Speckle Noise MAP Filtering Based on Local Adaptive Neighborhood Statistics

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Abstract. This work proposes the use of an adaptive neighborhood procedure to extract local statistical properties of images in order to improve a speckle noise "Maximum a Posteriori "(MAP) filtering performance. The strategy consists in growing the local statistically homogeneous area near the pixel in order to estimate its MAP filtering parameters. Measures evaluating both the signal-to-noise improvement and resolution loss due to filtering are computed. The use of region growing is investigated as a promising approach compared to a fixed size and shape neighborhood.

1-Introduction

The analysis of synthetic aperture radar (SAR) images requires in a first step of processing to reduce the speckle noise in order to improve the overall visual aspect of the image. The use of SAR images filtering improves the segmentation and classification considerably because filtered images are easier to classify. This kind of noise degrades images generated by coherent signal sources, such as radar signals. In speckle noise filtering there is a compromise between the smoothing of the homogeneous areas and the edges and detail preservation. The basic requirements of those filtering algorithms are: to provide a large amount of speckle noise reduction in homogeneous areas and to prevent edges and detail (resolution) blurring.

Various algorithms have been proposed to restore noisy images using local statistics, including those proposed by Lee [11] [12], Kuan [4] and Frost [10] which use fixed size and shape local neighborhoods to adapt the filtering techniques on a small square area around the noisy pixel. The adaptive strategy is to select a neighborhood of the pixel which is suitable for calculating statistical measures (mean, variance, for example) to update the central pixel according to a filter based on those statistics. Medeiros et al. [14] developed a speckle noise filtering technique that combines the "Maximum a Posteriori" estimation and the k-means clustering algorithm. The k-means over Changle Li's coefficient [8] is used to classify the noisy image in regions of homogeneous statistics which is used as a guide for choosing the best window size for parameter estimation [14]. The dependence of results on the shape and dimensions of the processing window is a well-known problem in image processing algorithms. According to the main characteristics of the image under analysis or the processing objective, the window can be carefully designed in linear or nonlinear algorithms in order to reduce the bias error [3]. However, it is well known that large filtering window sizes cause resolution degradation. So, the requirement for an edge preserving filter is to reduce the noise variance while preserving edges and details.

One of the contibutions of this paper is to propose the use of adaptive neighborhoods within the MAP approach, investigating the benefits and drawbacks. For the proposed algorithm, we aim to find a better subset around each pixel (without fixed shape and size) whose respective statistical information is more suitable to perform the MAP filtering. These subsets of pixels are expected to form statistically homogeneous regions on which the local statistics (mean and variance) used in the adaptive MAP filters are estimated. The estimation of the parameters is based only on those pixels of the grown region that are supposed to have the same statistics as the central pixel to be filtered. This work investigates the improvements that can be achieved by adopting such a methodology. The MAP filtering based on region growing approach is adapted to favor the speckle noise filtering in homogeneous areas.

This paper is organized as follows: section 2 presents a brief review of the multiplicative speckle model and describes the Kuan's filter [4] used to be compared with the proposed algorithm. In the third section the MAP technique combined with the region growing approach is described. In section 4 there is a description of the quality measures used to quantify the reduction of the speckle in the MAP filtering algorithm. Section 5 includes the simulations results, discussions about the advantages and limitations of this approach and concluding remarks.

2 - Background

2.1 - Speckle Noise Model

The degradation model used for the speckle noise is the multiplicative model. In equation (1), $z_{i,j}$ describes the noisy amplitude pixel, $x_{i,j}$ the original pixel (undegraded pixel) and $n_{i,j}$ the speckle noise with unitary mean and a standard deviation σ_n. The indices i and j indicate the spatial position over the image. The speckle noise, $n_{i,j}$, follows a Rayleigh density function, by assuming linear detection and one-look image [2].

$$z_{i,j} = x_{i,j} n_{i,j} \qquad (1)$$

As the signal and noise are assumed to be statistically independent, the average over z ($\bar{z}$ or the alternative notation μ_z) is given by:

$$\begin{aligned} \bar{z} &= \bar{x} \\ \mu_z &= \mu_x \end{aligned} \qquad (2)$$

with variance :

$$\sigma_z^2 = E\left[(xn - \overline{xn})^2\right] = \bar{z}^2 \sigma_n^2 \qquad (3)$$

and considering that over homogeneous areas the expected value of the square of original image is given by $E\left[x^2\right] = \bar{x}^2$.

