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Refined Filtering of Image Noise Using Local Statistics.

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An effective algorithm for digital image noise filtering is presented. Most noise filtering techniques, such as the Kalman filter and transform domain methods, require extensive image modeling and produce filtered images with considerable contrast loss. The algorithm proposed in this report is an extension of Lee's local-statistics method modified to use local gradient information. It does not require image modeling, and it will not smear edges and subtle details. For both the additive and multiplicative noise cases the local mean and variance are computed from a reduced set of pixels

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20. Abstract (Continued)

depending on the orientation of the edge. Consequently, noise along the edge is removed, and the sharpness of the edge is enhanced. For practical applications when the noise variance is spatially varying and unknown an adaptive filtering algorithm is developed. Experiments show its good potential for processing real-life images. Examples on images containing 256 by 256 pixels substantiate the theoretical development.

CONTENTS

REFINED FILTERING OF IMAGE NOISE USING LOCAL STATISTICS

INTRODUCTION

Recently Lee [1] developed noise-filtering algorithms for both additive and multiplicative noise. The techniques, based on the use of local mean and local variance do not require image modeling as do other methods using Kalman or Wiener filtering techniques [2-4]. The only assumption is that the sample mean and variance of a pixel is equal to its local mean and variance based on pixels within a fixed neighborhood surrounding it. In the additive noise-filtering case the a priori mean and variance of an image is calculated as the difference between the local mean and local variance of the noise-corrupted image and the mean and variance of the noise. It is well known that once the a priori mean and variance are given, it is straightforward to compute the optimal mean-square estimates of them. As shown in reference 1, the filtering algorithm is a linear weighted sum of the local mean and the image itself. The distinct characteristic is that in areas of very low contrast the estimated pixel approaches the local mean, whereas in high-constrast areas (edge areas) the estimated pixel favors the corrupted-image pixel, thus retaining the edge information. It is generally claimed that human vision is more sensitive to noise in a flat area than in an edge area. However, it is still desirable to reduce noise in the edge area without sacrificing the edge sharpness. This is the objective in this report.

The basic idea is to redefine the neighborhood (the area where the local mean and variance are computed) near the high-contrast region taking into account the orientation of the edge. In other words the local gradient is incorporated into the local-mean and local-variance filtering algorithm. For each high-local-variance pixel (high-contrast point) over a threshold, a gradient is computed for the local area to obtain the orientation of the edge. Next a subset of pixels in the local area on each side of the edge is defined, and then which of the two subsets the pixel under consideration belongs to is determined. Because this subset contains pixels on only one side of the edge, the local mean and variance computed in the subset is a more precise representation of the a priori mean and variance of the pixel under consideration. From another viewpoint the local variance will be greatly reduced; hence the noise along the edge will be removed.

In the next section, the local mean and variance method will be reviewed briefly, and the refined algorithm will be given in detail. In the third section an adaptive algorithm is developed for the case of an unknown noise variance. Extension of the refined algorithm to a multiplicative noise corrupted image is discussed in the fourth section. Remarks and conclusion are given in the final two sections. Experimental results for images of dimension 256 by 256 are given for each case.

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LOCAL-STATISTICS METHOD

For completeness this section briefly reviews the local-statistics filtering algorithm [1]. Then the next section will define the subsets of a neighborhood.

Let $z_{i,j}$ be the brightness of the pixel (i, j) in a two-dimensional N-by-N image and $x_{i,j}$ be the pixel before degradation. Then, for the additive noise case,

$$z_{i,j} = x_{i,j} + \omega_{i,j}, \tag{1}$$

where $\omega_{i,j}$ is the white random sequence with zero mean and σ^2 variance. In most filtering algorithms the a priori mean and variance of $x_{i,j}$ are derived from an assumed correlation model. The local-statistics method deviates from this by assuming that the a priori mean and variance ($\bar{x}_{i,j}$ and $Q_{i,j}$) are approximated by the local mean and variance of all pixels in the neighborhood surrounding $z_{i,j}$. From equation (1),

