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ABSTRACT

We reduced speckle noise in SAR imagery by retaining only those wavelet coefficients with significant third-order correlation coefficients. These coefficients were generated from the cross-correlation functions of the image and wavelet basis functions. Using this approach, we compared the results between directly applying our denoising method, and first preprocessing by taking the logarithm of an image. In our approach, we examined wavelet coefficients in an environment where the contribution from the second-order moment of the noise had been reduced.

Keywords: correlation coefficient, denoising, higher-order statistics, SAR, speckle, wavelet transform, higher-order statistics

1. INTRODUCTION

Synthetic aperture radar (SAR) can penetrate foliage and clouds, and be operated day or night. *SAR* is based on the generation of an effective long antenna through signal processing, rather than the actual use of a long physical antenna. Usually, only a single relatively small, physical antenna is used in most cases. When the antenna moves, the phase of each elementary signal is modified according to the distance between the target and the antenna. The signal is complex with a phase uniform distributed on $[0, 2\pi]$ and a magnitude having large random variations. Due to the interference of waves reflected from many elementary scatterers, a strong granulation in the resulting image called speckle is observed.

The speckle complicates image interpretation by reducing the effectiveness of image segmentation, classification and feature extraction. The earliest method of speckle noise reduction was obtained by the incoherent addition of two or more independent coherent views of a scene. The shortcoming however, is a loss of spatial resolution. Subsequent research efforts in speckle noise reduction have been directed toward methods acting on the images after they have been formed. The benefit of this approach is that speckle noise can be reduced without destroying resolution.

There have been many attempts at filtering speckle noise from SAR imagery; however, the most successful seem to be those base on nonlinear filters for wavelet transforms.[1-9] We also used a wavelet-based approach to reduce speckle from SAR imagery.[10] We retained or set to zero wavelet coefficients based on higher-order statistics. In the next section, we describe higher-order correlations as an extension of the more familiar second-order cross-correlation function. In the following section, we applied a third-order correlation technique to identify wavelet coefficients that contained mostly signal. Using this approach us to improve the separation between signal and noise. Finally, we apply our method to some simulated SAR imagery and compare the results between calculating or not calculating the logarithm of the image before processing.

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2. HIGHER-ORDER CORRELATIONS

The correlation between two functions has been often used as a measure of their similarity. The conventional correlation function is a second-order correlation, and is a special case of higher-order correlations.[11] The nth-order correlation of the signal $f(x)$ is defined as

$$f_n(\tau_1, \tau_2, \ldots \tau_{n-1}) \equiv \sum_{k=0}^{N-1} f(x) f(\tau_1 + x) f(\tau_2 + x) \ldots f(\tau_{n-1} + x) \quad (1)$$

where the nth-order correlation is a function of n - 1 independent variables. For n = 2, Eq. (1) becomes the second-order correlation of $f(x)$ which is the familiar autocorrelation function.

We considered the third-order or triple correlation because it is simpler and easier to calculate than other higher-order correlations. The third-order correlation, n = 3, of a one-dimensional function is a function of two variables. From Eq. (1) the third-order correlation of $f(x)$ is

$$f_3(\tau_1, \tau_2) = \sum_{k=0}^{N-1} f(x) f(\tau_1 + x) f(\tau_2 + x) \quad (2)$$

where $f_3(t_1,t_2)$ is symmetric with respect to its variables τ_1, and τ_2.

The third-order correlation coefficient $f_3(0,0)$, can be found by sampling the triple correlation $f_3(t_1,t_2)$, at zero displacement where $\tau_1 = \tau_2 = 0$. From Eq. (2), the third-order correlation coefficient becomes

$$f_3(0, 0) = \sum_{k=0}^{N-1} f^3(x) \quad (3)$$

which shows that the third-order correlation coefficient $f_3(0, 0)$, of $f(x)$, can be calculated directly as the sum of the cubes of $f(x)$ from k = 0 - N-1.

