Efficient Speckle Filtering of SAR Images

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Abstract

In this paper a new promising method of speckle filtering is described and applied to both, synthetically generated and real SAR-images. The new method, which we call EPOS (Edge Preserving Optimized Speckle-filter), is based upon the statistical properties of speckle noise. The knowledge of speckle variance allows the distinction of homogeneous areas from those, containing edges or single scattering targets. This discrimination method is used within a variable sized filter matrix to choose a region, which is suitable for calculating an intensity average, that is typical for the center pixel. Also a method for estimating speckle noise parameters is presented. This work is part of the project RADARMAP OF GERMANY, where a land use map from the whole area of Germany in a 1:200000 scale is produced. This project is sponsored by DARA.

INTRODUCTION

In radar image analysis the presence of speckle noise, produced by coherent illumination, will result in a high degree of misclassification. Since speckle noise is signal dependent, the distortion of the image increases with the intensity of the signal. To reduce the speckle induced variance within an image, averaging of statistically independent values is neccessary. This can be done by multilook processing, where independent looks of the same area are averaged. However, this procedure will result in a loss of spatial resolution, since all images used for averaging must be obtained from the same aperture.

A second way to reduce speckle is to average the values of neighbouring pixels. The easiest way to do this is to average all intensities within a given window around each pixel. This filter will increase the radiometric resolution, which is defined by the signal variance. On the other side, the spatial resolution will decrease, since edges within the image get blurred. Therefore the requirement for an edge preserving filter is to reduce the variance while preserving edges. The way to do this is to select those pixels from the neighbourhood, that are suitable for calculating an intensity average which is typical for the central pixel. Most speckle filters differ in the way to choose this subset of pixels. Either they use a statistic criterion for the determination of the subset, or they use the subwindow with the smallest variance of intensities. For the EPOS filter we aim to use such a statistical criterion within subwindows of different spatial arrangement and size. We use the local statistic of each subwindow to decide, which subwindows are homogeneous and therefore suitable for calculating an intensity average. Subareas which contains edges or single scattering targets are excluded from the averaging region, and therefore edges will be preserved. The advantage of this method is a better differentiation of the subset choosed for averaging, since we have statistical information from each subwindow. This better differentiation enables a strong condition for selecting subwindows, so the original window size may increase without a significant loss of spatial resolution. The obtained large window size will result in a strong reduction of speckle variance in SAR images.

STATISTICAL PROPERTIES

There are mainly two statistical properties of a SAR signal we aim to use within our procedure. The first follows directly from the multiplicative nature of speckle noise: The relative standard deviation $R = \frac{\sigma}{\mu}$ defined by the mean μ and the standard deviation σ remains constant in homogeneous areas of the image. For linear detection and N independent samples by multilook averaging we get from [ULABY, 1982]

$$R = \frac{\sigma}{\mu} = \frac{0.523}{\sqrt{N}}$$

for the relative standard deviation.

The second property is the distribution of the signal received from the radar sensor. From [ULABY, 1982] we know that the probability density function (PDF) is a chi-squared distribution using square-law detection, and a Rayleigh distribution with linear detection. If, for linear detection, the number of independent samples increases, the Rayleigh distribution approximates a gaussian distribution. Also the chi-squared distribution approximates a gaussian distribution for a large number of samples, but the tendency towards the gaussian distribution is slower than in the case of linear detection. In [ULABY, 1982] a number of four samples for the linear detection and of ten samples for the square-law detection is mentioned as sufficient for using the gaussian distribution. In practice this conditions are not always true. Nevertheless, we will use the assumption of a gaussian distributed signal in further considerations for simplicity.

From statistic books like [FISZ, 1962] we know, that the measure of the variance $\hat{\sigma}^2 = \frac{1}{N}\Sigma_{i=1}^{N}(x_i - m_x)^2$ from a set of independent values x_i is a biased estimator of the variance, if the mean $m_x = \frac{1}{N}\Sigma_{i=1}^{N} x_i$ is calculated from the same set of values. To get an unbiased estimator we have to calculate

$$\sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - m_x)^2.$$

For the remainder of this paper, all calculated variances are assumed to be of this kind.