$$\bar{x}_{i,j} = \bar{z}_{i,j} \tag{2a}$$

and

$$Q_{i,j} = E[(z_{i,j} - \bar{z}_{i,j})^2] - \sigma_1^2, \tag{2b}$$

where $\bar{z}_{i,j}$ and $E[(z_{i,j} - \bar{z}_{i,j})^2]$ are approximated by the local mean and variance. Under this assumption it is easy to obtain the minimum mean-square filter [1]. The estimated $x_{i,j}$, denoted $\hat{x}_{i,j}$, is given by

$$\hat{x}_{i,j} = \bar{x}_{i,j} + k_{i,j}\,(z_{i,j} - \bar{x}_{i,j}), \tag{3}$$

where

$$k_{i,j} = \frac{Q_{i,j}}{Q_{i,j} + \sigma_1^2} \tag{4}$$

Since $Q_{i,j}$ and σ_1^2 are both positive, $k_{i,j}$ will lie between 0 and 1. For a flat or low-contrast area, $Q_{i,j}$ is small, and $\hat{x}_{i,j} \approx \bar{x}_{i,j}$, whereas for an edge or high-contrast area, $Q_{i,j}$ is much larger than σ_1^2, and $\hat{x}_{i,j} \approx z_{i,j}$. For most noisy images this algorithm produces quite satisfactory results, since, as stated earlier, human vision is more sensitive to noise in a flat area than in an edge region. In many cases it is desirable, however, to smooth out the noise around the edge area.

IMPROVED FILTERING ALGORITHM FOR ADDITIVE NOISE

The window used in the local-statistics method is typically a seven-by-seven pixel region with $x_{i,j}$ at the center. The neighborhood of $x_{i,j}$ could be altered to improve its statistics. For illustration, figure 1 shows the neighborhood of $x_{i,j}$. It is apparent that $x_{i,j}$ is more likely to be a member of the subset of pixels in the unshaded area of the window rather than a member of the whole neighborhood. If the local mean and variance are computed based on pixels in this subset, the new $Q_{i,j}$ for this subset will be considerably smaller than the $Q_{i,j}$ computed for the whole set. Consequently from equations (3) and (4) $\hat{x}_{i,j} \approx \bar{x}_{i,j}$, where $\bar{x}_{i,j}$ is the local mean of the subset. In other words noise at the edge will be smoothed. Our computational experience shows that this procedure will also enhance the edges.

To determine the subset, one must know the orientation of the edge and on which side of the edge $x_{i,j}$ lies. A three-by-three-pixel local-gradient mask is used to determine the edge orientation. To minimize the noise effect on the local gradient, the window, assumed for the moment to be nine by nine pixels, is divided into nine three-by-three subareas, and the local mean of each subarea is computed. Then the three-by-three gradient mask is applied to the local means of these subareas, as shown in figure 2. Once the edge orientation is computed, the subarea means orthogonal to the edge are compared to determine to which side of the edge the $x_{i,j}$ belongs and hence to which of the two subsets. For the case shown in figure 2, comparison of $|m_{31} - m_{22}|$ and $|m_{13} - m_{22}|$ determines the subset.

For easier implementation, a seven-by-seven window is used, with each subarea still containing three by three pixels but now being overlapped with its neighbors, as indicated in figure 3. The subarea means are computed, and the simple three-by-three gradient masks [5] are applied to the subarea means. Only four of the eight directional gradient masks are required, because masks in opposite directions complement each other. The direction of the gradient mask with the maximum absolute value for the gradient is used as the direction of the edge. For convenience a directional index for the gradient masks is used as shown in figure 4.

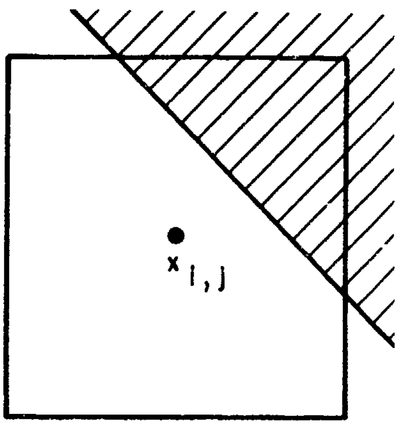

Figure 1 — Neighborhood of a pixel

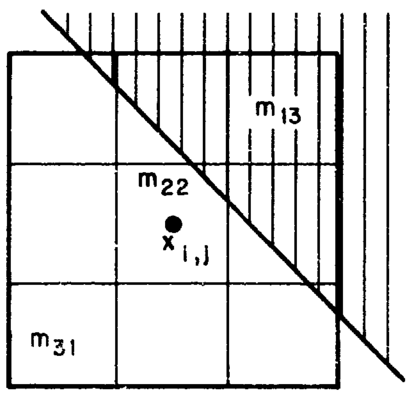

Figure 2 — Application of three-by-three subareas in a neighborhood of the pixel in figure 1, assuming that neighborhood to be nine by nine pixels

