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Nonlinear Edge-Preserving Smoothing of Synthetic Aperture Radar Images

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Abstract

Synthetic aperture radar (SAR) images are subject to prominent speckle noise, which is generally considered a purely multiplicative noise process. One interesting property of this multiplicative noise is that the ratio of the standard deviation to the signal value, the "coefficient of variation," is theoretically constant at every point in a SAR image. We use this property in conjunction with a new nonlinear filter structure based on mathematical morphology, the value-and-criterion structure, to design a filter that removes speckle noise from SAR images without blurring edges. First, the sample coefficient of variation at each point in the image is computed. In areas where there are changes in the signal, the sample coefficient of variation will be greater than the expected theoretical value. By using the new filter structure, a low-pass filter to remove speckle noise can be directed to operate only over regions where the coefficient of variation is close to the expected value. These regions are less likely to contain significant features or edges which would be distorted by low-pass filtering. We demonstrate the effectiveness of this new filtering method by comparing it to established speckle noise removal techniques on both phantom images with simulated speckle noise and real SAR images.

1. Introduction

Synthetic aperture radar (SAR) imaging of the earth's surface is a valuable modality for remote sensing in New Zealand, since SAR is able to penetrate cloud cover and is independent of solar illumination. However, speckle noise generated from the coherent imaging technique of SAR is a serious impediment to computer interpretation of SAR images. This speckle noise can be successfully modeled as a purely multiplicative noise process, and as a result several interesting properties of the noise can be exploited to help reduce the noise without blurring or distorting edges.

In theory, the ratio of the standard deviation to the signal value, the "coefficient of variation," is constant at every point in an image corrupted by purely multiplicative noise. We use this property in conjunction with a new nonlinear filter structure, the value-and-criterion structure, to design a filter that removes speckle noise from SAR images without blurring edges. The new filter structure is able to direct a low-pass filtering operation to act over the local areas where the signal is most nearly constant. By directing the smoothing operation away from edges, the filter reduces noise while sharpening edges.

The first step in this new filtering process is to compute the sample coefficient of variation at each point. In areas where there are changes in the signal, such as edges, the coefficient of variation is higher than the expected theoretical value because the signal changes increase the standard deviation in those regions. The new filter structure performs low-pass filtering only over regions where the coefficient of variation is low. These regions are less likely to contain significant features or edges than areas with a high coefficient of variation, and therefore blurring of edges by the low-pass filtering is avoided.

2. Noise model

Speckle noise in SAR images is usually modeled as a purely multiplicative noise process of the form given in equation (2.1) below. The true radiometric values of the image are represented by f, and the values measured by the radar instrument are represented by g. The speckle noise is represented by n.

$$g = f \cdot n \tag{2.1}$$

For single-look SAR images, n is Rayleigh distributed (for amplitude images) or negative exponentially distributed (for intensity images) with a mean of $\bar{n} = 1$. For multi-look SAR images with independent looks, n has a gamma distribution with a mean of 1. Further details on this noise model are given in a companion paper [1]. The noise model of equation (2.1) is also used to simulate 3-look speckle noise in Section 4.

3. Filter

3.1. Value-and-criterion filter structure

The value-and-criterion filter structure is a new nonlinear filter structure [2,3] based on mathematical morphology. The new structure allows the use of both linear and nonlinear operations within the shape-based structure of morphological filters. The standard morphological filters use only extreme order statistic (minimum and maximum) operators. Thus, the value-and-criterion filter structure is much more flexible than the standard morphological structure, but retains much of the shape control of morphology.

The value-and-criterion structure is based on the structure of the morphological operations opening and closing. These operators are each made up of two sequential ordering operations. Opening is a sliding minimum operation (erosion) followed by a sliding maximum operation (dilation); closing is dilation followed by erosion. A value-and-criterion filter, like opening or closing, gets its output from an operator acting on the results of a first filtering stage. However, instead of a single first operator such as erosion or dilation, a value-and-criterion filter has two separate operations in the first stage. The results of one of these first-stage operators (the *criterion* operator) are used to decide which of the outputs of the other first-stage operator (the *value* operator) will be the final output. This new filter structure encompasses many different types of nonlinear filters.

