. This is done for each wavelet coefficient individually.
3. Invert the wavelet transform, to get the estimated signal $\hat{f}_n^*(t)$.

The procedure has three distinct features: 1) The estimate does not exhibit any noise-induced structures, unlike most minimum mean square methods. 2) At the same time, sharp features are maintained. 3) $\hat{f}_n^*(t)$ achieves almost the minimax mean square error over a wide range of smoothness classes.

3. SPECKLE REDUCTION VIA WAVELET SHRINKAGE

3.1. The Details of the Method

Based on the above discussion, we propose the following method for speckle reduction:

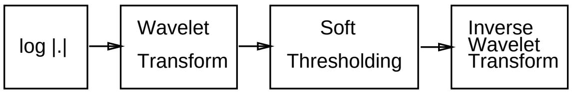

Figure 1. Speckle Reduction via Wavelet Shrinkage

Although, this is a straight forward application of the wavelet de-noising scheme of Donoho, a number of important factors have to be carefully decided.

Choice of wavelet: Under the name of wavelet analysis, there are a vast amount of choices, such as Daubechies' family of wavelets, Coiflets, M-band wavelets[7], wavelet packets[3], and space-varying wavelets [2, 8]. Longer wavelets with higher regularity tend to give a little better result in term of speckle reduction. However, if the wavelet filter is too long, details of the image might be oversmoothed. Also the computational complexity is nearly proportional to the length of the wavelets. So we choose length-4 Daubechies' wavelet, which achieves a balance between speckle reduction and the improvement in target-to-clutter contrast, and at the same time it is also computationally very efficient.

Levels of wavelet transform: In order to separate the back ground texture and local granular speckle phenomena, a number of levels of the wavelet transform is needed. Clearly, the level is also related to the length of the wavelet filter. For our choice of a D4 wavelet, we usually take at least 5 level of the transform.

Size of the wavelet transform: Wavelet transforms are taken block by block. In order to minimize the boundary effects, we use at least 128×128 blocks, often 512×512 blocks.

Thresholding Scheme: soft thresholding or hard thresholding. Although the soft thresholding is optimal in theory, the following hard thresoulding scheme, is shown to give better results for certain application [11].

$$\hat{w} = \begin{cases} w & \text{if } |w| > t \\ 0 & \text{otherwise} \end{cases}$$

So we test both of them, and compare the results.

The threshold: This is the most important factor of the algorithm. Since the noise variance is not known in practice, it must be estimated from the data. A number of approaches exist [5]. We found the following method is simple and very effective. Take the high/high part of the first level of the wavelet decomposition. The estimated noise variance is taken to be the standard deviation of the high/high part. For i.i.d. Gaussain noise, we found that $t = 1.5 \ldots 3\sigma$ yield excellent results. Using this range of thresholds , $86.6\% \ldots 99.7\%$ of the noise values have been suppressed. Our thresholding scheme is different from the one in Donoho's work, which oversmoothes the image. Also, we do not threshold the low/low part the final level of the wavelet decomposition. This guarantees that the mean of the processed image is the same as the mean of the original image.

3.2. Results of Speckle Reduction

This section presents numerical results obtained by applying the wavelet thresholding based speckle reduction method to actual SAR imagery. The data we are using were collected near Stockbridge, NY by the Lincoln Laboratory MMW SAR. We chose four type of clutter regions in the images: trees, scrub, grass and shadows. Discrete objects, like cars and powerline towers are considered as targets. We applied the wavelet based speckle reduction algorithm, and computed the following four statistics to evaluate the performance:

Standard-deviation-to-mean ratio (s/m)
: The quantity s/m(both in power) is a measure of image speckle in homogeneous region [6, 1, 4, 9]. We computed the s/m ratio for each type of clutter region to quantify the speckle reduction capacity of our algorithm.

Log standard deviation [10]: The standard deviation of the clutter data(in dB). This is an important quantity that directly affects the target detection performance of a standard two-parameter CFAR algorithm.

Target-to-clutter ratio(t/c): The difference between the target and clutter means(in dB). It measures how the target stands out of the surrounding clutter.

