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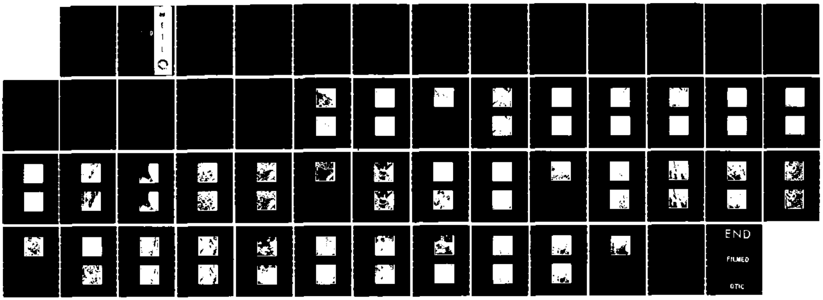

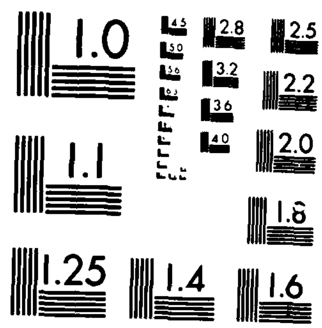

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Noise removal on radar imagery using local gradient and statistics

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Noise variance

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This report shows that the noise-removal algorithm using local gradient and statistics is most favorable to filter a noisy radar image without contrast loss. This report includes the summary of this algorithm with a suggestion of a practical method of estimating a local noise variance. Various noise-removal algorithms are compared with this algorithm based on a visual examination of their filtering results on a set of radar images. The final results of noise removal of the images are displayed along with the originals in the last section. A set of twenty-eight SAR (synthetic aperture radar) images, of size 512x512 pixels, was used for experimentation. Keywords: ... multiplicative noise

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PREFACE

The work documented in this report was performed under contract DACA76–84–C–0003 for the U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, by Mnemonics, Inc., Saline, Michigan. The Contracting Officer's Technical Representative was Dr. Frederick W. Rohde.

CONTENTS

List of Symbols

Z_{ij} - The observed brightness of the pixel of the i^{th} row and the j^{th} column

X_{ij} - The true brightness of the pixel of the i^{th} row and the j^{th} cloumn befor noise degradation

S^2 - Noise variance

W_{ij} - The white noise with a zero mean and noise variance S^2

$\bar{X}_{ij}$ - The mean of X_{ij}

Q_{ij} - The variance of X_{ij}

$E[y]$ - The expectation value of y

$\hat{X}_{ij}$ - The estimate of X_{ij}

U_{ij} - The multiplicative noise

$VAR(y)$ - The variance of y

1. Introduction

Noise removal is usually accompanied by image blurring which manifests itself in smeared edges or loss of subtle details. In general, image blurring becomes more serious as the window size of the noise removal operator increases. Image blurring can be divided into two kinds; blurring edges between heterogeneous regions and blurring texture in a homogeneous region. To solve such blurring problems, many adaptive filtering algorithms have been suggested. One of those algorithms is discussed here. The algorithm was originally suggested by Lee [1], [2] under an assumption that the sample mean and variance of a pixel equal the local mean and variance of its neighborhood. The neighborhood is redefined adaptively according to the edge orientation in a high contrast area such that the neighborhood contains only one side of a possible edge. Hence noise is removed along an edge and the edge is enhanced.

In the following section, this algorithm is summarized and then one practical method of estimating a local noise variance is presented.

2. Algorithm

Let Z_{ij} be the observed brightness of the pixel (i,j) and X_{ij} be the true brightness of the pixel before noise degradation.

a. For the additive noise case

$$Z_{ij} = X_{ij} + W_{ij} \tag{1}$$

where W_{ij} is white noise with a zero mean and variance S^2. The mean $\bar{X}_{ij}$ and variance Q_{ij} are approximated by the local mean and variance in a chosen window centered around (i,j).

$$\bar{X}_{ij} = \bar{Z}_{ij} \tag{2}$$

$$Q_{ij} = E[(Z_{ij} - \bar{Z}_{ij})^2] - S^2 \tag{3}$$

The local variance Q_{ij} is thresholded such that the area with a higher value of Q_{ij} than a certain threshold is regarded as containing an edge. The threshold is image dependent (e.g. for the radar images, the threshold of 5,000,000.0 gave the best results). The estimated ture *brightness of the pixel* ($\hat{X}_{ij}$) *is obtained by minimizing* the mean square error.

$$\hat{X}_{ij} = \bar{X}_{ij} + K_{ij}(Z_{ij} - \bar{X}_{ij}) \tag{4}$$

where

$$K_{ij} = \frac{Q_{ij}}{Q_{ij} + S^2} \tag{5}$$

In implementation, the noise variance S^2 is estimated by the average of the smallest five local variances in a block. Hence, the value of Q_{ij} will be always positive and the value K_{ij} is in between one and zero.

b. For the multiplicative noise case

$$Z_{ij} = X_{ij} U_{ij} \tag{6}$$

where

$$E [U_{ij}] = \bar{U}_{ij} \tag{7}$$

The mean and variance of Xij are given by

$$\bar{X}ij = \bar{Z}ij / \bar{U}ij \tag{8}$$

$$Q_{ij} = \frac{VAR (Z_{ij}) + Z_{ij}^2}{S^2 + \bar{U}_{ij}^2} - \bar{X}_{ij}^2 \tag{9}$$

The estimated ture brightness of the pixel ($\hat{X}_{ij}$) is obtained by applying the Kalman filtering algorithm to the above equations.

$$\hat{X}_{ij} = \bar{X}_{ij} + K_{ij} (Z_{ij} - \bar{U} \bar{X}_{ij}) \tag{10}$$

where

$$K_{ij} = \frac{\bar{U}_{ij} Q_{ij}}{\bar{X}_{ij}^2 S^2 + \bar{U}_{ij}^2 Q_{ij}} \tag{11}$$

Note that there still remains an unsolved problem; that is how to estimate the noise variance. Because the noise variance is unknown and spatially variant in most situations, it is not easy to estimate it correctly. Theoretically, the minimum local variance in the local area may be a good estimate of noise variance. The idea is that the local noise variance can be estimated by the local variance of a flat (or almost flat) area. During our experiments, it was found that this algorithm was sensitive to the estimated noise variance. If the noise variance is obtained from too small a block there may not be many flat areas to select on that block. Consequently the noise variance does not reflect the true situation, and hence the algorithm is not very effective. On the other hand, if the noise variance is obtained from too large a block it may be too global and it is not a local variance and hence the subtle details tend to be lost. Another big factor for choosing a good method of estimating a local noise variance is the processing time (i.e. cpu time). In our experiments it varied from about 1 minute to 40 minutes for processing a 256 x 256-pixel image depending on the method of estimating a local noise variance. One possible solution to this problem is to take one fixed estimate for every local noise variance corresponding to every pixel in the same row of the input image. The fixed estimate for the local noise variance corresponding to the pixel of the i^{th} row and the j^{th} column can be abtained by ordering the local variances (Q_{i1}, Q_{i2}, ..., Q_{in} ; n is the number of pixels in a row.) in size, choosing several of the smallest local variances, and averaging them. The local variance corresponding to a pixel is defined as the variance of the pixel values in the neighborhood of the pixel. Only one noise variance is estimated for each row so that a great amount of cpu time is saved. Although one noise variance for each row sounds too global, it turns out to be a computationally efficient method with high quality of noise removal and edge enhancement. The definition of a neighborhood using a local gradient is described next.