The two operators acting on the image $g(\mathbf{x})$ by a value-and-criterion filter are the "value" function, V, and the "criterion" function, C, which are defined over a structuring element (filter window) N. A "selection" operator, S, acts on the output of the criterion function, and is defined over the structuring element $\tilde{N}$, which is a 180° rotation of N about its centre. If N is usually symmetric about its centre, so $N = \tilde{N}$. Let $\hat{f}(\mathbf{x})$ denote the output of a value-and-criterion filter, and $v(\mathbf{x})$ and $c(\mathbf{x})$ denote the output of V and C, respectively. The filter output $\hat{f}(\mathbf{x})$ is then defined by equations (3.1)–(3.3) below [2].

$$v(\mathbf{x}) = V\{g(\mathbf{x});\, N\} \tag{3.1}$$

$$c(\mathbf{x}) = C\{g(\mathbf{x});\, N\} \tag{3.2}$$

$$\hat{f}(\mathbf{x}) = v\left(\left\{\mathbf{x}' : \mathbf{x}' \in \tilde{N}_{\mathbf{x}};\, c(\mathbf{x}') = S\{c(\mathbf{x});\, \tilde{N}\}\right\}\right) \tag{3.3}$$

$\tilde{N}_{\mathbf{x}}$ denotes the translation of $\tilde{N}$ such that it is centred at position $\mathbf{x}$.

The morphological opening is a value-and-criterion filter where V and C are both the minimum operator and S is the maximum operator. Similarly, the morphological closing is a value-and-criterion filter where V and C are the maximum operator and S is the minimum operator. New nonlinear filters are developed using the value-and-criterion structure by making V and C different.

The value-and-criterion filter structure develops a natural subwindow structure that is superior to earlier subwindow-based filtering schemes. The value-and-criterion filter structure with an $n \times n$ square structuring element has n^2 subwindows within an overall window of $(2n-1) \times (2n-1)$. These represent all the possible $n \times n$ subwindows within the overall window. Within each overall window, the subwindow with the "selected" criterion function value is chosen, and the value function output in that subwindow is the filter output for the overall window. The filter structure performs this operation in a very efficient manner, by computing the value and criterion function outputs all in advance.

3.2. Minimum Coefficient of Variation (MCV) filter

The Minimum Coefficient of Variation (MCV) filter is the value-and-criterion filter we have designed for suppressing speckle noise in SAR images without blurring or distorting edges. In an image corrupted only by purely multiplicative noise, the coefficient of variation is theoretically constant at each point in the image. The coefficient of variation is defined to be the ratio of the standard deviation of the noise to the signal value at a point. Estimating the coefficient of variation by computing the mean and standard deviation over a window in an image gives values near the expected theoretical value in places where the signal is constant over the window, but higher values in places where the signal changes over the window. Therefore, to avoid smoothing over areas that include edges and other signal changes, the value-and-criterion filter structure can be used to selectively filter over only windows that have a low coefficient of variation.

The MCV filter computes the coefficient of variation for its criterion function, the local mean (average) for its value function, and uses the minimum for its selection function. This means that at every point in the image, the filter effectively selects the $n \times n$ subwindow within an overall window of $(2n-1) \times (2n-1)$ that has the smallest coefficient of variation, and outputs the mean of that subwindow. Since subwindows with edges or other features in them will have a higher coefficient of variation than uniform subwindows, the average will be taken in regions away from edges and therefore edges are not blurred but instead are sharpened by this technique.

4. Examples

4.1. Other speckle reduction methods

Many techniques have been proposed for reducing speckle in images. The most widely used of these include the local statistics method [4-7], the sigma filter [5,6,8,9], the median filter, homomorphic filtering [10,11], and adaptive linear smoothing [12]. Durand *et al.* [7] compared 10 different filtering methods for speckle reduction in SAR images and concluded that a modified version of the local statistics method performed the best of the filters they examined. This filter is given in equation (4.1) below. The filter output is f, the input image is g, the local mean and standard deviation of the input image are given by $\bar{g}$ and σ_g, respectively, and the standard deviation of the noise is σ_n. For 3-look SAR speckle noise with independent looks, $\sigma_n = 0.2941$ (see Lee [6]).