Another well known property is the chi-squared distribution of the sum of squares from a gaussian distributed variable. Given the gaussian distributed variable $z = x_i - m_x$ with mean 0 and variance σ^2, the random variable $S^2 = \frac{1}{2N-1}\Sigma_{i=1}^{2N} z^2$ which is calculated from a sample of $2N$ independent values x_i is χ^2_{2N} distributed with $2N$ degrees of freedom. The parameter σ_χ^2 of the distribution is $\sigma_\chi^2 = \frac{\sigma^2}{2N}$ and the probability density function is given by

$$p_{2N}(x) = \begin{cases} \frac{x^{N-1}}{2^N \sigma_\chi^{2N} \Gamma(N)} \exp(-\frac{x}{2\sigma_\chi^2}), & x \geq 0, \\ 0, & x < 0, \end{cases}$$

where , () is the gamma function. Since the mean m_x is also calculated from the sample, it is also gaussian distributed with mean μ and variance $\frac{\sigma^2}{2N}$. It is hard to determine exactly the distribution of the squared relative standard deviation $\hat{R}^2 = (\frac{S}{m_x})^2$, since we have a sum over the squared quotient of two gaussian distributed random variables. If we choose the number of elements within the sample large enough, the variance of the mean m_x becomes small relative to the mean itself, and therefore we have approximately also the chi-squared distribution for the square of the relative standard deviation.

THE EPOS ALGORITHM

The relative standard deviation R remains nearly constant in homegeneous areas, while it increases in the presence of edges. Thus the knowledge of R within an image allows us to determine homogenious areas without edges, texture or single scattering targets. These areas are then used to calculate an average, that is typical for each pixel within the area. One way to estimate the value of R is described in the next section of this paper. The value of R can be predicted for SAR images, but in most cases a resampling or a geocoding process occurs before the filtering, which results in a change of the actual variance. Another reason for an actual estimation of the variance is the fact, that in real SAR data neighbouring pixels are not statistically independent. Therefore an estimation from the image is required.

We know from the last section, that the squared relative standard deviation R^2 is chi-square distributed. No we have to define a limiting value for R^2 along this distribution. One way is to choose that value as limit, where the probability of beeing less than the value is an a priori given number. Thus, independent from the size of a sample, we have the same probability of choosing a segment within an homogenious area. Actually we choose those values x_l where

$$P(x < x_l) = \frac{1}{2},$$

which may be obtained from a table for different degrees of freedoms. The whole EPOS algorithm contains the following steps:

- Estimation of the relative standard deviation R from the image.
- Calculation of the relative standard deviation $R(f)$ for all degrees f of freedom from the chi-squared distribution.
- Searching for the largest homogeneous area around each pixel.
- The area found is used for calculating the new greyvalue by averaging.

Now, one of the focal points of the algorithm is the way to choose the set of pixels for averaging. An increase of the number of elements within the sample will decrease the variance of the filtered image. Therefore we have to maximize the averaging area. On the other hand we will find no homogeneous areas, if the structures within the image are smaller than the a priori given size of the filter matrix, as it occurs in textured regions. To smooth the image even if it contains small structures, we have to choose a smaller window for the determination of homogeneous reagions. Therefore we reduce the size of the analyzed window, if no homogeneous area was found.

Thus the determination of the largest homogeneous area is done as follows:

1. Start with a given matrix size $m \times m$ of the surrounding window. (We took $m = 11$.)

2. Divide the $m \times m$ window in 8 even sized, mutually exclusive subwindows, restricted by 4 straight lines through the central pixel, and add the central pixel to each segment.

3. Calculate the relative standard deviation $R_i, \qquad i = (1, ..., 8)$ for each segment. The sample contains all sements.

4. While the relative standard deviation of the sample R_s is greater than the estimated value $R(f)$ with the according number f of elements within the sample, remove the segment with the greatest R_i from the sample.

5. If no segment with $R_i \leq R(f)$ was found, reduze matrix size by 2 and continue with step 2.

6. The remaining sample is the largest homogeneous area.

Using eight segments around each pixel, which are nearly independent (with a common central pixel), the probability for filtering in homogeneous areas is $P_8 = \frac{2^8-1}{2^8} = 0.996$. The chance of filtering also increases by the use of different window sizes.

PARAMETER ESTIMATION

Using the relative standard deviation as the criterion for a filter algorithm is based upon a estimation of noise parameters with a high degree of accuracy. A new simple method of estimating multiplicative noise parameters is described in this section.