This algorithm assumes that for any pixel with a high local variance over a certain threshold, there exists an edge in its neighborhood. By this assumption, in a high contrast region (i.e. edge area), the local statistics obtained from either side of an edge is more reliable than that obtained from its whole neighborhood. For such a high local variance pixel, its neighborhood is redefined in the following way.

1. The direction of a possible edge is obtained by applying directional gradient masks to the window centered around the pixel.
2. Which side of the edge the center pixel belongs to is determined.
3. The side of the edge determined in the above step is defined as the neighborhood of the pixel.

In implementation, four directional gradient masks were used. Hence only four directions of an edge and eight types of subarea as a redefined neighborhood were possible (see figure 1). The threshold for the local variance determines the presence of an edge in the window centered around each pixel such that a lower threshold gives more edge areas for which the neighborhoods are redefined.

1	1	1	1	0	0	0
1	1	1	1	0	0	0
1	1	1	1	0	0	0
1	1	1	1	0	0	0
1	1	1	1	0	0	0
1	1	1	1	0	0	0
1	1	1	1	0	0	0

Type 1

1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
0	0	0	0	0	0	0
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0	0	0	0	0	0	0

Type 2

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1	1	1	1	0	0	0
1	1	1	0	0	0	0
1	1	0	0	0	0	0
1	0	0	0	0	0	0

Type 3

1	1	1	1	1	1	1
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0	0	0	0	0	0	1

Type 4

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0	0	0	1	1	1	1

Type 5

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Type 6

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Type 7

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1	1	1	1	1	1	0
1	1	1	1	1	1	1

Type 8

Figure 1. Eight types of neighborhood (areas marked by 1's) in a high contrast region when a 7 x 7 window is used

In the next section, four noise removal algorithms including the one described above and their filtering results on radar images are discussed briefly. The comparison among those filtering techniques is then summarized at the end of the section.

3. Experiments

A set of radar images was used as test images. This set consists of twenty eight areas in Alabama and North Carolina. Each image consists of 512 x 512 pixels. Four different noise removal filters were tried on each of the images. The four filters were the weighted median filter, the average image filter, the Gaussian filter, and the adaptive filter which was introduced in the previous section.

a. Weighted median filter

The weighted median filter takes the median value of all the pixel values in a window centered around each pixel. The pixels are weighted such that a pixel with a weight, say 3, is counted 3 times in computing the median value. The traditional median filter is a special case of this filter with equal wights. Generally this filter removes noise without image blurring when the window size is not greater than 3 x 3 pixels. However, for an image which needs a larger size window or an image whose pixels have the values close to the median of their neighborhood, this filter does not work effectively. All the images of the Alabama area and some images of the North Carolina area appear to be such images.

Two weighted windows were used during the experiments (see Figure 2). Most of the radar image noise was removed more efficiently by using a 3 x 3-pixel window than a 5 x

5-pixel window. It was also found that iterative application of this filter on the images does not have a better effect on the noise removal than filtering once with a largar size window.

				1	1	1	1	1
1	1	1		1	2	2	2	1
1	3	1		1	2	4	2	1
1	1	1		1	2	2	2	1
				1	1	1	1	1
3 x 3 window				5 x 5 window				

Figure 2. Weighted windows used in the experiments

b. Equally weighted average filter

This filter takes the average value of all the pixels in a window centered around a pixel as the value for the pixel. It removes noise very efficiently on a homogeneous region containing a coarse textural pattern at a very fast processing speed. However, on a heterogeneous region or even a homogeneous region with a fine textural pattern, it blurs the image significantly. Unfortunately, most images of our experiments contain many such regions and hence the results were not very good. During the experiments, 3 x 3-pixel and 5 x 5-pixel windows were used.

c. Gaussian filter

The Gaussian filter takes an average value of weighted pixels in a window centered around a pixel as the value for the pixel. Each pixel value in a window has a weight which associates with the value of a normal probabilty density function such that the pixels far away from the center pixel have smaller weights. With this filter, the contrast of the image is maintained and the image has a good visual appearance. The noise is generally removed for any kind of texture. However the image is easily blurred because the filter has the property of averaging. In our experiments, it removed the noise well on most of the images with good visual effect but with some image blurring. The 5 x 5-pixel window with 0.75 standard deviation was used..

d. Adaptive filter

Since the neighborhood of each pixel is redefined adaptively within a chosen window, the average number of pixels involved in computing an output for each pixel is relatively smaller than that of any other filter when the same size window is used. Therefore it does not blur an image so much as the others. It enhances edges and contrast of an image. In homogeneous regions, however, it still tends to blur an image and wash out details such as thin lines, fine textural patterns, or weak edges. This undesirable blurring in homogeneous regions can be reduced by lowering the threshold for the local variance which determines the presence of an edge. In our experiments, most of the radar images were contrast stretched and edge enhanced with a minimal loss of detail.

e. Summary of experiments

The filtering results on radar images using the above four filters can be summarized on the basis of their visual effect (see table 1, and figure 3a thru figure 3e). The visual effect is judged for four aspects: noise removal, contrast stretching, edge enhancement, and preservation of texture.

	noise removal	contrast stretch	edge enhancement	texture preservation
Weighted median	good	fair	fair	good
Equal wgt averaging filter	fair	fair	fair	fair
Gaussian filter	good	excellent	fair	fair
Adaptive filter	good	excellent	excellent	fair

table 1. Comparison of the filters based on the filtering results of the set of radar images

4. Conclusion

The adaptive filter using local gradient and local statistics removes noise without contrast loss or edge blurring. In a homogeneous region it still tends to blur an image because it counteracts the blurring problem only in heterogeneous regions. The image blurring, however, can be reduced by lowering the threshold on the local variance which decides whether a region is homogeneous or heterogeneous. As summarized in table 1, the weighted median filter works better than the adaptive filter in terms of preservation of texture. This fact suggests a study of various adaptive filters such as an adaptive weighted median filter, adaptive Gaussian filter, adaptive averaging filter or a combination of them. Those are being studied now. In the next section, the final filtering results on the set of radar images, by the adaptive filter introduced in this report, are displayed along with the originals. For some of the images, the results of other filters are displayed also.

