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LEVEL II ⑫

IMAGE SEGMENTATION BY TEXTURE
USING PYRAMID NODE LINKING

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ABSTRACT

In a "pyramid" of successively reduced-resolution versions of an image, by linking nodes representing image blocks to nodes representing nearby larger blocks that most closely resemble them, we can construct trees (defined by the links) representing homogeneous parts of the input image. In this paper, we apply this approach to segmenting an image on the basis of texture. We start from an initial decomposition of the image into small blocks (e.g., 8 by 8); compute a textural property for each block, yielding an array of property values; build a "pyramid" of reduced-resolution versions of this array; and apply the node linking process to this pyramid. The resulting trees define a segmentation of the original image into unions of the small blocks. This segmentation is similar to that obtained by minimum-error thresholding of the textural property values. Substantially better results are obtained when this "bottom-up" block linking process is preceded by a "top-down" process in which large homogeneous blocks are linked to all of their subblocks; the bottom-up linking is then used only for the blocks that were not linked by the top-down process.

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"pyramid" of reduced-resolution versions of this array; and apply the node linking process to this pyramid. The resulting trees define a segmentation of the original image into unions of the small blocks. This segmentation is similar to that obtained by minimum-error thresholding of the textural property values. Substantially better results are obtained when this "bottom-up" blocklinking process is preceded by a "top-down" process in which large homogeneous blocks are linked to all of their subblocks; the bottom-up linking is then used only for the blocks that were not linked by the top-down process.

1. Introduction

Segmentation of an image into differently textured regions
is a relatively difficult problem [1]. In order to distinguish
reliably between two textures, we must examine relatively large
samples of them, i.e., relatively large blocks of the image.
But a large block is unlikely to be entirely contained in a
homogeneously textured region, and it becomes difficult to
correctly determine the boundaries between regions.

Chen and Pavlidis [2] have investigated a solution to the
block size problem based on the use of a "pyramid" of succes-
sively reduced-resolution versions of the given image. If the
image is 2^n by 2^n, the successive layers of the pyramid are,
e.g., 2^{n-1} by 2^{n-1}, 2^{n-2} by 2^{n-2}, ..., 2 by 2, 1 by 1. The
elements of the array at layer k (with the original image being
layer 0) thus represent image blocks of size 2^k by 2^k, and the
size of the array is 2^{n-k} by 2^{n-k}. We assume here, for sim-
plicity, that the elements in each layer correspond to nonover-
lapping 2 by 2 blocks of elements in the layer below. (Other
ways of constructing pyramids, based on overlapping blocks,
are also possible, as will be seen below.) Thus each 2^k by 2^k
block is the union of four 2^{k-1} by 2^{k-1} blocks, which are its
four quadrants. For each block we can compute any desired tex-
tural property, or a set of such properties; see [1] for a re-
view of textural properties. We can now define a top-down seg-
nentation of the image into unions of blocks, based on the

values of these properties, as follows; Starting from the top of the pyramid (a single node corresponding to the entire 2^n by 2^n image), we compare the property value(s) for each block with the values for its quadrants. If the values are sufficiently similar, we leave the block intact; if not, we split it into quadrants, and repeat the process for each quadrant. When this process is complete, each block that remains unsplit should be contained in a homogeneously textured region. Moreover, the maximal connected sets of blocks that have similar textural properties should correspond to the homogeneously textured connected components of the image. Note that we can use a special case of this method to segment an image into connected regions of different average gray level by simply using average gray level as the "textural property".

Recently, a different pyramid-based method of segmenting an image was proposed by Burt et al. [3-5]. It makes use of a pyramid defined by overlapping blocks - e.g., the elements at each level correspond to 4 by 4 blocks of elements at the level below, where these blocks overlap by 50% both horizontally and vertically; the levels thus shrink by powers of 2, just as in the nonoverlapped case. Thus an element of level k has 16 "sons" at level k-1, and it is easily verified that this implies that an element at level k-1 has four "fathers" at level k. Initially, we associate property values with the elements at each level by simple averaging the values of the

