

AN OVERVIEW OF SPECKLE NOISE FILTERING IN SAR IMAGES

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ABSTRACT

Synthetic Aperture Radar Images are corrupted by a signal-dependent noise called speckle, that decreases the potentiality of these images for human or automatic interpretation. This degradation is due to the coherent nature of the radiation that is used and its interaction with the roughness of the terrain. In this paper, a survey of the techniques that have been proposed for reducing speckle noise in a SAR image is presented. First, a statistical model for the speckle noise is presented. This model, multiplicative in its nature, leads to the majority of the algorithms for speckle noise reduction. We describe the Lee, Kuan, Frost and adaptive versions of the last three filters, which are the most well known algorithms, as well as the MAP filter and some heuristic filters. We also briefly present new algorithms based on the theories of Markov Random Fields and Robust Estimation. Finally, we describe techniques for the evaluation of speckle reduction filters.

1. INTRODUCTION

Speckle noise corrupts images that are obtained by coherent radiation, like SAR, ultrasound, laser, sonar, etc. The presence of this type of noise decreases the usefulness of these images for both human and automatic interpretation. In this paper we review the main algorithms that have been proposed for speckle noise reduction. We shall concentrate our review on single band images, ie, filters for multipolarization or multifrequency images will not be covered. Previous reviews of this subject were published by Durand et al [Ref. 1], Sadjadi [Ref. 2], Dewaele et al [Ref. 3] and Lee et al [Ref. 4].

2. A Statistical Model for Speckle

The statistical model for speckle noise is usually based on the assumption that the resolution cell contains a large number of scatterers of radiation with a wavelength that is comparable to the roughness of the terrain. In this case, the returned wave is the result of the superposition of all these reflected components. If we represent each of these reflected waves by a phasor, we have the following diagram that is a realization of a random walk process in the plane:

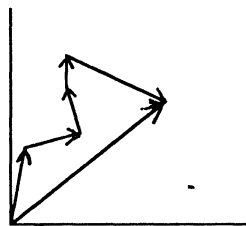


Figure 1- Phasor diagram showing the addition of the contributions of different scatterers.

The signal due to the i^{th} scatterer can be expressed by:

$$V_i \exp[j(\omega t + \theta_i)] = V_i \exp(j\phi_i) \quad (1)$$

where V_i is the magnitude and ϕ_i is the instantaneous phase. The return from N scatterers results in an instantaneous voltage given by:

$$V = \sum_{i=1}^N V_i \exp(j\phi_i) \quad (2)$$

We can express V in the following polar form:

$$V = V_e \exp(j\phi) \quad (3)$$

V can be decomposed in the two cartesian components V_x and V_y . For a large value of N , it is possible to apply the Central Limit Theorem and these components will have a Gaussian distribution. It is easily seen that V_x and V_y have zero means and are non-correlated. As a consequence, the joint probability density function of V_x and V_y will be given by:

$$f(V_x, V_y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{V_x^2 + V_y^2}{2\sigma^2}\right) \quad (4)$$

There are two kinds of detection systems employed in SAR. In the first one; called linear detection, the envelope voltage V_e determines the brightness of the pixel in the image. In the second detection system, called quadratic detection, the square of V_e is used for this purpose.

In the first case, it is possible to derive the joint probability density function of V_e and ϕ and to conclude that they are independent random variables, V_e being Rayleigh distributed and ϕ being uniformly distributed between 0 and 2π . In the second case, V_e^2 has an exponential distribution.

Under the linear detection, the ratio of the standard deviation to the expected value over homogeneous areas (no signal variation) is constant and equal to .5227, with one look. Under quadratic detection, this ratio is equal to one. In any case, the standard deviation is proportional to the expected value, and this fact is the basis for the multiplicative model of the speckle noise. At the same time, it also implies that speckle is a signal-dependent noise.

It is possible to reduce the standard deviation of the speckle by dividing the synthetic aperture into N parts, generating N images of the same scene with independent noise and obtaining the mean of these images. The reduction of the standard deviation is by a factor of $N^{1/2}$. The price being paid is a reduction by a factor of N of the resolution in the azimuth direction. Better results are obtained by using the information content of the image on the speckle reduction process, as it happens with several of the filters that will be described in this article.

3. Heuristic Filters

It is possible to devise heuristic schemes to reduce the speckle, without taking into consideration any statistical criterion.