3. DENOISING USING HIGHER-ORDER STATISTICS

One can think of a wavelet coefficient as a correlation between a wavelet and the input signal. However, the third-order correlation coefficient cannot be calculated from the second-correlation coefficient. In order to calculate the third-order coefficient useful for signal detection, we needed to first compute the second-order cross-correlation function between the input image and each wavelet. Considering only one dimension, the resulting correlation function was labeled as $b_{jk}(\tau)$. Using Eq. (3), we calculated the third-order autocorrelation coefficient of the second-order correlation result, which was described as

$$b3_{jk}(0,0) = \sum_{\tau=1}^{2m=1} \left(b_{jk}(\tau)\right)^3 , \tag{4}$$

where m is the length of the wavelet, and the summation is performed only on that portion of the signal. The block diagram of the system is shown in Fig. 1. Because the preprocessed input signal could be considered as a signal plus noise, we considered the output of the second-order correlation as consisting of two parts. One part was the correlation between the input signal and a wavelet, and the second part was the correlation between the noise and the wavelet. The second-order correlation result was written as

$$b_{jk}(\tau) = fb_{jk}(\tau) + nb_{jk}(\tau) , \tag{5}$$

where $fb_{jk}(\tau)$ and $nb_{jk}(\tau)$, represented the signal-wavelet correlation, and the noise-wavelet correlation respectively. Substituting Eq. (5) into Eq. (4), and rearranging, the expression for the third-order autocorrelation coefficient can be written as[12]

$$b3_{jk}(0,0) = \sum_{\tau=1}^{2m-1} \left(fb_{jk}(\tau)\right)^3 + 3\sum_{\tau=1}^{2m-1} \left(fb_{jk}(\tau)\right)^2 nb_{jk}(\tau) + \sum_{\tau=1}^{2m-1} fb_{jk}(\tau)\left(nb_{jk}(\tau)\right)^2 + \sum_{\tau=1}^{2m-1} \left(nb_{jk}(\tau)\right)^3 . \tag{6}$$

The last term is the only all noise term and will have a contribution from the third-order moment of the noise. The second term will be proportional to the mean of the noise. The first term is only term that is strictly due to the signal. The third term is related to the product of signal and the noise power. It can be minimized if the mean of the signal is set to zero.

4. EXPERIMENTAL RESULTS

We compared the performance of our approach with and without taking the logarithm of the signal before denoising. We used simulated SAR imagery corrupted by speckle by performing a Laplacian on an input image and multiplying noise signals consisting of a Rayleigh distribution for different values of β, where β is the square root of the variance, divided by the mean. We used a threshold in the wavelet domain of $t = 3\sigma^2$, where σ was the estimate of the variance of the noise from the first level of the wavelet transform as indicated in Fig. 1. In all cases, we used three levels of the wavelet transform and used Daubechies minimum-phase orthogonal 4-tap wavelets with 2 vanishing moments.

In our experiments we used the two images in Fig. 2. A typical view of the same images that were synthesized to appear as speckle-corrupted SAR versions are shown in Fig. 3. Due to computational burden of the third-order approach, we denoised each row separately, then denoised each column of the original noisy separately, then, averaged the two results. The results of the denoising approach applied to the images in Fig. 3 without preprocessing are shown in Fig. 4. The results using the logarithm as a preprocessing step resulted in the images in Fig. 5. The results in Figs. 4 and 5 appear similar, with perhaps the absence of preprocessing giving slightly better visual results. We compared the mean-squared error (MSE) as a function of β for both approaches in Figs. 6 and 7. The MSE was calculated between the denoised image and the simulated SAR image without speckle for comparison. In addition, we used four independent noise samples and averaged the four results to produce a 4-look image. In one of the images, the use of preprocessing made little difference, and in the other the preprocessing generally increased the MSE. As expected the 4-look image had a lower MSE than the 1-look image, especially at larger noise levels.

5. CONCLUSION

We found that using a higher-order correlation-based method for signal denoising of speckle noise yielded reasonable results. Preprocessing in the form of performing the logarithm of an image was not necessary. Due to the computational burden, the process can be carried out by operating on the rows and columns of an image independently.