Deflection ratio: This is the two-parameter CFAR detection statistic.

$$M = \frac{y - \hat{\mu}_y}{\hat{\sigma}_y} \tag{3}$$

where y is the scalar pixel value of the cell, $\hat{\mu}_y$ is the estimated mean of y, and $\hat{\sigma}_y$ is the estimated standard deviation of y. After speckle reduction, M should be higher at known reflector points and lower elsewhere.

Table 1, 2 and 3 show those four values for original and processed images for four typical regions. The large reductions of s/m and log-standard deviation indicate that a significant amount of speckle has been removed. Soft thresholding scheme performs much better in terms of s/m and $log - std$ than the hard thresholding scheme. Both of them performs equally better in terms of deflection ratio. However, for target-to-clutter ratio (t/c), hard thresholding gives better results than soft thresholding. This is not surprising since the pick value is reduced by soft thresholding of the wavelet coefficients.

To visualize the result, we show the the original and the wavelet processed HV-polarization image in figure 2 and 3. We can see from the image that speckle is greatly reduced while sharp features are maintained. The computational complexity of the wavelet shrinkage method is of $O(N)$, where N is the size of the data. Thus our proposed method is efficient.

Table 1. s/m for clutter data

	Trees	Scrub	Grass	Shadow
Original HH	1.8207	1.3366	1.0590	1.2152
Soft Threshold	1.0602	0.5740	0.4251	0.5137
Hard Threshold	1.7783	1.2454	0.9283	1.1272

Table 2. $log - std$ for clutter data

	Trees	Scrub	Grass	Shadow
Original HH	7.2431	6.0598	5.4190	5.6231
Soft Threshold	4.3230	2.4263	1.8283	1.9988
Hard Threshold	5.5608	3.8532	2.9457	3.1140

Table 3. Target-to-clutter ratio(t/c) and Deflection ratio for clutter data

	t/c	Deflection ratio
Original HH	31.1813	5.1456
Soft Threshold	18.4149	7.5897
Hard Threshold	28.6837	7.2191

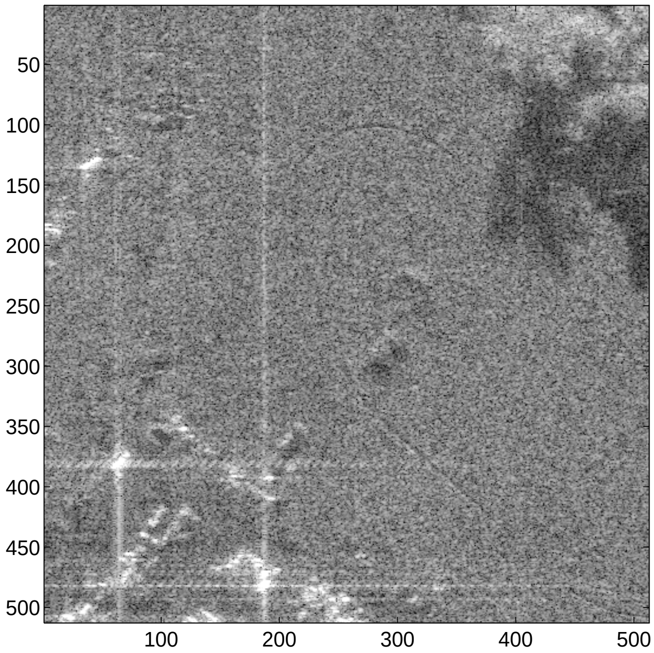

Figure 2. SAR image of a farm area (HV)