A simple moving average (eg, 3x3, 5x5 window) over the image tends to reduce the speckle, due to the fact that there is a tendency for a moderately low correlation between adjacent speckle samples, if the point spread function of the sensor is not too wide. However, this low-pass filter tends to indiscriminately blur the image. The geometrical filter [Ref. 5] or the analogous morphological filter [Ref. 6] have also been proposed for speckle reduction. Like the moving average filter, they are efficient over homogeneous areas. However, although they tend to preserve edges well, these two filters erase point target responses, thin curvilinear structures and high frequency texture variations [Ref. 7]. Median filters have also been proposed on a heuristic basis, but, as will be described later in this paper, they can be introduced through the formal framework of robust estimation theory.

The most effective filters for speckle reduction are adaptive and based on appropriate models for the backscatter and the speckle statistical properties.

4. The Multiplicative Model

The fact that, over homogeneous areas, the standard deviation is proportional to the mean suggests a multiplicative model for the speckle that has been widely used for deriving speckle reduction schemes. It has been expressed as:

$$z_{i,j} = x_{i,j} \cdot n_{i,j} \quad (5)$$

The subscripts i and j represent the spatial position of the pixel over the image; z represents the noisy observed value of the pixel, x is the original signal (backscatter) and n is the speckle noise, with unitary mean and described by a probability density function that depends on the type of detection and the number of looks. The random variables x and n are independent.

The multiplicative model suggests that a possible method for filtering the speckle would be based on homomorphic techniques. It is based on taking the logarithm to transform the multiplicative noise into an additive one. Omitting the subscripts for simplicity, one obtains the following relation:

$$\log z = \log x + \log n \quad (6)$$

Once the additive model is obtained, there is a large number of techniques that could be used to derive noise reducing filters. At the final stage, an exponential operation is performed to obtain an estimate of the original image. Homomorphic filters have been used for speckle removal with some success by Jain and Christensen [Ref. 8], Lim and Nawab [Ref. 9], Arsenault and Denis [Ref. 10], Arsenault and Levesque [Ref. 11], Harvey and April [Ref. 12] and Franceschetti et al [Ref. 13]. It should be noted 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 distribution much faster than the intensity distribution. This fact was used by Guo et al [Ref. 14] in their wavelet-based method for speckle reduction.

5. Lee's Filter

Lee [Ref. 15] developed a widely used local statistics filter for speckle noise reduction. A pointwise linear filter minimizing the mean square error has the form:

$$x' = x_m + b(z - x_m) \quad (7)$$

where

$$b = \text{var}(x) / \text{var}(z) \quad (8)$$

and x_m and $\text{var}(x)$ (a priori mean and variance of the original signal) can be estimated through measurements of the sample mean and sample variance of the noisy image and knowledge of the type of detection and number of looks by the expressions:

$$x_m = z_m / n_m = z_m \quad (9)$$

and

$$\text{var}(x) = \frac{\text{var}(z) - z_m^2 \sigma_n^2}{\sigma_n^2 + 1} \quad (10)$$

In the derivation of Lee's filter a first order Taylor expansion for the multiplicative model (eq. 5) is performed around the mean value. In this case, the b term of eq. (7) has the form:

$$b' = \text{var}(x) / [z_m^2 \sigma_n^2 + \text{var}(x)] \quad (11)$$

In order to apply the filter, one has to check if the value of $\text{var}(x)$ given by eq. (10) is negative. In this case, we have a very homogeneous area, $\text{var}(x)$ should be set to zero and the estimate x' is given by the local mean z_m . On the other hand, if the numerator of eq. (10) is very large, this indicates a very high contrast region (or an edge presence) and $x' = z$. These extreme cases are in accordance with the bayesian approach that is adopted in this linear minimum mean square error filter.

6. Kuan's Filter

Kuan et al [Ref. 16] and Nathan and Kurlander [Ref. 17] also developed a local linear minimum mean square error filter under multiplicative noise. The difference with respect to Lee's filter is that there is no approximation involved. The multiplicative model is exactly transformed into an additive model with uncorrelated signal and noise and the pointwise Wiener filter is derived. The local statistics are computed by the same expressions as with Lee's filter (eqs. 9 and 10) and the b term in the filter expression (eq. 7) has the exact expression:

$$b = \text{var}(x) / [z_m^2 \sigma_n^2 + (1 + \sigma_n^2) \text{var}(x)] \quad (12)$$

The same observations that were made for the limit cases in the bayesian estimation procedure for the Lee's filter are valid for Kuan's filter. In practice, it has been observed that Lee's and Kuan's filters display a very similar performance.

