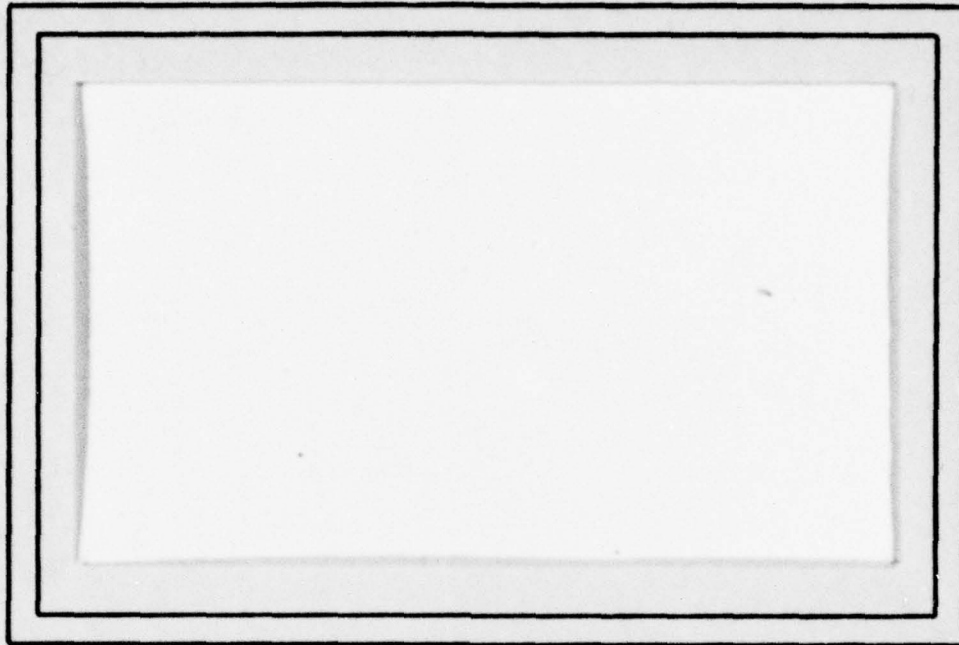


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⑮ ✓ DARPA Order-3206

⑪ Mar 1979

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⑥ SOME NEW IMAGE
SMOOTHING TECHNIQUES .

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Abstract

This report documents a collection of new techniques for image smoothing, and gives examples of their performance. The techniques involve averaging over half-neighborhoods, weighted averaging, and averaging based on local property probabilities.

The support of the Defense Advanced Research Projects Agency and the U.S. Army Night Vision Laboratory under Contract DAAG-53-76C0138 (DARPA Order 3206) is gratefully acknowledged, as is the help of Dawn Shifflett in preparing this paper.

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1. Introduction

A wide variety of methods have been proposed for smoothing noisy images; see [1] for an introduction to this subject. Most of these methods involve some type of local averaging, since in a uniform region, averaging preserves the mean gray level while reducing the variability. However, simple local averaging blurs edges, which is undesirable. A number of methods have been devised to preserve edge sharpness while still achieving some degree of smoothing; for example, one can take a local median instead of a local mean, or one can average only a selected subset of each point's neighbors, chosen in such a way that they are likely to belong to the same region as the point itself. Many of these methods are compared in [2].

This report describes several new image smoothing techniques, and gives examples of their performance. Section 2 deals with techniques based on averaging a point with five of its consecutive neighbors. Section 3 uses methods based on weighted averaging, where the weight given to a neighbor depends on how close that neighbor's gray level is to that of the point. Section 4 introduces methods that make use of global probabilities, rather than gray levels, to choose the neighbors with which to average. The methods were successful to varying degrees; several of them seem to be potentially useful.

For comparison purposes, the methods were all tested on the same two pictures that were used in [2]. These pictures are shown as parts (a) of Figures 1-2. Figure 1a is a 128 x 128

picture of an octagon of gray level 33 (on a scale of 0-63) on a background of gray level 28, with Gaussian noise of $\mu = 0$, $\sigma = 5$ added. Figure 2a is a 127 x 127 portion of a LANDSAT picture, with Gaussian noise of $\mu = 0$, $\sigma = 8$ added. As a comparison standard, the results of applying one of the best methods used in [2] to these two pictures are shown in Figures 1-2. In this method, each point is averaged with the five of its neighbors that are closest to it in gray level. (Rationale: If the point is on a relatively straight edge between regions, about five of its neighbors should belong to the same region as it does.) This process is iterated; parts b-h of Figures 1-2 show iterations 1,...,7. We see that this results in strong smoothing but does not blur edges, particularly in the case of Figure 2.

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2. Half-neighborhood methods

The five-neighbor method illustrated in Figures 1-2 is expected to choose those neighbors which lie in the same region as the given point, when the point lies on an edge. A more refined criterion might require that these neighbors be consecutive, since if the point is on a relatively straight edge, it should have five consecutive neighbors that belong to the same region as it does.

To define such a criterion, let N be the set of eight neighbors of the point P , and let $N = N_1 \cup N_2$, where N_1 is a set of three consecutive neighbors and N_2 consists of the five remaining neighbors. The eight possible choices of N_1 are shown below (asterisks denote neighbors in N_1):

...	..	.				*	..
P	P*	P*	P*	P	*P	*P	*P
		.	..	...	..	*	

Let $\bar{N}_1$ and $\bar{N}_2$ denote the average gray levels of N_1 and N_2 . Two criteria based on the $N_1 \cup N_2$ concept were investigated:

- a) Choose the N_2 for which $\bar{N}_2$ is closest to the gray level of P . If for this N_2 we have $|\bar{N}_1 - \bar{N}_2| > t$, average P with N_2 ; otherwise average it with all of N . (If $|\bar{N}_1 - \bar{N}_2| > t$ we assume that P is on a region edge; if not, we assume that it is interior to a region.) Results using five iterations of this method are shown in Figures 3-4 for $t = 30$, in Figures 5-6 for $t = 10$, and in Figures 7-8 for $t = 0$ (i.e., we always average P with N_2). There is little difference among the cases, and the results are more blurry than those in Figures 1-2.

b) Choose the N_2 for which $|\bar{N}_1 - \bar{N}_2|$ is greatest. If this is greater than t , average P with N_2 ; otherwise, average it with all of N . In other words, we pick the strongest edge through P 's neighborhood, and if this edge is strong enough, we average P only with the half-neighborhood on its own side of the edge. Results using five iterations of this method are shown in Figures 9-10 for $t = 30$ and in Figures 11-12 for $t = 10$; the value of t makes little difference. For the LANDSAT image, this method produces excellent smoothing and sharp borders, though it does introduce a slight jaggedness in the borders.

