A SAR SPECKLE FILTERING ALGORITHM TOWARDS EDGE SHARPENING

Yunhan Dong*, Anthony K Milne**, and Bruce C Forster*
*School of Geomatic Engineering, **Office of Postgraduate Studies
The University of New South Wales
Sydney 2052, Australia
y.dong@unsw.edu.au, t.milne@unsw.edu.au, b.forster@unsw.edu.au

Working Group VII/6

KEY WORDS: Radar**,** Speckle Reduction, Texture, Image Processing.

ABSTRACT

One of the major difficulties when classifying synthetic aperture radar (SAR) images is the existence of speckle due to coherent processing. Existing speckle filtering algorithms can effectively reduce the speckle effect but unfortunately also smear edges and blur images. It is realized that fluctuations in an image can be due to either local oscillations or edge crossings. An appropriate filtering algorithm should react differently to these two types of fluctuations: to smooth local oscillations to reduce the speckle level and to enhance edge crossings to avoid blurring. Such a goal is achieved via two steps. First edge crossings are detected using the second order derivative of the Gaussian function with a proper dilation factor as the wavelet transform function; and then the traditional mean filtering algorithm using a moving window is applied only within the region in which no edge crossings exist. As a result uniform areas are smoothed and edges are effectively sharpened and enhanced. The algorithm can be used in conjunction with other popular SAR speckle filters in order to sharpen smeared edges.

1   INTRODUCTION

Speckle reduction is becoming a routine process in synthetic aperture radar (SAR) image applications for terrain classifications. It is well known that speckle is multiplicative noise. In consequence, a number of filtering algorithms dealing with multiplicative noise have been proposed and widely used in the SAR image processing. The most Notable ones include Lee's filter (1986), Frost's filter (Frost et al, 1982), Kuan's filter (Kuan et al, 1987), the polarimetric whitening filter (Novak and Burl, 1990). Filters designed for polarimetric SAR data have also proposed, such as the minimum mean square error (MMSE) filter (Goze and Lopes, 1993) for one-look data, and filters given by Lopes and Sery (1997), Lee and Grunes (1999), for multi-look data. In addition, filters such as median filter (Tukey, 1977), geometric (Crimmins, 1986), morphological (Dougherty, 1992), wavelet transform (Dong et al, 1998) filters have also found to be useful in suppressing speckle level. Comparisons and evaluations of these various filters have been reported elsewhere (Lee et al, 1994, Dong et al, 1998).

 Quantitative evaluation of a filter includes several criteria such as equivalent number looks, mean bias, edge preservation, and texture preservation. Among these the most important are:

1. Preservation of the mean;
2. Reduction of the standard deviation;
3. Preservation of edges; and
4. Texture preservation (restoration).

Existing speckle filtering algorithms can effectively reduce the speckle level. These algorithms however also, more or less, smear edges and blur images. Adaptive filters, such as Lee's, Kuan's, Frost's and MMSE filters, take account of a speckle distribution model, compute local statistics in a moving window, and assign pixels' values accordingly, often leading to better results compared to non-adaptive filters. However smoothing uniform areas and at the same time preserving and enhancing edges is difficult to accomplish, because the former requires abandonment of high frequency components, while the latter needs the preservation of high frequency components as much as possible. One method to minimizing the deficiency of smearing edges, for instance, is to use edge-directed windows, rather than the traditional square windows (Lee, 1981).

2 ALGORITHM

2.1 One Dimensional Algorithm

Let us consider a one-dimensional signal, $f(x)$. Fluctuations in $f(x)$ can be due to either local oscillations or edge crossings. An appropriate filtering algorithm should react differently to these two types of fluctuations: to smooth the local oscillations to reduce the speckle (noise) level and to enhance edge crossings to avoid blurring. Figure 1 depicts the ideally expected filtering results for these two types of fluctuations.

