A LEAST COMMITMENT APPROACH FOR SAR IMAGE FILTERING

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Abstract: This paper presents a new filtering approach based upon the detection of homogeneous regions. The reliability and ordering of decisions are analysed through the least commitment principle. The first decisions should use a priori information and be performed on a pixel basis. The characteristics of radar images are combined with spatial constraints to select the best homogeneous region around each pixel. A segmentation technique based upon confidence intervals is used. The average value of a region inside a window is calculated and assigned to the center pixel. An airborne C/X SAR 580 image of a forestry area is used to test the filter. The speckle in homogenous areas is smoothed while the edges and textures are preserved.

I. Introduction

Synthetic aperture radar (SAR) systems provide high-resolution images for remote sensing applications. The utilisation of the microwave band makes the image acquisition mostly independent of weather conditions. SAR images are generally affected by speckle due to the interference of reflected waves from many elementary scatterers. The speckle complicates image interpretation and reduces the effectiveness of automatic image analysis techniques. The speckle is generally modeled as multiplicative noise.

Several filtering methods have been proposed such as the Lee filter [2], the Kuan filter [4] and the Gamma filter [5]. These filters are adaptive and use local statistics on a fixed size window to determine the weighting factor. These filters are better than the Box filter or the median filter because they consider the multiplicative nature of the speckle noise. However, they use an estimation of the coefficient of variation of the signal intensity to make a decision about the homogeneity of an area. In some cases, this estimation may not be reliable and produces poor results.

In this paper, a new speckle filtering approach is proposed. The approach determines the largest homogeneous area around each pixel within a moving window. It uses a statistical model of a SAR image, a segmentation technique and a spatial constraint to select the homogenous areas. The filter is tested on a SAR image of a forestry area and interesting results is obtained.

Mathematical model

Radar images are mainly characterized by the presence of speckles. The radar signal can be modeled as a random process. The probability density function (pdf) of the signal intensity or power, for a fully developed speckle, is given by [5]:

$$p(I)=1/P_0\exp(-I/P_0)$$

where I is the signal intensity and P_0 is the average signal intensity over a homogenous area. This is an exponential distribution where the mean value, μ_I, and the standard deviation, σ_I, are equal: $\mu_I = \sigma_I = P_0$. This shows clearly the large variance of the radar signal. The variance can be reduced by performing multi-look processing, i.e., by averaging L independent views of the data. The pdf of a L-look signal follows a Gamma distribution:

$$p(I)=1/G(L)(L/P_0)^L I^{L-1}\exp(-LI/P_0)$$

In this case, the mean value and the standard deviation of the signal intensity are: $\mu_I = P_0$,
$\sigma_I = P_0 /$. As the standard deviation varies with the mean value, we generally use the variation coefficient to express the signal variation: $C_I = \sigma_I / \mu_I = 1 /$.

The multiplicative aspect of the speckle noise component is also illustrated by the following model of the radar signal:

$$I(x,y)=R(x,y)´U(x,y)$$

where t = (x,y) represents the spatial coordinates of an image point and I(t) is the observed image intensity at t = (x,y). R(t) is the ground reflectivity and corresponds to the variable that should be estimated by the filtering process. The multiplicative speckle noise, U(t), is statistically independent of R(t).

Image Filtering

A good filter should maintain the signal mean value and reduce the speckle while preserving the edges. Thus, the estimator should have no bias, and its dispersion around the mean should be small. A simple filtering technique, the Box filter, consists in the calculation of the intensity mean value over a moving window. The mean is a good estimator when the window is in a homogeneous area. However, if the window covers two distinct areas, there will be a bias in the estimated value. This corresponds to the blurring of region boundaries or linear features.

The window size should be adjusted so as to cover only a homogeneous area. Frost [1] uses a weighting window corresponding to the convolution of the observed image with the impulse response of the filter. The impulse response is exponential and its width is automatically adjusted. A different approach to adaptive filtering is to use a fixed window size and a weighting factor for the window average value:

$$\hat{R}(t) = w(t) I(t) + (1 - w(t)) \bar{I}(t)$$

where w(t) is the weighting factor with a value between 0 for homogeneous area and 1 for heterogeneous area. Different filters use different formulas to calculate the weighting factor [2] [4] [5]. The weighting factor is based upon the coefficient of variation estimated over the window. The coefficient of variation is used to decide if an area is homogeneous or not, and to adjust consequently the weighting factor. Image filtering can thus be viewed as a decision process and the quality of the results is related to the reliability of the decisions. Unfortunately, the estimation of the variation coefficient is very noisy and the decisions that use it are unreliable.