7. Adaptation Procedures

Several adaptation procedures were proposed to cope with space varying statistics and the presence of features like edges. Li [Ref. 18] introduced the variance ratio given by $R = \sigma_x^2 / \sigma_z^2$ as a means of controlling the size of the window for computing the statistics given by eqs. (9) and (10). Under the multiplicative model, this ratio is given by:

$$R = \frac{1 - (z_m \sigma_n / \sigma_z)^2}{1 + \sigma_n^2} \quad (13)$$

This ratio varies from zero (very homogeneous areas) to one (strong contrast areas) and determines the size of the used window. Small (large) values of R indicate the use of large (small)

windows. The problem with this technique is the empirical choice of the thresholds on R to determine the window sizes.

Lopes et al [Ref. 19] proposed a modification on Lee's filter to include a lower limit (equivalent to the estimated $\text{var}(x)$ being greater or equal to zero in eq. (10)) and an upper limit on scene homogeneity, measured by the coefficient of variation σ_z/z_m . This upper limit is set experimentally or theoretically, based on several factors, like the number of looks, spatial resolution, scene properties, etc [Ref. 4]. Lopes et al [Ref. 7] introduced the use of edge detectors like the ratio detector of Touzi et al [Ref. 20] to be used in conjunction with that upper limit in order to define the shape and size of the window.

The same philosophy of limiting the size of the window was adopted by Lee [Ref. 21] in his Refined Local Statistics Filter; through the use of edge detection or by Wu and Maitre [Ref. 22] by determining the window size as a function of the maximum homogeneous region.

Lee [Ref. 23] introduced the idea of limiting the size of the averaging window to filter the speckle, by assuming a gaussian distribution and only averaging over those pixels that lie in the range of two standard deviations of the center pixel within a scanning window (that includes 95.5% of the distribution). Under the multiplicative model, this range is given by $(z - 2\sigma_n z, z + 2\sigma_n z)$, by assuming that z is the mean of the distribution.

8. Frost's Filter

A linear minimum mean square error convolutional filter for multiplicative noise reduction was proposed by Frost et al [Ref. 24]. The observed process is assumed to be further convoluted by a point spread function $h(t)$, although this blurring is ignored in the derivation of the filter, which has the form:

$$x'(t) = z(t) * m(t) \quad (14)$$

where $m(t)$ is an isotropic impulse response of the spatial filter given by an exponential expression:

$$m(t) = K_1 \alpha \exp(-\alpha|t|) \quad (15)$$

K_1 is a normalizing constant that guarantees the preservation of the mean value and α is given by:

$$\alpha^2 = (2a/\sigma_n^2)[\text{var}(x)/(\text{var}(x) + x_m^2)] + a \quad (16)$$

where x_m and $\text{var}(x)$ are evaluated by eqs. (9) and (10), respectively, over a 5×5 window and $\exp(-a)$ is the correlation coefficient between adjacent pixels of the original image $x(t)$. By assuming an autoregressive model for the original non-noisy backscatter image, Quelle and Boucher [Ref. 25] proposed an implementation of Frost's filter including an estimation of that correlation coefficient.

Although Frost's filter was shown to be not optimal [Ref. 26], it has been widely used for speckle noise reduction.

9. The Pointwise MAP Filter

An adaptive non-linear pointwise filter that satisfies the criterion of maximum a posteriori was proposed by Kuan et al [Ref. 27]. The authors assumed the multiplicative model for the speckle, one look and quadratic detection, which implies that the conditional probability density function $f(z/x)$ is exponential, with parameter x . The a priori probability density function for the signal x was supposed to be gaussian, with mean x_m and variance $\text{var}(x)$. Under these conditions, the estimate for x (x') must maximize the a posteriori probability density function $f(x/z)$, which is obtained by the Bayes rule. The estimate x' is a solution of the following third order equation:

$$x'^3 - x_m x'^2 + \text{var}(x)x' - \text{var}(x)z = 0 \quad (17)$$

The estimates for x_m and $\text{var}(x)$ are obtained by eqs. (9) and (10), respectively. Out of the three roots of the equation, x' is selected as the real, positive value that lies between x_m and z . This is in accordance with the bayesian approach of the MAP criterion, which gives a balance between the observation and the a priori mean.

The gaussian a priori density function is not a very appropriate model for describing the backscatter, which is necessarily a non-negative quantity. Therefore, Lopes et al [Ref. 28] proposed MAP estimates with densities defined on the non-negative real line, like the beta and gamma densities. The latter one has been proposed by several authors to describe the backscatter and, in the quadratic detection situation, it implies a K-distribution for the noisy signal [Refs. 29-31].

10. The ICM Filter

The natural extension of the pointwise MAP filter is to develop block filtering, taking into

consideration the correlation properties of the backscatter and/or the speckle. This possibility faces numerical difficulties due to the non-linearity of the system of equations and it was examined by Luttrell [Ref. 32].