<center>(a)   (b)</center>
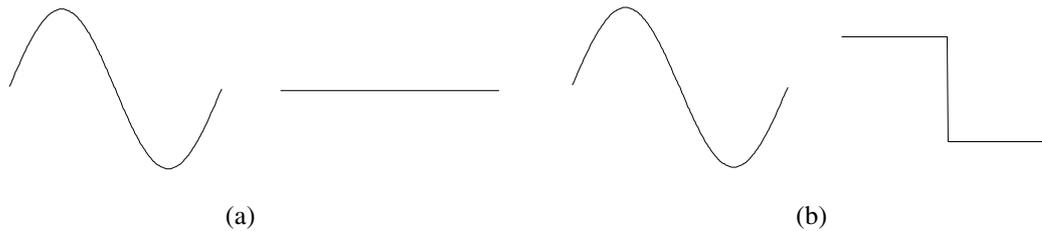
<center>Figure 1. The ideal filtering results for (a) local oscillations and (b) edge crossings.</center>

Wavelet transform techniques have been used extensively in data processing, where wavelet function can be chosen for different purposes, such as data compression, noise smoothing and edge detection (Mallat and Zhong, 1992). One of the distinct advantages of wavelet transforms lies in the adaptive dilation of the wavelet. As a result, the wavelet transform can capture rapid changes in the signal at small dilation factors, or be not so sensitive to rapid but small changes at large dilation scales. Denoting

$$g_s(x) = \frac{1}{s} g\left(\frac{x}{s}\right) \tag{1}$$

the dilation by a scaling factor s of any function $g(x)$ in the space domain, the Fourier transforms of $g(x)$ and $g_s(x)$ are,

$$G(\omega) = \int_{-\infty}^{+\infty} g(x) \exp(-i\omega x) dx \tag{2}$$

$$G_s(\omega) = \int_{-\infty}^{+\infty} g_s(x) \exp(-i\omega x) dx = G(s\omega) \tag{3}$$

The second order derivative of Gaussian function, which has been shown to be a good edge detector (Canny, 1986), is selected in this paper as the wavelet function for detecting edge crossings. Local oscillations, which are often faster in frequency and smaller in amplitude, compared to edge crossings, can be suppressed using a proper scaling factor, s. Let $q_s(x)$ be the edge crossing detector defined by the wavelet transform as,

$$q_s(x) = f(x) * g_s(s) \tag{4}$$

Where * denotes one-dimensional convolution and $g_s(x)$ is the second order derivative of Gaussian function with a scale factor of s.

$$g(x) = \frac{d^2}{dx^2}\left(\frac{1}{\sqrt{2\pi}\sigma} \exp(-x^2/2\sigma^2)\right) \tag{5}$$

where σ is the standard deviation of the Gaussian function ($\sigma = 1$ has been chosen for use in the paper). The computation of (4) can be easily implemented by use of the DFFT (discrete fast Fourier transform) technique in the frequency domain. The computation can also be achieved by direct convolution in space domain, as $g(x)$ rapidly approaches to zero at both ends.

The detected edge crossing points correspond to $q_s(x) = 0$. A region between two consecutive edge crossing points is either a peak ($q_s(x) < 0$) or a valley ($q_s(x) > 0$). With the assistance of such information, and using a moving window, the new value $\hat{f}(x_i)$ for pixel x_i is determined as,

1. the mean value of the original signal if there is no any edge crossing point in the moving window; or

2. the mean value of the original signal in the peak or valley region where the current pixel x_i is located if there exits one or more than one edge crossing point in the moving window.

As the mean calculation is adapted according to the existence of edge crossings, the algorithm does two things together: smoothing uniform areas and sharpening edges. If the algorithm is used recursively, the final results can converge to the ideal situations. Figure 2 shows iteration results for signals with a local oscillation and an edge crossing, respectively.

