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USE OF QUADTREES FOR EDGE ENHANCEMENT

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ABSTRACT

A quadtree approximation of a $2^n \times 2^n$ gray level image
tends to enhance edges that are strong in the original image
and suppress those that are weak. An edge detector applied
to such an approximation produces edges that are in general
stronger than those obtainable from the original, though
slightly displaced. Methods of combining the edge maps ob-
tained from the original image and its quadtree approximation
are examined. It is shown that the choice of a suitable com-
bination rule results in an edge map which is superior to
that obtainable by conventional means.

1. Introduction

A $2^n \times 2^n$ binary image can be represented by a quadtree by successively subdividing it into four quadrants [1]. Quadrants which contain both white and black areas give rise to branch or "gray" nodes in the tree, while those which are either all black or all white are black or white leaf nodes and are not further subdivided. A quadtree representation is useful, for example, for efficient computation of moments [2], or for the approximation of shapes [3].

An approximate quadtree representation can also be used for $2^n \times 2^n$ gray level images. In this case quadrants through which edges pass, or that have a busy texture, will correspond to branch nodes in the tree, while those that are sufficiently homogeneous will be represented by leaf nodes. Clearly, the measure of homogeneity used for classifying a quadrant as a leaf or branch is important not only for the size of the tree but also for the quality of the image when it is reconstructed from the tree. If the measure is too strict, the size of the tree will be prohibitively large, whereas if it is too loose, the quality of the reconstructed "q-image" will be poor. For a discussion of different measures of homogeneity and their effects on the size of the resulting quadtrees and the quality of the corresponding q-images see [4]. The usefulness of the quadtree representation is not, however, limited to image compression. This paper considers its use for detecting and enhancing edge information in an image.
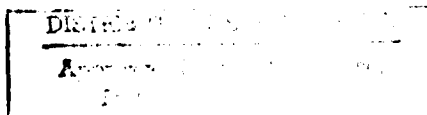
2. Edge detection

Edge detection is a fundamental part of image analysis
since it can aid in locating regions or objects in the image.
Edge detection techniques in current use (e.g., see [5]) are
based on examining a fixed neighborhood of a point, and for
this reason often produce "noise" or spurious edges, i.e.,
edges that would not be regarded as such in the context of the
whole image. However, since noise edges typically tend to be
weak, they can effectively be removed or disregarded by
thresholding. Unfortunately, a global threshold cannot in
general be calculated, since there is no way to predict the
edge response for an arbitrary image. A common technique used
to enhance edges is non-maximum suppression [5], while another
which is applicable only to straight edges is described in [6].

Edge information can also be obtained from the quadtree ap-
proximation of an image, either by traversing the tree and exa-
mining the neighbors of leaf nodes, or by applying an edge
operator to the q-image. This information is characterized in
four ways. Firstly, since the gray level of a leaf in the quad-
tree is uniform, edges will occur only on the boundaries of
leaves. Secondly, all the edges will be continuous. Thirdly,
weak edges in the original image will tend to be suppressed
while strong ones will be enhanced. This is because the reason-
ably homogeneous regions, which we can expect to contain the

weak edges, correspond to leaf nodes that are of approximately
constant gray level. Fourthly, a great majority of the edges
will be either vertical or horizontal, with the result that
curved edges in the original image will be represented by step
edges, giving the resulting edge picture a false, blocky appear-
ance.

Figure 1 shows three pairs of images and Figure 2 shows
their respective histograms. Figure 1(a) shows the image of
a tank and its corresponding q-image. Note that the q-image is
a good approximation to the original image. This is confirmed
by the histograms in Figures 2(a). (As an aside also note that
a valley which is barely discernible in the first histogram is
significantly enhanced in the second. The bottom of this valley
corresponds to a threshold separating the tank from the back-
ground, suggesting the usefulness of the quadtree representation
for segmentation [7]).

Figure 1(b) shows the results of applying the Prewitt edge
operator to the two images in (a). The first image shows that
there are numerous weak edges and proportionately fewer strong
ones. In the second image a large proportion of the weak edges
have been eliminated, and those that remain are much better
defined, though "blocky" as mentioned above. Comparison of
the two histograms in Figure 2(b) confirms this observation.
Figure 1(c) shows the results of applying non-maximum suppression

based on edge direction to the two images in (b). In both images this process results in the thinning of edges. However a large number of spurious edges still remain, as is evident from Figure 3 which shows the images in Figure 1(b) and 1(c) thresholded at 0. Table 1 shows the total numbers of edge points in these images.