16 "underlying" elements at the level below. We then define
"links" between elements at successive levels based on the
similarity of their values; e.g. [3], we link each element to
that one of its four "fathers" which is most similar to it.
(For variations on this idea see [4-5].) We now recompute
each element's value by averaging the values of only those
of its sons that are linked to it (if any).   This causes
the similarities to change, so we may need to change some
of the links; we then recompute the values again, and repeat
the process. The links tend to stabilize after a few itera-
tions. If we trace them up to a level near the top of the
pyramid (e.g., the 2 by 2 level), they define trees of linked
image blocks. The sets of pixels at the leaves of such a tree
constitute a homogeneous subpopulation of image pixels (but
not necessarily a connected region!), so that the trees define
a segmentation of the image into (at most four) subsets.

In the experiments described in [3-5], the property used
was simply (average) gray level, so that the images were seg-
mented into subsets having different average gray levels.
This paper investigates a generalization of the "pyramid link-
ing" approach of [3-5] which makes use of textural properties.
Since such properties are not meaningful for single pixels, we
begin with a fixed partition of the image into small blocks
(e.g., 8 by 8), and compute a textural property for each block;
this yields a 2^{n-3} by 2^{n-3} array of property values, which we

use as input to the pyramid linking process. The trees defined by pyramid linking thus have 8 by 8 blocks, rather than single pixels, as their leaves, and the original image is segmented into unions of such blocks.

Since textural properties measured on 8 by 8 blocks are quite noisy, the pyramid linking process will not always yield a segmentation into the desired regions; for example, a block near the border of a region whose property value is close to that of the neighboring region may get linked to that region, and clusters of nearby blocks interior to a region whose property values differ from that of the region may support one another and become linked to a different subtree. In [6] it was found that smoothing the array of textural property values, e.g. by median filtering, greatly improves texture classification performance; note that a process such as median filtering tends to smooth the values within a homogeneous region without blurring them across region boundaries. Property value smoothing is also used in the present paper to produce more reliable values, thus improving the results of the linking process.

Considerable further improvement is obtained by combining the "bottom-up" linking process described above with a "top-down" process similar to that used by Chen and Pavlidis. Here blocks judged to be homogeneous are linked to all of their subblocks (i.e., the links are created top down), and bottom-up

linking is used only for those blocks that are left unlinked
by the top-down process. This process will be described in
further detail in Section 4.

In Sections 3 and 4 of this paper, the pyramid linking
approach is applied to the two 512 by 512 test images shown
in Figure 1. These images are composed of the geological
terrain textures used in earlier studies of texture classi-
fication [6,7]; (a) is Mississippian Limestone and Shale
above the 45° diagonal and Lower Pennsylvanian Shale below
it (labeled M/L), while (b) is Lower Pennsylvanian Shale
above and Pennsylvanian Sandstone and Shale below (labeled
L/P).

2. Texture Features and Feature Arrays

The texture feature used was the second-order gray level statistic "CONTRAST", which is the moment of inertia of the co-occurrence matrix about its main diagonal [1]. Co-occurrences were tabulated for a one pixel displacement is the horizontal direction. This feature was chosen because it performed quite well in the texture feature studies of Weszka et al. [7], and it is also computationally cheap, since it can be computed from a difference histogram rather than from a co-occurrence matrix. Many other texture features could have been used, but we restricted ourselves to one feature because our primary interest was in the relative performance of pyramid linking schemes in comparison with standard methods.

The features were computed for nonoverlapping small windows (blocks) of the image. The sizes of these windows were 8 by 8 or 16 by 16 pixels. The size of the resulting feature array was 64 by 64 or 32 by 32. For example, if we compute the features for a 512 by 512 image in 8 by 8 blocks, the size of the feature array is 64 by 64. In the computation of these "CONTRAST" feature arrays we used a fast algorithm which reduced the computation time drastically compared to the conventional method. Instead of tabulating the co-occurence matrices for each of the 4096 (or 1024) blocks and deriving the "CONTRAST" features from these matrices, we derived the features from a difference histogram (in effect) by simply summing the squared differences of those pairs of pixels which had the required

displacement. With this approach the whole feature array was computed during one image scan.

