

NOISE REDUCTION FROM SYNTHETIC APERTURE RADAR IMAGERY

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ABSTRACT

The characteristic of the noise in SAR images differs quite much from that of more conventional digital spaceborne or airborne images. Removal of such usually high-amplitude speckle noise without losing too much high-frequency information requires at least some kind of adaptiveness from the filter. In this paper some adaptive spatial filters are described and results of their use are compared.

1. INTRODUCTION

Speckled noise in SAR (Synthetic Aperture Radar) images is usually found as a problem when thinking of interpretation or segmentation and classification. The noise appears as heavy granularity even in homogeneous areas containing no natural texture. Adaptiveness of the filter is required to reduce this granularity sufficiently while preserving meaningful edges and objects. These objects can be very bright (strong reflectors) because the dynamic range in SAR images is usually much wider than in images in visible or infrared regions. Adaptiveness is usually carried out by taking into account in different ways statistical or spatial properties of the image and objects on it.

2. FADING AND SPECKLE

Inside a ground element (ground cell, resolution cell) there are usually many individual scatterers contributing to the signal received by the radar antenna. The signals from these individual scatterers have different phases and the summation of the individual signals varies because of the relative motion between the radar and the scatterers. Fading is a concept connected with this variation. Fading frequency means the interval on the frequency scale after which the total signal decreases down to null value. The fading frequency of the imaging system depends on the spacing between individual scatterers, speed of the radar platform, used wavelength and the distance from object to radar. In homogeneous areas containing no dominant individual scatterers certain noiselike statistics apply for fading.

Speckle is the visual effect of those random fluctuations in the return signal caused by the summation of the randomly phased phasors inside one ground element. Actually speckle is not really noise but usually disturbing and useless information related to particular SAR imaging system and target. Speckle can carry some interpretable information about the object surface but Gaussianly distributed speckle doesn't do it. In figure 1 two grey level histograms of different homogeneous areas are shown as an

example. The areas are from the Seasat-A test data used for making this article.

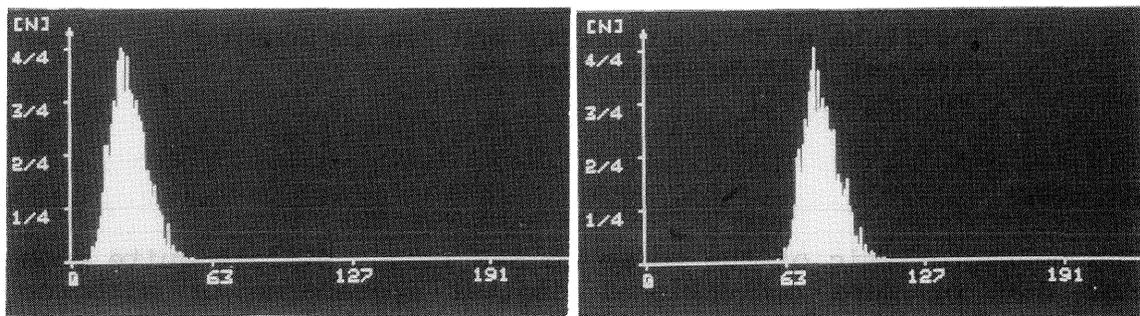


Fig. 1. Two histograms of different homogeneous areas.

Multiplicative speckle (noise) model is mostly used because the intensity value of a pixel is the sum of many independent random variables. It has been found that the signal voltage due to backscattering from a distributed target may be described in terms of Rayleigh statistics. Hence in homogeneous areas holds theoretically

$$\begin{aligned} \text{dev} &= 0.523 * \text{mean} / N^{1/2}, \text{ for amplitude images} & (1a) \\ &= \text{mean} / N^{1/2} \quad , \text{ for intensity images} & (1b) \end{aligned}$$

where mean is the mean voltage corresponding to the average scattering coefficient of a ground cell and dev is the standard deviation associated with the measurement (estimate) of that cell. This knowledge has been made use of in some of the adaptive filtering methods described later.