This means that for images in which the number of looks, N, is unknown, the standard deviation, σ_n, can be estimated over homogeneous areas by plotting σ_z versus $\bar{z}$. Along of this paper $\bar{z}$ and μ_z are alternatively used to represent the mean.

2.2 – Kuan's Local Statistics Filter

In order to evaluate the performance of the proposed algorithm we applied Kuan's filter using a 5x5 window size to the set of test images. Kuan et al. [4] proposed a local linear minimum square error filter based on the multiplicative model. To perform the adaptive speckle noise pointwise filtering the local statistics are computed using a fixed neighborhood. The noisy pixel is updated by the expression: $\hat{x} = \mu_x + K(z - \mu_x)$, where $\hat{x}$ is the minimum mean square estimate of x, μ_x (or $\bar{x}$) is obtained from the local mean of the noisy pixel computed in the fixed neighborhood, z is the noisy pixel and K is given by:

$$K = \frac{\sigma_x^2}{\mu_z{}^2 \sigma_n^2 + (1 + \sigma_n^2)\sigma_x^2} \qquad (4)$$

$$\sigma_x^2 = \frac{\sigma_z^2 - \sigma_n^2 \bar{z}^2}{1 + \sigma_n^2} \qquad (4a)$$

where $\sigma_n{}^2$ represents the noise variance and σ_x^2 is the variance of the original image. In the absence of a precise model for the signal x, the noisy image is used to estimate the "a priori" mean and variance of the signal from the local mean and the local variance (μ_z) [13].

This adaptive filter has a good performance because it smooths out homogeneous areas more than edge areas. Rangayyan & Das [1] proposed a region-based filtering technique for restoring images with multiplicative noise using Kuan's filter. This new method produced better restored images than the 3x3 median filter and the 3x3 multiplicative noise filter of Kuan in terms of both visual quality and MSE.

3 - The MAP Filtering Procedure Based on the Region Growing Approach

The "Maximum a Posteriori" approach for SAR image speckle filtering was first proposed by Kuan et al. in [5], assuming the multiplicative model for the speckle noise, as well as one-look, quadratic detection and Gaussian "a priori" density, to propose an adaptive non-linear pointwise filter that satisfies the MAP criterion [2]. Lopes et al. [9] suggested a MAP filter that takes into account quadratic detection, gamma and beta distributions as "a priori" statistical models for the scene improving the Kuan et al. MAP filter [5]. In Mascarenhas et al. [7] the MAP estimation technique was used to filter the Poisson noise presented in tomographic projections using several “a priori” densities. Medeiros et al. [14] proposed the use of a clustering algorithm (the k-means clustering procedure) on a one-dimensional form, over the Changle Li’s variance ratio [8] as a formal way for choosing those thresholds and the window sizes.

The MAP estimate of x is obtained by maximizing the “a posteriori” probability density function $f(x/z)$, which can be related to the “a priori” distribution, $f(x)$, through the equation given by:

$$f(x \mid z) = \frac{f(z \mid x) f(x)}{f(z)} \qquad \frac{\partial}{\partial x} \ln(f(x \mid z)) = 0 \tag{5}$$

where $f(z \mid x)$ corresponds to the speckle distribution and *ln* is the natural logarithm.