Prior to pyramid segmentation the feature values were scaled to make them suitable for the pyramid algorithms, which were designed to operate on input data in the range 0-63. Also, because texture features measured over small windows are unreliable, smoothing was applied to the feature arrays. The smoothing method used was median filtering (value replaced by the median of the feature values in the neighborhood), which was found in [6] to be effective for texture feature value smoothing. In the present studies we applied 0-5 iterations of median filtering (using a 3 by 3 pixel neighborhood) to the feature arrays and then we scaled these arrays linearly to have values ranging between 0 and 63.

3. Experiments Using Iterative Bottom-up Linking

In all segmentation experiments we used ten iterations
in the pyramid node linking computations, although in most
cases the segmentation converged earlier to a stable state.
In the pyramid initialization, the methods with unweighted
averaging of sixteen or four sons were used. Forced linking
was performed on one pyramid level at a time, and the segmen-
tation was forced to give just two classes. These and other
modifications of the original pyramid process are described
in [4] and [5].

The effect of median filtering prior to segmentation is
illustrated in Figure 2 for the image M/L. Figure 2a shows
the median filtered 32 by 32 pixel feature arrays after 0 to
5 iterations of median filtering. The pyramid segmentation
results for these six cases are presented in Fig. 2b. For
comparison, Fig. 2c shows the corresponding segmentations
using a minimum error thresholding method (the threshold that
gives the minimum number of misclassified pixels is used to
segment the feature array into two classes). It can be seen
that the median filtering effectively reduces the error rate
and that the results for these two segmentation methods (pyramid
node linking and minimum-error thresholding) are quite similar.
The selection of the minimum error threshold is very difficult
for the images with 0 to 1 iterations of median filtering, be-
cause the feature value histograms are not bimodal in these
cases.

Figs. 3 and 4 illustrate the use of 4 and 16 sons in pyramid initialization for the 64 by 64 feature arrays M/L and L/P. Figs. 3a and 4a are the median filtered arrays after five iterations and 3d and 4d after three iterations of median filtering. In Figures 3b, 4b, 3e and 4e are the corresponding segmentations using four-son initialization, while in Figs. 3c, 4c, 3f and 4f are the results for sixteen sons. 16-son initialization gave slightly better results for these noisy feature arrays, while for less noisy gray level images the 4-son initialization appears to be preferable [4].

To make the evaluation of the results easier, error rates were computed for each case. The error rate is defined to be the percentage of misclassifications for the unmixed windows in the original image [6]. The error rate is based on the unmixed windows since the mixed windows (on the diagonal) always have 50% error.

In Table 1 are presented the error rates for 64 by 64 feature arrays derived from M/L and L/P and for a 32 by 32 array derived from M/L using 16 by 16 windows. In each case 0 to 5 iterations of median filtering were used before segmentation. Error rates for minimum error thresholding, for pyramid segmentation with 16-son initialization, and for the top-down/bottom-up linking method (described in Section 4) are shown. It can be seen that the error rates for bottom-up pyramid segmentation are very close to the error rates for minimum error thresholding. The minimum error thresholds were found empirically by looking

for a threshold which gives the minumum error rate. It was found, however, that these thresholds can be derived automatically with fairly good accuracy by Gaussian fitting to feature value histograms obtained from properly selected training samples.

To reduce the effects of some very high feature values in some of the feature arrays we also did experiments in which the feature values were truncated by setting the values above a threshold equal to the value of the threshold. After this the arrays were again linearly scaled. Using this method the results were slightly better. This suggests that it is desirable to use some kind of nonlinear scaling of features, if we have feature values that are too dominating even after median filtering. It was also found that reduction of the gray level range of the original image prior to feature value computation did not have much effect on the segmentaion results. When 32 or 16 gray levels were used instead of 64, the error rates were only slightly higher.