The images in Figure 1(c) are rather unsatisfactory as edge maps of the object in Figure 1(a): the first because of the large number of noise edges and the lack of an algorithmic method to obtain a single global threshold for deleting them, and the second because of the false grid-like appearance of the edges. The following section investigates approaches to combining the edge response from the original and q-images so as to obtain an edge map that is superior to both.

3. Edge enhancement

From the discussion in the previous section it is apparent that an edge detector applied to the q-image will tend to suppress weak edges and enhance strong ones present in the original image. These edges are likely to be displaced, since edges can only occur at boundaries of leaves, i.e., if in the original an edge appears in an area corresponding to the interior of a leaf, it will appear in the q-image at the nearest leaf boundary. However, if the q-image approximates the original one reasonably well, the displacements are likely to be small. This fact enables us to use edges obtained from the q-image ("q-edges") as a guide to preserve strong edges obtained from the original image.

Suppose that E_0 represents the edge response from the q-image and E_1 represents the edge response from the original image. E_0 and E_1 can be combined by some function $f_0(E_0, E_1)$ to give a new edge map E_2. The function f_0 must be chosen such that points having high values in both E_0 and E_1 are enhanced, while those with low values in both E_0 and E_1 are suppressed. However, since edges in the q-image are likely to be displaced, f must be modified to include a neighborhood, rather than a single point in E_1. Thus a point in the new image E_2 is given by

$$E_2(x,y) = f(E_0(x,y), g(E_1(x,y)))$$ (1)

g must reflect the requirements that the likelihood of a q-edge

corresponding to a real edge at (x,y) decreases as its distance from (x,y). Thus g could take the form

$$g_1(E_1(x,y)) = \frac{M}{d} \qquad (2)$$

where M is the maximum q-edge value in an mxm neighborhood about (x,y), and d is the distance of this point from (x,y). If the direction of the edge at (x,y) is known, then we can define $g = g_2$, in which M is based on only those points that are in the appropriate edge direction in the mxm neighborhood about (x,y). Another form of g, $g = g_3$, is simply an average of the q-edge values in the mxm neighborhood about (x,y).

The function $f_1(e_0, e_1)$ where $e_0 = E_0(x,y)$ and $e_1 = E_1(x,y)$, must reflect the requirement that the likelihood of a strong edge increases when both e_0 and e_1 are high, and decreases when they are both low. Thus a suitable form for f is

$$f_1 = 1 - \frac{1}{1+e_0+e_1} = \frac{e_0+e_1}{1+e_0+e_1} \qquad (3)$$

However, from (3) it is seen that even if $e_1=0$, f may still have a non-zero value. This results in edge points appearing in the new map E_2, even though none were present in the corresponding positions in E_1. Re-defining f so that

$$f_2 = \begin{cases} 0 & e_1 = 0 \\ 1 - \dfrac{1}{1+e_0+e_1} & e_1 > 0 \end{cases} \qquad (4)$$

will ensure that no new edges appear in E_2. However, it is still possible that weak edges that are very near strong ones

may also be enhanced. Since the edge directions at all points in E_1 are known, a remedy for this broadening effect is to apply non-maximum suppression to the new edge map E_2. Another approach to prevent the broadening effect is to modify f so that the value of a point in E_1 is allowed to decrease (leading to the suppression of weak edges) but not to increase (preventing broadening). f then takes the form

$$f_3 = \min(E_1(x,y), f_2) \tag{5}$$

An alternative form of f could be

$$f_5 = \min(E_1(x,y), f_4) \tag{6}$$

where $f_4 = 1 - \dfrac{1}{1+e_0 e_1}$.

The relation (1) can be generalized so that

$$E_{i+1}(x,y) = f(E_0(x,y),\ g(E_i(x,y))) \tag{7}$$

i.e. the edge enhancement process can be iterated. This kind of iterative enhancement will only be useful in the case the function g is an average of the mxm q-edge values in the neighborhood about (x,y), since for $g=g_1$ or g_2, iterations after the first will have no effect.

In the discussion that follows, $f = f_3$, $g = g_3$, and a 3x3 neighborhood is used. Figure 4(a) shows an image E_2 where E_0 and E_1 are the images in Figure 1(b) and 1(c) respectively. Figure 5(a) shows Figure 4(a) thresholded at 0, and Figure 6(a) shows the histogram of the non-zero points in Figure 4(a). Comparison of Figure 4(a) with Figure 1(c) shows that a large proportion of the weak edges have been eliminated. Contrasting