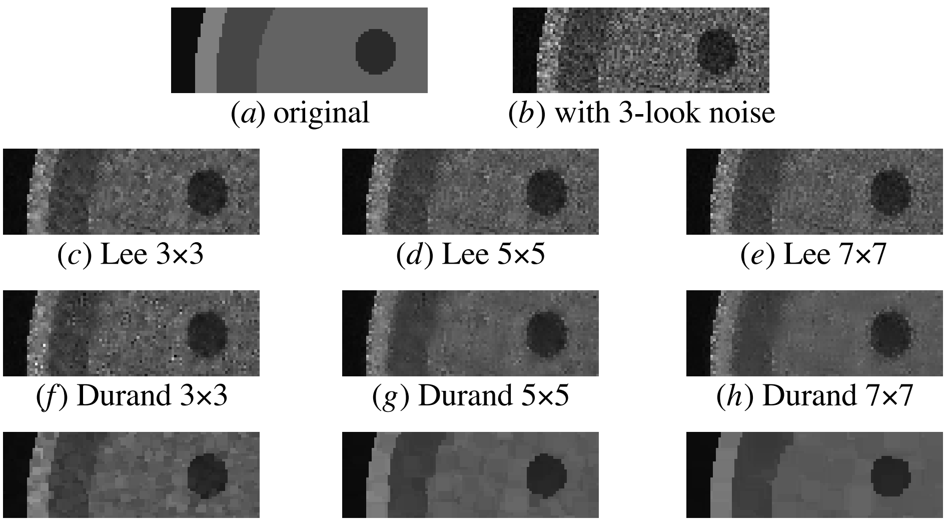
$$\hat{f} = \bar{g} + \left(g - \bar{g}\right) \cdot \frac{\left(1 - \bar{g}^2 \cdot \dfrac{\sigma_n^2}{\sigma_g^2}\right)}{\left(1 + \sigma_n^2\right)} \tag{4.1}$$

4.2. Comparison on phantom image with simulated 3-look speckle noise

To compare the MCV filter with the established SAR filtering techniques, we have developed a simple phantom image with ellipsoidal and square features. Using the noise model of Section 2 above, the effects of 3-look speckle noise (with independent looks) on this image can be simulated. The filters may then be applied and the results compared with the known original image using the mean absolute error (MAE) and mean square error (MSE) criteria. A small (96×32 pixels) portion of the phantom image is shown in Figure 1, along with the corrupted and filtered versions. The MCV filter clearly removes the speckle noise most effectively of the three filters. These observations are verified by the results in Table 1, showing that the MAE and MSE between the filtered and original images are lowest for the 5×5 MCV filter.

Table 1. MAE and MSE for various SAR noise reduction algorithms for a phantom image corrupted by simulated 3-look speckle noise.

Algorithm	Window Size	MAE	MSE
(unprocessed)	—	10.38	290.2
local statistics method (Lee)	3×3	6.66	133.2
	5×5	6.51	128.4
	7×7	6.59	132.7
modified local statistics method (Durand)	3×3	6.83	148.9
	5×5	5.50	92.1
	7×7	5.39	89.9
MCV filter	3×3	4.81	72.8
	5×5	4.43	66.6
	7×7	4.94	87.2



(*a*) original
(*b*) with 3-look noise
(*c*) Lee 3×3
(*d*) Lee 5×5
(*e*) Lee 7×7
(*f*) Durand 3×3
(*g*) Durand 5×5
(*h*) Durand 7×7
(*i*) MCV 3×3
(*j*) MCV 5×5
(*k*) MCV 7×7

Figure 1. Portion of phantom image with simulated 3-look SAR noise filtered by Lee's local statistics method [4], the modified method of Durand [7], and the MCV filter.

4.3. Comparison on a SAR image

Figures 2–4 below illustrate the effect of MCV filtering compared to Durand's modified local statistics filtering on a SAR image taken by the JERS-1 satellite of Oruawairua Island in the Marlborough Sounds. JERS-1 images are 3-look SAR images that closely match the noise model of Section 2; further details are given in a companion paper [1]. The MCV-filtered image (Figure 4) has much sharper edges and less noise than the local statistics filtered image (Figure 3). This impression is supported by edge maps of the two filtered images, shown at 1:2 reduction in Figure 5. These maps were formed by a simple Prewitt gradient operator acting on the images followed by thresholding at the same level. The edges detected from the MCV-filtered image are much clearer and there are far fewer false edges as well.