4. Experiments Using Noniterative Top-down/Bottom-up Linking

The top-down phase of this new linking method resembles the split-and-merge algorithm used by Chen and Pavlidis in [2]. But instead of using a quadtree data structure we do split-and-link operations in the pyramid structure. The following steps are used in this segmentation approach.

a) Initialize the node values of the pyramid by block averaging of each node's four sons.

b) Start linking at a specified level k. Find the minimum and maximum values of each node's four sons (at level k-1). If the difference between the maximum and mimimum values is less than a selected threshold, link all four sons to their father, and go to level k-1. At this level, link all four sons (at level k-2) to those nodes which are linked to their fathers, i.e. which belong to uniform blocks at level k. For the remaining nodes, apply the same test that was applied at level k, and link a node's sons to it if their range of values is below the threshold.

c) Link each unlinked node to one of its four fathers (closest in value). Do this at all levels starting from level 0. This process is done only once, rather than being iterated as in [3-5]. The resulting tree defines the final segmentation of the image.

For all test images the top-down linking was done from level 4 to level 1. The selection of the threshold value for block uniformity testing was done empirically. The same threshold value was used at each level. Because the error rates seemed not to be very sensitive to changes in this threshold value, it should not be difficult to find the value automatically.

The error rates obtained by the top-down/bottom-up linking method are also shown in Table 1. It can be seen that these error rates are much lower than the results for bottom-up linking and for minimum error thresholding. The results are quite good even without using median filtering.

Figure 5 shows the best results for the 64 by 64 feature arrays. Figs. 5a and b show the M/L and L/P feature arrays after five iterations of median filtering and Figs. 5c and d show the corresponding segmentation results. Figure 6 shows the segmentation results for the same feature arrays without median filtering.

Figure 7 shows the results for the 32 by 32 feature array M/L (features computed in 16 by 16 blocks). Fig. 7a shows the feature arrays after 0-5 iterations and Fig. 7b shows the segmentation results.

Tne results obtained by top-down/bottom-up linking are very good. It is evident that in order to get good segmentation results for texture images, we should use global information obtained from the upper pyramid levels to guide the

segmentation at lower levels. If we use only bottom-up linking, the feature arrays are too noisy for good segmentation.

Many variations on the top-down/bottom-up linking method are possible, but the exploration of these variations is beyond the scope of the present study. Further studies in this area are planned.

5. Conclusions

This study shows that the pyramid node linking method can be successfully applied to segmentation by texture. By using iterative feature value smoothing prior to segmentation quite small windows can be used for texture feature computation. This means that the dividing line between two texture types can be found with reasonable accuracy.

The accuracy of segmentation obtained by the basic bottom-up linking approach is comparable to the accuracy obtained by minimum error thresholding of the feature array. The advantage is that we need not look at the feature value histogram. Determining the appropriate threshold (or thresholds) from the histogram is often very difficult.

A great improvement in segmentation accuracy can be obtained by using a top-down/bottom-up linking method. In this approach global information obtained from upper pyramid levels is used to locate large homogeneous areas, while more accurate boundary information about tnese areas is obtained by linking nodes on lower levels to the nodes representing these major areas.
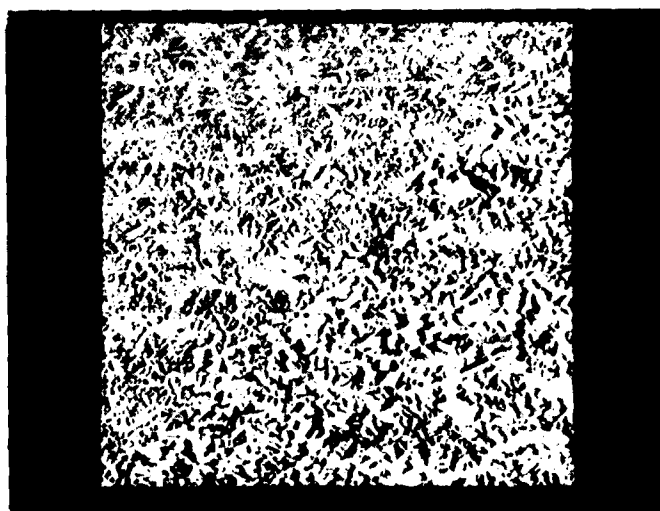
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Image	Iterations of median filtering	Minimum error thresholding	Bottom-up linking	Bidirectional linking
M/L (Fig. 1a)	0	39.4	37.8	18.0
	1	30.7	27.7	10.7
	2	26.5	24.0	8.6
	3	24.3	19.4	8.5
	4	22.8	23.7	8.3
	5	22.0	21.0	8.0
L/P (Fig. 1b)	0	25.7	25.0	2.9
	1	10.7	9.9	2.2
	2	6.8	5.2	2.2
	3	5.2	4.6	1.6
	4	4.3	6.3	2.0
	5	3.5	3.3	1.6
M/L (Fig. 1a) using 16x16 windows	0	33.7	36.0	14.7
	1	19.1	19.8	5.5
	2	13.7	11.1	6.0
	3	10.8	12.2	5.2
	4	8.8	8.0	2.6
	5	7.7	6.4	2.8