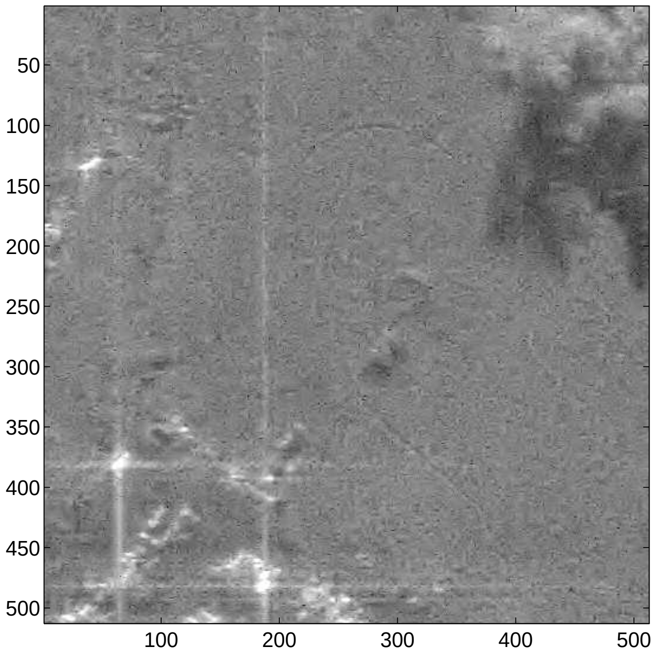

Figure 3. Processed image, using Daubechie's length-4 wavelets(HV), soft thresholding.

4. SPECKLE REDUCTION IN MULTIPOLARIZATION SAR IMAGERY

The availability of fully polarimetric SAR data makes it possible to reduce the speckle by utilizing the correlations between the co-polarized (HH, VV) and cross-polarized (HV, VH) images. Novak [10] derived a polarimetric whitening filter(PWF) which in theory is optimal if the correlations between HH, HV, and VV are known for every pixel. However, study [9] shows that this is rarely the case. Lee [9] proposes an adaptive method which estimates the correlations using a moving window. However, the optimal window size is hard to choose.

We proposes three methods for fully polarimetric SAR data. They are different combinations of the PWF and wavelet speckle reduction method. Due to the nonlinear nature of the wavelet shrinkage method, they are not equivalent.

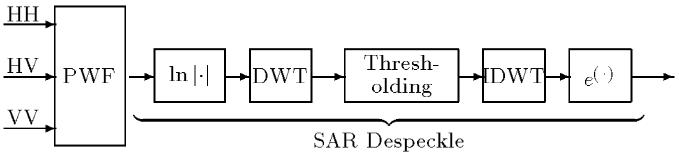

Figure 4. Method 1, Step 1: Perform PWF. Step 2: Perform wavelet denoising.

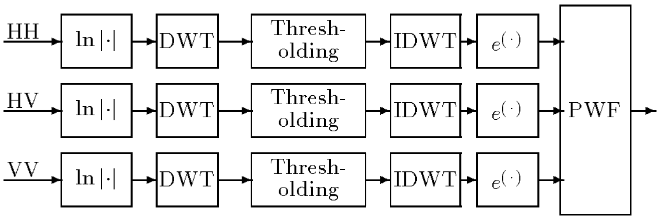

Figure 5. Method 2, Step 1: Denoise individual polarimetric images HH, HV and VV. Step 2: Combine with PWF.

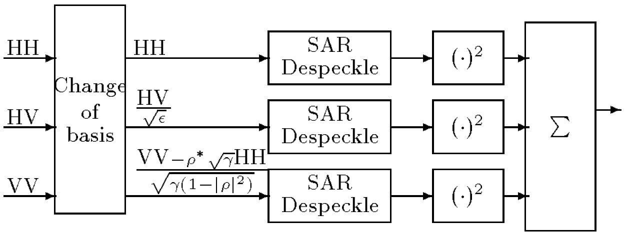

Figure 6. Method 3, Step 1: Decorrelate with PWF matrix. Step 2: Denoise with wavelet alg. Step 3: Add resulting three images in magnitude.

Using the fully polarimetric SAR data, we tested the three methods. The statistics are shown in the table 4, 5 and 6. The further reductions of s/m and log-standard deviation indicate that a significant amount of speckle has been removed. To demonstrate these results visually, we show the PWF processed image of the same farm scene in figure 7. Figure 8 shows the wavelet processed image. Since three methods produce visualy similar result, only the result of method 1 with soft thresholding is shown.