The measure of the relative standard deviation of the image, by calculating mean and variance from a number of pixels will result in a loss of precision for the estimated value, since edges, texture and single scattering targets will cause an increase of variance. It's hard to find a limiting value between the measure of speckle variance and the variance caused by edges. The estimated value, no matter whether the median or the mean or what else is choosen to estimate it, will be a more or less linear function of the arbitrarily choosen limiting value. On the other hand, the estimated value will also be a function of the number of values within each sample, since the probability of covering an edge increases with the number of pixels in the sample. Further, if neighbouring pixels are correlated, the variance estimated will increase with the size of the sample.

To solve those problems we will analyze the probability density function $f(R^2)$ of the squared relative standard deviation $R^2 = (\frac{\sigma}{\mu})^2$. As we saw above, the variance σ^2 is known as chi-square distributed, and if the sample is large enough, also R^2 is approximately chi-square distributed. The normalized and smoothed histogram of R^2 obtained from the image, now approximates the chi-squared probability density function ($\chi^2 - PDF$), if the image contains no information but only the noise. If the image contains information, the PDF will be distorted. For each R^2 of the histogram, a given percentage of pixels will have an increase of variance, and will therefore appear at a higher R^2 within the histogram. The percentage of shifted pixels for each R^2 is given by the degree of information contained in the image. Since the shift direction of pixels is always from lower to higher R^2, we have a high degree of distortion for a high R^2, while the density of a low R^2 is only decreased by the given percentage. Thus we can use the histogram at lower values of R^2 to estimate the mean of R^2, i.e. the noise within the image. Since we dont know the a priori degree of information within the image, there is no sense in approximating the histogram directly by the $\chi^2 - PDF$. However it is possible to approximate the shape of the histogram. The whole estimation algorithm is as follows:

- Calculate a histogram of R^2 values from the image.
- Normalize and smooth the histogram.
- Approximate the shape of the histogram by the $\chi^2 - PDF$ within the range 0 and that value, where the histogram reaches halve of its maximum. A least square fitting may be used for the approximation. To approximate the shape instead of the histogram itself, multiplicate the $\chi^2 - PDF$ with the rate

of the sums of histogram- and $\chi^2 - PDF$-values within the approximated interval, so the sum within the interval is the same for both.

- The mean of the approximated $\chi^2 - PDF$ estimates the value of R^2.
- Take the median of all R^2 values estimated from different sized samples, where sample size is approximately between 14 and 25.

Calculating the histogram of R^2 we did a scale for the R^2 values in the way, that the maximum of the histogram is at a third of the array holding the values. So the algorithm has a better adaption to different values of R^2. Each calculated R^2 is rounded up and down to the next integer value available. Smoothing of the histogram is very neccessary, since we are only interested in the shape of the graph and not in differences between neighbouring R^2 values. We did it easily by convolution with the main lobe of the $\frac{sin(x)}{x}$ function choosing a rectangular window. The length of the filter we used is defined by a tenth of R^2 at the maximum of the histogram. The design of digital filters is described for example in [HAMMING, 1977].

The determination of an ingenious sample size has two aspects. First the sample should not be to large, since the information contained within the image will corrupt the estimation as mentioned above. On the other hand, a small sample will result in the estimation of a smaller standard deviation, if neighbouring pixels are correlated. The approximation of the histogram by a $\chi^2 - PDF$ is also limited to samples that are not to small. From measurements within images containing only gaussian noise, we derived a minimum value of 14 pixels within a sample. All estimations with less than 14 pixels sample size failed, while we had a stabilisation of the estimated value for 14 and more pixels within one sample. To make the estimation more reliable, we decide to choose the median from the estimated values derived by using different sized samples between 14 and 25 pixels. So the largest sample of 25 pixels may be calculated from a 5 by 5 window.

RESULTS AND DISCUSSION

To demonstrate the efficiency of the filter algorithm we have chosed two images, one from the SAR-instrument of the ERS-1 sattelite, the other is a synthetically generated image. The originial