Another kind of filtering method is used by the Sigma filter [3]. The Sigma filter is based upon the sigma parameter of a Gaussian distribution. The image noise is filtered by averaging only those pixels within a two-sigma range of the center pixel of the window. The filtering process determines the two sigma limits for each pixel and calculates the average value of the pixels inside the limits over a moving window. This filter should be applied repeatedly.

II. A new approach for speckle filtering

The least commitment principle

Image filtering can be viewed as the estimation of the ground reflectivity, R(x,y). In the Box filter, the estimator corresponds to the average value calculated over a window. The ideal estimator would have no bias and little dispersion around its mean value. The reduction of speckle noise is directly related to the reduction of the estimator dispersion. Smaller dispersions are obtained by using a larger window. If the window covers two distinct areas, the estimated value will be a combination of the actual reflectivity of both areas. This introduces a bias in the estimator: the mean value of the estimator does not correspond to the true value of either area. In fact, the Box filter blurs the edges in the image, corresponding to the introduction of a bias in the estimator near the edges.

Adaptive filters use a decision process to adapt the filter and reduce the bias (the blur). The coefficient of variation is used to decide if the window covers a homogeneous area or contains an edge. If an edge is detected, the smoothing is reduced to preserve the edge and avoid the introduction of a bias in the estimator. The coefficient of variation is estimated over the window and remains rather noisy. Therefore, the decision process based upon the coefficient of variation is unreliable.

The reliability of the first decisions is important. Their results will be used by the following decisions. Wrong decisions in the first steps will propagate and greatly affect the quality of the final results. The first decisions are made from the raw input data, e.g., the SAR image data. We should look for reliable decisions that can be made from this data. They should be simple decisions that provide only a limited amount of new knowledge. With time, the new knowledge will accumulate and will allow more difficult decisions to be made in a reliable manner. This approach corresponds to the "least commitment principle" of Marr. The principle states that unreliable decisions should be delayed. Reliable decisions should be made first and used to accumulate confidence about more risky decisions. This is also described as "evidence gathering." Decision processes are used in image filtering and we should examine new ways to organize those decisions following the "least commitment principle."

Homogeneous area detection

To be reliable, an estimator should be calculated from samples coming from the same population, or in the image filtering case, over a homogeneous area. How can we find homogeneous areas? Edge preserving filters provide one approach to this problem. Usually, they consider a window centered on a pixel. The window is divided into many overlapping sub-windows of varying shapes, all containing the central pixel. A homogeneity measure is then calculated over each sub-window. The best sub-window is selected and used to calculate the mean value that will be assigned to the central pixel. Unfortunately, in SAR images, the homogeneity measure will be noisy, or if the sub-windows are large, biased.

The least commitment principle says that we should use simple decision processes exploiting a priori knowledge. Hence, decisions should not be made on a window basis but on a pixel basis. For each pixel, we should use a priori information to decide if it will be used in the calculation of the estimator (the averaging process).

Utilisation of a priori information

In a homogeneous area, Gamma distribution is often used to describe the radar signal. We usually know the number of looks of an image. Furthermore, if we assume that we know the average backscattering intensity of an area, P_0, then we know the pixel distribution of the area. Knowing the pdf, we can design a reliable decision process to decide if a pixel belongs or not to the region. Hence, we can define an interval [min, max] with a confidence coefficient of α, i.e., Prob($I \in$ [min, max]) = α. Figure 1 shows the distribution corresponding to a 4-look signal. For a selected confidence coefficient (e.g., 50%), we can calculate the interval limits, *min* and *max*. We often assume that cumulated probabilities of both tails of the distribution are equal (= $(1-\alpha)/2$). The interval can be calculated for any kinds of distribution. The interval is a function of P_0, the average backscattering intensity. Let the interval be [$min_{1.0}$, $max_{1.0}$] when $P_0 = 1.0$, then for any P_0 the interval will be [$P_0 \times min_{1.0}$, $P_0 \times max_{1.0}$] (see Figure 2). This results from the multiplicative nature of the speckle noise.