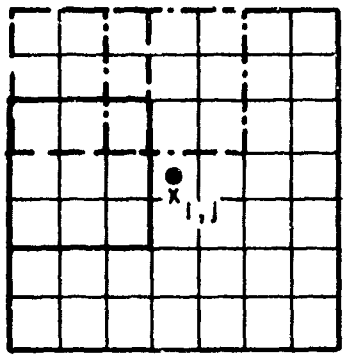

Figure 3 — Overlapping of three-by-three subareas in a seven-by-seven neighborhood

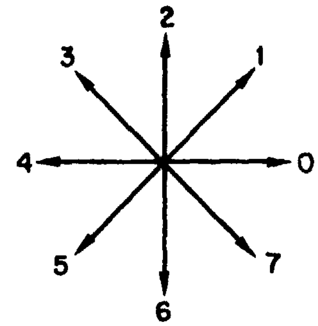

Figure 4 — Directional indexes

Suppose the gradient mask in the direction labeled 2 has the maximum gradient. Then (figure 5) subarea means m_{12} and m_{32} are compared with m_{22} to determine whether the subset is in direction 2 or 6. The possible subsets corresponding to all the directions in figure 4 are listed in figure 6 for a seven-by-seven window. If $|m_{32} - m_{22}| < |m_{12} - m_{22}|$, subset 6 will be chosen and all pixels in the unshaded area are used in the computation of local mean and variance.

For clarity the following numerical example of a vertical noisy edge in a seven-by-seven window is given:

99	105	124	138	128	34	62
105	91	140	98	114	63	31
107	94	128	138	96	61	82
137	129	136	(105)	100	55	85
144	145	113	132	119	39	50
102	97	102	110	103	34	53
107	146	115	123	101	76	56

edge boundary

The center pixel valued at 105 is the pixel to be filtered. If the original local-statistics filter is used, the seven-by-seven mean = 99 and the seven-by-seven variance = 1029.24. Then, if a noise variance $\sigma_1^2 = 300$ is assumed, $k_{i,j} = 0.708$ and $\hat{x}_{i,j} = 103.25$. Since the local variance is high, a considerably higher weight is assigned to the observed pixel that is valued at 105.