3. Neighbor-weighting methods

The method used in Figures 1-2 can be regarded as a "weighted" averaging scheme in which the five neighbors that have gray levels closest to that of P are given weights of $\frac{1}{6}$ each (as is P itself), while the three remaining neighbors are given weights of zero. A "softer" approach might be to give the neighbors weights that depend on the differences of their gray levels from that of P , with closer gray levels implying higher weights. Two versions of this approach were tried, in which the relative weight given to a neighbor Q of P was determined as follows:

- a) 4, if $|P-Q| \leq 5$; 1, otherwise
- b) $1 - |P-Q|/5$, if $|P-Q| \leq 5$; 0, otherwise

Results using three iterations of each of these methods are shown in Figures 13-14 and 15-16, respectively. We see that method (a) smooths well, but also blurs slightly, while method (b) does not eliminate high-contrast noise (note that it does no smoothing at all if every neighbor differs from P by more than five gray levels).

Another idea which was also tried was to average with all neighbors if the variability of the neighborhood was small, and with only the most similar neighbors if it was large. In the implementation, variability was measured by $v = \sum_Q |Q - \mu|$, where μ is the mean gray level of the neighbors; if $v \geq 6$, we averaged with only the three closest neighbors, and if

$v < 6$, with all eight neighbors. The results, shown in Figures 17-18 for three iterations, are relatively smooth and sharp, but noise is preserved in the vicinity of edges. This method is related to, but simpler than, the method described in Section 2.8 of [2].

4. Probability-based methods

Rather than choosing neighbors for averaging based on their gray levels, one can choose them based on the probabilities of their gray levels, as estimated from the histogram of the picture. In particular, suppose that we average P with those of its neighbors whose probabilities are most similar to that of P ; if P is on an edge between two regions, these neighbors should be likely to lie in the same region as P . Unfortunately, this idea does not work well in practice, as seen from Figures 19-20, which show the results of three iterations of averaging with the seven* neighbors having most similar probabilities; considerable blur is evident.

More interesting results are obtained if we average with the neighbors that have highest probabilities; adjacent to an (unsharp) edge, this will favor averaging with points interior to the region, which should have higher-probability gray levels than points on the edge slope itself. Figures 21-22 show results of seven iterations, using the seven* most probable neighbors. Here small regions are smoothed out, but the borders between large regions remain relatively sharp.

Another possibility is to base the neighbor selection on the probability of the difference value (e.g., digital gradient or magnitude absolute Laplacian value) at the neighbor, rather than on the probability of the neighbor's gray level. If P is adjacent to an edge, the neighbors lying in the region should have difference value probabilities that are higher, and closer

* These techniques were also tested using five neighbors instead of seven; the LANDSAT picture was somewhat less blurred when five were used, but using the five most probable neighbors totally erased the octagon.

to that of P , than the neighbors that lie on the edge ramp. Figures 23-24 and 25-26 show results of three iterations using the seven neighbors with closest gradient and Laplacian probabilities, respectively; these results are blurry. Figures 27-28 and 29-30 show results of five iterations using the seven neighbors with highest gradient and Laplacian probabilities, respectively; these results too are blurry, but the Laplacian results are not too bad.

Still another approach is to choose neighbors based on joint probabilities of pairs of properties, e.g., gray level and gradient, gray level and Laplacian, or gray level and local average gray level. Adjacent to an edge, these joint probabilities should be higher, and closer to that of P , for neighbors that lie in the same region as P . Figures 31-32, 33-34, and 35-36 show three-iteration results for the closest joint probabilities of gray level and gradient, gray level and Laplacian, and gray level and local average gray level, respectively. Figures 37-38, 39-40, and 41-42 are analogous using highest joint probabilities. Like the previous methods, all of these give blurry results.

5. Concluding remarks

All of the methods described in this report seemed potentially reasonable, but only a few of them actually achieved good smoothing without blurring. We have described both the successful and unsuccessful methods, since even the negative results are useful in improving our insights into the capabilities of such methods.

References

1. A. Rosenfeld and A. C. Kak, Digital Picture Processing, Academic Press, New York, 1976, Section 6.5.
2. J. P. Davenport, A comparison of noise cleaning techniques, University of Maryland, Computer Science Technical Report TR-689, September 1978.

Key to Figures

<u>Nos.</u>	<u>Caption</u>
1-2	Seven iterations of the best-five-neighbor method
3-4	Same with $t = 10$
5-6	Five iterations of half-neighborhood method (a) with $t = 30$.
7-8	Same with $t = 0$
9-10	Five iterations of half-neighborhood method (b) with $t = 30$
11-12	Same with $t = 10$
13-14	Three iterations of neighbor-weighting method (a)
15-16	Same for method (b)
17-18	Same for method based on neighborhood variability
19-20	Three iterations of averaging with neighbors having most similar probabilities
21-22	Seven iterations of averaging with neighbors having highest probabilities
23-24	Three iterations of averaging with neighbors having most similar gradient probabilities
25-26	Same for Laplacian
27-28	Five iterations of averaging with neighbors having highest gradient probabilities
29-30	Same for Laplacian
31-32	Three iterations of averaging with neighbors having most similar (gray level, gradient) joint probabilities

<u>Nos.</u>	<u>Caption</u>
33-34	Same for (gray level, Laplacian)
35-36	Same for (gray level, average gray level)
37-42	Analogous to Figures 31-36, but using highest joint probabilities

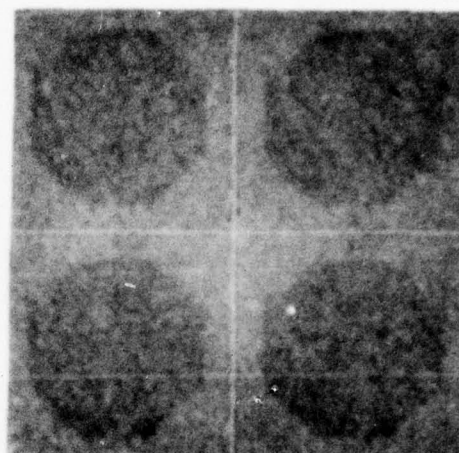
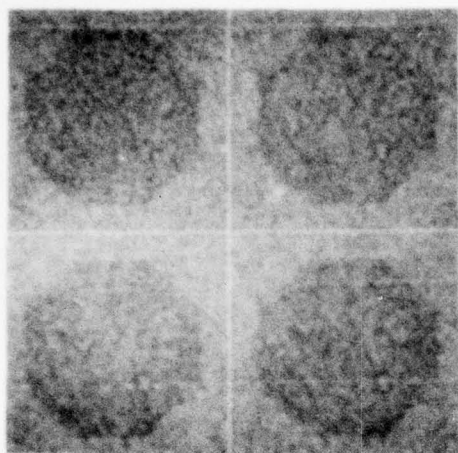