Using the Gaussian “a priori” density in the MAP equation and combining with it the conditional probability density function of the speckle (Rayleigh type), the estimator of the original pixel is given by the solution of the equation [14]:

$$2x^4 - 2\mu_x x^3 + 4\sigma_x^2 x^2 - \sigma_x^2 \pi z^2 = 0 \tag{6}$$

where the μ_x and σ_x parameters are calculated using equations 2 and 4.a. The real and positive root of equation 6 whose value is between the mean and the observed pixel is taken as the filtered pixel value. Several different distributions such as gamma, exponential, chi-square, beta, log-normal, Rayleigh and Weibull were used as the “a priori” model yielding different filters.

The idea behind the use of this new approach is to consider each pixel of the noisy image as a seed to be grown. In this paper the statistical homogeneity of these regions is used to determine the best neighborhood of the noisy pixel to extract the MAP filtering statistics to update it.

Differing from those methods that use a fixed size and shape neighborhood, we present a method that uses a variable size neighborhood and shape to extract the statistical information of the region near the pixel to be filtered. The filter is adapted to each pixel according to the surrounding region statistics. The parameters of the MAP filter are based on contextual information of the pixel (seed) rather than a fixed group of pixels in a window.

The methodology for determining the adaptive neighborhood for a pixel in the noisy image is as follows: the method starts with the pixel to be filtered as the seed and compares it with its 8-connected pixels. At first, the tolerance index (standard deviation to mean ratio) is calculated in a fixed 5x5 window size centered at the seed until its region grows more than 5 pixels. When the region grows up to 5, the tolerance index used as the aggregation factor is calculated using only the pixels that belong to the grown region. An indicator that considers the speckle noise fluctuations is the standard deviation to the mean ratio (σ_T) calculated over homogeneous areas. It is the homogeneity measure used as the tolerance index in the proposed approach to aggregate pixels in the region growing. Connected pixels are accepted to be incorporated into the region grown if the calculated tolerance index (σ_T) including it, does not exceed the standard deviation of the speckle noise for amplitude and one-look image (σ_n) by a small value. If a connected pixel meets the criterion, or in the same way $\sigma_T \le \sigma_n + \delta$, it means that it is accepted in the region and the homogeneity is still preserved with its inclusion, but when σ_T is outside this interval the pixel is not accepted. In this approach, the process recursively continues with all the pixels in the region and its connected until it stops growing. When this occurs, it means that the homogeneity was reached. The strategies used to stop growing are: (a) when there are no more connected pixels whose calculated index are below to this one-sided interval (b) the region reaches a specified maximum size. The one-sided interval which defines the neighborhood homogeneity is given by:

$$\sigma_T \le \sigma_n + \delta \qquad \sigma_n = 0.5227 \qquad \sigma_T = \frac{\sigma_{RG}}{\mu_{RG}} \tag{7}$$

where σ_n is the theoretical standard deviation of the speckle noise, δ is a small value added to σ_n to establish the upper interval, σ_T is the calculated index and σ_{RG} and μ_{RG} are respectively, the standard deviation and local mean in the region growing. As the region stops growing, the mean and variance are calculated over the adaptive neighborhood. Those statistical measures are used in the parameters estimation of the a priori distributions used in the MAP algorithm. The noise filtering is performed by updating the seed with the solution (root) of the MAP estimator using a Gaussian “a priori” distribution, that is between the mean and the observed pixel [14]. In case the solution is outside this interval we choose among the real roots the one that is closest to the mean or the observed noisy pixel. If there is no real root the noisy pixel is updated by the observed pixel or by the mean using a window size defined according to a threshold based on the Changle Li’s variance ratio (R) [8].