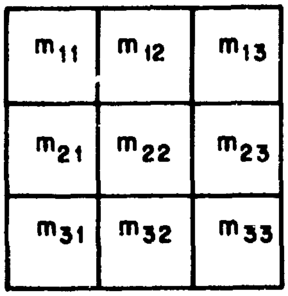

Figure 5 — Subarea means

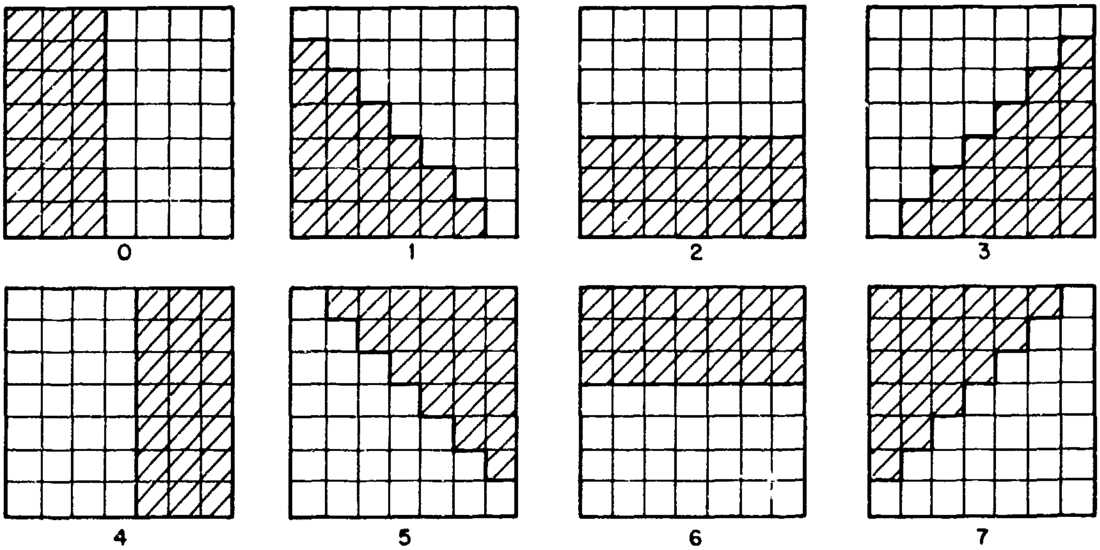

Figure 6 — Definition of directional subsets (unshaded areas) on one side of an edge. The subsets are numbered in the same way as the directional indexes were numbered

If the improved algorithm is used and applied to the original seven-by-seven window, then the subarea means are formed as follows:

$$\left.\begin{array}{rrr} 99 & 105 & 124 \\ 105 & 91 & 140 \\ 107 & 94 & 128 \end{array}\right\} 110 \qquad \left.\begin{array}{rrr} 124 & 138 & 128 \\ 140 & 98 & 114 \\ 128 & 138 & 96 \end{array}\right\} 123$$

$$\left.\begin{array}{rrr} 107 & 94 & 128 \\ 137 & 129 & 136 \\ 144 & 145 & 113 \end{array}\right\} 126 \qquad \left.\begin{array}{rrr} 128 & 138 & 96 \\ 136 & 105 & 100 \\ 113 & 132 & 119 \end{array}\right\} 119$$

and so forth, yielding the values

110	123	75
126	119	76
119	113	70

Application of three-by-three simple gradient masks shows that the maximum absolute value of the gradients is in direction 0. Comparison of $|126 - 119|$ and $|76 - 119|$ shows that the pixel is on the left side of the edge. Hence subset 4 (figure 6) is chosen with the subset mean = 118 and the subset variance = 303, which variance represents a reduction by a factor 3. The new $\hat{x}$ = 117.8, which is much closer to the average of the left side of the edge.

This improved filtering algorithm should not be applied to every pixel of the image, because improvement in noise filtering is more significant in edge areas (or high-local-variance areas) than in flat areas. A local-variance threshold is set up, and only those pixels with local variance exceeding it are processed with this more sophisticated algorithm. Consequently only a moderate increase in computation time is expected.

Figure 7a shows a test image for which the difference in gray levels between the dark area and bright area is 40 and to which uniformly distributed (between -30 and 30) white noise is added. Images filtered by the original algorithm and the improved algorithm are shown in figures 7b and 7c respectively. The edge area is noisier in 7b than in 7c. This improvement in figure 7c is also shown in the intensity profiles along a scan line for all three images (figures 7d, 7e, and 7f). Two other images contaminated by additive noise with $\sigma_1^2 = 300$ and their filtered versions are shown in figure 8. In both images local variance thresholds are set at 500. Both images display sharp edges and also preserve subtle details. In particular, edges in the filtered image of the girl are enhanced to the extent that the desirable softness of the image is somewhat damaged.

ADAPTIVE FILTERING ALGORITHM FOR ADDITIVE NOISE

In most practical applications the noise variance is unknown and spatially variant. It is well known that the noise variance of a local area can be estimated by the local variance of a flat area. Based on this idea, an adaptive algorithm is devised to estimate the local noise variance to be used in the improved algorithm developed in the preceding section. Theoretically, after the local variances associated with each pixel in a small block are computed, the minimum of the variances in this block is a good estimate of error variance. However, because of the small sample size involved in computing the local variance, an average of the five smallest variances is a better estimate when the block size is seven by seven. Incorporation of this procedure into the aformentioned improved algorithm results in a practical noise filtering algorithm without any necessity for a priori image modeling or evaluation of the noise statistics. This algorithm, to be referred to as the adaptive algorithm, requires little additional computation than for the improved algorithm, since the major computational load is in calculating the local mean and variance for each picture element.