(a)   (b)
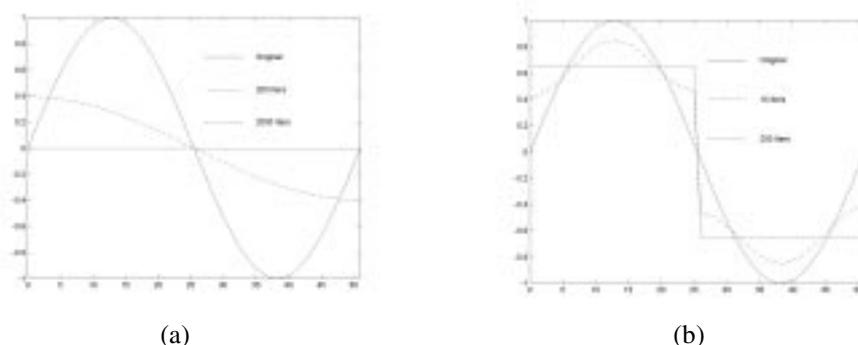
Figure 2. Convergence of the algorithm: (a) for local oscillations and (b) for edge crossings.

2.2 Two Dimensional Algorithm

Theoretically the above one-dimensional algorithm can be easily extended to two dimensions by considering edge detection in the x and y directions. That is, for a two dimensional function, $f(x, y)$ edge crossings can be found by evaluating edge detecting functions in the x and y directions together:

$$q_s^x(x, y) = f(x, y)**g_s(x)\delta(y) \tag{6}$$

$$q_s^y(x, y) = f(x, y)**\delta(x)g_s(y) \tag{7}$$

where ** denotes two-dimensional convolution, and $\delta(\cdot)$ is the Dirac delta function. This implies that for a direction $\hat{r} = \hat{x}\cos\theta + \hat{y}\sin\theta$, the directional edge detection function is

$$q_s^r(x, y) = q_s^x(x, y)\cos\theta + q_s^y(x, y)\sin\theta \tag{8}$$

This method works well for most images. However, it is found that due to speckle in SAR images, the discontinuity of the discrete function $f(x, y)$ is very serious and the correlation between neighboring pexels is low, so the information given by $q_s^x(x, y)$ and $q_s^y(x, y)$ is not sufficiently accurate to indicate edge information in (8). Therefore, the directional edge detecting function is defined as,

$$q_s^r = f(r)*g_s(r) \tag{9}$$

where $f(r)$ is one dimensional function whose elements consists of pixels along the $\hat{r}$ direction. It is found that for images having high correlation among neighboring pixels, results of (8) and (9) are the same. However, the result of (9) is much better than that of (8) for images having low correlation among neighboring pixels, such as found in SAR images.

Based on the above analysis, the proposed filtering algorithm for two-dimensional SAR image consists of two steps:
1. Apply the one-dimensional filtering algorithm to an image in four directions, namely, vertical (zero-degree), vertical (90-degree), 45-degree diagonal and 135-degree diagonal directions, respectively, to obtain four directionally filtered images.
2 The final filtered image is the mean of the four directionally filtered images, i.e., the final value for each pixel is the mean of the corresponding pixels in the four diretionally fitltered images.

Each pixel in an image is, therefore, considered and filtered in four (eight) directions as depicted in Figure 3.
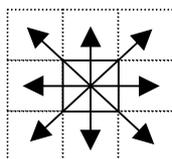
Figure 3. Each pixel in an image is filtered in four (eight) directions.

3   RESULTS

To evaluate the performance of the proposed filtering algorithm, we have to follow the criteria for a speckle filter. As indicated above, the most important ones include mean preservation, reduction of standard deviation, edge preservation and texture preservation (restoration).

3.1   Mean Preservation

Because this is an adaptive mean filter, it guarantees the preservation of the mean.

3.2   Standard Deviation Reduction (Smoothing Uniform Areas)

As indicated, most existing speckle filtering algorithms can effectively reduce the speckle level, and this algorithm is no exception. Meanwhile, suppression of speckle is somehow at the cost of losing local details. For example, using a larger moving window always reduces more standard deviation but also smears local detail. A comparison of smoothing uniform areas should be associated with the comparison of preservation of edges. To avoid such complex comparison, we assume that this algorithm be used in conjunction with other speckle filtering algorithms. In this way, it only needs to examine if edges are sharpened. The following subsection looks closely at the edge enhancement.