5. Final results

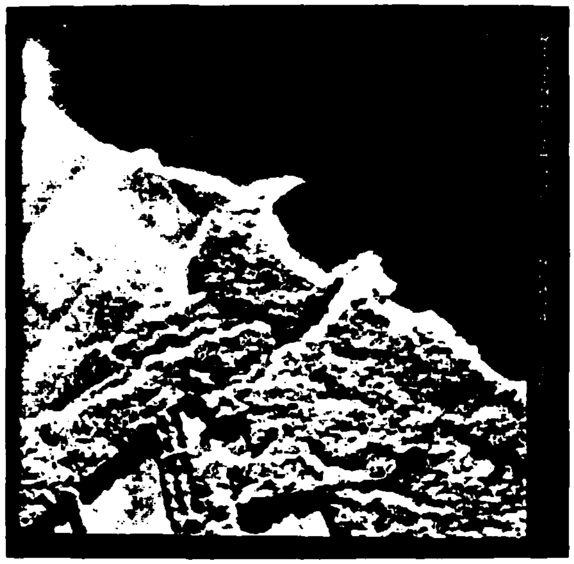


Figure 3a. Radar image of the part of Elizabeth city area, North Carolina

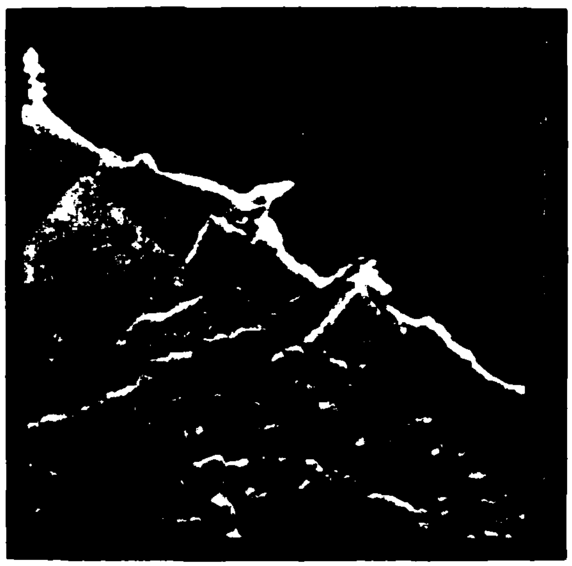


Figure 3b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

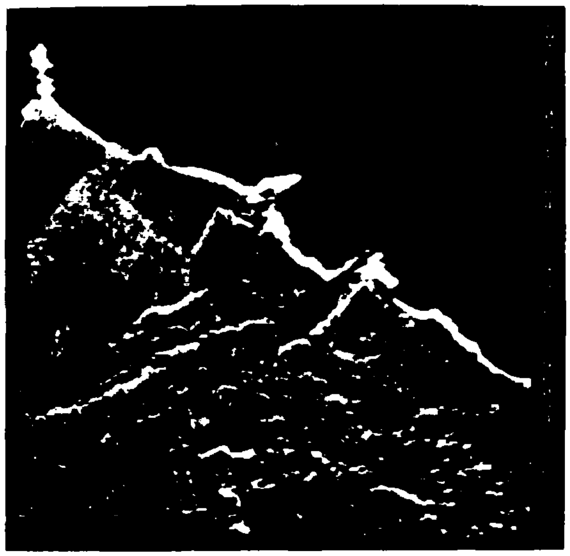
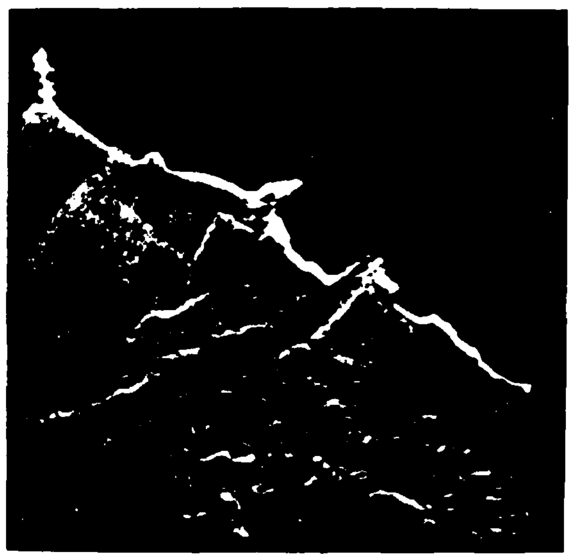


Figure 3c. Filtered image with the Gaussian filter using the 5 x 5 window and the standard deviation of 0.75



Figrue 3d. Filtered image with the weighted median filter using the 3 x 3 window

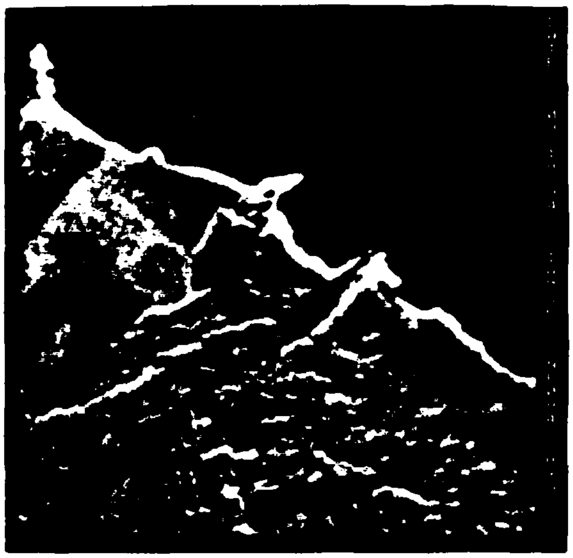


Figure 3e. Filtered image with the equal weight average filter using the 3 x 3 window