Table 1. Error rates (%)

(a)

(b)

Figure 1. Test images
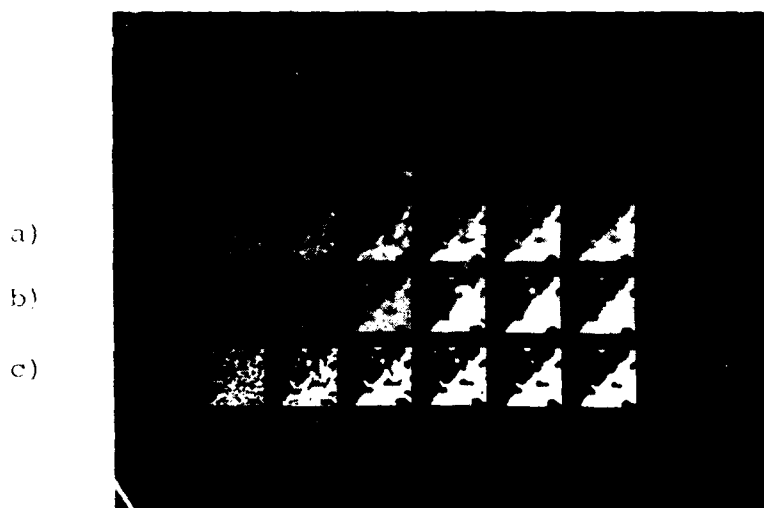
a)

b)

c)

Figure 2. a. Feature arrays using 16x16 windows
              (after 0-5 iterations of median filtering)
           b. Pyramid segmentation results
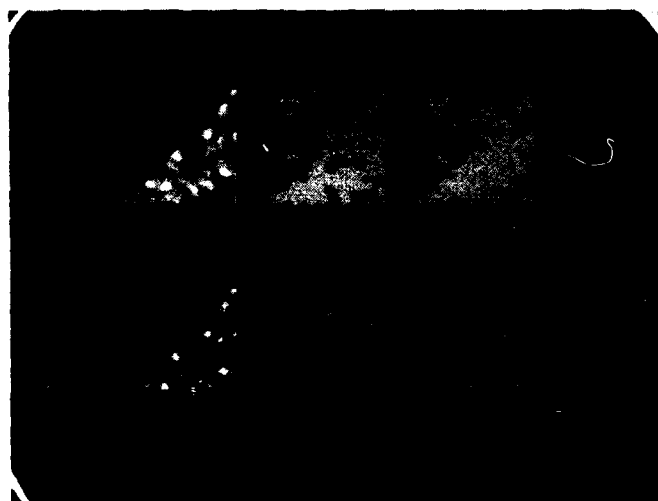   c. Minimum-error thresholding results

Figure 3. Pyramid segmentation results for the image in
              Figure 1a using 8x8 windows