3.3   Edge Sharpening and Enhancement

Shown in Figure 4 is a 512 x 512 AirSAR C-band HH image of Alligator River of Northern Territory, Australia, acquired by the NASA/JPL AirSAR system in 1996. The image is filtered using various filters including the Lee filter, Kuan filter, Frost filter, mean filter and the proposed filer. Results are compared using numerical analysis for, in particular, two areas, each consisting of a 40 x 40 pixel block, one representing a uniform area and one an edge crossing area as shown in Figure 4.
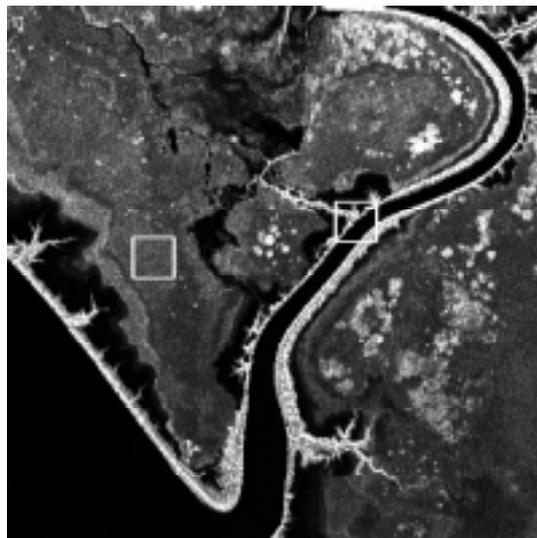
Figure 4. A 512 x 512 pixel NASA/JPL AirSAR CHH image. Indicated are two 40 x 40 pixel blocks representing a uniform area and an edge crossing area, respectively.

To evaluate the performance of a filter, one can analyze data in the frequency domain. In order to view frequency component changes, each block of data is treated as one-dimensional data with 1600 pixels consisting of consecutive lines of pixels in the block. The DFFT is then used for data analysis. Figure 5 shows differences of frequency components between the original data and the filtered data for the uniform area. It can be seen in the figure that behaviors of the four filters, i.e., the mean filter, Lee filter, Frost filter and the proposed filter, are very similar for uniform areas, as expected. The difference in frequency components to be positive indicates the frequency components have been reduced, thus the data in spatial domain have been smoothed. It is worth noting that each figure is symmetrical to the center, and the frequency components spread from high at the center to low at two ends. The Kuan filter is nearly identical to the Lee filter, and its result is therefore not shown in the figure.

Performances of the four filters for an edge crossing area, are, on the other hand, quite different as shown in Figure 6. The mean filter shows a significant amount of positive frequency values indicating it smears edges. Lee' filter does little in edge crossing area, as it was designed to preserve edges (in edge crossing areas where the variance of the data is much higher that the variance of uniform areas, Lee's filter tends to maintain the original data value). Frost's filter also smears edges but it is better than the mean filter. The proposed filter shows a significant amount of negative values in the difference, indicating frequency components have been added in order to sharpen and enhance edges.

| (a) Mean | (b) Lee | (c) Frost | (d) Proposed |
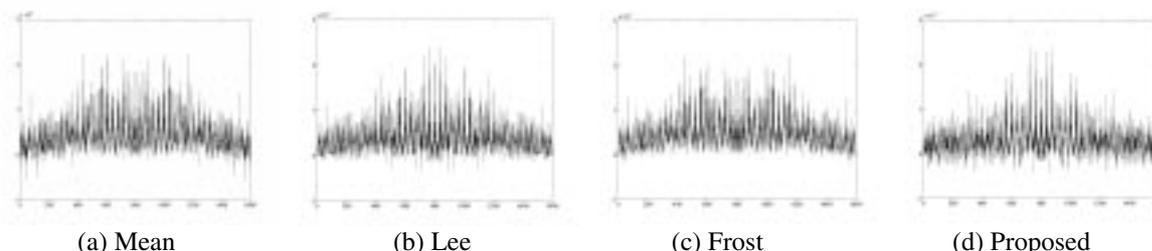
Figure 5. Difference in frequency components between original data and the filtered data for a uniform area. The performances of four filters are very similar. Positive values indicate that the uniform area has been smoothed.