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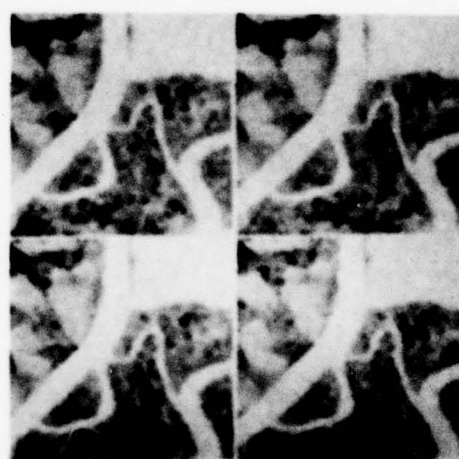
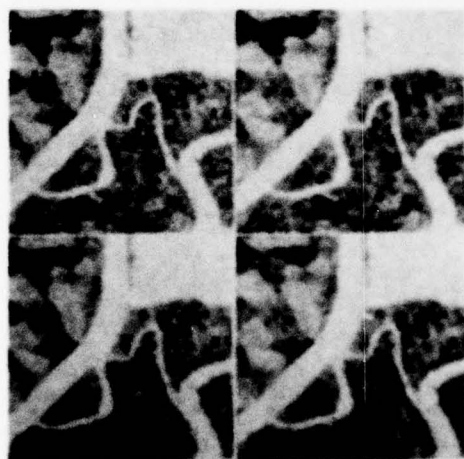


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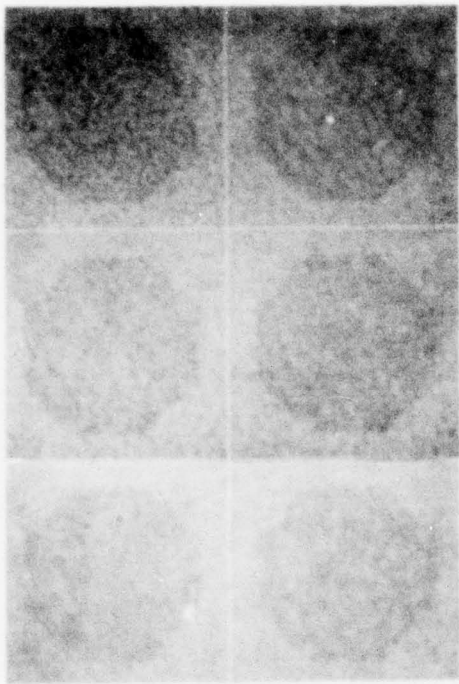


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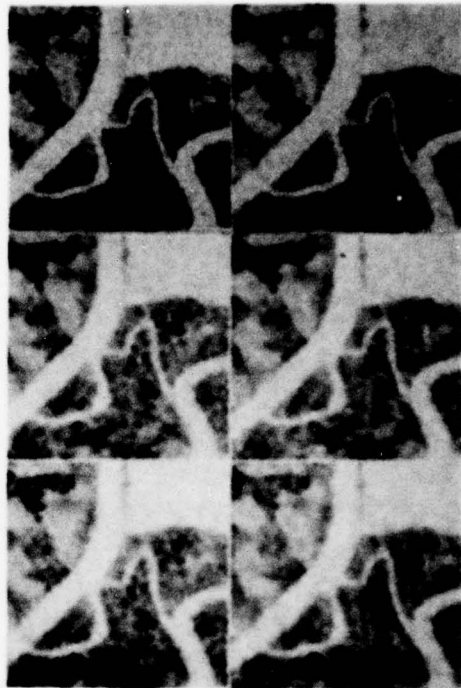


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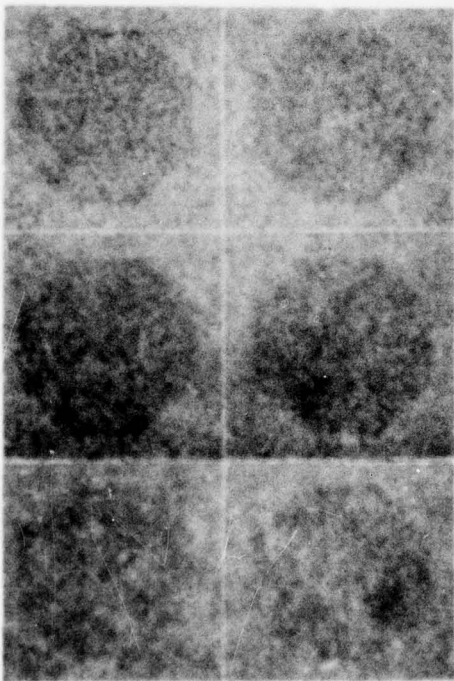


Figure 5

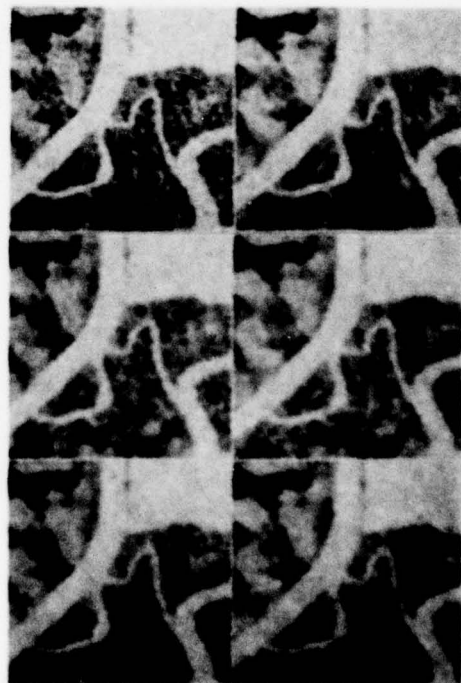


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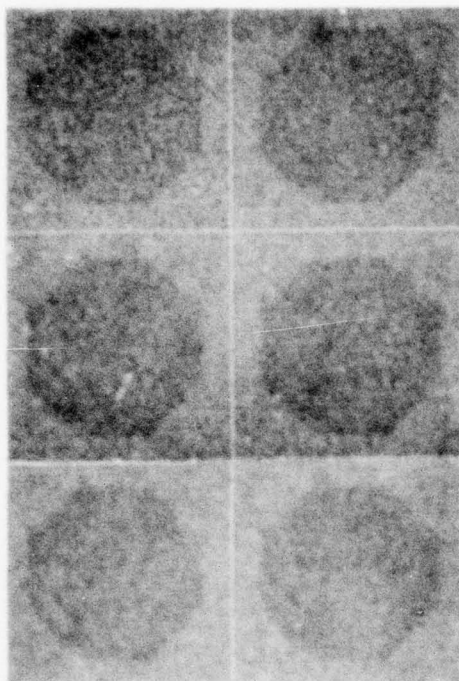