(*a*) Edge map of Figure 3. (*b*) Edge map of Figure 4.

Figure 5. Edge maps (at 1:2 reduction) of Figures 3 and 4.

5. Conclusions

In this paper we have developed the MCV filter, a new nonlinear filter based on mathematical morphology, for reducing speckle noise in SAR images without blurring edges. This new filter design incorporates the speckle noise model for SAR images and is shown to outperform existing filtering methods on simulated and real radar images.

References

1. Q. X. Wu and M. A. Schulze. “Statistical properties of three-look JERS-1 SAR data.” *Image and Vision Computing New Zealand Workshop (IVCNZ’95),* 1995.
2. M. A. Schulze and J. A. Pearce. “A morphology-based filter structure for edge-enhancing smoothing.” *1994 IEEE International Conference on Image Processing (ICIP-94),* Austin, Texas, November 1994. pp. 530-534.
3. M. A. Schulze and J. A. Pearce. “Value-and-criterion filters: A new filter structure based upon morphological opening and closing.” In *Nonlinear Image Processing IV, Proc SPIE*, v. 1902, San Jose, California, February 1993. pp. 106-115.
4. J.-S. Lee. “Speckle analysis and smoothing of synthetic aperture radar images.” *Comp Graph Image Process*. v. 17 n. (1981) pp. 24-32.
5. J.-S. Lee. “A simple speckle smoothing algorithm for synthetic aperture radar images.” *IEEE Trans Syst Man Cyber*. v. 13 n. 1 (1983) pp. 85-89.
6. J.-S. Lee. “Speckle suppression and analysis for synthetic aperture radar images.” *Opt Eng*. v. 25 n. 5 (1986) pp. 636-643.
7. J. M. Durand, B. J. Gimonet, *et al.* “SAR data filtering for classification.” *IEEE Trans Geosci Remote Sens*. v. 25 n. 5 (1987) pp. 629-637.
8. J.-S. Lee. “Digital image smoothing and the sigma filter.” *Comput Vision Graphics Image Process*. v. 24 n. 2 (1983) pp. 255-269.
9. J.-S. Lee and I. Jurkevich. “Coastline detection and tracing in SAR images.” *IEEE Trans Geosci Remote Sens*. v. 28 n. 4 (1990) pp. 662-668.
10. G. Franceschetti, V. Pascazio, *et al.* “Iterative homomorphic technique for speckle reduction in synthetic-aperture radar imaging.” *J Opt Soc Am A*. v. 12 n. 4 (1995) pp. 686-694.
11. H. H. Arsenault and M. Levesque. “Combined homomorphic and local-statistics processing for restoration of images degraded by signal-dependent noise.” *Appl Opt*. v. 23 n. 6 (1984) pp. 845-850.
12. V. S. Frost, J. A. Stiles, *et al.* “An adaptive filter for smoothing noisy radar images.” *Proc IEEE*. v. 69 n. 1 (1981) pp. 133-135.

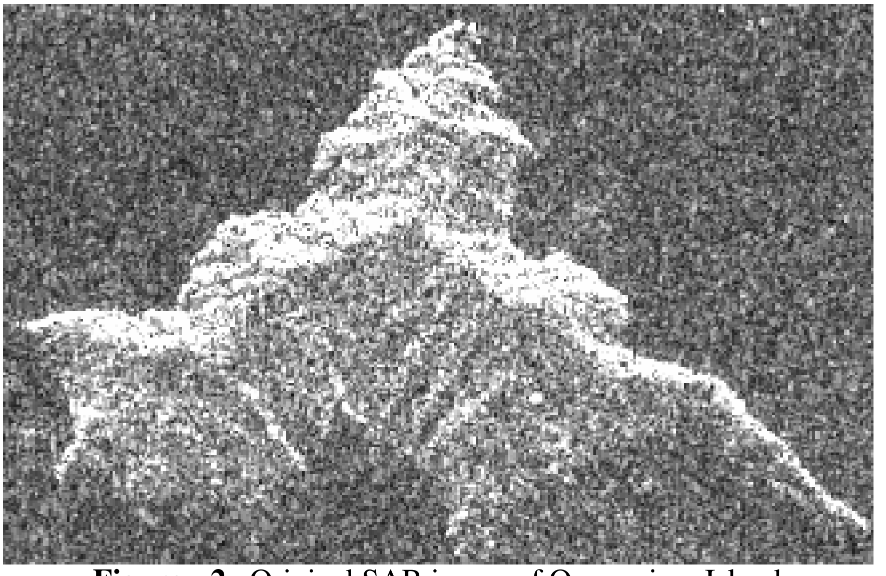


Figure 2. Original SAR image of Oruawairua Island.