the histogram in Figure 6(a) with that in 2(c) confirms this
clearly--whereas in Figure 1(c) weak edges by far outnumber
the strong ones, in 4(a) the numbers of strong and weak responses
are more even. Note from Table 1 that the total number of
edge points in Figure 4(a) for the case $g=g_2$ is only about
one third of the number of edge points when non-maximum sup-
pression is applied to the edge response for the original image
in Figure 1(a). This clearly demonstrates the effectiveness of
this kind of edge enhancement scheme. The corresponding results
for the case $f=f_2$ and $g=g_2$ are shown in Figures 4(b), 5(b),
and 6(b) respectively. The effectiveness of iterative edge
enhancement using the relation (7), $f=f_3$ and $g=g_3$ are shown in
Figure 7. Figure 7(a) is an image of a part of the Frederick,
Md., airport. Figure 7(b) is the result of non-maximum suppres-
sion applied to the Prewitt edge detector response for 7(a),
thresholded at 0.   Figures 7(c) to 7(g) are the successive
results of five iterations of the enhancement process, and
Figure 7(h) is a plot of the number of edge points surviving
after each iteration. Note that iteration 0 corresponds to
Figure 7(c). The number of edge points surviving after each
iteration diminishes significantly.

4. Discussion

Table 1 shows additional results for the tank image for the cases where $f = f_2$ and/or $g = g_2$. It is seen that the best result is obtained for $f=f_3$ and $g=g_3$. This can be explained by noting first of all that the averaging implicit in g_3 tends to suppress weak values more effectively than $g=g_2$. The fact that f_3 is better than f_2 is not evident after the first iteration but becomes apparent after further iterations as is seen from Table 2. This is because f_2 allows the value of a point in E_2 to increase and the broadening thus caused becomes increasingly noticeable with successive iterations.

It should be noted that although iterative enhancement using $f=f_3$ and $g=g_3$ is quite effective, too many iterations cause edges that were originally continuous to break to an unacceptable degree. This effect, though not excessive, can be seen in Figures 7(c) to 7(g).

5. Conclusion

It has been shown that a quadtree approximation of a 2^n by 2^n gray level image can be useful in eliminating much of the noise obtained when a conventional edge operator is applied to the original image. The usefulness stems from the observation that strong edges in the original tend to be enhanced in the q-image. An edge operator applied to the q-image yields clean, stronger and continuous, though possibly somewhat displaced, grid-like edges. These edge responses can be combined with those obtained from the original image to give a new edge map that is superior to both.

Clear, noise-free edges are critical to several segmentation schemes such as that described in [8]. The application of quadtrees of gray level images to image segmentation will be considered in a later paper.

References

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f,g	Number of non-zero edge points	Non-zero edge points after non-maximum suppression
Prewitt	3720	1589
$f=f_2$, $g=g_2$	869	581
$f=f_2$, $g=g_3$	523	425
$f=f_3$, $g=g_2$	620	518
$f=f_3$, $g=g_3$	520	427

Table 1. Results of the first iteration of the enhancement process applied to the image in Figure 1(c).

Iteration	$f=f_2$	$f=f_3$
0	523/425	520/427
1	318/263	313/260
2	246/227	229/211
3	227/207	196/184
4	208/192	179/172

Table 2. Results of successive iterations of the enhancement process applied to the image in Figure 1(c) using $g=g_3$ before and after non-maximum suppression.

Figure 1. (a) Image of a tank and its corresponding q-image;
(b) the results of applying the Prewitt edge operator
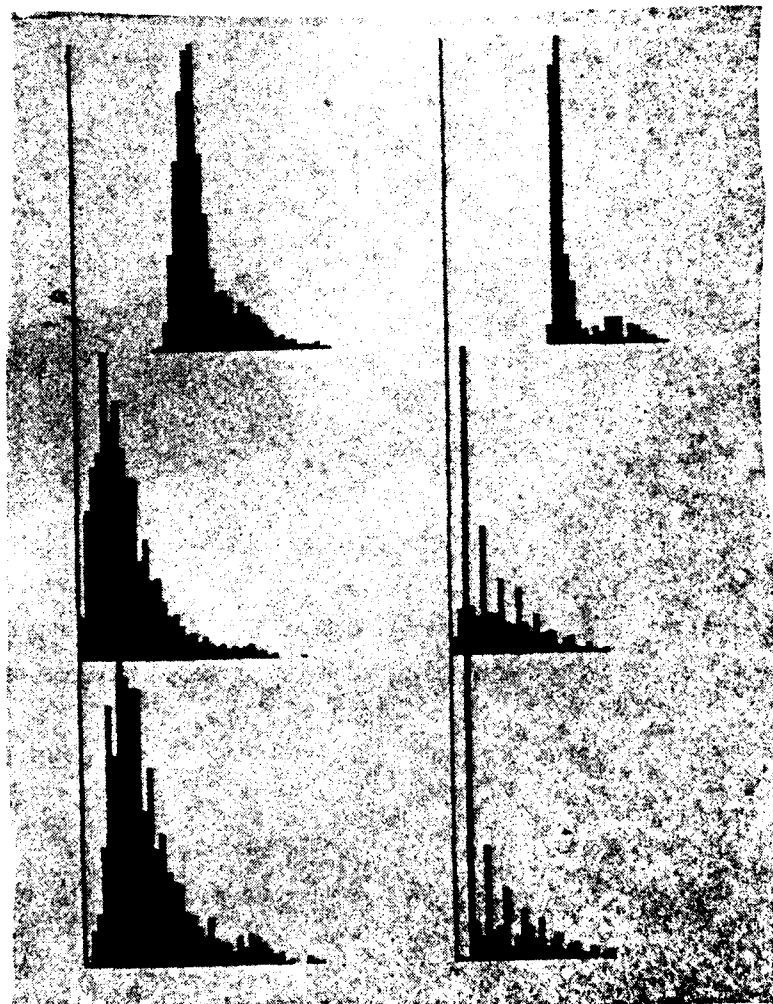to (a); (c) the results of applying non-maximal
suppression to (b).