A practical example is given in figure 9. A Seasat synthetic-aperture-radar image is shown in figure 9a, and the noise-filtered version using this adaptive algorithm is shown in figure 9b.

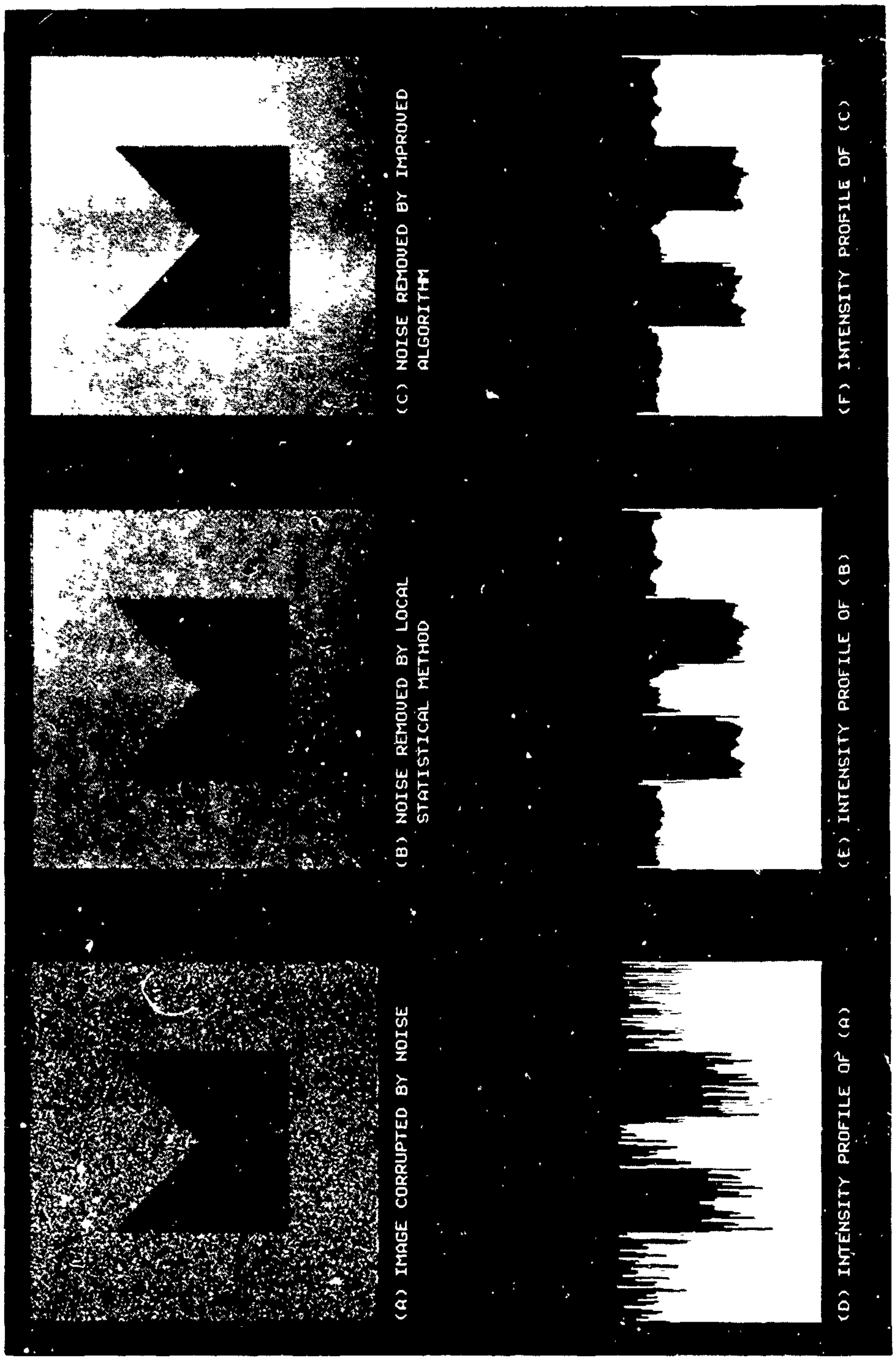

Figure 7 — Test images and their line intensity profiles

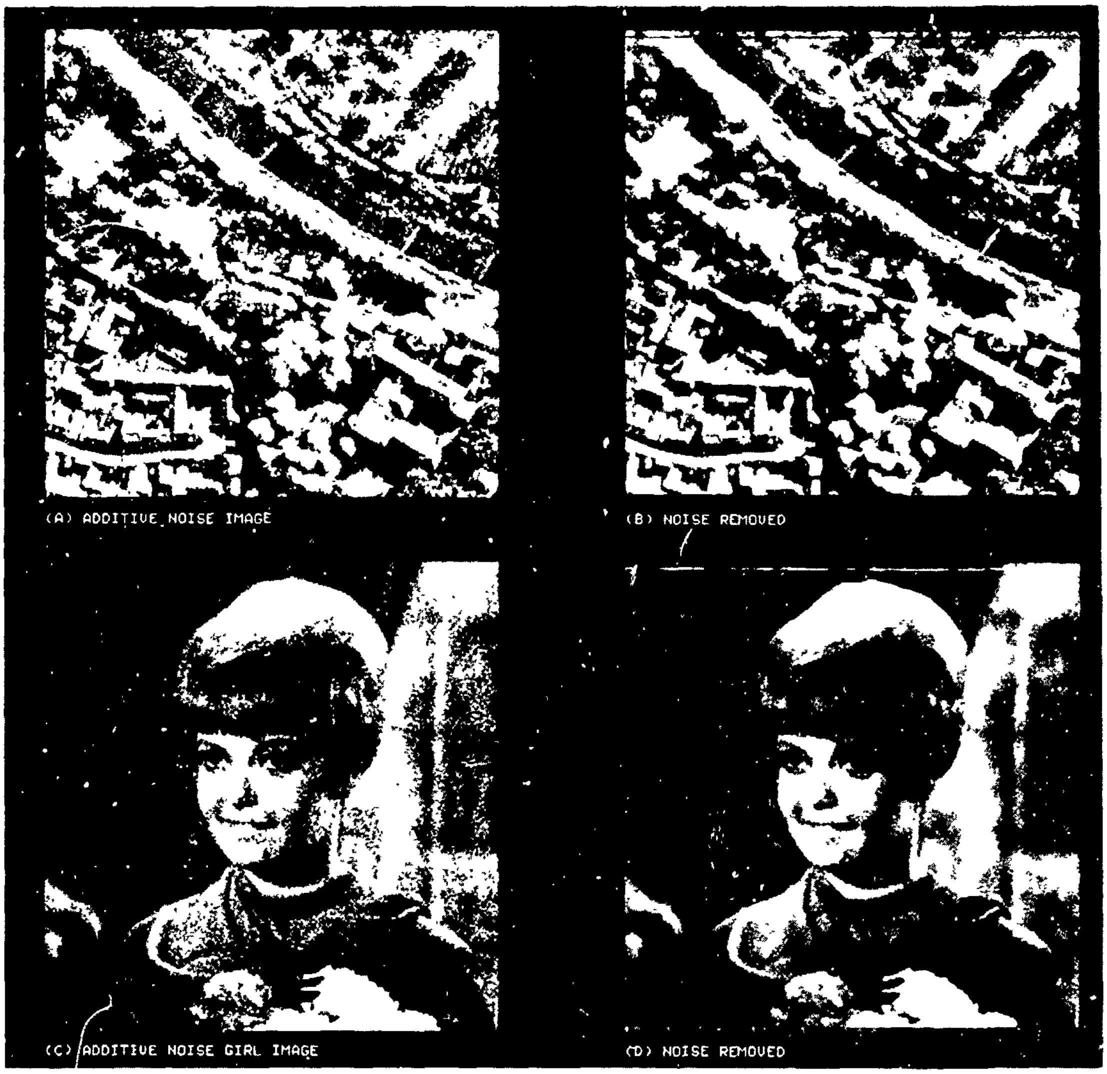

Figure 8 — Removal of additive noise from test images by the improved algorithm

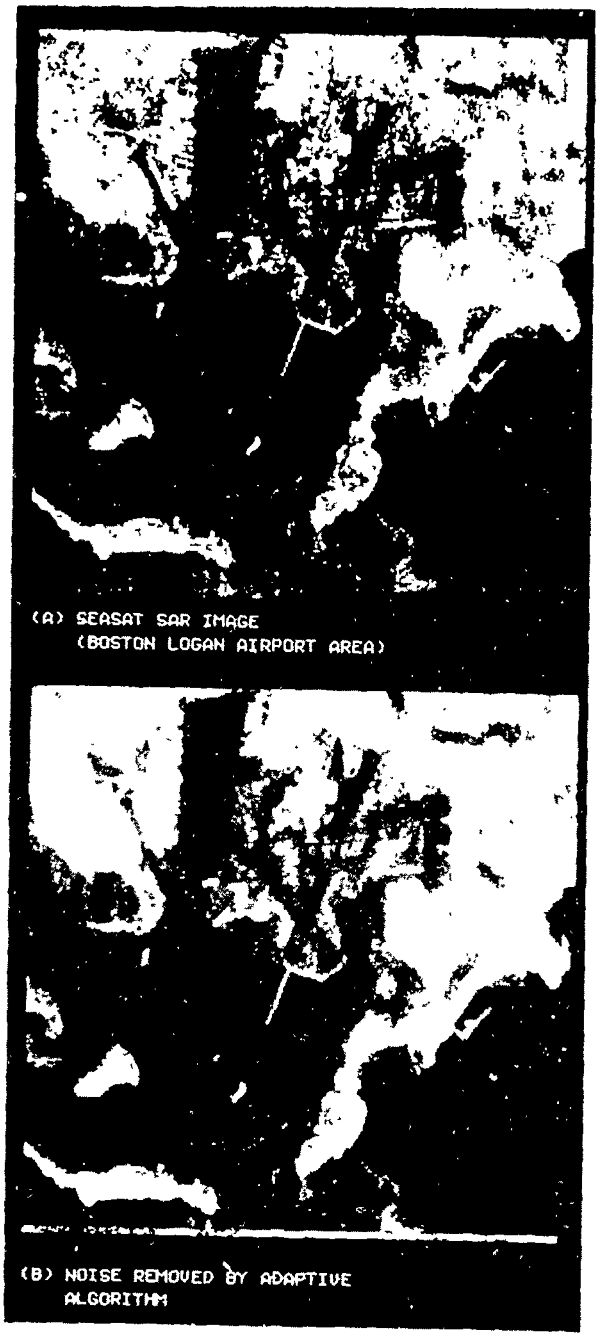

Figure 9 — Removal of additive noise from a test image by the adaptive algorithm

EXTENSION OF THE IMPROVED ALGORITHM TO MULTIPLICATIVE NOISE

The improved noise-filtering algorithm can be extended directly to filtering problems involving multiplicative noise. In Lee's local-statistics algorithm [1] a linear approximation is made for multiplicative noise. The use, as discussed in the present report, of partial areas to compute local means and variances improves the multiplicative-noise-filtering algorithm