Table 4. s/m for clutter data

	Trees	Scrub	Grass	Shadow
PWF	1.3033	0.8240	0.6549	0.7007
Method 1, Soft	0.9233	0.4464	0.3034	0.3578
Method 2, Soft	0.8712	0.3757	0.2889	0.3327
Method 3, Soft	0.8272	0.3719	0.2754	0.3141
Method 1, Hard	1.1950	0.6971	0.4979	0.5527
Method 2, Hard	1.4507	0.8947	0.7249	0.7665
Method 3, Hard	1.3579	0.8650	0.6868	0.7285

Table 5. $log - std$ for clutter data

	Trees	Scrub	Grass	Shadow
PWF	4.9404	3.4292	2.9528	2.8999
Method 1, Soft	3.8321	1.8809	1.3264	1.3068
Method 2, Soft	3.5897	1.5279	1.1681	1.2310
Method 3, Soft	3.4680	1.5062	1.1371	1.1659
Method 1, Hard	4.4482	2.6858	2.0449	1.9409
Method 2, Hard	4.8833	3.1973	2.6807	2.6915
Method 3, Hard	4.7115	3.1115	2.6087	2.5732

Comparing the results for soft thresholding and hard thresholding for all the three methods, we see that soft thresholding gives consistently better results in terms of s/m, $log - std$ and deflection ratio, while the hard thresholding is better in terms of t/c. Method 1 gives overall better performance, and method 1 with hard thresholding is the only combination that increase the performance in term of all the four statistics.

After speckle reduction, the deflection ratio should be higher at known reflector points and lower elsewhere. In ATD/R systems [10], the deflection ratio is calculated for each cell, and compared to a constant that defines the false alarm rate. As shown in table 6, the deflection ratio is much higher in the wavelet processed images than that in

Table 6. Target-to-cluter ratio(t/c) and Deflection ratio for different methods.

	t/c	Deflection ratio
PWF	34.0269	11.1842
Method 1, Soft	29.5359	18.0767
Method 2, Soft	24.3769	16.5064
Method 3, Soft	23.7384	16.4851
Method 1, Hard	35.3883	15.5491
Method 2, Hard	37.2382	13.0932
Method 3, Hard	32.2843	11.6748

the PWF processed image. We also tested both PWF and wavelet shrinkage methods on a SAR image that contain several standard reflectors. At these points, the deflection ratio value is 30% to 50% higher in wavelet processed image than that in PWF processed image. Elsewhere in the image, the deflection ratio values are roughly the same for both methods. This strongly indicates the advantage of our method, and suggests a big improvement in detection performance. Also, cleaner images suggest potential improvements for classification and recognition.

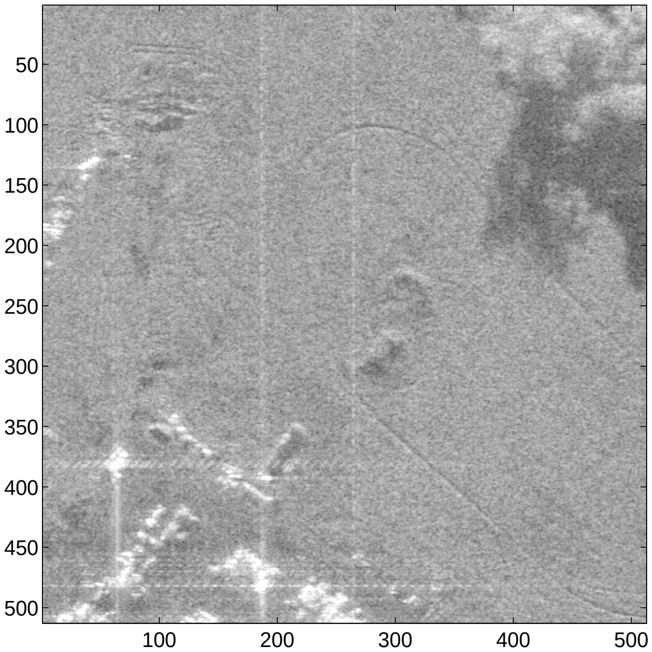

Figure 7. PWF image of a farm area, uses HH, HV, and VV data

5. SUMMARY

This paper developed wavelet based techniques for speckle reduction. The method is computationally efficient and can significantly reduce the speckle while preserving the resolution of the original image. Considerably increased deflection ratio strongly indicates improvement in detection performance. Also, cleaner images suggest potential improvements for classification and recognition.