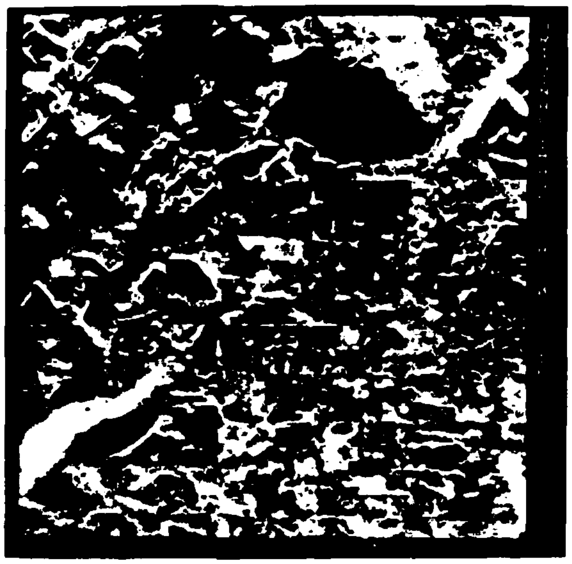


Figure 4a. Radar image of the part of Huntsville area, Alabama

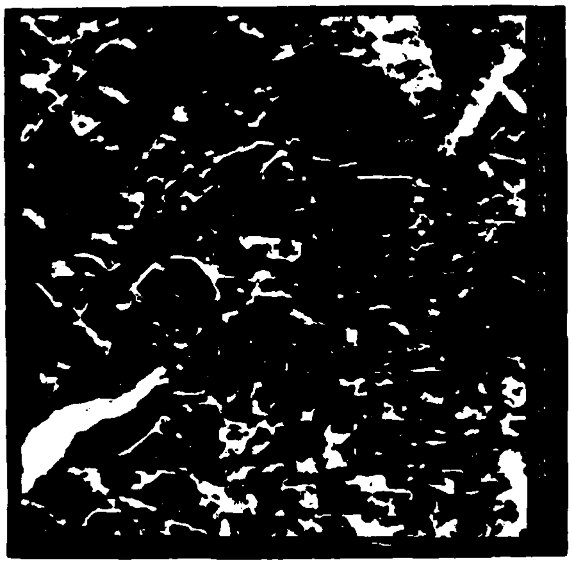


Figure 4b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

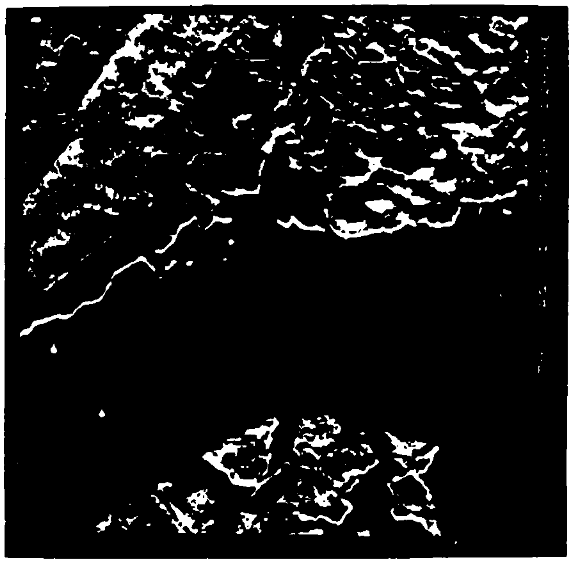


Figure 5a. Radar image of the part of Huntsville area, Alabama

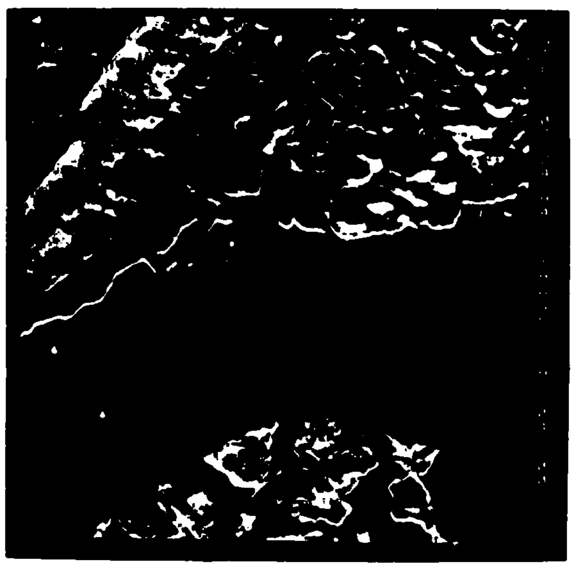


Figure 5b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

Figure 6a. Radar image of the part of Huntsville area, Alabama

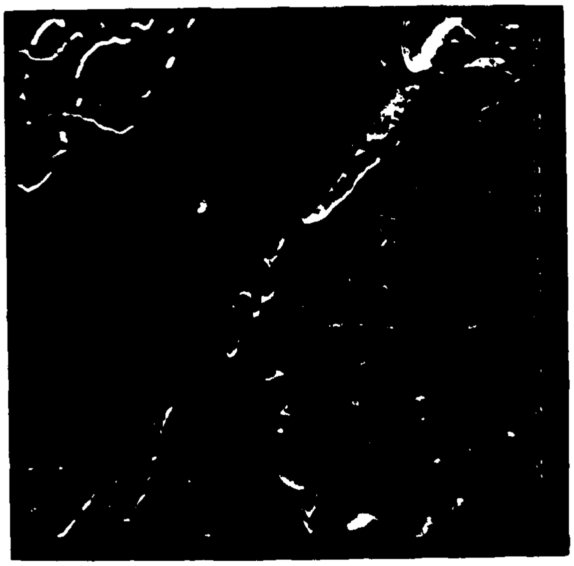


Figure 6b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

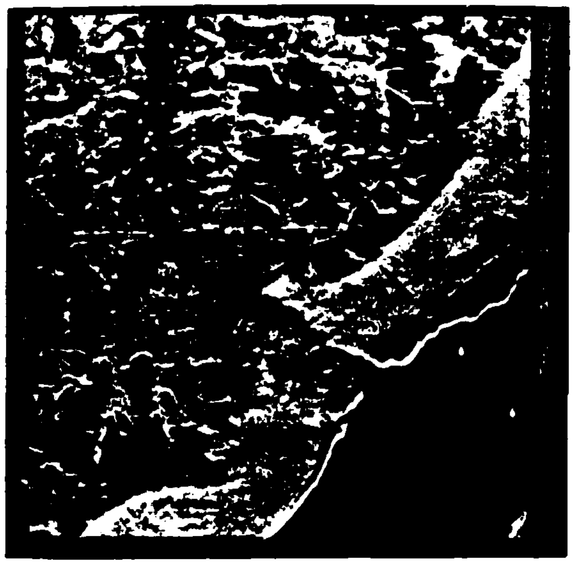


Figure 7a. Radar image of the part of Huntsville area, Alabama

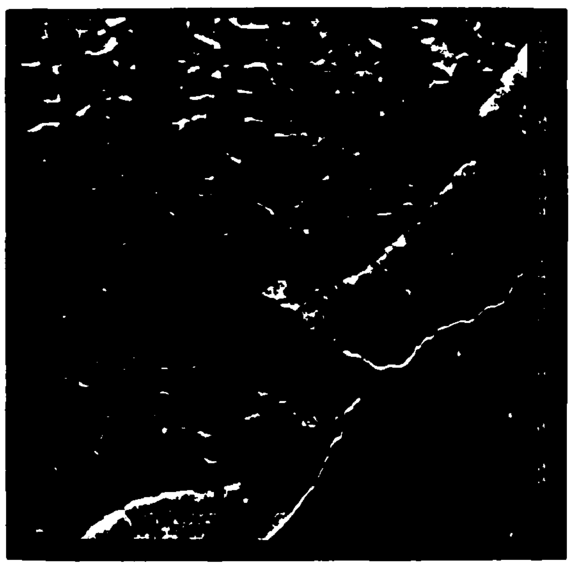


Figure 7b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

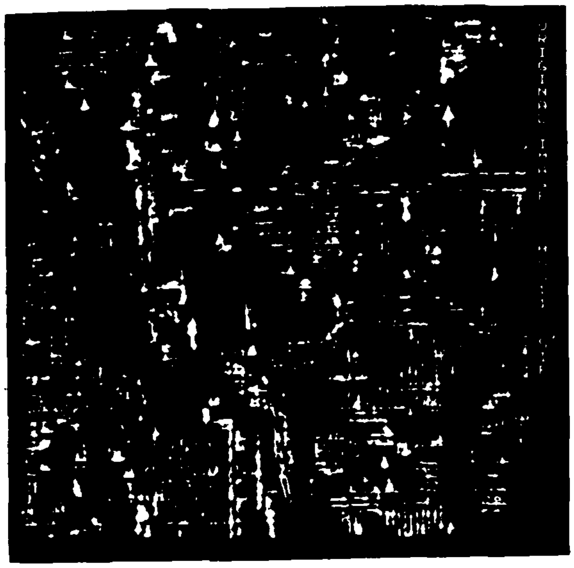


Figure 8a. Radar image of the part of Huntsville area, Alabama

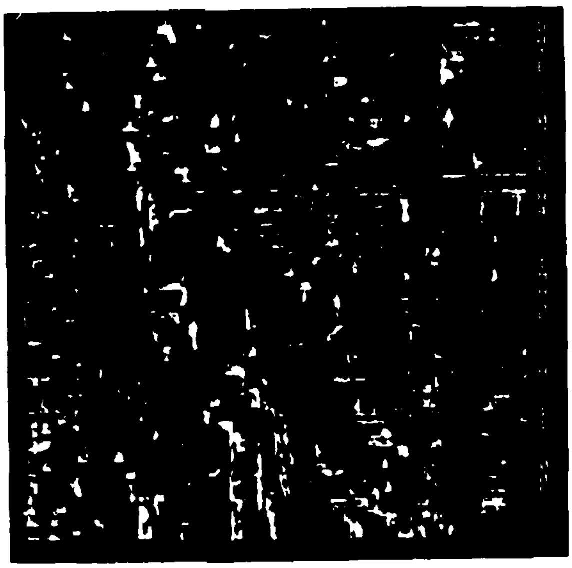


Figure 8b. Filtered image with the apdative filter using the threshold of 5,000,000.0