The test data used in this article was originally an intensity image (square law detection during observing followed afterwards in SAR processing stage by incoherent averaging). Later it had been square-rooted thus becoming a square-root intensity image. In this case the normalized standard deviation of a ground cell measurement should be approximately the same as in amplitude images in which the observations are made in linear detection mode before averaging. Here the incoherent averaging means averaging of smaller resolution cells to form a final pixel in the image and it is done to reduce the worst speckle effect. Unfortunately this incoherent averaging (increasing the number of independent samples per pixel) reduces the spatial resolution respectively.

In the test data here the pixel size is $12.5 \times 12.5 \text{m}^2$ each pixel consisting of four ($N=4$) independent samples about $6 \times 6 \text{m}^2$ each. From this data eight different homogeneous areas were chosen and the standard deviation to mean value ratios (dev/mean) were computed. The average value for this ratio was 0.261 while minimum was 0.230 and maximum was 0.293. The theoretical value would be according to Rayleigh statistics for amplitude images 0.2615 ($0.523/4^{1/2}$) so the ratio values with this data seem to fit well to the theory. In homogeneous areas with multiplicative noise model the mean to standard deviation ratio (m/s) can be used directly to approximate signal-to-noise ratio. This has been done later in this paper to compare different filtering methods.

3. DIFFERENT METHODS

Quite many studies have been presented about the filtering of multiplicative noise both in frequency domain (e.g. homomorphic filtering, Wiener filtering) and in spatial domain. In this paper only spatial domain methods are described. Often in practise signal-to-noise ratio in SAR images is low, too low e.g. for Wiener filtering to achieve good results. The window size used in the following methods has been either 5 or 7. In adaptive filtering the window size is not very critical factor.

In reference [3] 10 different filters, four of which adaptive, have been compared for noise reduction and classification. There the non-adaptive methods were simple averaging and its logarithmized variant to transform the multiplicative noise into an additive one (and exponentiation after), median filtering and iterative median filtering. To some extent adaptive but without any speckle model was a method of choosing the average value of the most homogeneous subwindow (the one with smallest variance among four subwindows). Also a logarithmized variant of this method was tested.

One adaptive method was Frost-filtering which assumes that the useful information in a small neighbourhood has an exponential autocorrelation function. Here the image is filtered with an exponentially shaped weighting function and the midpixel value of this window is estimated (the weighted sum)

$$y' = k * a * e^{-a(|x-x_0|+|y-y_0|)} * z(x,y)$$

where $z(x,y)$ is the image pixel value and (x_0,y_0) is the location of the window's central pixel. So the weighting of the window is

$$w(x,y) = k * a * e^{-a*D}$$

where k is a normalizing constant (filter weights sum to unity) and

$$a = (4/(n*s^2)) * dev^2 / mean^2 \quad (n \times n - \text{window})$$

where dev is the standard deviation of the image pixels inside the window and $mean$ is the mean value respectively. So the weighting of the midpixel increases when the standard deviation to mean ratio inside the window increases. The value of s (reference, assumed real speckle standard deviation) can be computed from (1) by setting the mean value to 1 for multiplicative noise. It can also be estimated from homogeneous areas by collecting (normalized) $z/mean$ values.

Another method was a maximum likelihood filtering where the most likely estimate y' for N -look intensity images is the actual positive root of the equation

$$y'^3 - mean*y'^2 + N*s_y^2*y' - N*s_y^2*z = 0$$

where z is the window's midpixel value in the image to be filtered and

$$s_y^2 = (dev^2 - mean^2*s^2) / (1+s^2).$$

The third method aims at minimizing the mean square error for each pixel value assuming that the noise is additive with a mean value equal to zero. Thus logarithmic transformation is needed before and exponential after filtering. Now the estimate y' for a pixel

value is

$$y'_{\log} = \text{mean}_{\log} + (z_{\log} - \text{mean}_{\log}) * (\text{dev}_{\log}^2 - s_{\log}^2) / \text{dev}_{\log}^2$$

where the speckle variance s_{\log}^2 can be estimated from homogeneous areas as described earlier or be set values $1.645/N$ or $0.465/N$ for intensity and amplitude images respectively.