Figure 2. Histograms of the images in Figure 1. Note that
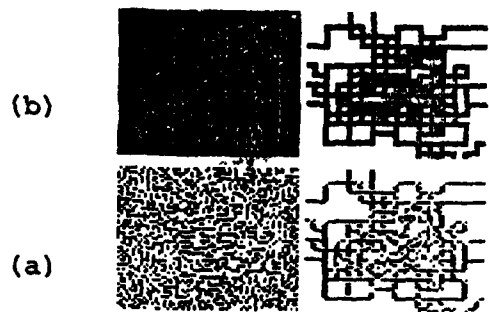only non-zero values are histogrammed in (b) and (c).

(b)

(a)

Figure 3. (a) Images in Figure 1(b) thresholded at 0.
        (b) Images in Figure 1(c) thresholded at 0.

(a)   (b)

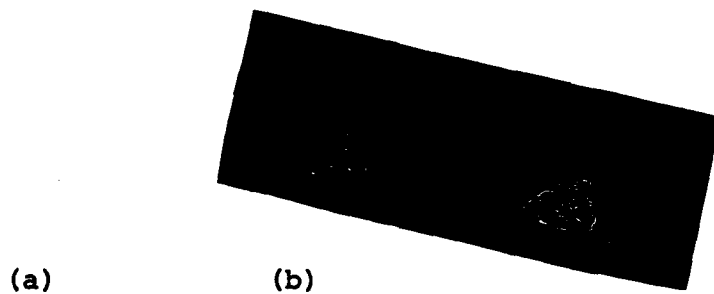Figure 4. (a) Resulting image E_2 for the case $f=f_2$.
        (b) Resulting image E_2 for the case $f=f_3$.

(a)   (b)

Figure 5.   (a) Figure 4(a) thresholded at 0.
                (b) Figure 4(b) thresholded at 0.
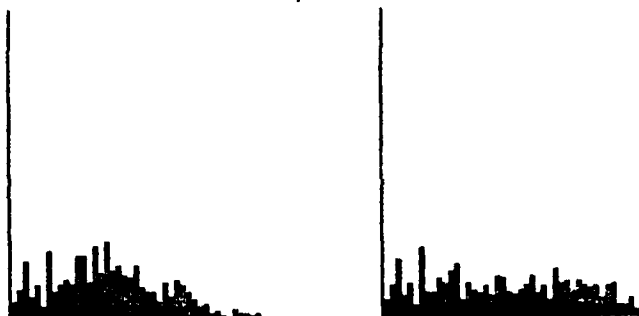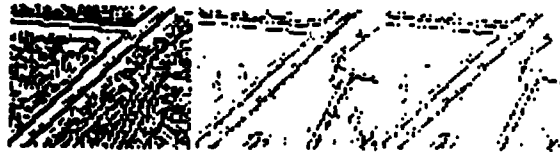

Figure 6.   (a) Histogram of non-zero values for Figure 4(a).
                (b) Histogram of non-zero values for Figure 4(b).
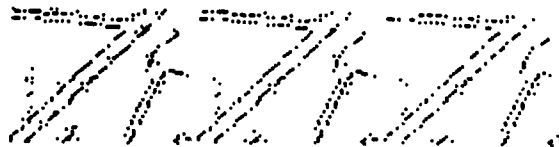
(a)