Figure 9a. Radar image of the part of Huntsville area, Alabama

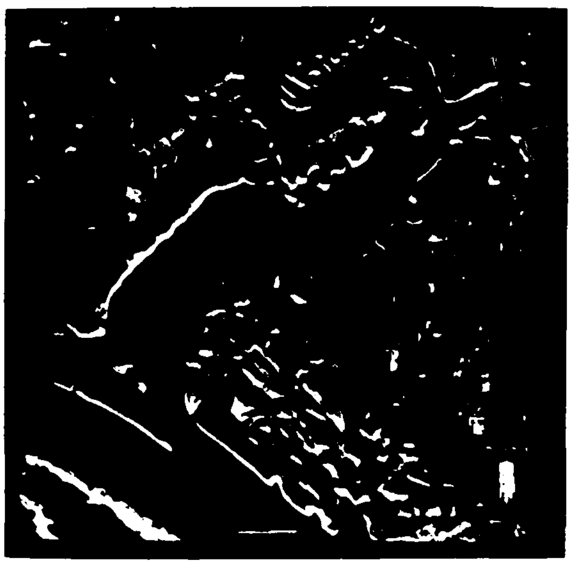


Figure 9b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

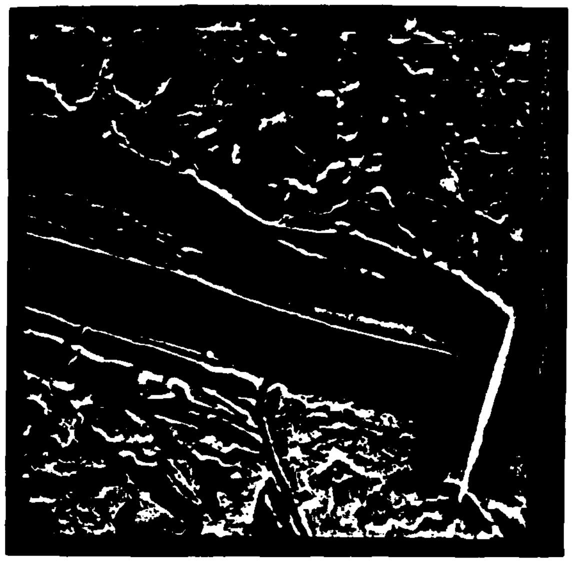


Figure 10a. Radar image of the part of Huntsville area, Alabama

Figure 10b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

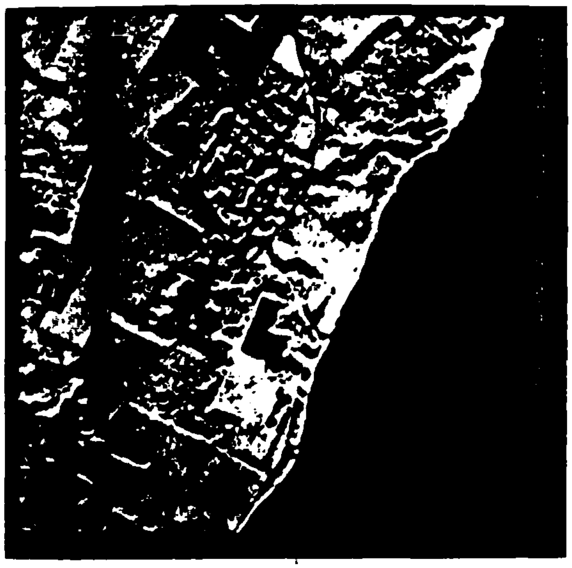


Figure 11a. Radar image of water, shoreline, farms, small town

Figure 11b. Filtered image with the adaprive filter using the threshold of 5,000,000.0

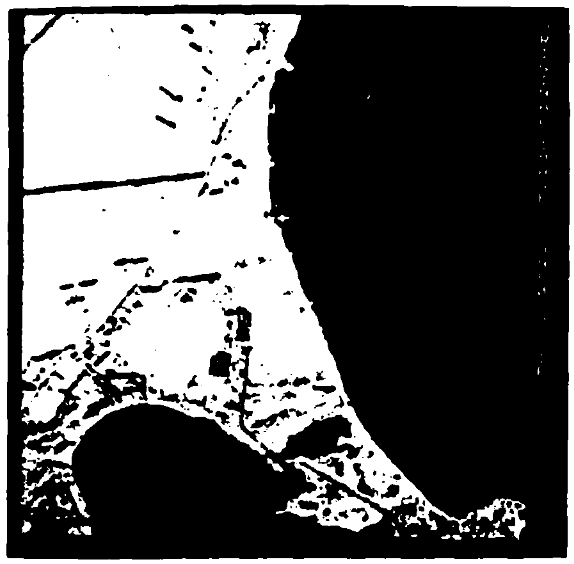


Figure 12a. Radar image of the part of Elizabeth city area, North Carolina

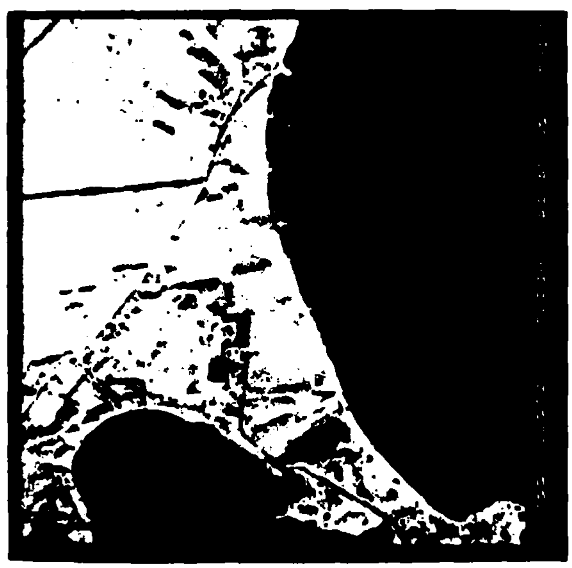


Figure 12b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

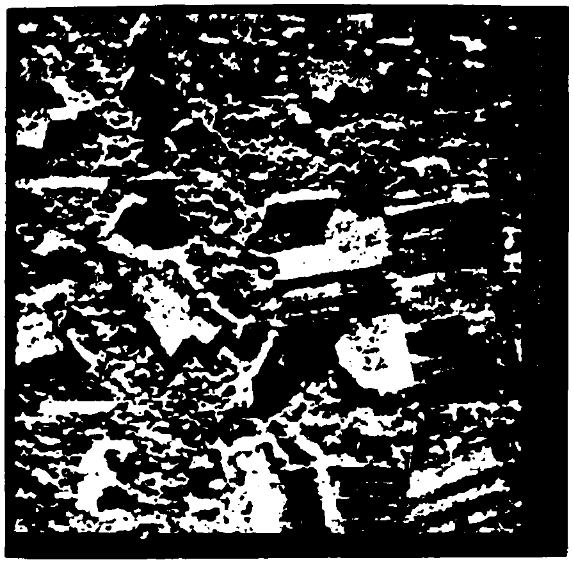


Figure 13a. Radar image of the part of Elizabeth city area, North Carolina

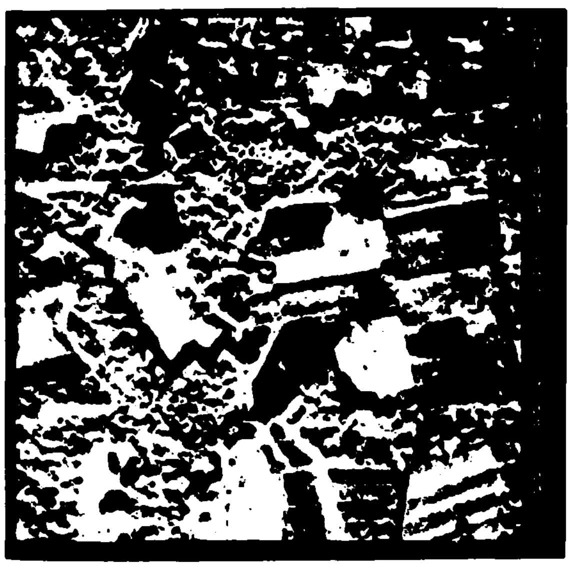


Figure 13b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

Figure 14a. Radar image of the part of Elizabeth city area, North Carolina

Figure 14b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

Figure 14c. Filtered image with the weighted median filter using the 3 x 3 window