The fourth method is like the previous one but assuming the multiplicative noise model with the mean value of 1. Now the filtered midpixel value estimate

$$y' = \text{mean} + (z - \text{mean}) * (1 - \text{mean}^2 * s^2 / \text{dev}^2) / (1 + s^2).$$

The last method was found best in [3] and it is tested in this work too named here method 1. Here the value s for speckle was first computed from (1a). With $N=4$ it gives $s=0.523/2$. The filtered image (window size $n=7$) and the greyvalue profile of the marked image row are shown in fig. 2 middle row while the original image and the row profile are shown on the upper row. The m/s ratio of the whole image increased from the original 1.53 to 1.78 and in homogeneous areas averagely from 3.26 up to 6.26. So the improvement was much larger in homogeneous areas. Also the row profile shows that edges and details are well preserved.

Method 2 in this study is introduced by the writer and is very much like the previous one. Here (1a) again is used to conclude whether and how homogeneous the area is inside the window. From (1a) the reference speckle standard deviation is 0.261. the filtered midpixel value

$$y' = \text{mean} + k * (z - \text{mean}) \quad , \quad \text{where the factor } k \text{ is simply} \\ k = | 1 - \text{dev} / (0.261 * \text{mean}) | \quad \text{cut into interval } [0, 1].$$

In homogeneous areas the dev/mean ratio should be near the value 0.261 and then k is about zero and averaging is done inside the window. The more the dev/mean ratio differs from 0.261 the more obviously window area contains an edge, details or some texture and less averaging is done. With this method the m/s ratio of the whole image was a little smaller (1.71) than with method 1 and in homogeneous areas it increased from 6.26 to 6.61. Also the row profile shows that some details are better preserved while e.g. the water area is a little more flattened (lower row in fig. 2).

A variant of method 2 was also tested here where the reference noise standard deviation was computed from a big water area to get a statistically reliable practical estimate. The new reference value was then 0.310. The result of filtering is shown in fig. 3 upper row. The m/s ratio in homogeneous areas increased up to 6.97 and in the whole image the ratio increased slightly. So the filter was more effective but seemed to blur a little originally unsharp edges.

A second variant of this method was to use window sizes 7, 5 and 3 for every pixel choosing the window with smallest dev/mean ratio. The aim was to filter effectively areas also quite beside edges. Unfortunately the unreliability of small window statistics caused the loss of some details although e.g. edges between water and land areas were sharpened. There were no significant changes in m/s ratios. The result is shown in fig. 3 middle row.

Method 3 was presented in reference [4] and is much like the Frost-filter described earlier. Here the weighting function is