4 - Algorithms Evaluation Measures

The performance of the filtering algorithms is established using some measures. Some of them evaluate the filtering with respect to the strength reduction of the speckle in the filtered images, the effects on edges and radiometric distortion. To compute the following quality measures, the original image, the noisy version and the filtered image are used as follows:

a) The first one is presented in [6] and consists of the ratio of the noisy pixel, $z_{i,j}$, to the estimated one, $x_{i,j}$, represented by the expression:

$$r_k = \frac{z_{i,j}}{\hat{x}_{i,j}}$$

$$ratio\_MED = \frac{1}{Q}\sum_{k=1}^{Q} r_k \qquad (8)$$

$$STD\_ratio = \sqrt{\frac{1}{Q}\sum_{k=1}^{Q}(r_k - 1)^2}$$

where Q is the number of pixels in the image.

The ratio, r_k, should correspond to the statistics of pure speckle noise (speckle fluctuations) with unit mean (*ratio_MED*). When the observed mean value differs significantly from one, it is an indication of radiometric distortion. If the reconstruction follows the original image too closely, the standard deviation (*STD_ratio*) would be expected to have a lower value than predicted (e.g. when the original image has 2.2 effective looks, the expected standard deviation for the intensity ratio image is 0.674) [6].

b) The mean-squared error (*MSE*) between the original and the MAP filtered image is calculated by the following equation:

$$MSE = \frac{1}{MN}\sum_{i,j=1}^{M,N}\left[x(i,j) - \hat{x}(i,j)\right]^2 \qquad (9)$$

where MxN represents the image dimensions, $\hat{x}$ is the filtered image and x is the original one.

c) In [7] the quantification of the results is taken in terms of the root mean square normalized error of estimation (*RMSNE*) given by

$$RMSNE = \sqrt{\frac{\sum_{i,j=1}^{M,N}(x_{i,j} - \hat{x}_{i,j})^2}{\sum_{i,j=1}^{M,N} x_{i,j}^2}} \qquad (10)$$

where $\hat{x}_i$ is the estimator value and MxN is the number of pixels in the image.

d) The signal to noise ratio follows directly from the multiplicative model of the speckle and is defined by the standard deviation to mean ratio. It is a good measure to evaluate the speckle strength reduction over homogeneous areas. For one-look and linear detected images this ratio is described by the expression (in case of filtered images):

$$\beta = \frac{\sigma_{\hat{x}}}{\mu_{\hat{x}}} \qquad (11)$$

The equivalent number of looks (*ENL*) is measured in terms of the β index. For one-look and linear detected images it is defined as

$$ENL = \left(\frac{0.5227}{\beta}\right)^2 \qquad (12)$$

where 0.5227 is the value of the standard deviation of the speckle over homogeneous areas.

e) The retention of the mean value over the homogeneous areas of the filtered image is an important aspect of speckle filtering algorithms. In this paper it is also used to evaluate the filters performance.

f) The Hough Transform is used in this work to extract information about the dispersion along straight borders in the filtered images. The fact that man-made structures usually present straight lines and the test images contain this kind of structures motivated the use of the Hough transform as an evaluation tool of edge preservation (after filtering). Considering that digital curves are (piecewise) composed of digital lines, the proposed methodology can be also extended to general images [2]. The implementation of this technique in this article follows the polar representation of a straight line:

$$x\cos\theta + y\sin\theta = \rho \qquad (13)$$

where x, y indicate the spatial position of the pixel over the image. The parameters (ρ,θ) represent the normal distance from the line to the image origin and its orientation, respectively. A straight line passing through the point (x,y) represents a sinusoidal curve in the Hough space. Hence, a set of collinear points points on the binary image space correspond to intersections of multiple sinusoids on the parameter space. To find a straight line in the binary image we can set up a two-dimensional array in the Hough space (ρ,θ) and for each point (x_i,y_i) in the binary image, we increment all the cells in the ρ,θ space that correspond to the sinusoidal curve for that point. After doing that for all points, we apply a threshold (backmapping) to the accumulator array in order to eliminate spurious information. This is a post-processing and is calculated according to [2]. The surroundings of the peaks obtained in the final Hough Transform (backmapping) are analysed in order to quantify the distortions (dispersion) in straight features known to exist in the original image (e.g. images including man-made structures such as buildings, etc.). The average value of the areas of the regions surrounding the peaks were obtained and used as a measure of straight edge preservation [2]. The measure used to evaluate the results is given by

$$S = \frac{\sum_{i=1}^{N} C_i}{N} \qquad (14)$$

where C_i is the area around the peak and N is the number of peaks.