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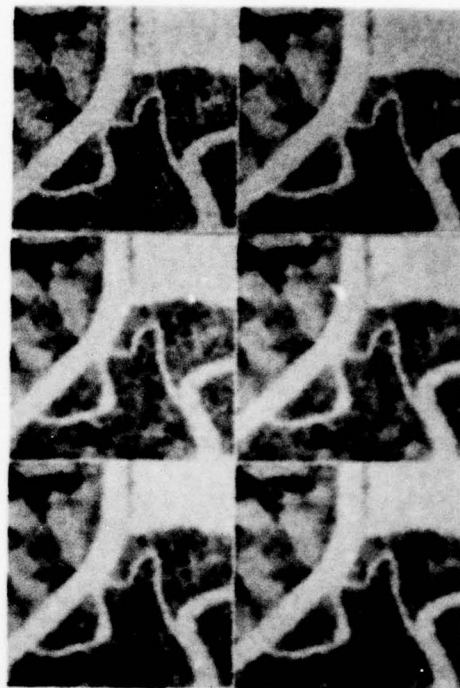


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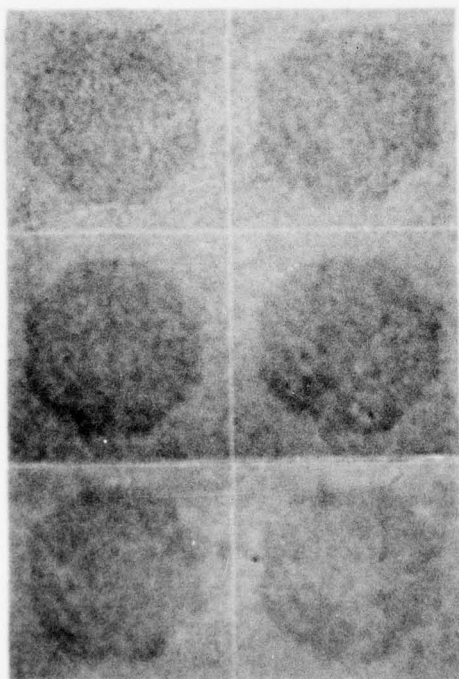


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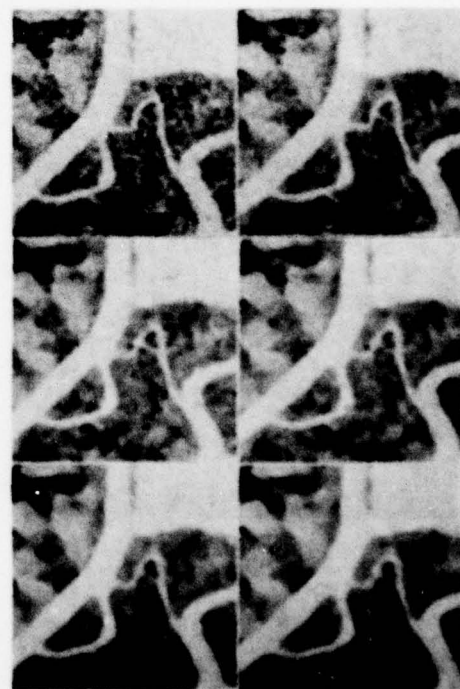


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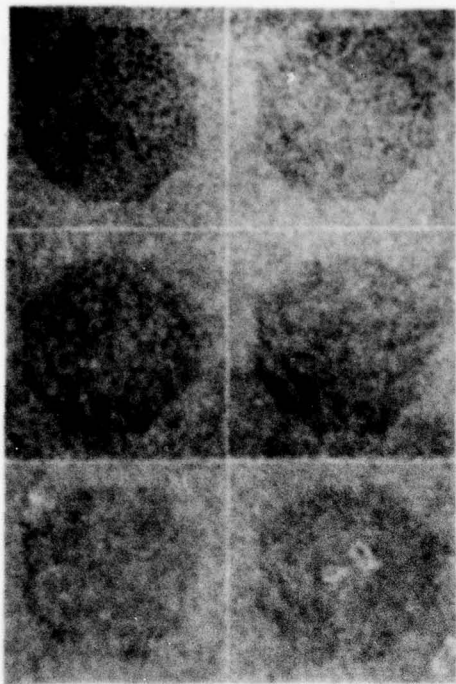


Figure 11



Figure 12

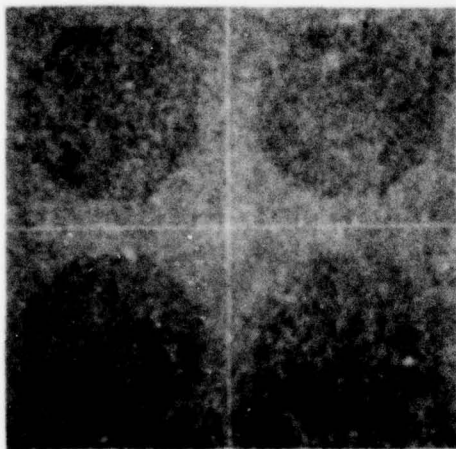


Figure 13



Figure 14

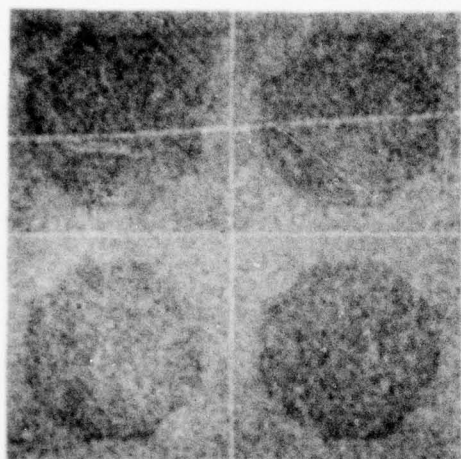


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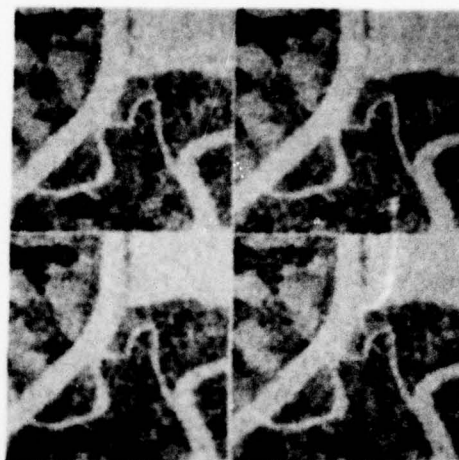


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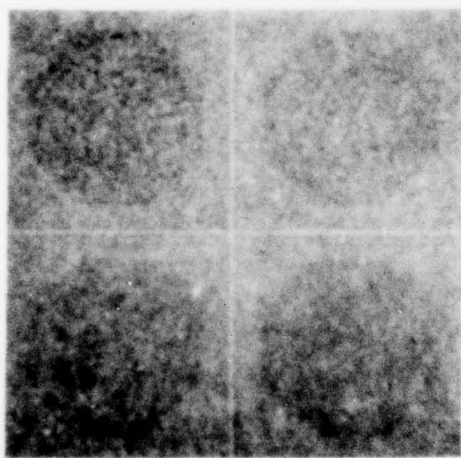