of reference 1. An example is given in figure 10. Figure 10a shows an image corrupted by multiplicative noise uniformly distributed between 0.8 and 1.2. A special characteristic of this noise is that the brighter the area, the noisier it is. Figure 10b shows the filtered image with the improved algorithm.

REMARKS

It was mentioned that the subareas of a seven-by-seven array are overlapped for easier implementation. Intuitively, however, nonoverlapped subareas are more desirable in reducing the error in the location of an edge direction.

The three-by-three simple gradient mask is used in this report. Other three-by-three gradient masks may perform better than the one used. We did experiment with Robinson's gradient mask [5] and found that it makes more errors in locating the direction of a noisy edge than the simple gradient mask.

The main computational load is in calculating the local mean and local variance. This report does not attempt to optimize the efficiency of this algorithm but rather to present the basic idea. More efficient algorithms, either by approximation [6] or by interaction, can be devised depending on individual computer configurations.

CONCLUSION

Improved and adaptive noise-filtering algorithms based on local statistics are presented here by incorporating local gradient information. The local mean and variance are computed from a reduced set of neighborhood pixels. The reduced set contains only those pixels which are found on one side of an edge. Examples show great improvement compared with the previous algorithms. Future research in the image-processing area favors the use of local operators, because they are naturally suitable for parallel processing.

ACKNOWLEDGMENT

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Figure 10 — Removal of multiplicative noise from a test image by the improved algorithm

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