5 - Simulations Results and Discussion

The noisy versions of the test images have been produced by multiplying its samples by generated unitary-mean noise following the one-look and amplitude speckle statistics. Using the multiplicative model as defined in equation 1 we applied the speckle noise generated by the MATLAB function *random* '*rayl*' with the Rayleigh parameter ('backscatter') equals to 0.7963 as a way to have a unitary mean Rayleigh density.

In the following tables we display the measures calculated for a simulated noisy speckled image (Bla) and a real SAR amplitude and one-look image (SAR580). The original speckled image has a very broad histogram while the filtered one tends to have valleys in its histograms, resulting in a better discrimination of classes. It is visually noticed from the images that the speckle fluctuations were reduced, specially for homogeneous areas while edges were preserved. For the image Bla several filtered images were computed using region growing according to different thresholds of rejection homogeneity. We investigated how far the region grows and its implications on the speckle reduction over homogeneous areas. Figures 1(a) and (b) show the results of this computation. In Figure 1(a) the relation between the threshold of the homogeneous region growth and the speckle index reduction is shown. When the upper threshold of growth is set to 0.5446 the smoothing of homogeneous areas is more effective than to lower values of threshold. There is an optimum point at this threshold meaning that there is a homogeneity limit to region growth. Figure 1(b) shows the relation between the threshold of the homogeneous region growth and the equivalent number of looks. The results from the variable size and shape neighborhood are close to the fixed neighborhood because of the similarities between them for the image Bla. This similarity is due to the fact that in the fixed case the statistics are computed in a 5x5 window, and in the new approach the maximum region size is 25 pixels. So, for higher thresholds the regions tend to grow to dimensions close to the fixed neighborhood resulting on a slightly superior performance.

In tables 1 and 2 the evaluation measures using fixed neighborhood are presented and table 3 refers to the variable size and shape neighborhood. The images Bla and sar580 are numbered in the tables as I and II respectively. It is shown in tables 1, 2 and 3 that there is a slight superiority in the region growing approach compared with Kuan's filter and Gaussian MAP filter (fixed neighborhood) with respect to the ratio_MED and STD_values, meaning that the radiometric distortion introduced by the filtering is very small.

With respect to retention of the mean over homogeneous areas, our results were obtained in uniform regions of 11x11 pixels in the test images (SAR580 and Bla). In order to compare the MAP region based filtering algorithm with other algorithms, the mean values over an homogeneous area were calculated for each image using the Gaussian MAP filters (with fixed neighborhood and combined with k-means clustering algorithm and Kuan filter). The Figure 2 shows the mean value over the noisy homogeneous area and over the filtered ones. The overall mean retention values over the Bla speckled image and Gaussian MAP filtered images with fixed and variable neighborhood are respectively 102.4, 99.8 and 99.9. This study demonstrated that this approach seems to be a promising one and it can be further improved.

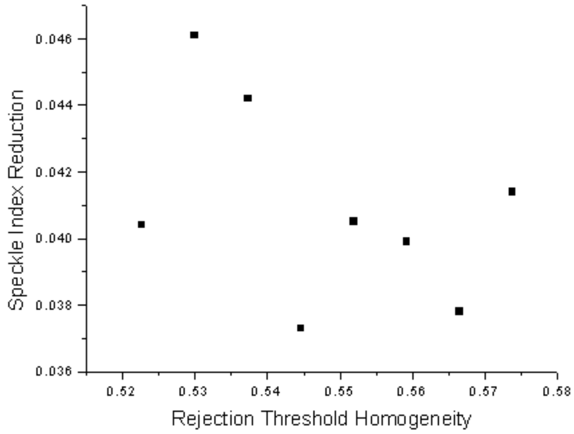

Figure 1 (a)- Scatterplot of speckle index reduction versus rejection threshold (image Bla).