| (a) Mean | (b) Lee | (c) Frost | (d) Proposed |
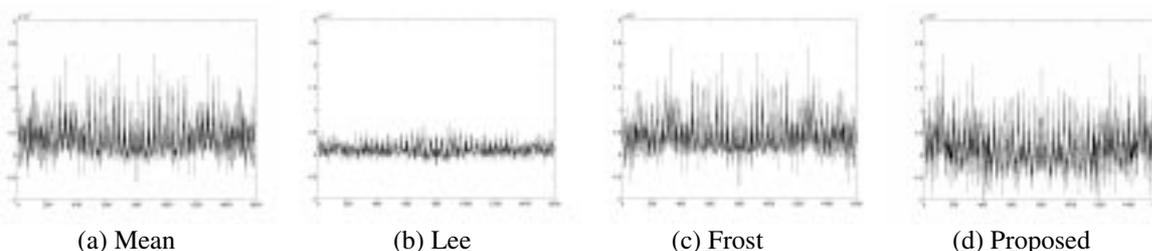
Figure 6. Difference in frequency components between original data and the filtered data for an edge crossing area. The performances of the four filters are quite different.

Details of multi-pixel occupied edge crossings can be viewed in Figure 7, where the 40 x 40 pixel block of the edge crossing area is plotted in three dimensions. Most edge crossings occupy 3-4 pixels in the original data as well as in the filtered data by the Lee and Frost filters. These edge occupancies are however reduced to only about 1 pixel after the data being processed by the proposed filter. The mean filter produces the poorest result in terms of edge preservation and thus not being shown in the figure.

3.4 Texture Preservation (Restoration)

Texture preservation is another criterion when evaluating a speckle suppression filter, as texture is important information presented in an image. The most widely used textural measures are considered as estimates of the statistics of the various histograms (Haralick et al, 1973, Anys and He, 1995). In particular, four first-order textural measures based on the histogram (density distribution) and four second-order textural measures based on the co-occurrence matrix are selected and used to evaluate filters in terms of texture preservation. These used textural measures are:

- mean (first-order, first-degree statistics);
- standard deviation (first order, second-degree statistics);
- skewness (first order, third-degree statistics);
- kurtosis (first order, forth-degree statistics);
- absolute value (second-order, first-degree statistics);
- moment (second-order, second-degree statistics)
- contrast (second-order, second-degree statistics)
- correlation (second-order, second-degree statistics).

It has been found that apart from the mean preservation, none of existing filters is able to maintain other textural measures unchanged, as image data are changed by filters. In fact, texture in SAR images can be considered as consisting of two components: intrinsic texture of the scene backscatter and texture due to speckle. Speckle filtering algorithms should aim at reducing the speckle texture and preserving the intrinsic texture. Obviously, the texture of an image with speckle and the texture of the same image without (or with less) speckle are different. The appropriate term for evaluating filters, therefore, should be referred to texture restoration (referring to preserving the intrinsic texture and removing speckle texture). To investigate, an artificial SAR image with a higher speckle level is generated. The image is then filtered using various filters. The textural measures of the filtered images are then compared with another