Another possibility comes from the theory of Markov Random Fields. In this case, a bayesian framework is also adopted and the a priori global distribution of the backscatter is chosen as a Gibbs distribution. By choosing the MAP criterion, the direct solution involves a very large number of variables and the technique of simulating annealing associated with the Gibbs Sampler of Geman and Geman [Ref. 33] could be used, but with a very high computational load.

A method that provides a local optimum is the ICM (Iterated Conditional Modes), originally proposed by Besag [Ref. 34]. This method was used by Frery and Mascarenhas [Ref. 35] for the binary segmentation of SAR images and later, by increasing the number of levels of the a priori model (Multilevel Logistic or the Potts-Strauss model), by Mascarenhas and Frery [Ref. 36] for speckle filtering.

The ICM algorithm uses both the conditional probability density of the noisy observation, given the backscatter (given by the Rayleigh distribution in the case of one look and linear detection) and the conditional probability of the backscatter x at a certain pixel, given the values of the backscatter values over the neighborhood (δx) of this pixel. This last expression has the form:

$$\Pr(x/\delta x) = \exp(\beta \cdot \#(t \in \delta x : x = x_t)) \quad (18)$$

Therefore, the expression to be maximized by the choice of x at each pixel in the iterative procedure is given by:

$$\exp(\beta \cdot \#(t \in \delta x : x = x_t)) \cdot (z/x^2) \exp(-z^2/2x^2) \quad (19)$$

The 4-neighborhood was chosen and the parameter β was estimated at each cycle of the iteration by the maximum pseudolikelihood estimation procedure [Ref. 37]. The iteration process was started by the pointwise maximum likelihood classification of the pixels in one of the selected number of backscatter values (from 16 to 256), using the Rayleigh probability density function.

An airborne SAR-580, L-Band, HH polarization, one-look, linear detected image over Freiburg, Germany, was used to test the ICM algorithm. Figure 2 shows the original 128x128 image and

the result of applying the Nagao Matsuyama filter [Ref. 38], for comparison. Figure 3 displays the results of the ICM with 16 and 32 levels and Figure 4 with 256 levels. There is an effective noise reduction with the ICM, as compared to the original image. It is also noticeable the effect of blocking, i.e., the noise reduction is performed by the grouping of observations with similar grey levels. The blocking effect is more pronounced with the Nagao-Matsuyama filter, yielding a visually less natural solution.

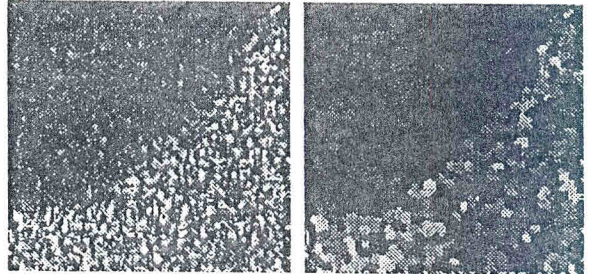


Figure 2- Original Image (l), 256 levels, and the result of applying the Nagao-Matsuyama filter (r).

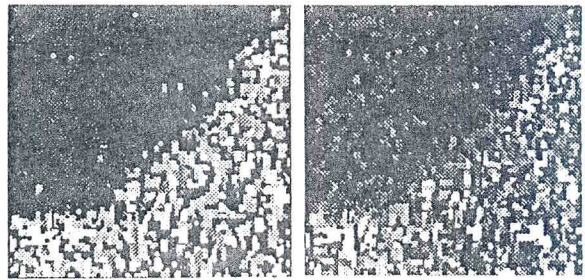


Figure 3- Filtered image with the ICM algorithm: 16 and 32 levels.

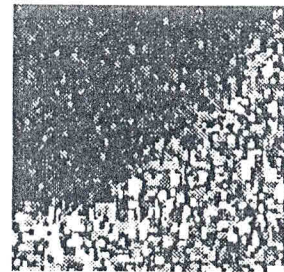


Figure 4- Filtered image with the ICM algorithm: 256 levels.

11. The Robust Filters

In general, the proposed filters for speckle noise reduction assume that all the samples come from the same distribution (eg, the Rayleigh distribution over homogeneous areas, with linear detection and one look) and are independent, given the backscatter. These assumptions may be violated, for example , over edges between different regions, by mixture of distributions, or by correlation between speckle values, due to the point spread function of the sensor. In these cases, it may be useful to derive estimators that are robust to the contamination of the samples.

Frery and Sant'Anna [Ref. 39] proposed speckle reduction filters based on the theory of robust estimation [Ref. 40]. Two kinds of robust estimators were considered: two based upon the idea of trimming extremal observations and three based on order statistics, including the median filter.