Figure 15a. Radar image of the part of Elizabeth city area, North Carolina

Figure 15b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

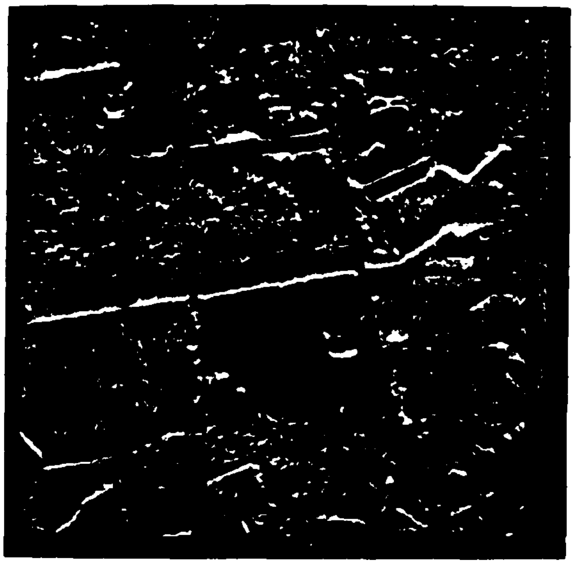


Figure 16a. Radar image of the part of Elizabeth city area, North Carolina

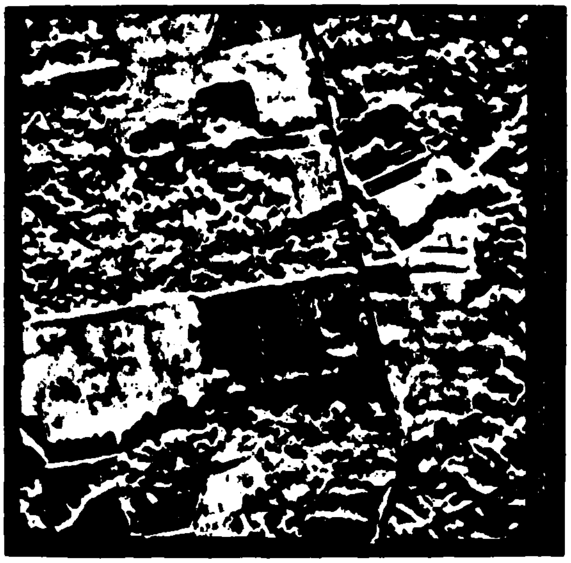


Figure 16b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

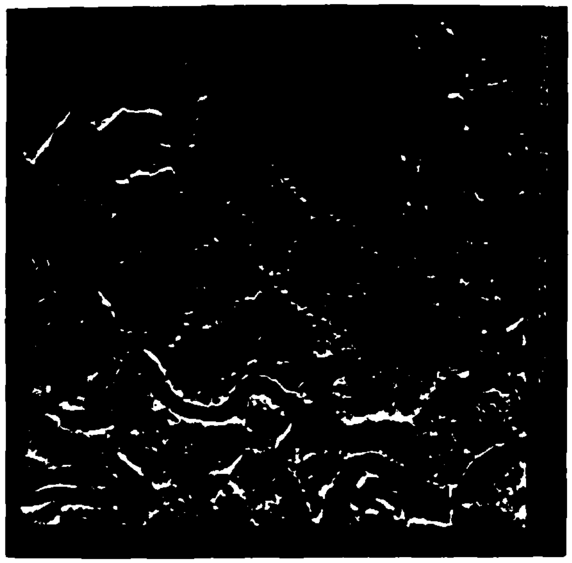


Figure 17a. Radar image of the part of Elizabeth city area, North Carolina

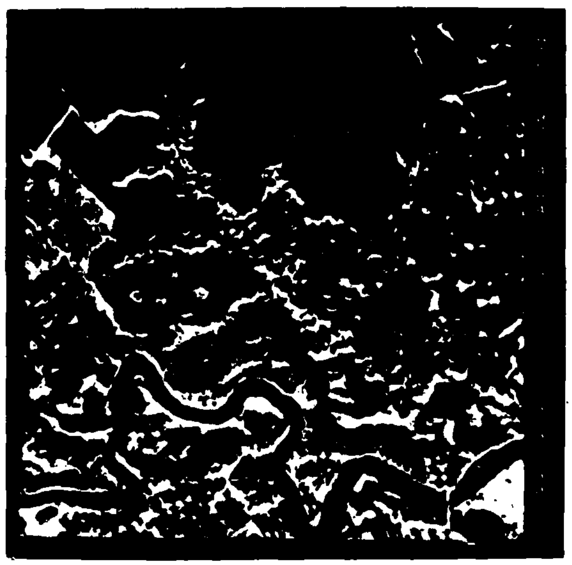


Figure 17b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

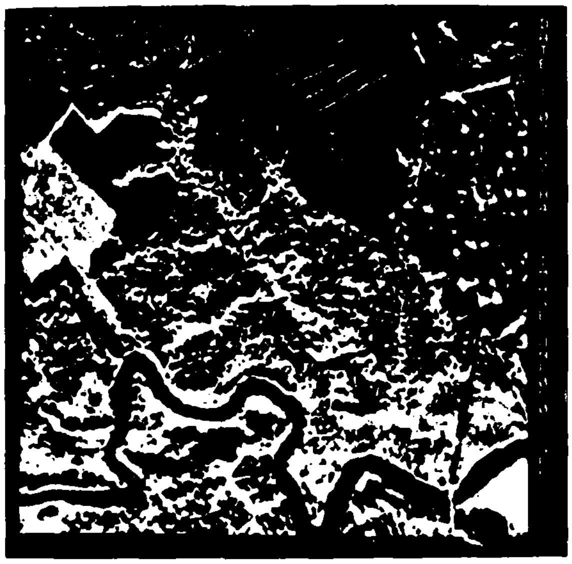


Figure 17c. Filtered image with the Gaussian filter using the 5 x 5 window and the standard deviation of 0.75