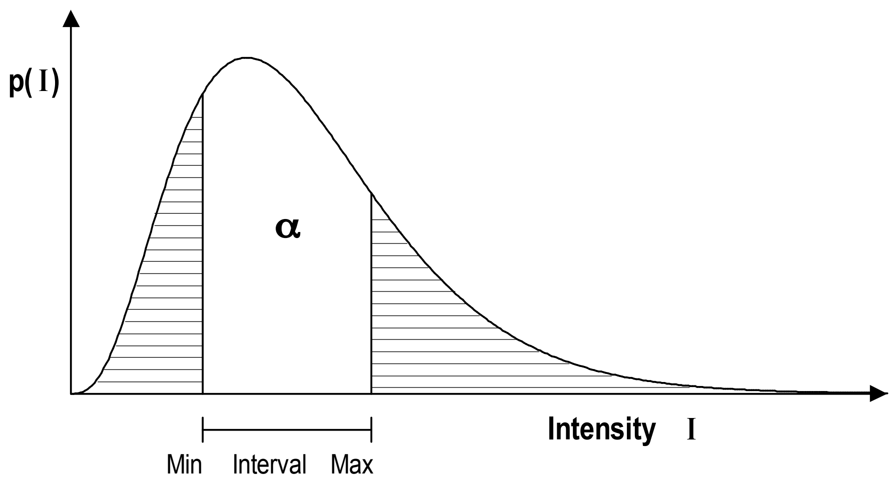

Figure 1: The probability density function of the radar signal and the decision interval.

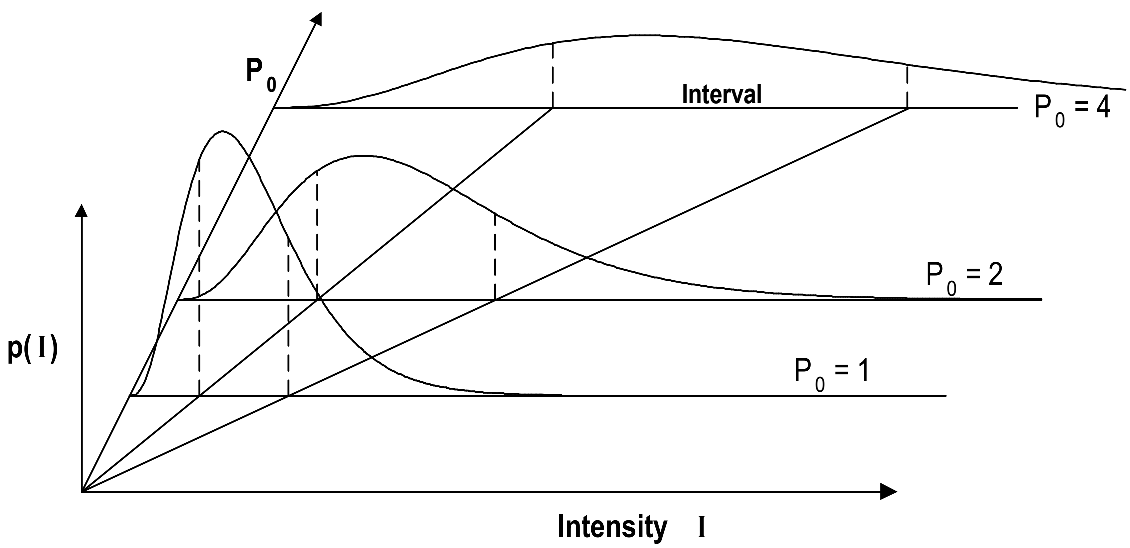

Figure 2: The decision interval vs. the average backscattering intensity P_0.

In image filtering, the mean value should be calculated over a homogeneous area. The interval is used to decide if a pixel belongs to the homogeneous area defined by the P_0 parameter. The decision is made on a pixel basis. Two types of error can occur. Type I is when we reject a pixel that belongs to the area and type II when we accept a pixel that does not belong to the area. Changing the decision process (i.e., the interval) affects the probability of both types of error. Reducing the interval increases the probability of type I errors and reduces the probability of type II errors. In the filtering process, we want to ensure that the averaging is performed only on pixels belonging to the homogeneous area. Therefore, we should ensure that the probability of type II errors is low. This is done by using a low value for the confidence coefficient α ($\leq 50\%$).