Figure 5 displays the histogram of the original image over the same area of Figure 2. It can be seen that, even though there are two distinct backscatter areas, the speckle noise completely masks the valley of the histogram. Figure 6 shows the image obtained with one of the robust filters, the trimmed maximum likelihood filter, while Figure 7 displays the corresponding histogram. The reduction of the speckle noise is quite clear, by observing the valley in the histogram.

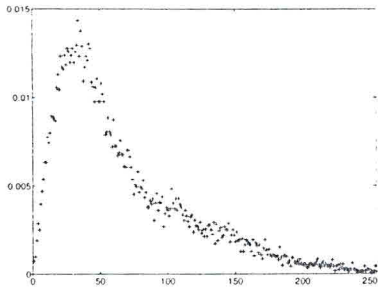


Figure 5- Histogram of the original image



Figure 6- Trimmed maximum likelihood filtered image

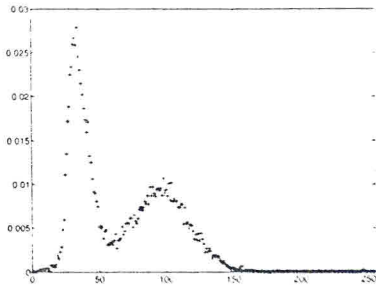


Figure 7- Histogram of the trimmed maximum likelihood filtered image

12. Filter Evaluation

The evaluation of a filter performance should consider several factors [Ref. 4]: retention of mean value over homogeneous areas, (unbiasedness), speckle reduction capability, edge sharpness and thin features preservation, point target preservation, texture preservation, computational efficiency and implementation complexity.

The speckle reduction capability is usually measured by the equivalent number of looks (ENL). For the linear detection, this quantity is evaluated over homogeneous areas by the expression:

$$ENL = 0.2732 (z_m^2 / var(z)) \tag{20}$$

For the quadratic detection the expression is:

ENL = (p_m²/var(p)) (21)

where p = z².

An experiment was performed [Ref. 41] using the SAR-580 image, part of which is displayed if Figure 2. The image was filtered using the mean, the median, Lee, Kuan and Frost filters with a 5x5 window, as well as the filters by Lee and Kuan by incorporating Li's adaptation procedure. The number of looks was measured over homogeneous areas, where the fit of the histogram to the Rayleigh distribution was quite good. The results are summarized in Table 1 below.

Image	ENL
Original	1.0
Mean	5.5
Median	4.3
Lee	5.1
Lee - Adapt. Wind.	8.2
Kuan	5.1
Kuan - Adapt. Wind.	8.6
Frost - ρ = 0.6	3.8
Frost - ρ = 0.8	4.4

Table 1 - Equivalent number of looks for several filters, over homogeneous areas

Edge sharpness was measured by Lee et al [Ref. 4] by using three pixel wide strips on both sides of the edge, taking the sample means and variances over these strips and the absolute difference in the means as the measure of edge sharpness. The square root of the sum of the two variances is a measure of the speckle noise level along both sides of the edge. Sant'Anna and Mascarenhas [Refs. 42, 43] used two edge detectors: a) the coefficient of variation over a 3x3 window, thresholded to the average of the three-pixel wide strip around the edge of the non-noisy image on the simulation and b) the parametric edge detector proposed by Bovik and Munson [Ref. 44]. In the first case, the figure of merit of Abdou and Pratt [Ref. 45] was used and in the second case a measure depending on the percentage of correctly and incorrectly detected as well as the percentage of non-detected edge pixels was computed.

The evaluation of one pixel wide line targets by Lee et al [Ref. 4] was made by estimating the contrast between the line and its background by using the line pixels and two one-pixel wide strips on both sides of the line. The difference between the mean value of the line pixels and the mean value of the background pixels is the

measure of line preservation. A similar measure was adopted for point target preservation. Sant'Anna and Mascarenhas [Ref. 40] measured the widening of the point spread of an airborne radar to evaluate the point target preservation of different speckle reduction filters.

Retention of texture information is difficult to quantify, so the judgement is usually performed by visual inspection. In general, filters using small windows (3x3 or 5x5) have a better performance in this respect.

13. Concluding Remarks

In this paper, a brief overview of several speckle reducing filters was presented. It is very difficult to make a statement about which filter is the best. The ideal filter should perform well with respect to all items of last section.

Lee et al [Ref. 4] consider the Refined Lee Filter very adequate for visual interpretation, due to preservation of edges, linear features, point targets and texture information. For segmentation, the Geometrical Filter and most of the adaptive filters, iteratively applied, are adequate, due to their very good speckle smoothing capability.

14. References

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