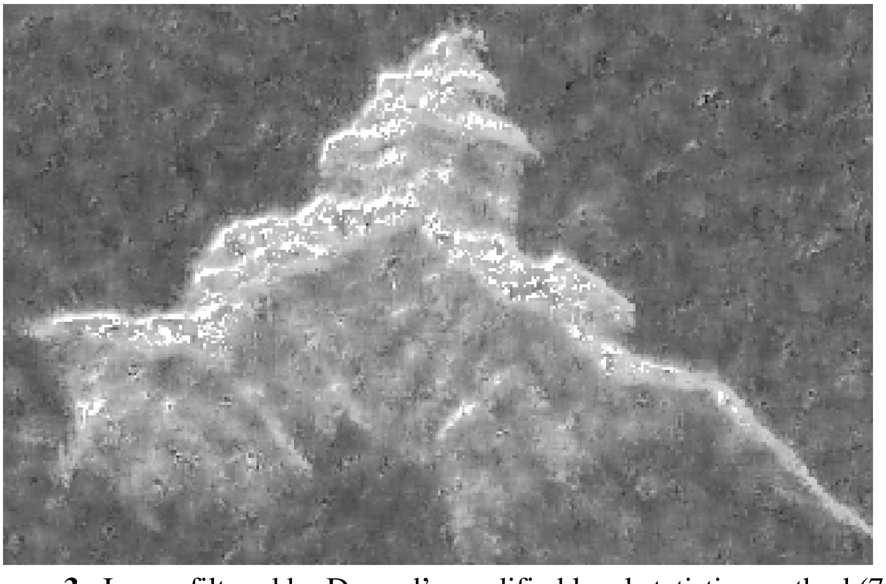


Figure 3. Image filtered by Durand's modified local statistics method (7×7).

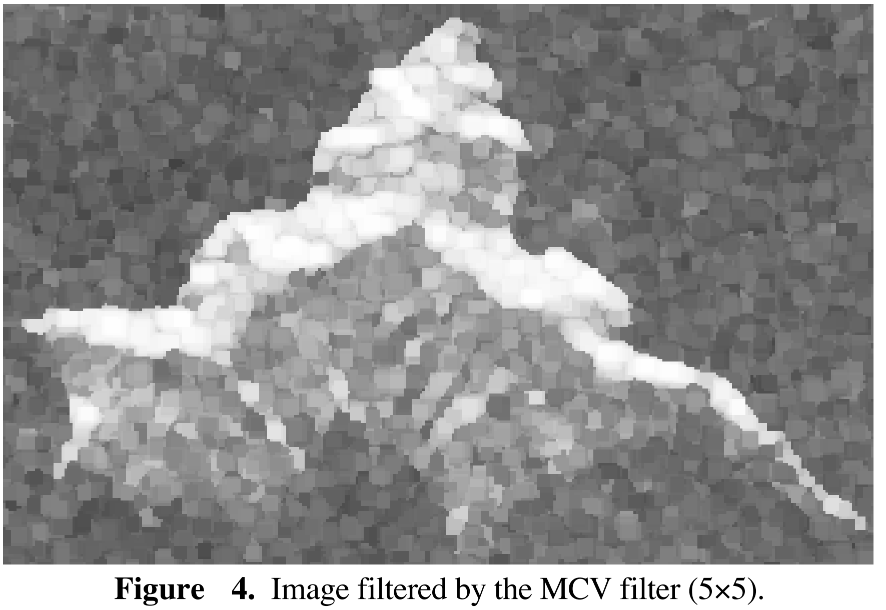


Figure 4. Image filtered by the MCV filter (5×5).