REFERENCES

[1] H. H. Arsenault and G. April. Properties of speckle integrated with a finite aperture and logarithmically transformed. *J. Opt. Soc. Am.*, 66:1160–1163, November 1976.

[2] A. Cohen, I. Daubechis, and P. Vial. Wavelets on the interval and fast wavelet transforms. *Applied and Computational Harmonic Analysis*, 1(1):54–81, December 1993.

[3] R. R. Coifman and M. V. Wickerhauser. Entropy-based algorithms for best basis selection. *IEEE Trans. Inform. Theory*, 38(2):1713–1716, 1992.

[4] P. Dewaele, P. Wambacq, A. Oosterlinck, and J.L. Marchand. Comparison of some speckle reduction techniques for SAR images. *IGARSS*, 10:2417–2422, May 1990.

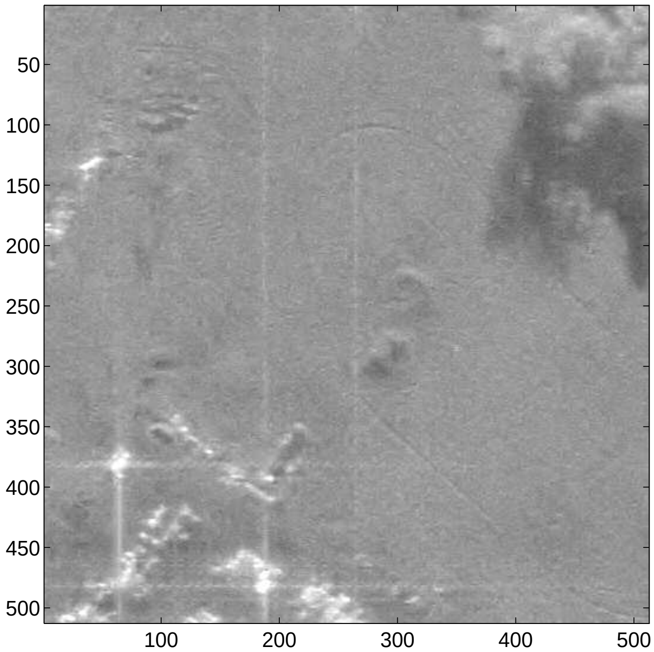

Figure 8. Method 1 processed image with Daubechie's length-4 wavelets, and uses HH, HV and VV data, soft thresholding.

[5] D. L. Donoho. De-noising by soft-thresholding. *IEEE Trans. Inform. Theory*, 1994. Also Tech. Report, Department of Statistics, Stanford University,1992.

[6] J. W. Goodman. Some fundamental properties of speckle. *J. Opt. Soc. Am.*, 66:1145–1150, November 1976.

[7] R. A. Gopinath and C. S. Burrus. Wavelets and filter banks. In C. K. Chui, editor, *Wavelets: A Tutorial in Theory and Applications*, pages 603–654. Academic Press, San Diego, CA, 1992. Also Tech. Report CML TR91-20, September 1991.

[8] R. A. Gopinath and C. S. Burrus. A tutorial overview of wavelets, filterbanks and interrelations. In *Proc. of the ISCAS*, Chicago, IL, May 1993. IEEE.

[9] J. Lee, M. R. Grunes, and S. A. Mango. Speckle reduction in multipolarization, multifrequency SAR imagery. *IEEE Trans. Geoscience and Remote Sensing*, 29:535–544, July 1991.

[10] L. M. Novak, M. C. Burl, and W. W. Irving. Optimal polarimetric processing for enhanced target detection. *IEEE Trans. AES*, 29:234–244, January 1993.

[11] Naoki Saito. Simultaneous noise suppresion and signal compression using a library of orthonormal bases and the minimum description length criterion. In *Wavelet Applications*, volume 2242, pages 224–235, Bellingham, WA, 1994. SPIE.