Utilisation of spatial information:

Spatial information is used to make the decision process more robust. Let us define a region as a set of connected pixels, i.e., pixels such that any two pixels of the region are connected by a path inside the region. We add the new spatial constraint that the mean value is calculated only over connected pixels. The decision interval [min, max] is used to define the pixels belonging to the region and averaging is performed only on the pixels connected to pixel at the center of the window. The calculation of the output value for a pixel consists therefore in using a centered window and in calculating the mean value of the pixels inside the window belonging to the interval [min, max] and spatially connected to the central pixel. The spatially connected constraint is used to detect changes in the image structure such as the presence of edges or lines, and to limit the extent of the image averaging process.

In homogeneous areas, the spatial constraint should not limit the extent of the averaging process. Consider an interval with a confidence value of 70% and a window of N×N pixels. In a homogenous area, 70% of the pixels of the window will have a value within the interval and will form a connected region. The pixels with a value outside the interval will be distributed randomly in the window and will compose small segments (regions) that will not be able to divide the window into isolated parts. If a part of the window covers an area with a different P_0 parameter, then the pixels in that part will mostly be outside the interval. If the difference between the P_0 parameters is small, many pixels of the second area will belong to the interval but usually they will form small isolated segments and will not be connected to the pixels of the first area. For example, the second area could be a line that passes through the window. The window will then be divided into two segments and the pixel average will be calculated only on one of the segments, corresponding to one side of the line.

Search for the best P_0 value:

The P_0 value is used to define the decision interval (see Figure 2), and up to now, in our discussion of the least commitment approach, we have assumed that we know which P_0 value to use for each pixel. In fact, however, we do not know in advance the P_0 values. Therefore, we propose to execute the filtering process with every possible P_0 value and then use the output results to select the best one for each pixel. For each pixel and each P_0 value, we calculate the mean value of the pixels belonging to the interval and connected to the central pixel of the window. We also calculate the size of the connected region. The region size is used to select the best P_0 value: we select the P_0 value producing the largest region. If we use an inappropriate P_0 value for an image area, few pixels will belong to the interval and the region size will be small. The region size will increase as the P_0 value used get closer to the true P_0 value of the area.

III. Algorithm implementation and experimental results

The algorithm

The algorithm performs iterations on all possible P_0 values. Let $\{P_0^k\}$ define the set of considered P_0 values for k = 1 to NK. From $\{P_0^k\}$, we define the set of intervals $\{[min_k, max_k]\}$. In the iteration k, we use the interval $[min_k, max_k]$ to segment the image into connected regions belonging to the interval $\{R_j\}$. Then we examine each pixel (x, y) of the image. If the pixel belongs to one of the regions R_j, then we calculate the mean value of the pixels belonging to the same region R_j and inside a window centered on the pixel (x, y). We also count the number of pixels used to calculate the mean value. The calculation is performed for all possible P_0 values, and for each pixel (x, y), we keep only the mean value associated with the largest count number.

Distribution independent intervals

In the algorithm, the knowledge of the radar signal distribution is only used to calculate the values of the interval set $\{[min_k, max_k]\}$. Knowing that the speckle noise is multiplicative, we have developed a way to specify the interval set independently of the signal distribution. We define the interval relative range, rr, as the ratio of the interval range to its mean:

$$rr =$$

The multiplicative nature of the speckle noise ensures that the relative range is independent of the P_0 value (see Figure 2). Knowing the radar signal distribution and the desired confidence coefficient, the user can calculate the relative range and provide it as an input parameter to the algorithm.

The user should also indicate the range of the radar signal values. For example, for 8 bit data the possible values are from 0 to 255. For 12 bit data, the possible values are from 0 to 4095. Conceptually, the algorithm should iterate on each of these possible values. In order to reduce the computing time, we reduce the number of considered values. For example, if we know that a 12-bit image has no value below 100 and no value above 2000, then we will iterate only on values between 100 and 2000. Another way to reduce the number of iterations is to skip some values between each iteration, i.e., to use an iteration step larger that one. The iteration step could be set as a fraction of the interval range, e.g., 5% of the interval range. This implies that the iteration step will increase with the signal value. For each iteration value, V_k such that $1 \le k \le NK$ and $V_k = V_{k-1} + step_{k-1}$, we can calculate the decision interval $[min_k, max_k]$ where $min_k = V_k \times (1 - rr/2)$ and $max_k = V_k \times (1 + rr/2)$.