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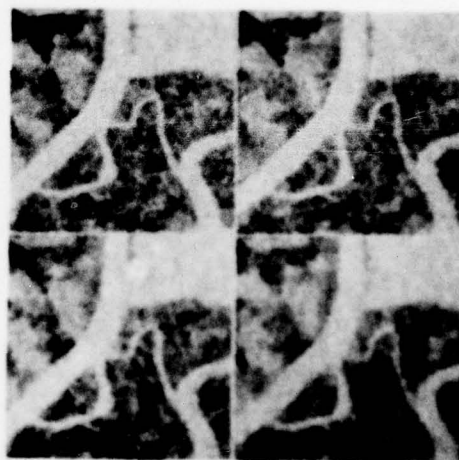


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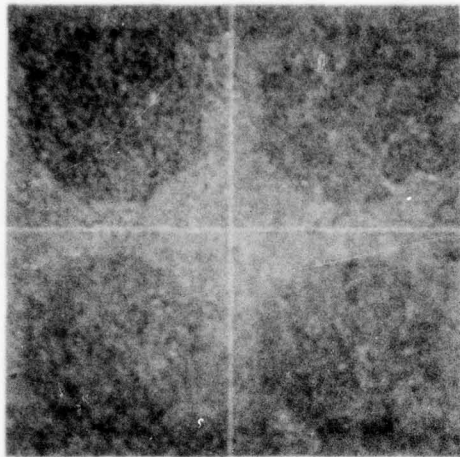


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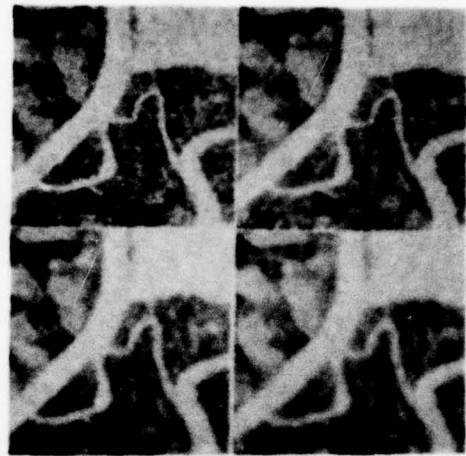


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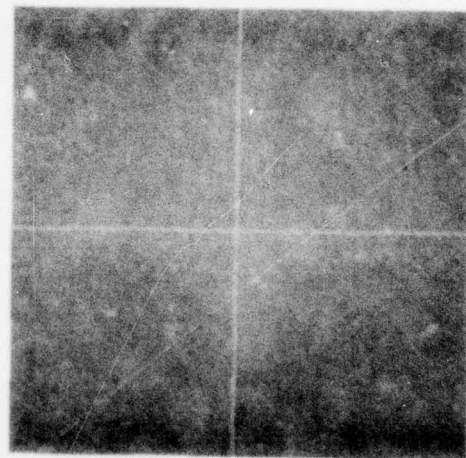
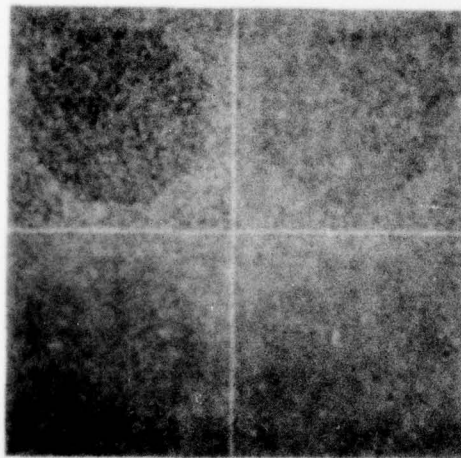


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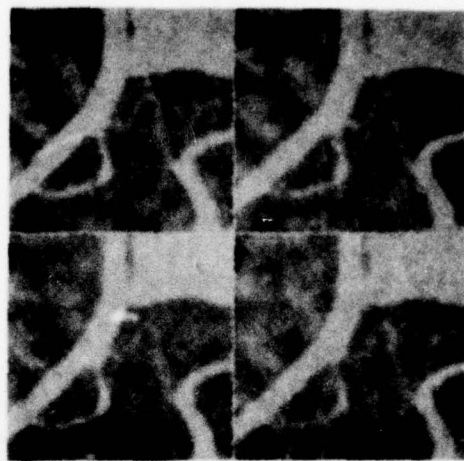
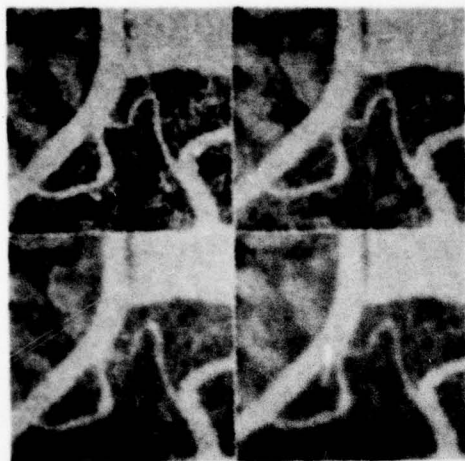


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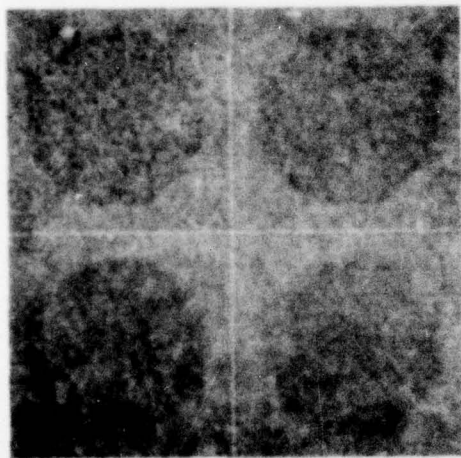


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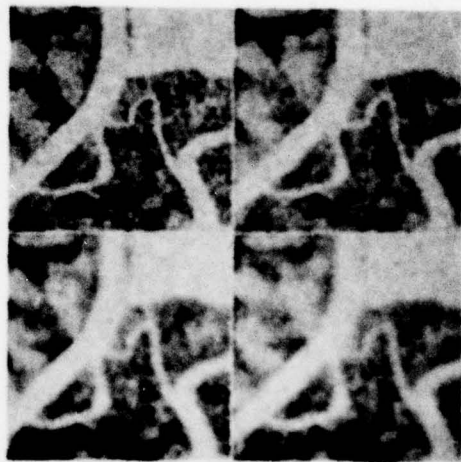