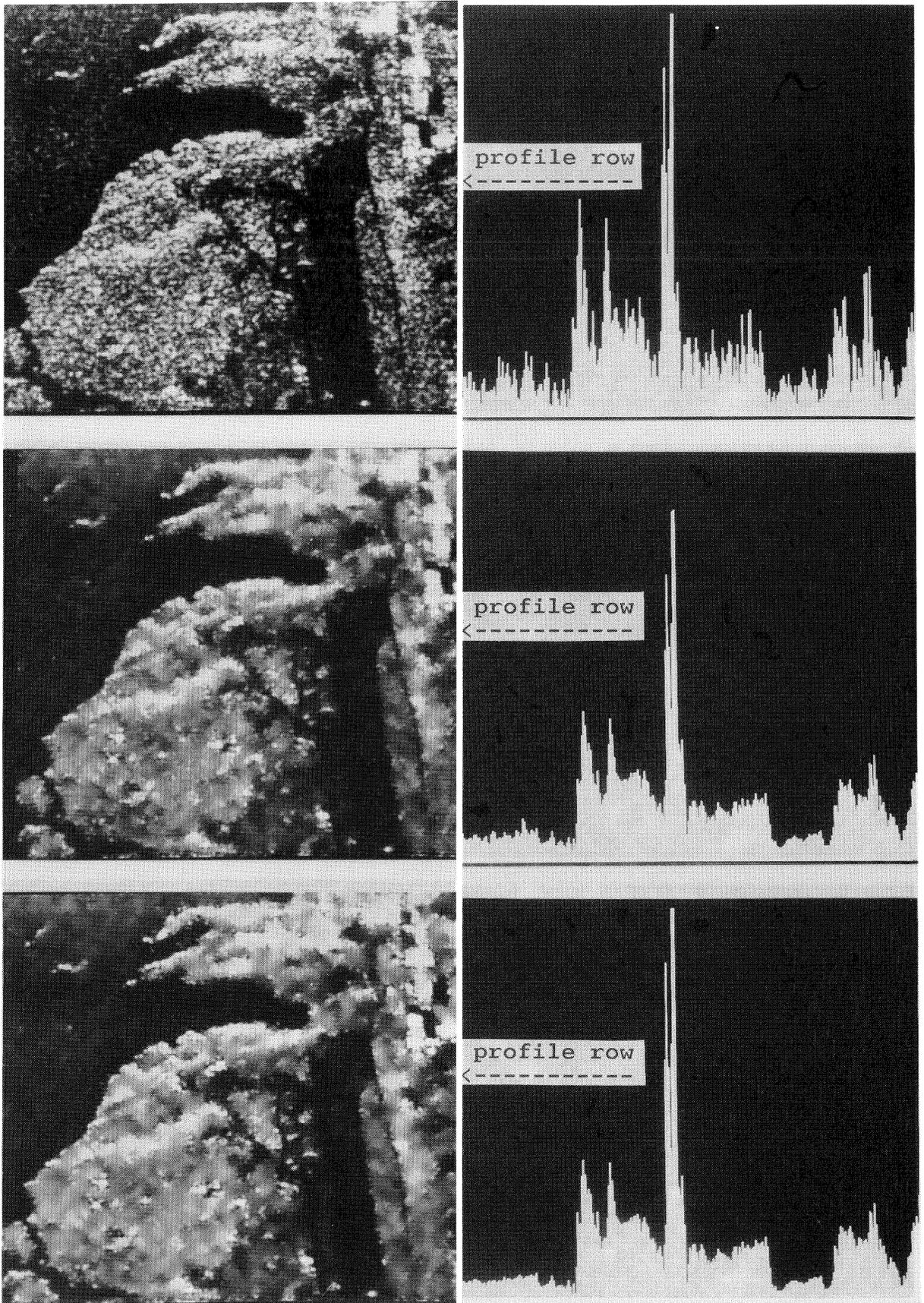


Fig. 2. From upper left corner: Original SAR image and the profile of the marked row, method 1 applied, method 2 applied.