The segmentation technique

Given an interval [min, max], we use a threshold approach to extract the segments of the image. The first step is to assign a class label to each pixel according to its intensity value:

$$class(x,y)=\begin{cases}\text{IN if } I(x,y)\in[min,max]\\ \text{OUT if } I(x,y)\notin[min,max]\end{cases}$$

Then, we use a pixel labeling algorithm to assign the same label to the connected pixels belonging to the same class. The pixels which have the same label are connected and form part of a single segment.

The experimental results

The new filtering technique has been tested on forestry and agricultural images. We present here the results for an airborne C/X SAR 580 image of the Montmorency forest, north of Quebec City. It is a 7-look image with 802x701 pixels. Figure 3 shows a 800x400 pixel area of the image. We have applied the algorithm with different relative ranges (rr = 0.3, 0.4 and 0.5) and a window size of 11x11. The smoothing is small for rr = 0.3 and becomes very visible for rr = 0.5. Figure 4, 5 and 6 present the results for the relative ranges of 0.3, 0.4 and 0.5 respectively. Figure 4 shows that the filter preserves the image structures while reducing the speckle noise. The roads, the contours of rivers, lakes and forest cuts are all well preserved. Figure 5 and 6 show more smooth areas. The roads and contours are still well preserved. Isolated small targets with strong contrast are also well preserved. This illustrates that the technique is able to smooth homogeneous areas without blurring the contours. 131 iterations or decision intervals are used when the image is filtered with a relative range of 0.3. The computing time on a Sun workstation was 13 minutes. For relative ranges of 0.4 and 0.5, the computing times were 16 and 17 minutes, respectively.

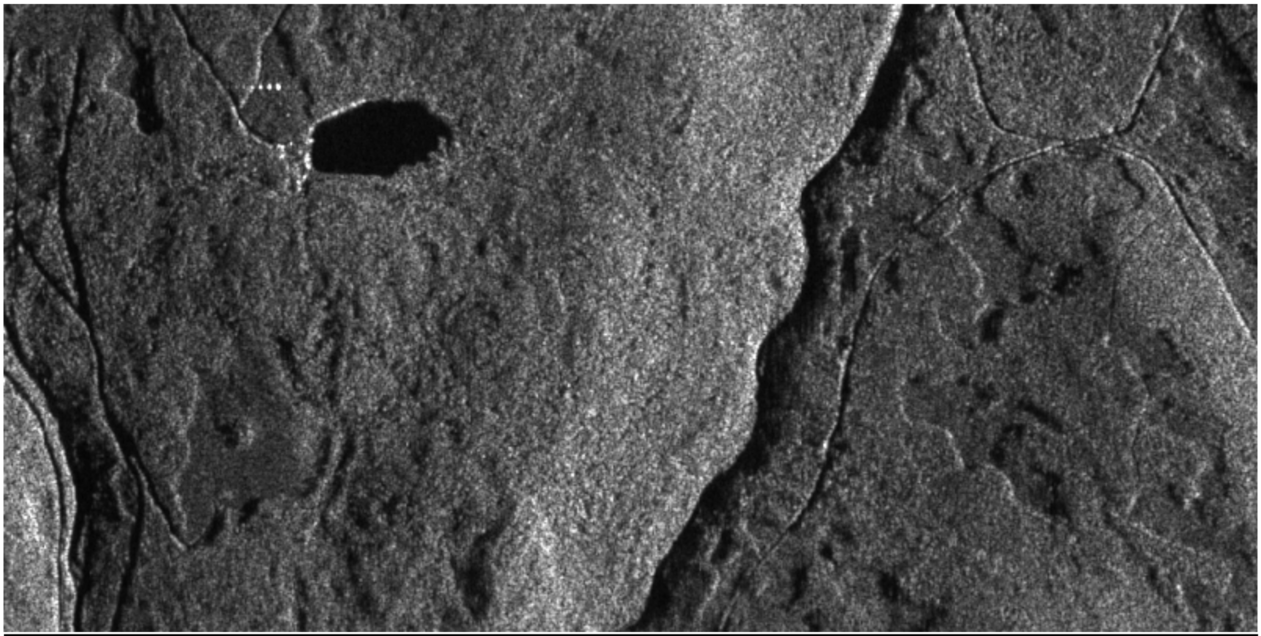

Figure 3: The image of the Montmorency forest, airborne C/X SAR 580 image, 7 looks, 800x400 pixel.