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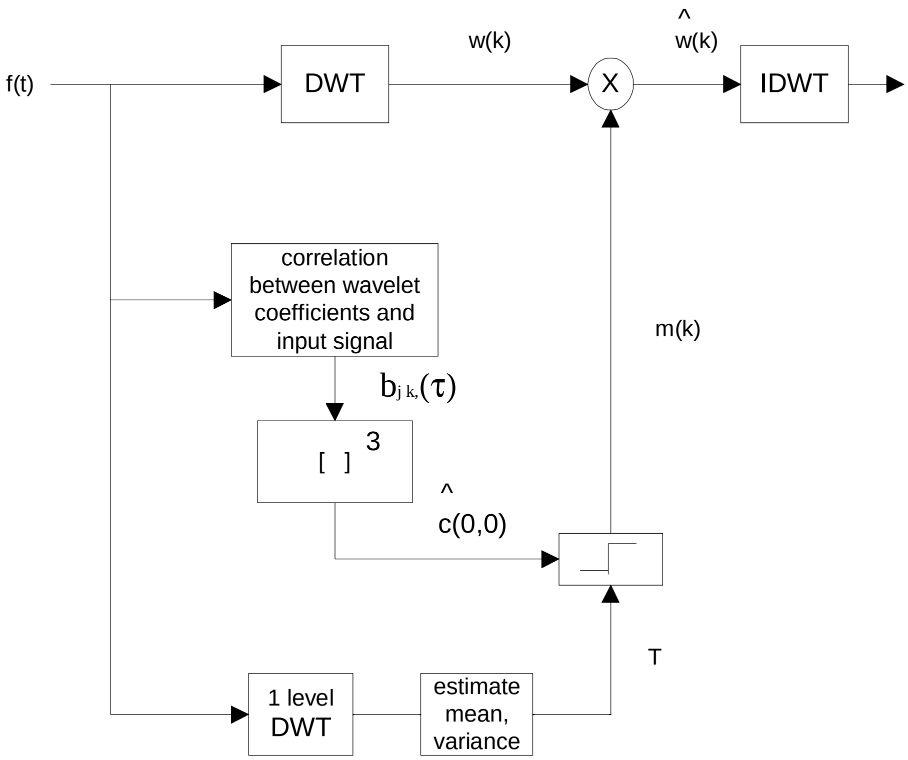
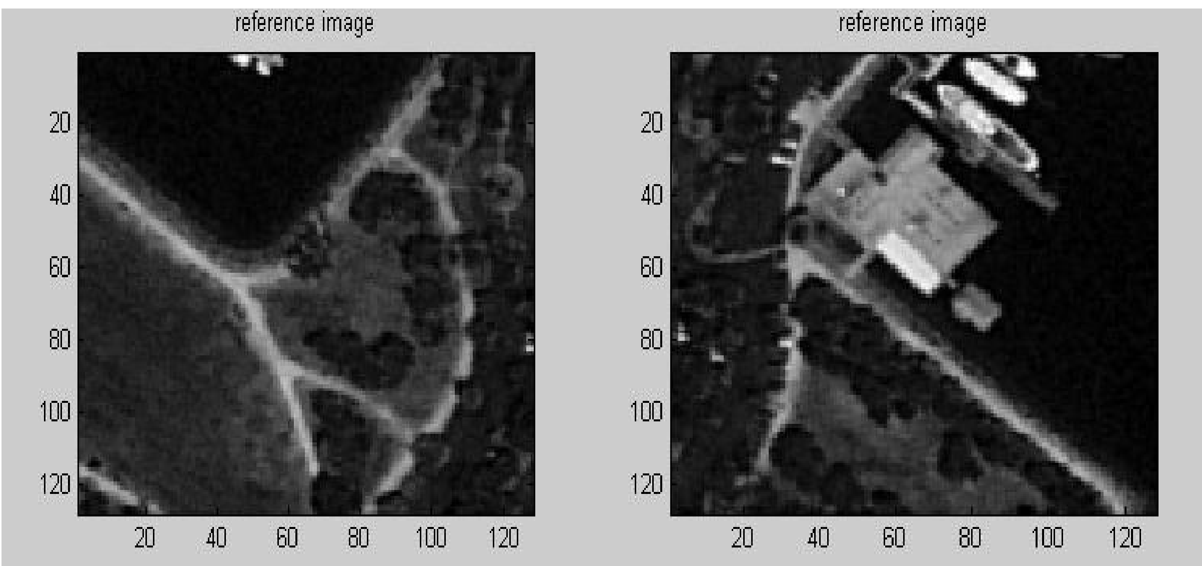


Figure 1 Block diagram of speckle denoising method.



(a) (b)

Figure 2 Images used in experiments.