(b)   (c)   (d)
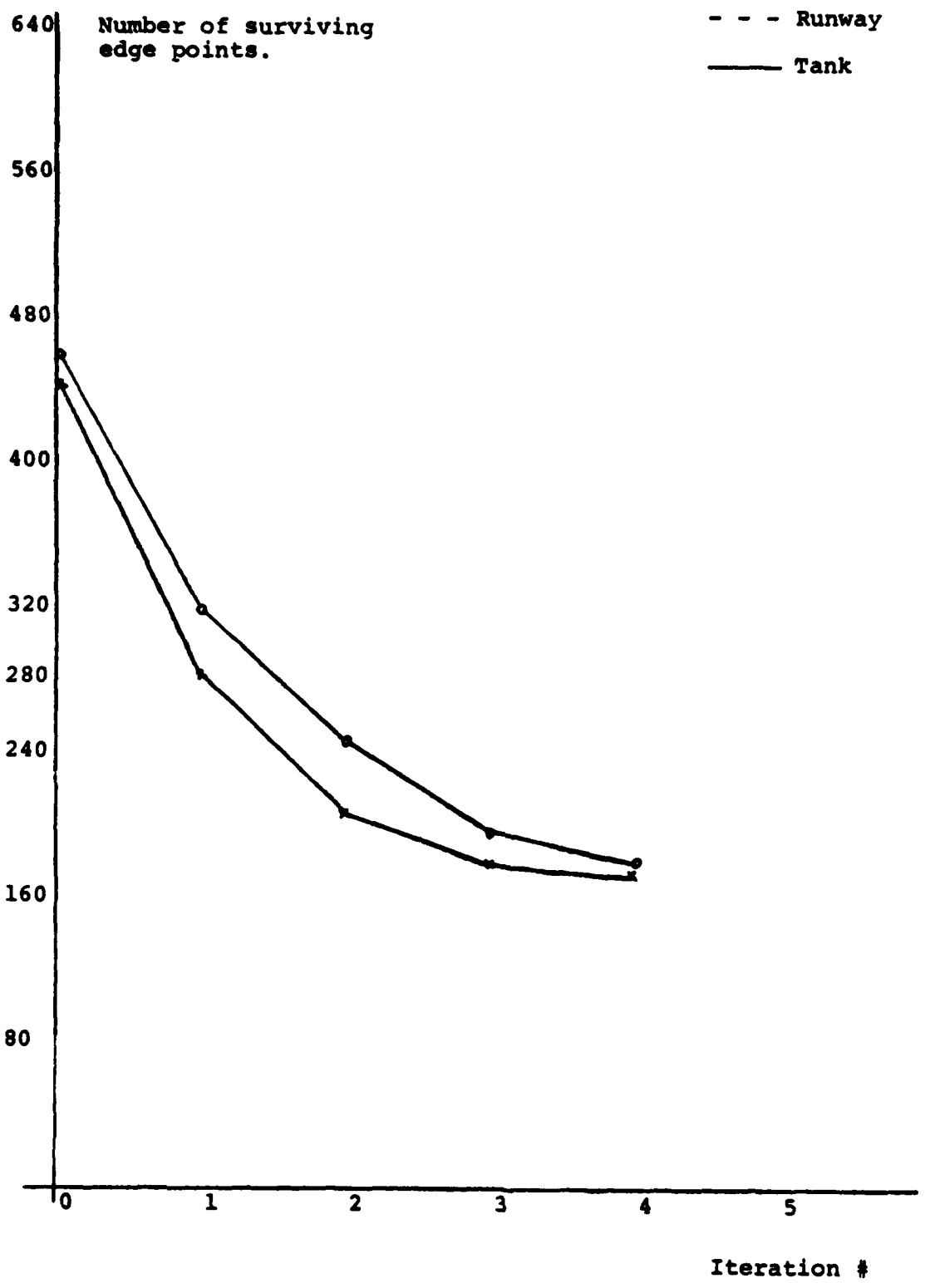
(e)   (f)   (g)

Figure 7.   (a) Image of a part of Frederick Airport.
            (b) Result of non-maximum suppression applied to
                the Prewitt edge detector output for 7(a)
                thresholded at 0.
            (c) to (g) Results of successive iterations of the
                enhancement process thresholded at 0.

Number of surviving edge points.

- - - Runway
———— Tank

Iteration #

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A quadtree approximation of a $2^n \times 2^n$ gray level image tends to enhance edges that are strong in the original image and suppress those that are weak. An edge detector applied to such an approximation produces edges that are in general stronger than those obtainable from the original, though slightly displaced. Methods of combining the edge maps obtained from the original image and its quadtree approximation are examined. It is shown that the choice of a suitable combination rule results in an edge map which is

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