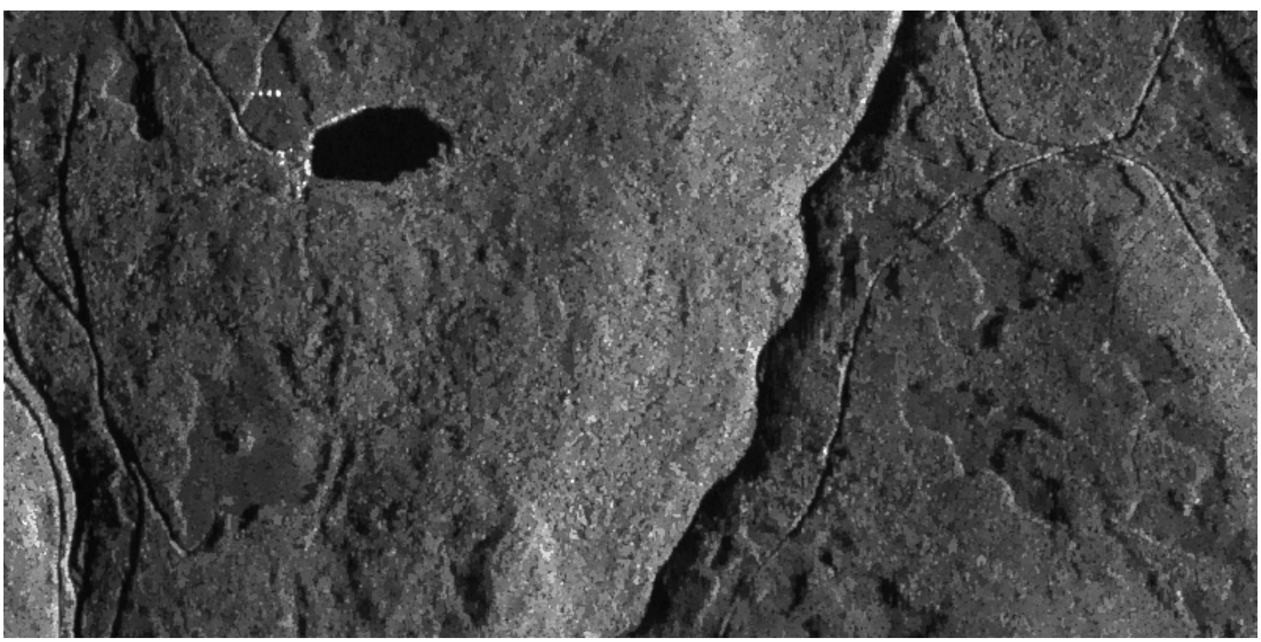

Figure 4: The image after filtering with a relative range of 0.3.