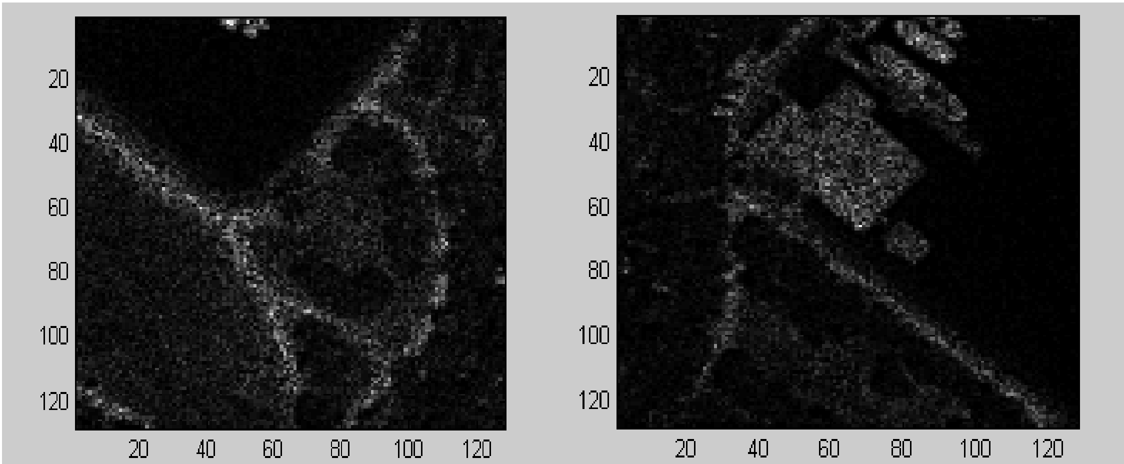


Figure 3 Single-look simulated SAR image.

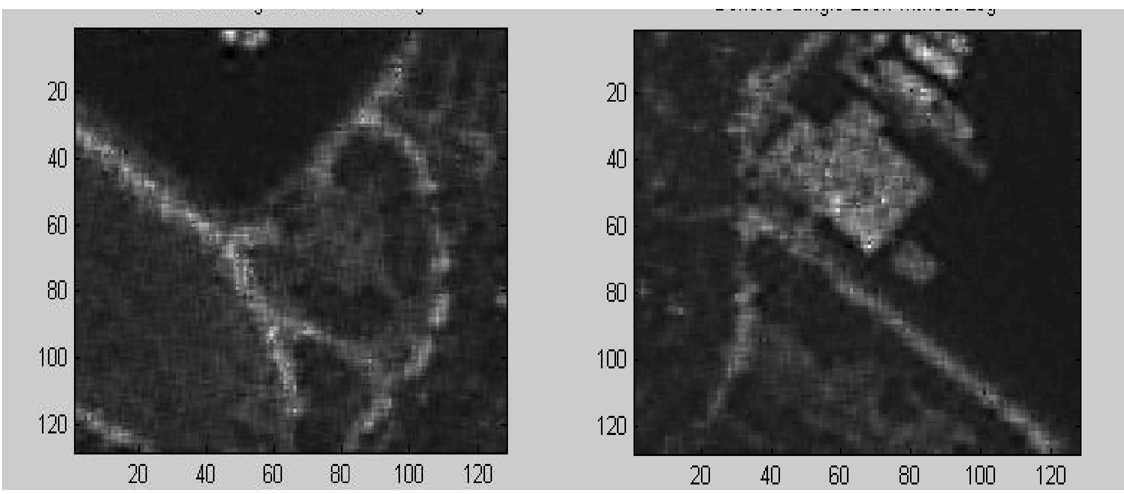


Figure 4 Denoised images of Fig. 3 without preprocessing.