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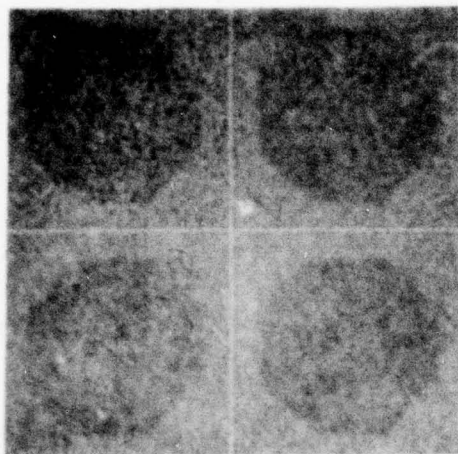


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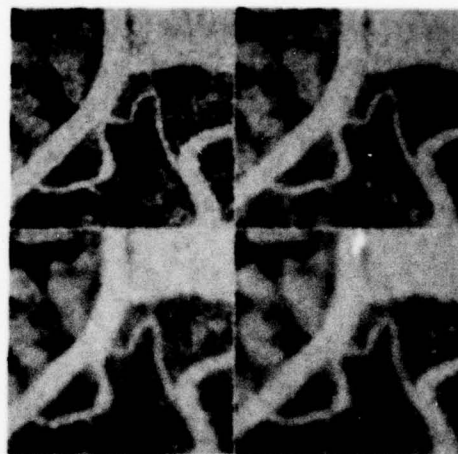


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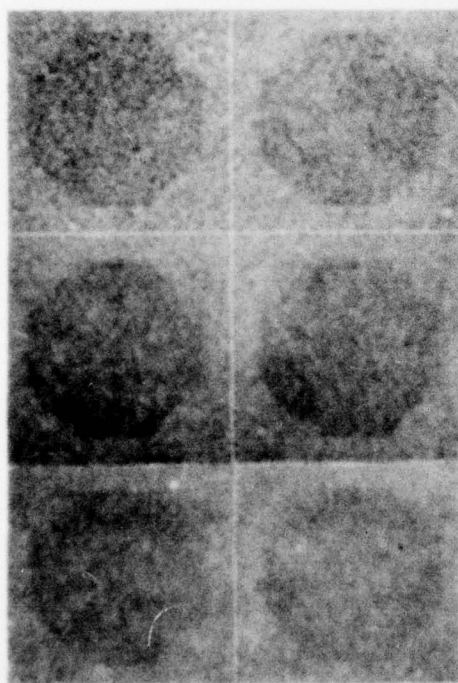


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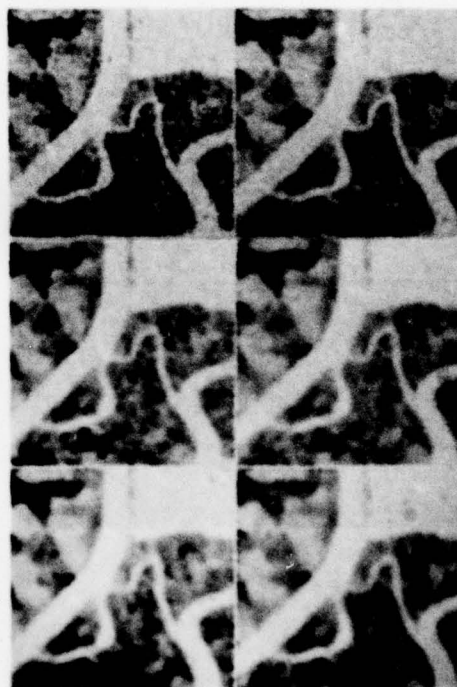


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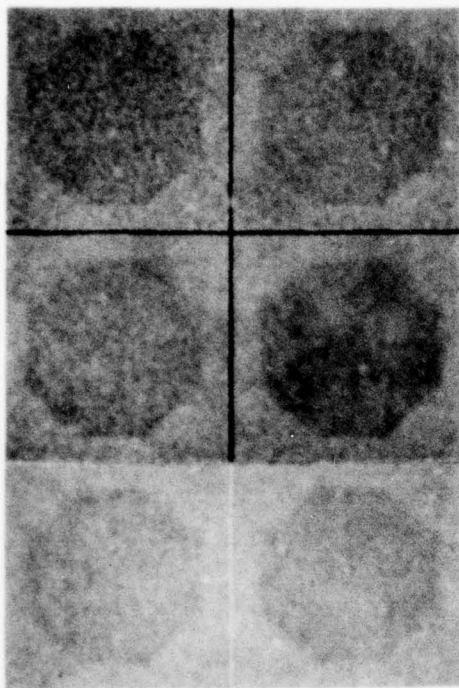


Figure 29



Figure 30

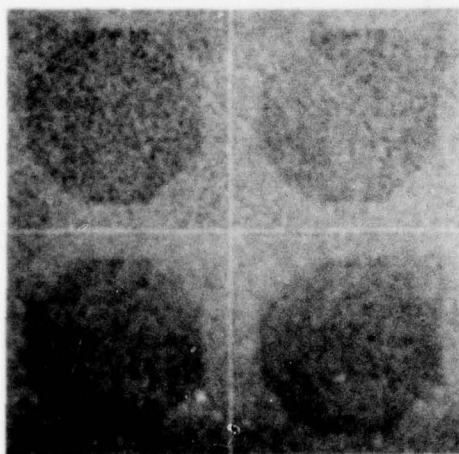


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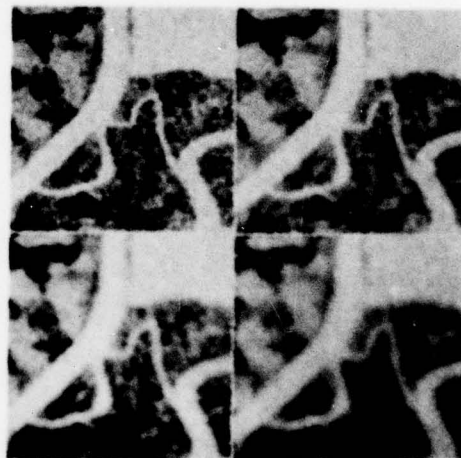


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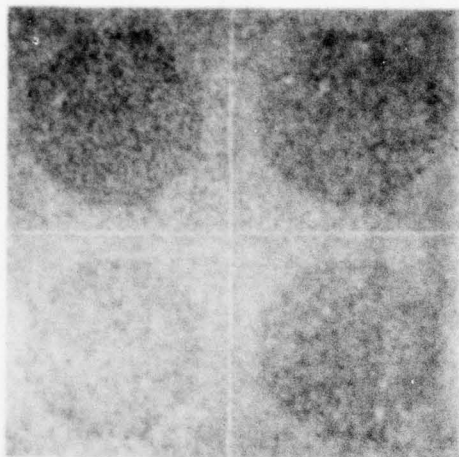