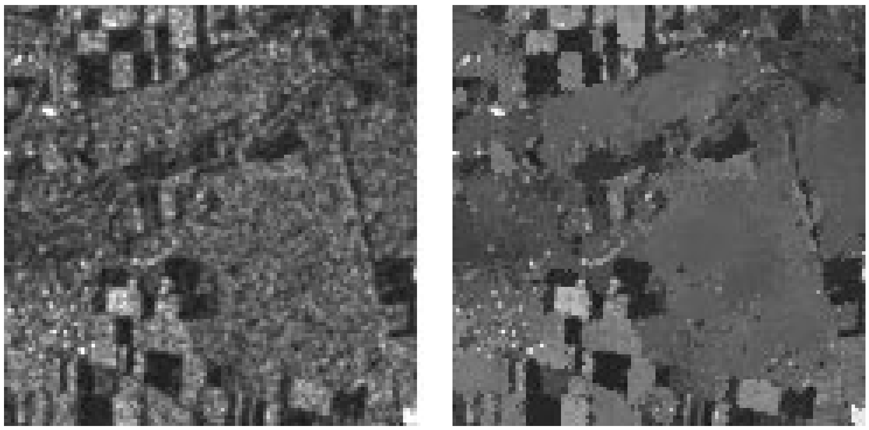

Figure 1: ERS-1 Original and EPOS-filtered.

and the filtered SAR image is shown in figure 1. There is a high decrease of variance within the homogenious areas while edges are preserved. Figure 2 shows a synthetically generated image without and with multiplicative noise added. The results of the synthetically generated image is shown in figure 3 for the EPOS filter on the left and for the sigma filter of [LEE, 1983] on the right side. With the EPOS filter the image is nearly fully restored. Edges dont get

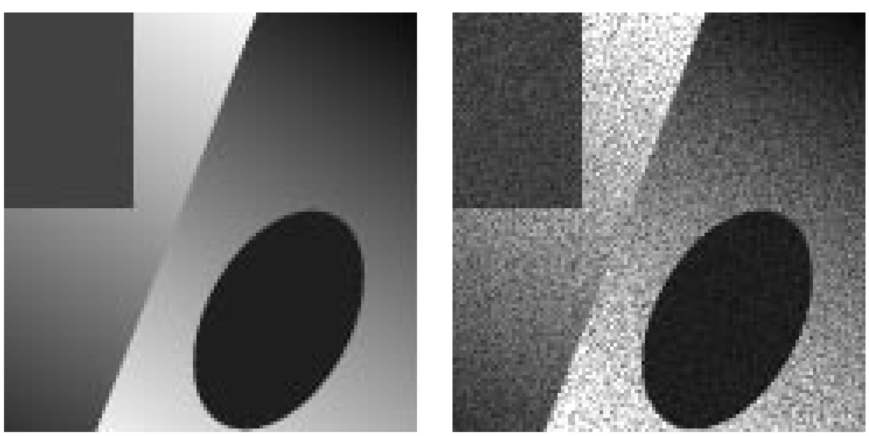

Figure 2: Synthetically generated image.

blurred as with the sigma filter, wich we applied twice to the image using a 7×7 matrix.

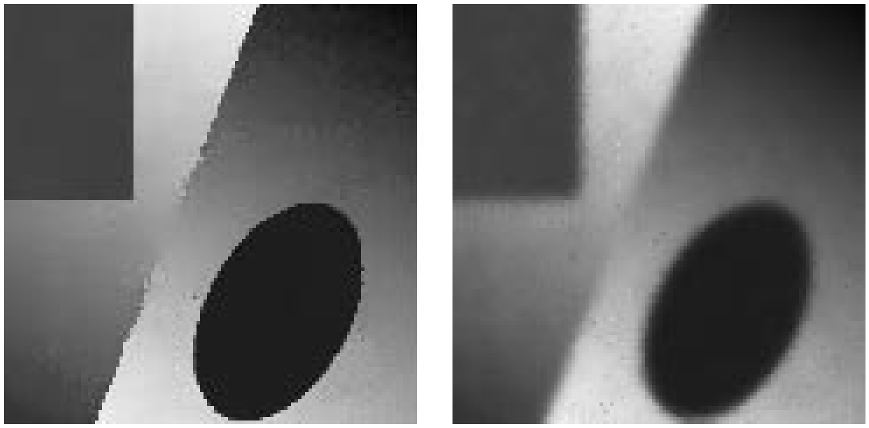

Figure 3: Filtered with EPOS and sigma.

The algorithm of noise estimation was applied to 7 different synthetically generated images, containing well known multiplicative gaussian noise. The value of R^2 of the synthetically added noise was in the range of 0.005 to 0.03. The relative error of the estimated values varies from 0.001 to 0.046, so we expect the error in estimation to be less than five percent in most cases. Of course its difficult to give a general limiting value for the error, since the estimation is not fully independent from the information contained within the picture.

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