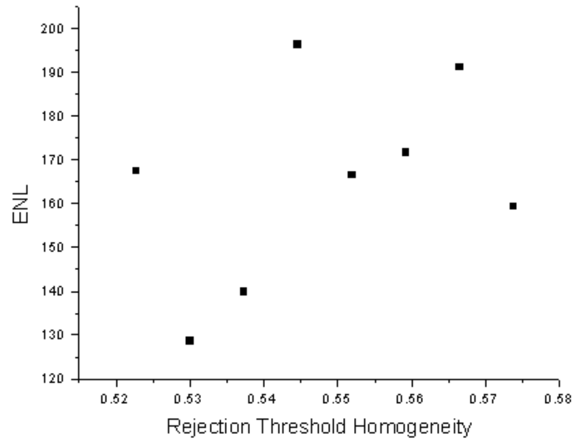

Figure 1 (b)- Scatterplot of equivalent number of looks versus rejection threshold (image Bla).

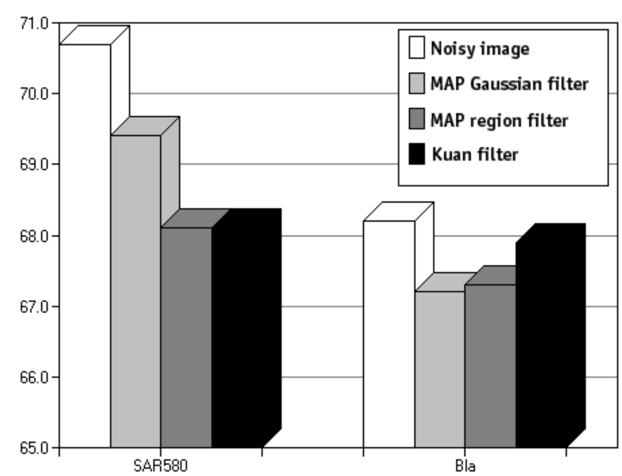

Figure 2 - Retention of mean values over homogeneous areas.

IMAGE	Kuan Filter					
	STD_ ratio	ratio_ Med	*RMSNE*	β	*MSE*	S
I	0.29	0.97	21.04	0.07	336.40	1.13
II	0.17	0.91	______	0.09	_____	1.33

Table 1- Kuan filter evaluation measures (fixed 5x5 neighborhood).

IMAGE	Gaussian MAP					
	STD_ ratio	ratio_ Med	*RMSNE*	β	*MSE*	*S*
I	0.20	1.00	21.88	0.08	427.87	1.28
II	0.16	0.81	______	0.10	_____	1.34

Table 2- Gaussian MAP filter evaluation measures (fixed 5x5 neighborhood).

IMAGE	Gaussian MAP Grow					
	STD_ ratio	ratio_ Med	*RMSNE*	β	*MSE*	*S*
I	0.20	1.00	21.92	0.03	431.94	1.20
II	0.19	0.98	______	0.05	_____	1.34

Table 3- Gaussian MAP region growing filter evaluation measures.

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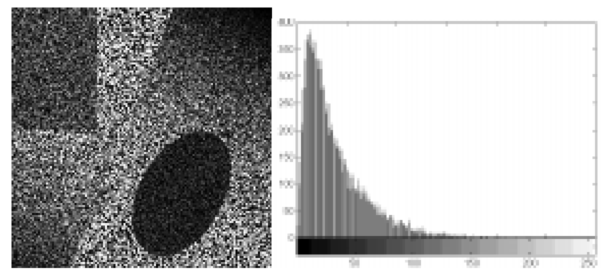