Figure 18a. Radar image of the part of Elizabeth city area, North Carolina

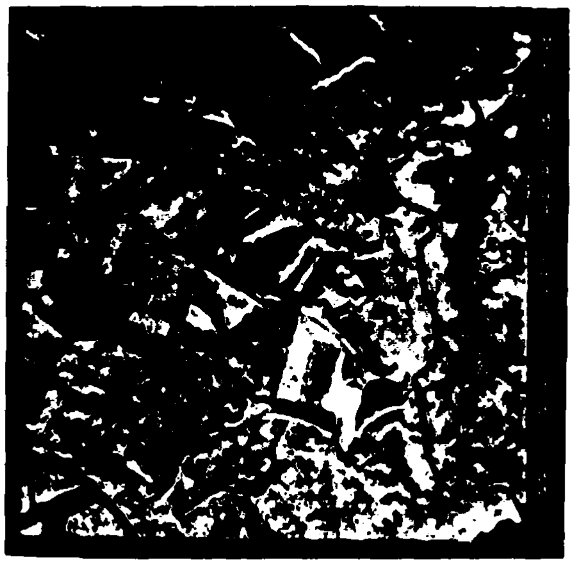


Figure 18b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

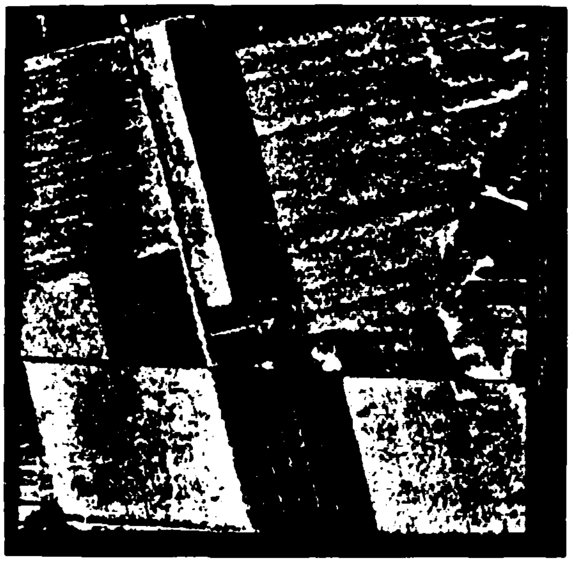


Figure 19a. Radar image of the part of Elizabeth city area, North Carolina

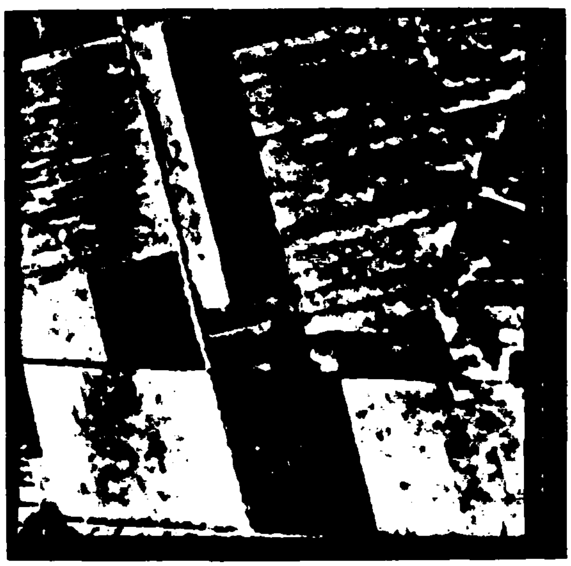


Figure 19b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

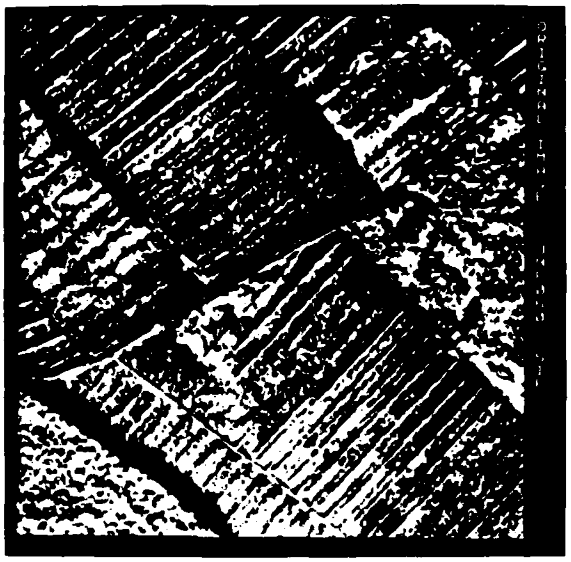


Figure 20a. Radar image of the part of Elizabeth city area, North Carolina

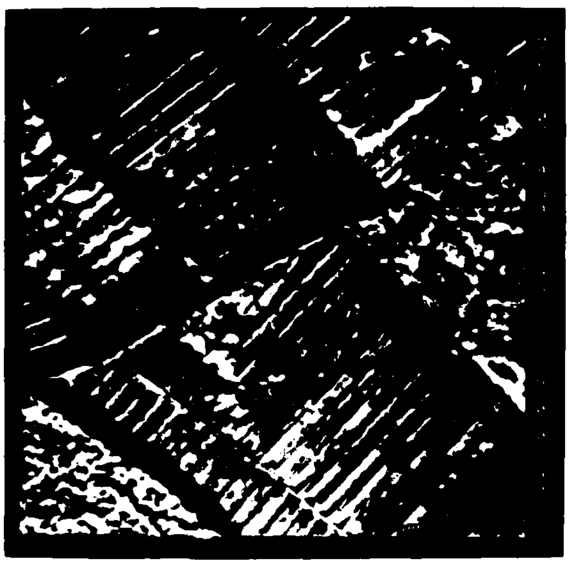


Figure 20b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

Figure 21a. Radar image of the part of Elizabeth city area, North Carolina

Figure 21b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

Figure 21c. Filtered image with the weighted median filter using the 3 x 3 window