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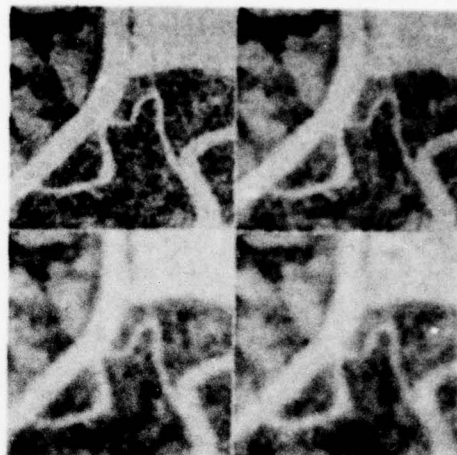


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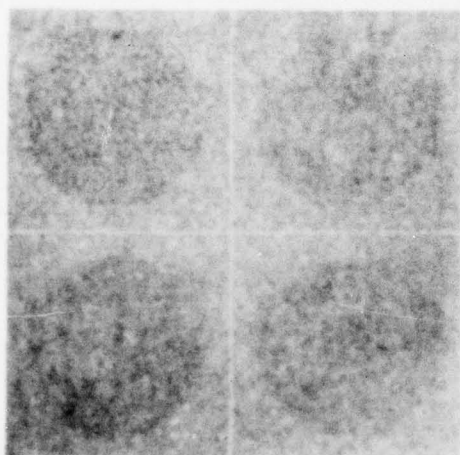


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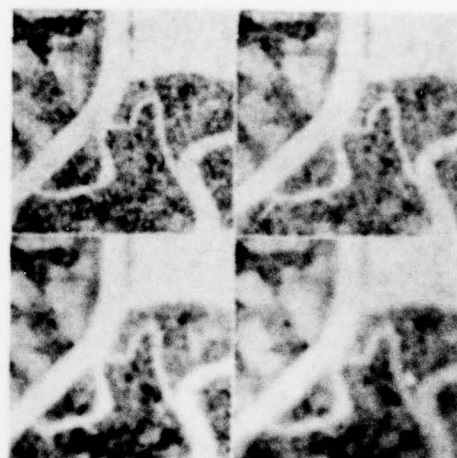


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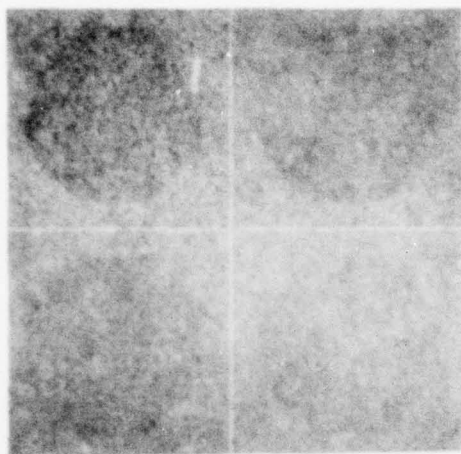


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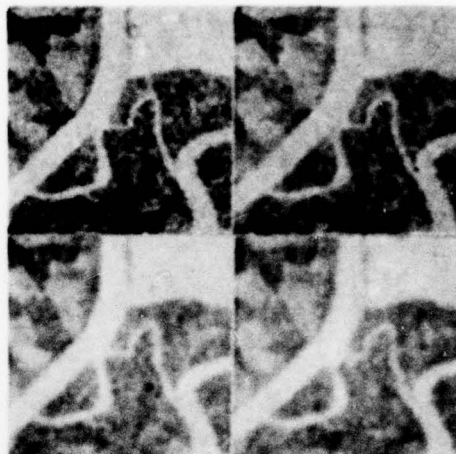


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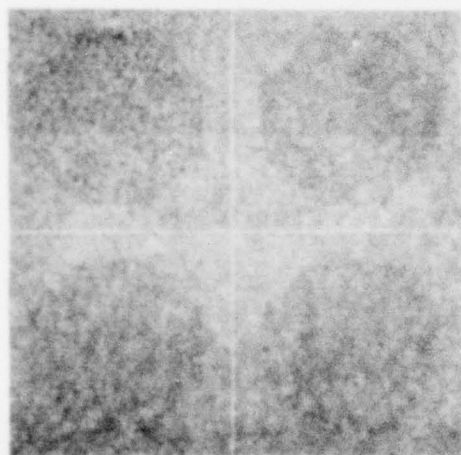


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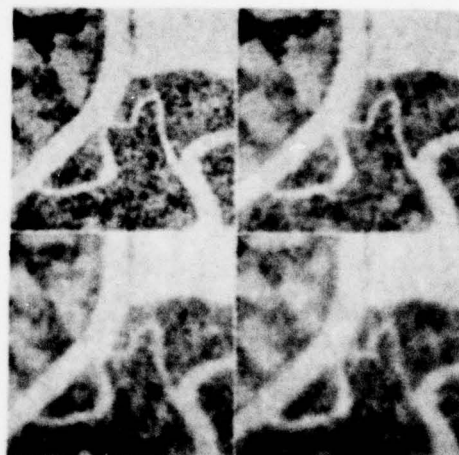


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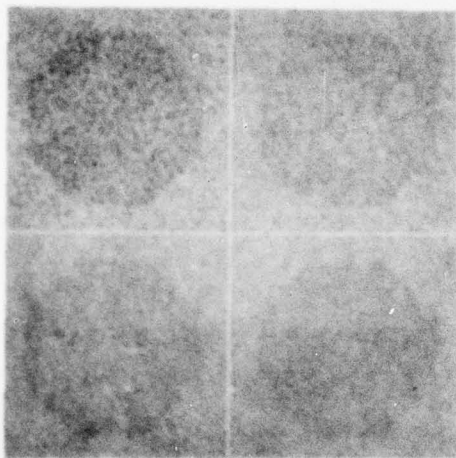


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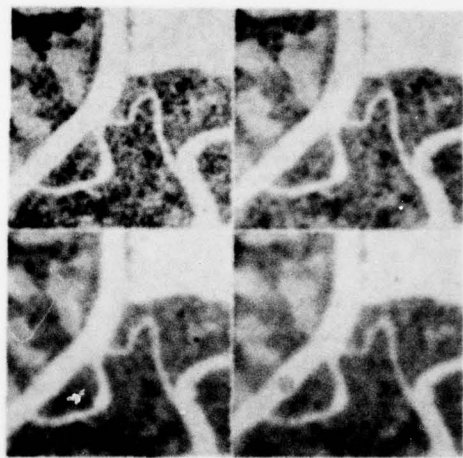


Figure 42

Addendum

Another method based on neighborhood variability, analogous to the last method described in Section 3, was also implemented. Let μ and σ be the mean and standard deviation of the eight neighbors of the given point P . Then

If $\alpha|P-\mu| < \sigma$, P is averaged with its four most similar neighbors

Otherwise, P is averaged with all eight of its neighbors

Here α is a weighting factor, taken to be 1, 2, and 1/2 in Figures A-B, C-D, and E-F, respectively, each of which shows five iterations of this process. We see that $\alpha = 2$ yields too much blur, but $\alpha = 1$ and 1/2 yield sharp results in which the high-frequency noise has been eliminated. Thus this method produces very good smoothing. [A variation which was also tried was to average with the neighbors having gray levels on the same side of μ as P , rather than with the most similar neighbors, when $\alpha|P-\mu| < \sigma$. However, this variation produced unacceptable effects at the edges.]