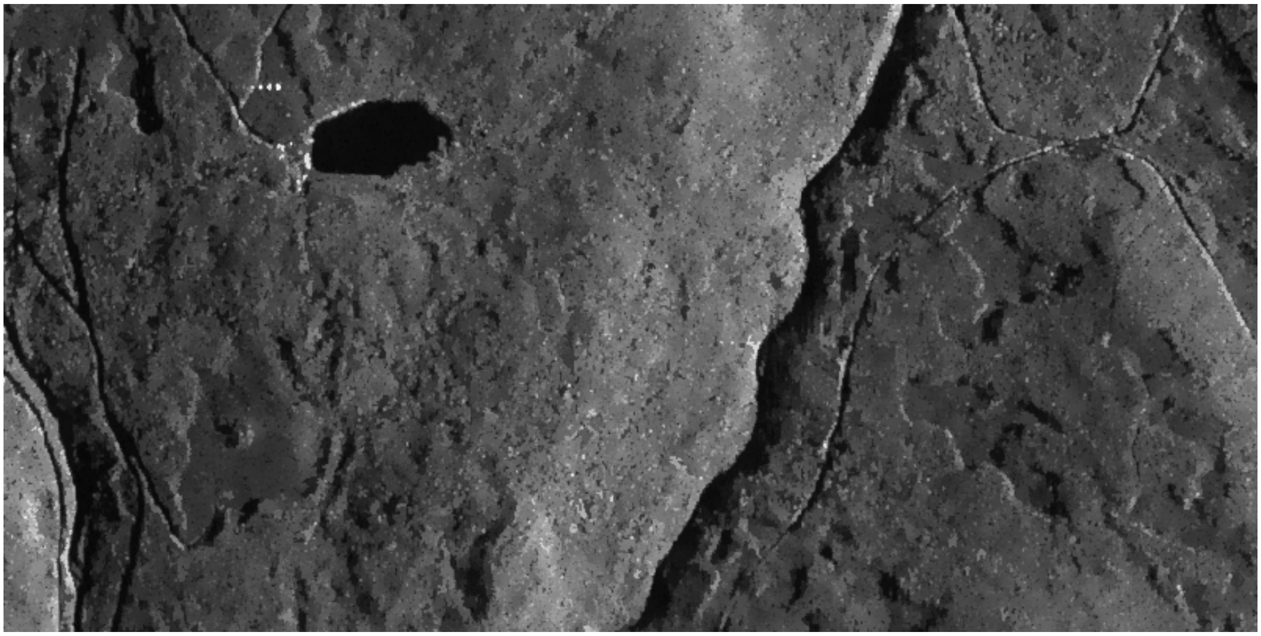

Figure 5: The image after filtering with a relative range of 0.4.

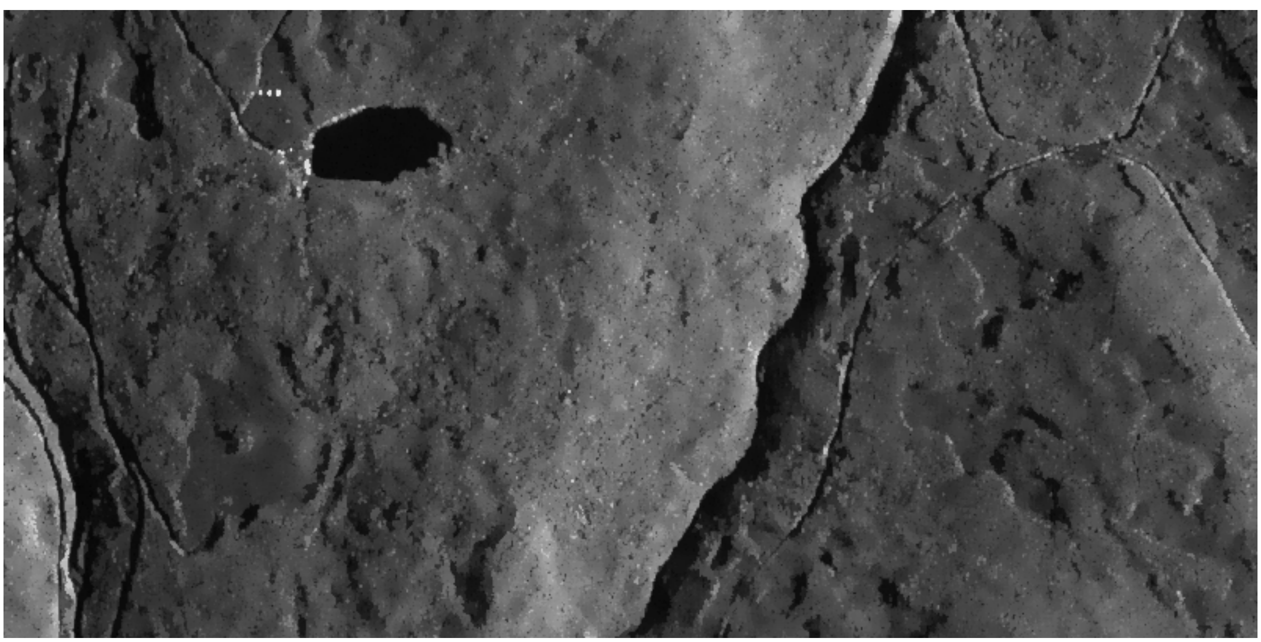

Figure 6: The image after filtering with a relative range of 0.5.

IV. Conclusion

A new speckle filtering approach for SAR images is proposed. The filter is similar to the Sigma filter as it does not use all the window pixels to calculate the mean value. However, the new filter takes into consideration more faithfully the characteristics of radar images. It also uses spatial constraints and a segmentation technique to determine the largest homogeneous area around each pixel. The filter was tested on real SAR images and interesting results were obtained. A new filter evaluation approach is proposed in [6] where the new filter is compared with standard adaptive filter techniques using synthetic SAR images.

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