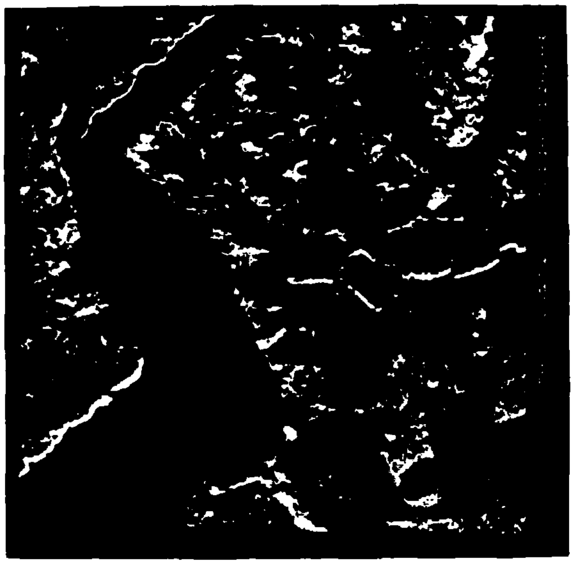


Figure 22a. Radar image of the part of Elizabeth city area, North Carolina

Figure 22b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

Figure 23a. Radar image of the part of Elizabeth city area, North Carolina

Figure 23b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

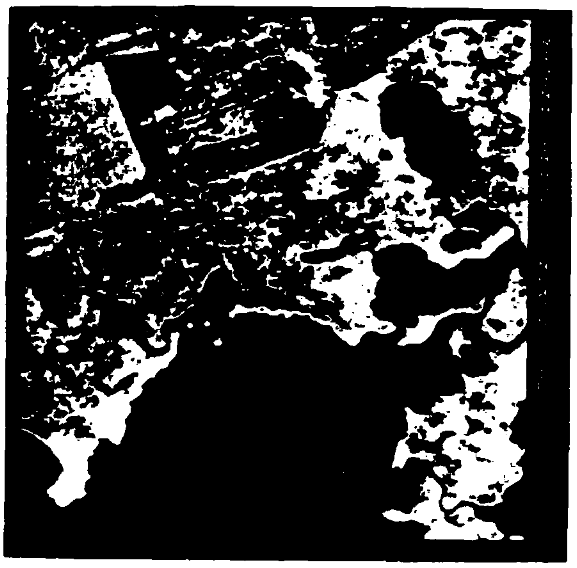


Figure 24a. Radar image of the part of Elizabeth city area, North Carolina

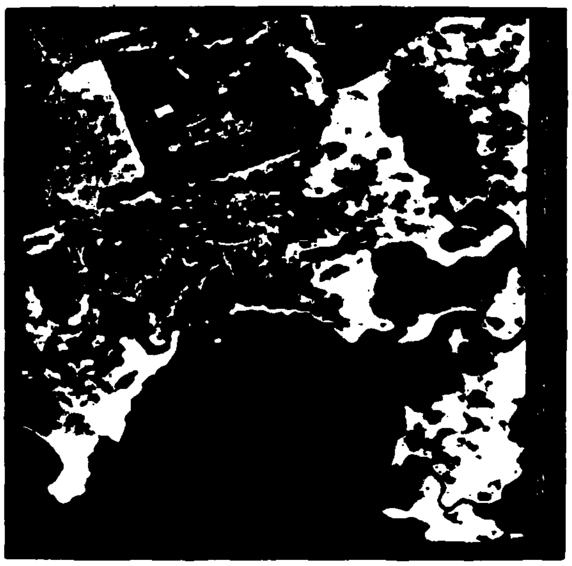


Figure 24b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

Figure 25a. Radar image of the part of Elizabeth city area, North Carolina

Figure 25b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

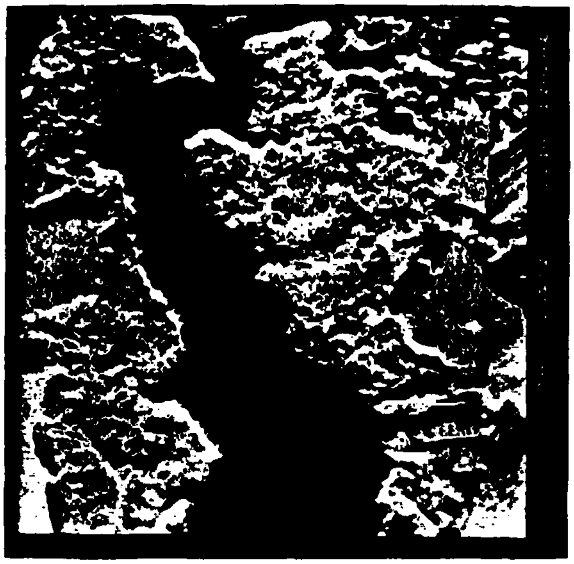


Figure 26a. Radar image of the part of Elizabeth city area, North Carolina

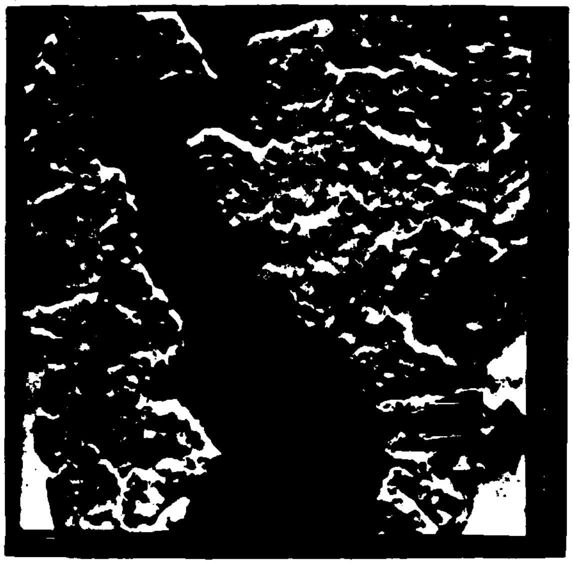


Figure 26b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

Figure 27a. Radar image of the part of Elizabeth city area, North Carolina

Figure 27b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

Figure 28a. Radar image of the part of Elizabeth city area, North Carolina

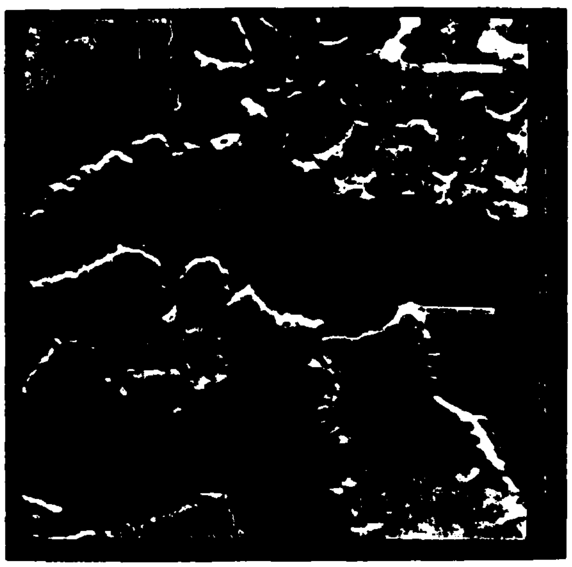


Figure 28b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

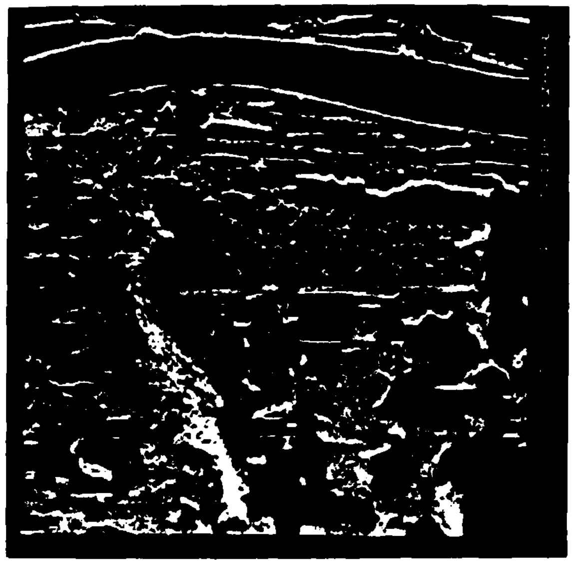


Figure 29a. Radar image of the part of Huntsville area, Alabama

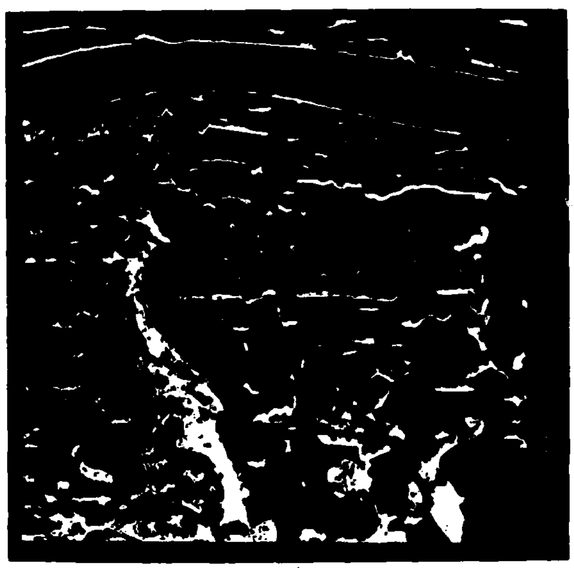


Figure 29b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

Figure 30a. Radar image of the part of Elizabeth city area, North Carolina

Figure 30b. Filtered image with the adaptive filter using the threshold of 5,000,000.0

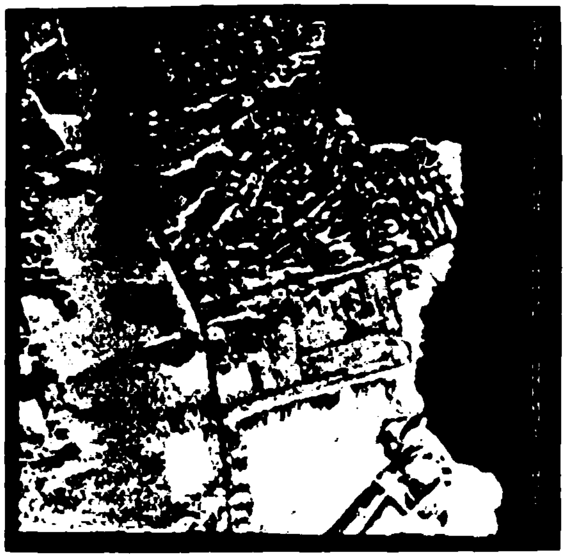


Figure 30c. Filtered image with the weighted median filter using the 3 x 3 window

REFERENCES

[1] J. S. Lee, Digital image enhancement and noise filtering by the use of local statistics, IEEE Trans. PAMI PAMI-2, NO. 2, 1980, 165 - 168

[2] J. S. Lee, Refined filtering of image noise using local statistics, Computer Graphics and Image Processing 15, 1981, 380 - 389

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