                      abc
                      def

           a,d. Feature array after 5(8) iterations of
                median filtering
           b,e. Pyramid segmentation using 4-son initial-
                ization
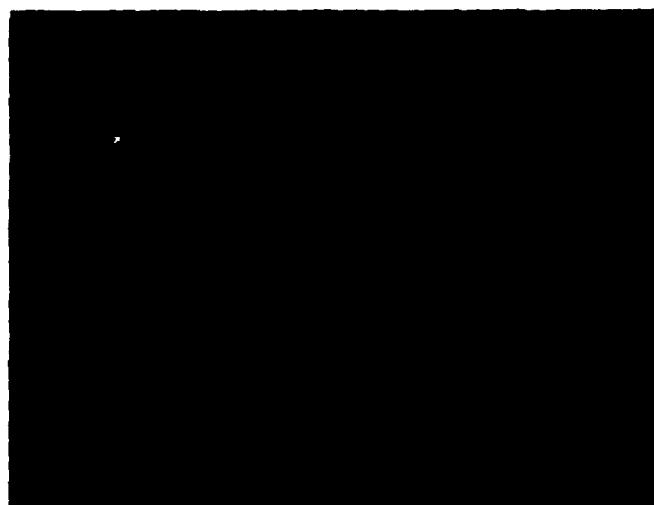   c,f. Same using 16-son initialization

Figure 4.   Analogous   to Figure 3 for the image
             in Figure 1b

a)   b)

c)   d)

Figure 5.   Bidirectional linking results
             a,b. Feature arrays for Figs. 1a-b after 5
                  iterations of median filtering
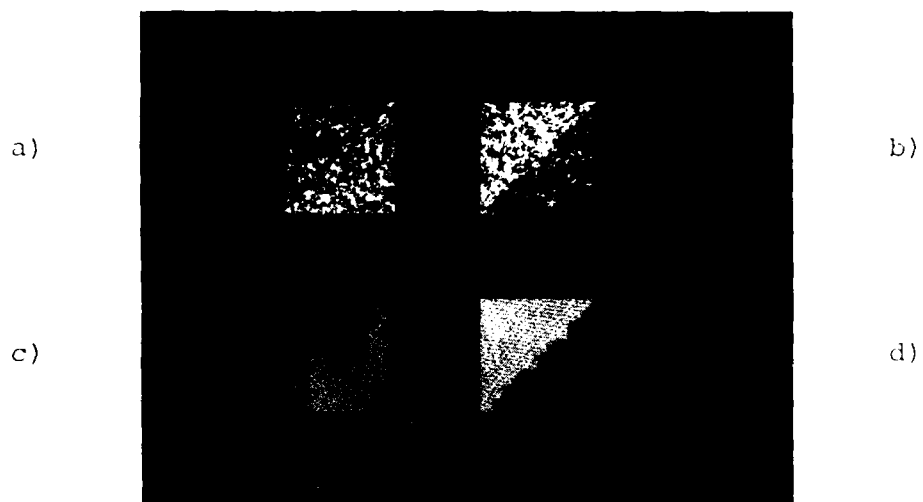   c,d. Segmentations

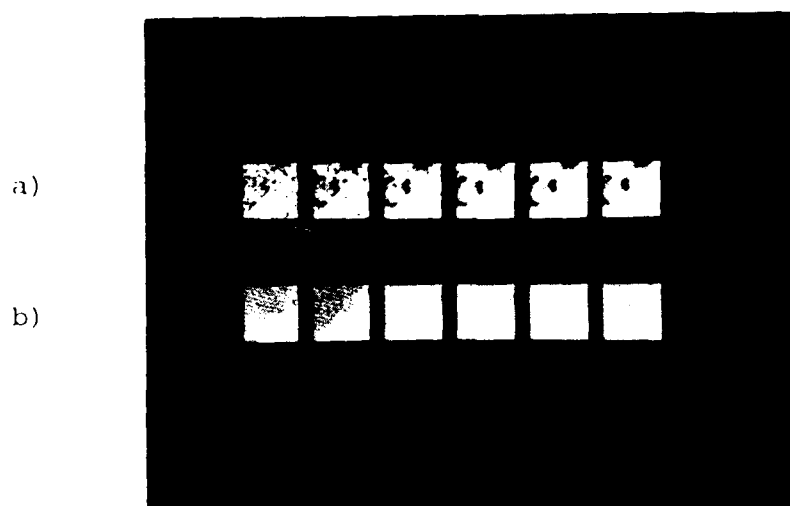Figure 6. Analogous to Figure 5 but without median filtering

Figure 7. Bidirectional results using 16x16 windows and
0-5 iterations of median filtering
a) Feature arrays
b) Segmentations

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