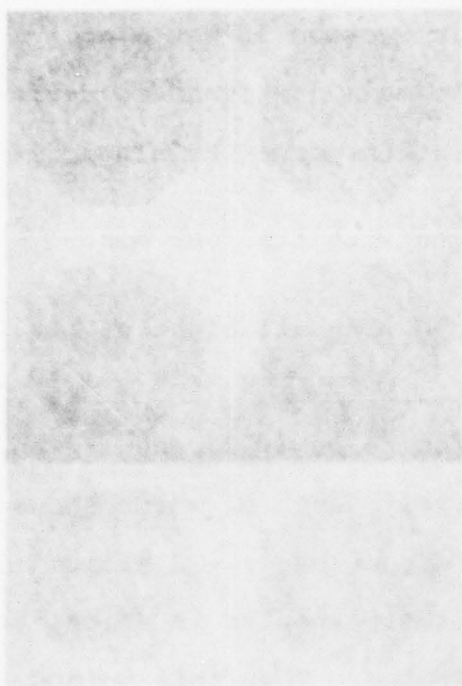


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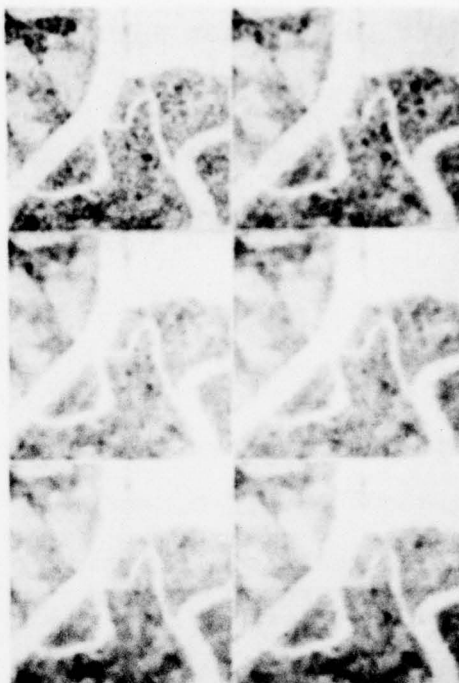


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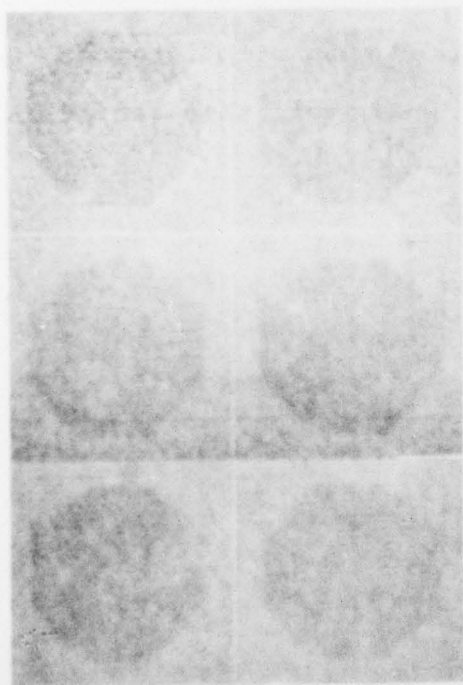


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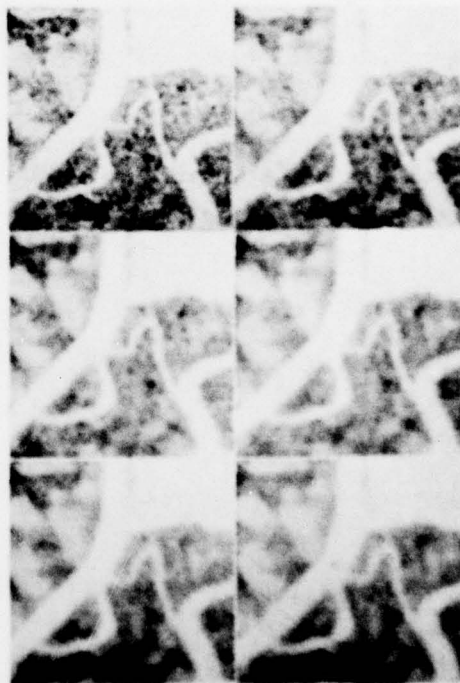


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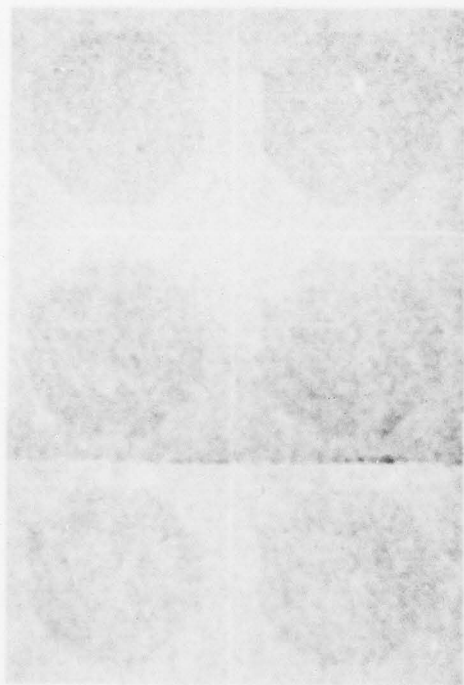


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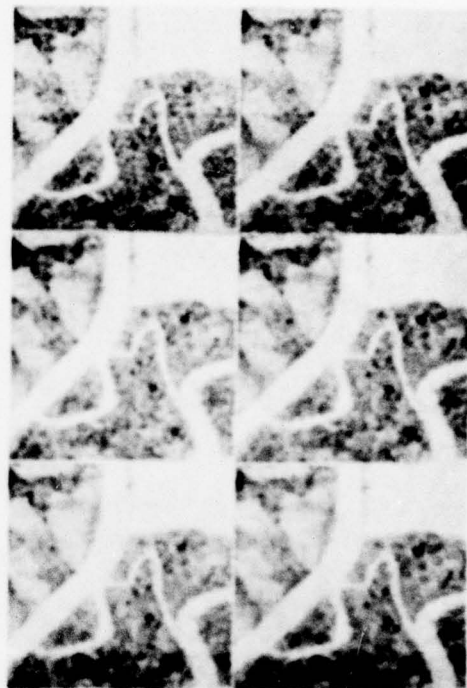


Figure F

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number) This report documents a collection of new techniques for image smoothing, and gives examples of their performance. The techniques involve averaging over half-neighborhoods, weighted averaging, and averaging based on local property probabilities.		

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