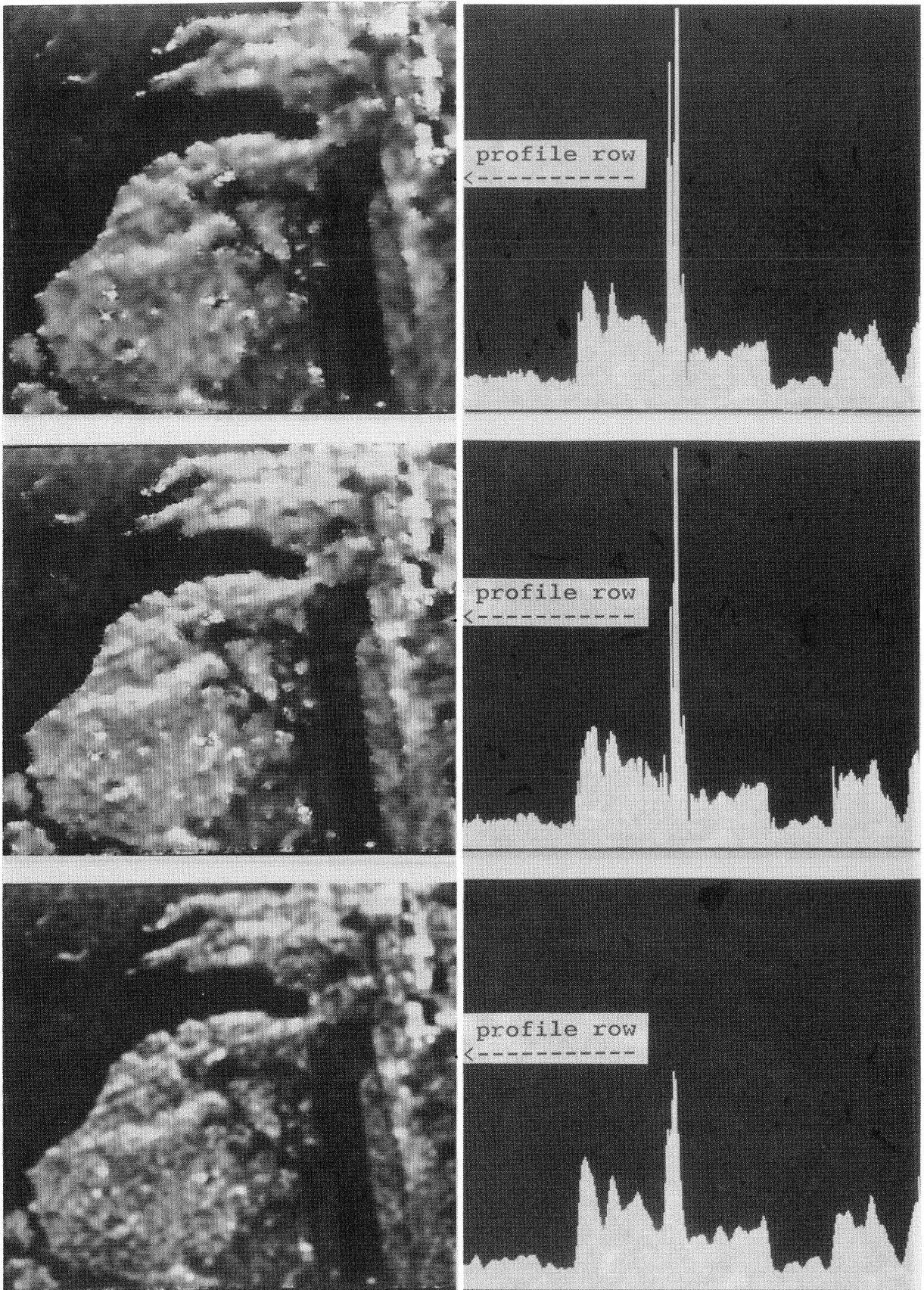


Fig. 3. From upper left corner: The first and second variants of method 2 and method 3 applied.