Figure 2(a) Speckled noisy image (b)histogram

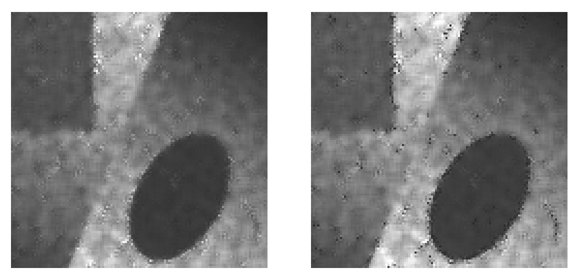

Figure 2(c) Kuan filtered image (d) Gaussian MAP filtered image (fixed neighborhood 5x5).

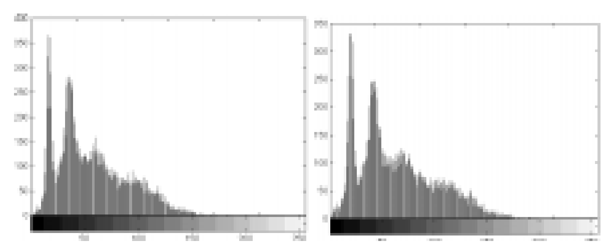

Figure 2(c) Kuan filtered image histogram (d) Gaussian MAP filtered image histogram

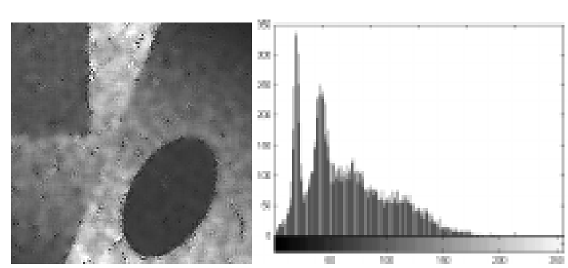

Figure 2(e) Gaussian MAP region growing filtered image (f) histogram

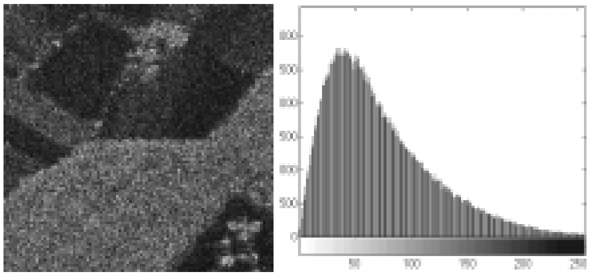

Figure 2(a) SAR580 image (b) histogram

Figure 3(c) Kuan filtered image (d) Gaussian MAP filtered image

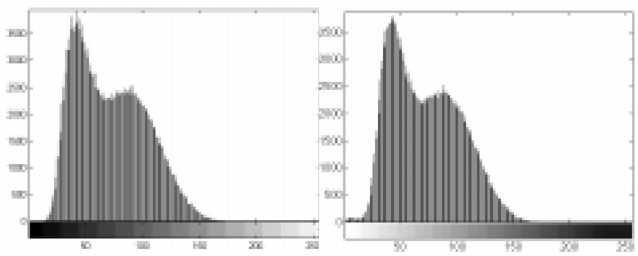

Figure 3(e) Kuan filtered image histogram (f) Gaussian MAP filtered image histogram (fixed neighborhood 5x5).

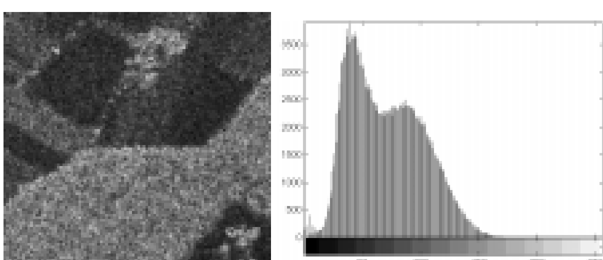

Figure 3(g) Gaussian MAP region growing filtered image (h) histogram