artificial unfiltered image having as the approximately same speckle level as in the filtered images. It has been noticed that even though the filtered and the unfiltered images have the same mean and standard deviation, the appearance of the filtered images look coarser than the unfiltered image. That is the data distribution in the co-occurrence matrix of the filtered images is wider than that of unfiltered image. In general, among all the filters tested including the mean, median, Lee, Kuan, Frost, and proposed filters, the median filter gives the worst result in terms of the second-order texture restoration, which is true at least for the image used in the test. As known, the median filter assigns the median value to the central pixel in the moving window. As a result, it has been found that, quite a few of pixels are assigned as the same values as their adjacent pixels, causing a dramatic distortion in the co-occurrence matrix compared to the co-occurrence matrix of the unfiltered image. As far as uniform areas are concern, the mean filter shows the best result of restoration of the intrinsic texture. However, the mean filter also gives the poorest result in edge areas. Other adaptive filters perform better in edge areas, but seem not as well as the mean filter does for uniform areas. In general the texture of filtered images has been dramatically improved to a level very close to what the unfiltered image has. Details of texture restoration of filters can be found elsewhere (Dong and Milne, 2000).

(a) Original

(b) Lee
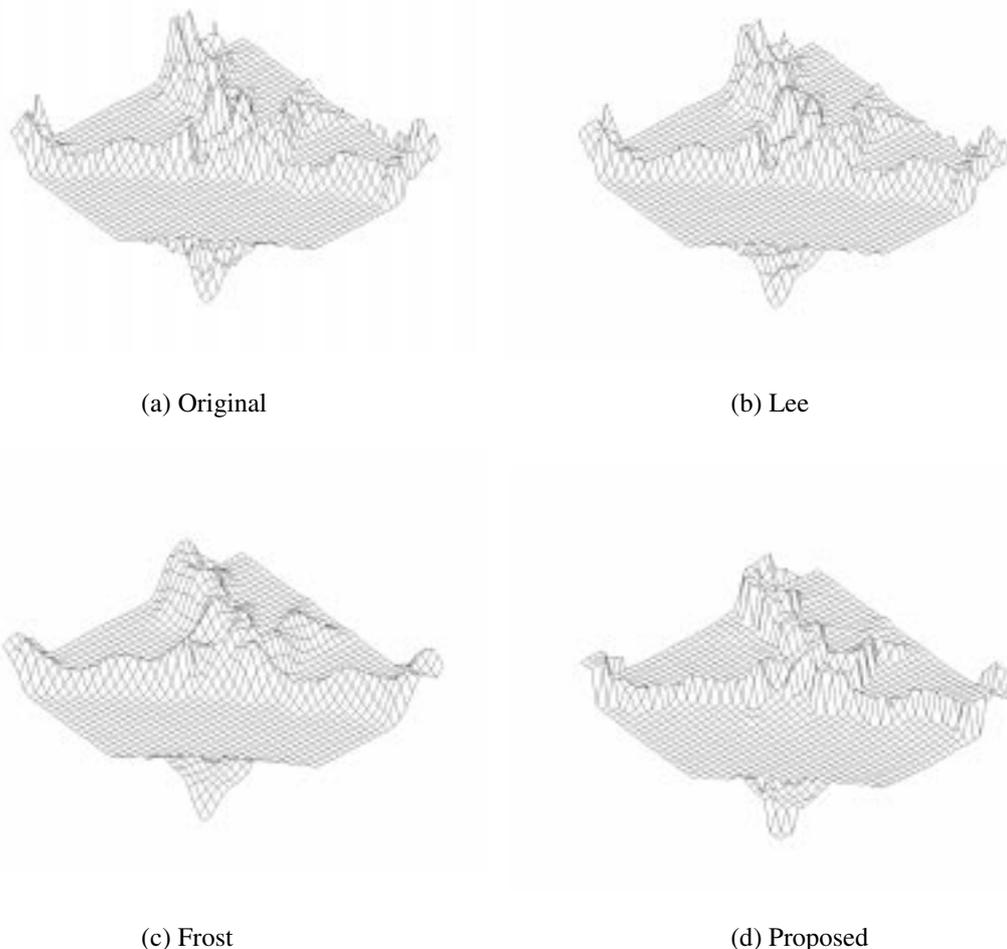
(c) Frost

(d) Proposed

Figure 7. Three-dimensional view of an edge crossing area of 40 x 40 pixels. Figures shown in (a), (b), (c) and (d) correspond to the original data, and the data processed by Lee, Frost and the proposed filters, respectively.