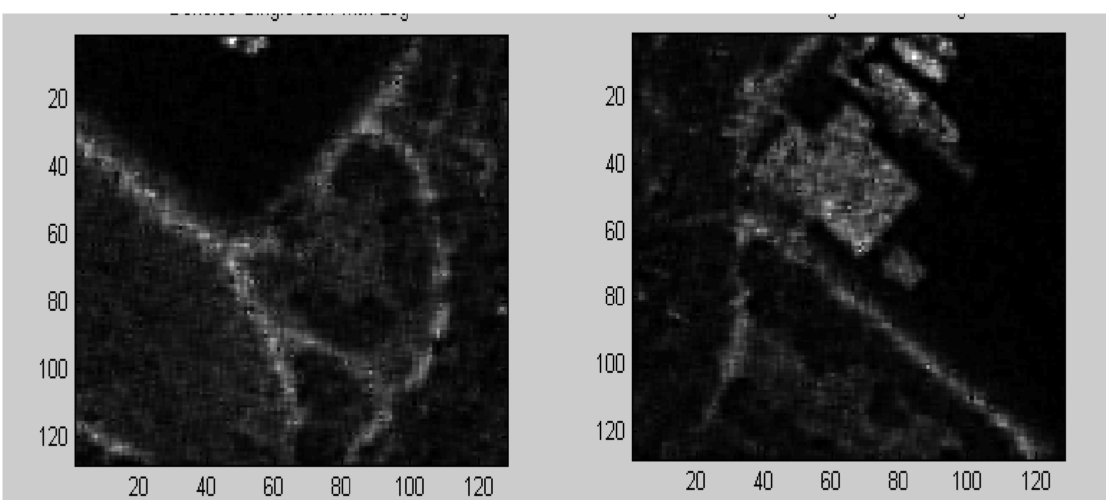


Figure 5 Denoised images of Fig. 3 using the logarithm as preprocessing.

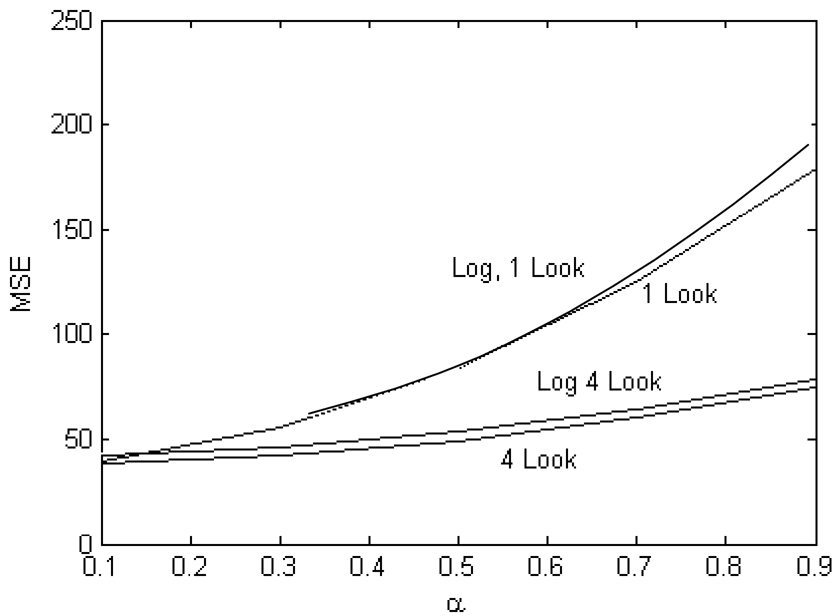


Figure 6 MSE as a function of b for 1- and 4-look images with and without preprocessing for image (a).

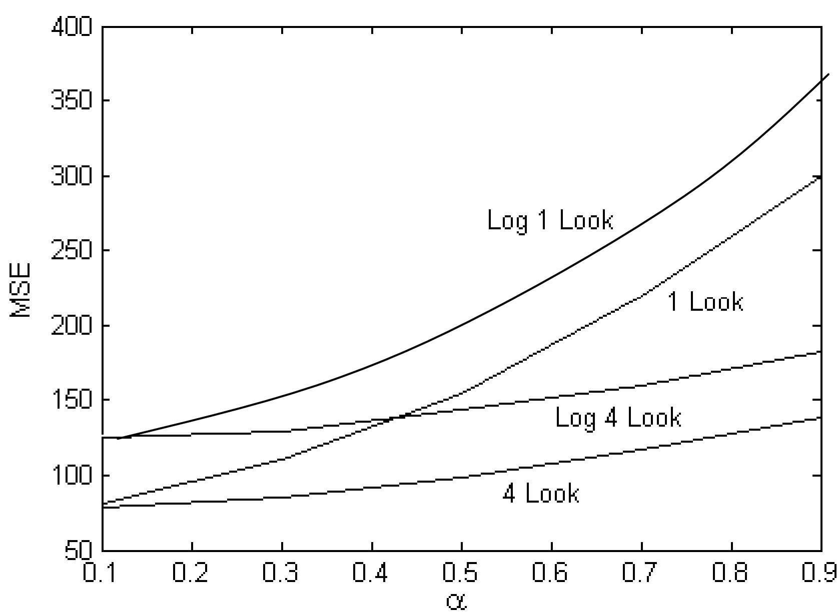


Figure 7 MSE as a function of b for 1- and 4-look images with and without preprocessing for image (b)..