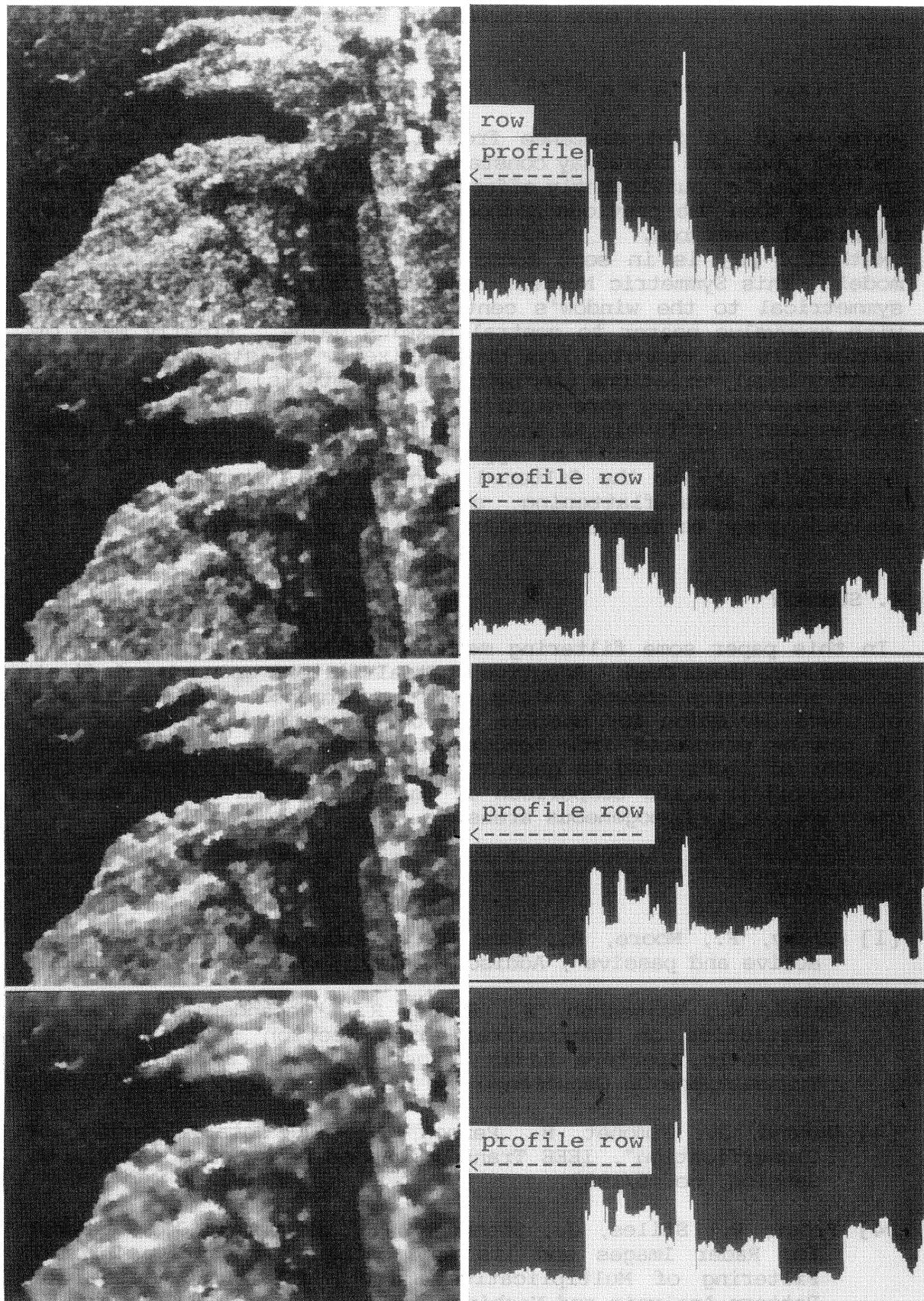


Fig. 4. From upper left corner: Method 4 (Symmetric Nearest Neighbour filter) applied to original image with 1, 3 and 5 iterations and to the filtered image from fig. 3 upper row.

also exponential and made narrower in areas with higher dev/mean ratio;

$$w(x,y) = k * a * e^{-a|x,y|}$$

where $|x,y|$ is the distance from a window element to window's central pixel and the decay constant a is approximated $a = \text{dev}/\text{mean}$. In this case a sufficiently effective filtering seems to cause more blurring than the previous methods. The result with $n=5$ is shown in fig. 3 lower row.

Method 4 [5] is in some sense also adaptive but without noise model. This Symmetric Nearest Neighbour filter takes pixel pairs symmetrical to the window's central pixel and chooses the pixel with greyvalue nearer to central pixel's value. Finally mean or median value is computed from chosen pixels. This filter tends to flatten local variations (including small details) while preserving and even emphasizing more significant edge structures. The filter can be used iteratively as shown in fig. 4 ($n=5$). In fig. 4 lower row is shown the result of applying Symmetric Nearest Neighbour filter with $n=5$ to the filtered image in fig. 3 upper row. The effects of area flattening, small detail weakening and edge sharpening can be seen especially from the profile image.

4. SUMMARY

In this paper some filtering methods for noise reduction in SAR images were described. Adaptive spatial filters using local first order statistics showed fairly good performance. The reference standard deviation for speckle can be theoretically evaluated or it can be estimated from homogeneous areas. In the case of N (number of looks used to generate the image) being unknown N can be inferred from the comparison of theoretical and actual speckle distribution in homogeneous areas.

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