4 CONCLUSIONS

A speckle filtering algorithm for edge sharpening and enhancement has been proposed. Its performance in terms of edge enhancement as well as mean preservation and standard deviation reduction has been analyzed. The preservation (restoration) of the intrinsic texture of the filter is also tested, and found to be comparable to other adaptive filters. The algorithm can be applied in conjunction with other speckle filters in order to sharpen edges which might be smeared. Even for images with unsmeared edges it may be still worth implementing edge enhancement, as the response of a pulse (a sharp edge) by SAR systems is a *sinc* function (a smeared edge with local oscillations) due to systems' limited bandwidths.

ACKNOWLEDGEMENTS

REFERENCES

Anys, H., and He, D. C., 1995. Evaluation of textural and multipolarization radar features for crop classification. IEEE Trans on Geoscience and Remote Sensing, 33 (5), pp. 1170-181.

Canny, J, 1986. A computational approach to edge detection. IEEE Trans on Pattern Analysis and Machine Intelligence, 8, pp. 679-689.

Crimmins, T. R., 1986. Geometric filter for reducing speckle. Optical Engineering, 25, pp. 651-654.

Dong, Y, Forster, B. C, Milne, A. K., and Morgan, G. A., 1998. Speckle suppression using recursive wavelet transforms. International Journal of Remote Sensing, 19 (2), pp. 317-330.

Dong, Y, and Milne A. K., An review of SAR speckle filters: Texture restoration and preservation. Proceedings of IGARSS 2000.

Dougherty, E., 1992. An Introduction to Morphological Image Processing. SPIE Optical Engineering Press, Bellingham.

Frost, V. S., Stiles, J. A., Shanmugan, K. S., and Holtzman, J. C., 1982. A model for radar images and its application to adaptive digital filtering of multiplicative noise. IEEE Trans on Pattern Analysis and Machine Intelligence, 4, pp. 157-165.

Goze, S. and Lopes, A. 1993. A MMSE speckle filtering for full resolution SAR polarimetric data. Journal of Electronic Waves and Applications, 7 (5), pp. 717-737.

Haralick, R. M., Shanmugam, K., and Dinstein, I., 1973. Textural features for image classification. IEEE Trans on Systems, Man, and Cybernetics, 3 (6), pp. 610-621.

Kuan, D. T., Sawchuk, A. A., Strand, T. C, and Chavel, P., 1987. Adaptive restoration of image with speckle. IEEE Trans on Acoustic Speech and Signal Processing, 35, pp. 373-383.

Lee, J. S., 1981. Refined filtering of image noise using local statistics. Computer Graphics and Image Processing, 15, pp. 380-389.

Lee, J. S., 1986. Speckle suppression and analysis for synthetic aperture radar. Optical Engineering, 25(5), pp. 656-643.

Lee, J. S., Jurkevich, I., Dewaele, P., Wambacq, P., and Oosterlinck, A., 1994. Speckle filtering of synthetic aperture radar images: A review. Remote Sensing Reviews, 8 (4) pp. 313-340.

Lee, J. S., Grunes, M. R., and de Grandi, G., 1999. Polarimetric SAR speckle filtering and its implication for classification. IEEE Trans on Geoscience and Remote Sensing, 37 (5), pp. 2363-2373.

Lopes, A., and Sery, F., 1997. Optimal speckle reduction for the product model in multilook polarimetric SAR imagery and the Wishart distribution. IEEE Trans on Geoscience and Remote Sensing, 35 (3), pp. 632-647.

Mallat, S., and Zhong, S., 1992. Characterization of signals from multiscale edges. IEEE Trans on Pattern Analysis and Machine Intelligence, 14, 710-732.

Novak, L. M., and Burl, M. C., 1990. Optimal speckle reduction in polarimetric SAR imagery. IEEE Trans on Aerospace and Electronic Systems, 26, pp. 293-305.

Tukey, J. W., 1977. Exploratory Data Analysis. Addison-Wesley, Reading, Massachusetts.