Textural Boundary Analysis

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***Abstract*—A procedure is demonstrated for locating textural boundaries in the digital image representation of a natural scene. The technique involves development of an edge operator capable of integrating multiple textural features into a single boundary determination. The process is designed to simulate actual perception of textural discontinuities. Success of the system is demonstrated on pictures with prominent perceived boundaries not detectable by methods based only on differences in average brightness.**

***Index Terms*—Pattern recognition, picture processing, scene segmentation, textural edge detection, texture.**

I. Introduction

Texture is being increasingly recognized as an important cue for the analysis of natural imagery [1], [2]. The analysis of textural properties is particularly valuable for scene segmentation systems. In fact, readily perceived textural boundaries may be apparent in a scene where no obvious discontinuities in average brightness exist.

A number of authors have developed successful procedures for using image texture in the scene segmentation process. Bajcsy incorporates Fourier based measures into a region merger system [2]. Rosenfeld and Thurston describe an edge oriented approach capable of incorporating textural properties [3]. In the edge based system, a local operator sensitive to some property such as orientation or coarseness is applied at multiple points in a scene. Spatial discontinuities in the output of a given operator are assumed to correspond to textural boundaries. This approach has been employed in a number of subsequent papers which investigate different local operators and different criteria for making boundary determinations [4]–[6]. No clear mechanism has yet been suggested, however, for integrating the results from multiple operators. Thus, the approach must be limited to specific classes of imagery.

This correspondence describes a technique for incorporating multiple textural cues into a boundary analysis system. Furthermore, the procedure which is developed is designed to simulate actual human perception of textural discontinuities. The system is demonstrated on pictures with prominent perceived boundaries which could not be found by conventional techniques based on differences in average brightness.

II. Similarity Measures

A central feature of any scene segmentation system using textural properties must be a meaningful measure of textural similarity. Textural edges may be defined as contiguous image regions of perceptually differing texture. Region oriented systems must merge or split regions based on measures of visual similarity. Unfortunately, few of the existing systems for scene segmentation make use of a textural similarity measure with any psychophysical foundation.

A previous paper described the construction of a textural distance function [7]. This function can numerically quantify the perceived degree of dissimilarity between two image regions. A prominent feature of the distance function is that it has been developed to accurately simulate human perception of textural differences. This is important in a system designed to describe a scene in a manner comparable to what a human observer would "see" in that scene.

Textural similarity is usually estimated by comparing specific image statistics in the two regions of interest. For example, one of the many numerical characterizations of texture [2], [8] could be evaluated in both regions. An absolute value difference of the two measures might be used as an indication of similarity (the smaller the value, the greater the similarity). Experience has shown, however, that none of the commonly used statistics, taken alone, is adequately correlated with perceptual response. The distance function model is able to integrate a large number of simple, statistical measures into a value which more closely corresponds with actual perception. Specifically, it was shown that in certain applications, a particular linear combination of simple difference measures was quite successful in simulating the perception of textural differences.

As an example, let $a_i(n)$ be the ith textural property of region n. Then, we can define the difference between regions l and m based on property i as

$$d_i(l,m) = |a_i(l) - a_i(m)|.$$

Each d_i represents an elementary difference function. A single estimate of region dissimilarity may be found by examining a collection of elementary measures. In particular, it is usually possible for an appropriate set of measures to find a set of coefficients $\{c_i\}$ such that the value

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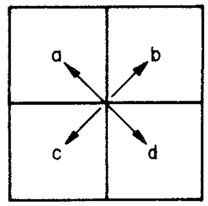

Fig. 1. Template for textural edge operator.

$$D(l,m) = c_1 d_1(l,m) + \cdots + c_n d_n(l,m)$$

accurately reflects the perceived difference between the textures in region l and the textures in region m.

With such a function on pairs of image regions, it is now possible to quantitatively specify a "significant difference" in perceived textures. It is important to recognize the utility of this approach. The distance function model is applicable to most of the existing systems incorporating texture as a cue to segmentation. More generally, systems dependent on differences in average brightness may be expanded to include textural considerations with little change in the basic computational framework. Texture may then be used, along with brightness, color, and any desired semantic processing, in determining object boundaries. The utility of textural boundary detection will be demonstrated in an edge oriented system.

III. Textural Edge Operator

Many authors have developed edge finding systems which search for major discontinuities in the brightness function of an image [9]. This is normally done by computing an estimate of the derivative or gradient of the image and then finding peaks in the derivative function. Many operators have been suggested for this purpose. A common and often successful function is called the modified Roberts cross operator [10], [9] and is defined as

$$R(i,j) = |p(i,j) - p(i+1,j+1)| + |p(i+1,j) - p(i,j+1)|.$$

Thus, the Roberts "gradient" is found by summing brightness differences in two orthogonal directions. Many more sophisticated operators are possible [11]. In particular, an operator which returns edge orientation may be quite useful.

A procedure was developed to search for edges defined by textural properties in a manner similar to the Roberts operator. At specified intervals in the scene to be processed, four image regions arranged in a square pattern were considered (see Fig. 1). The sum of the estimated perceived textural differences between regions a and d and between regions b and c was found. As with conventional gradient operations, it was postulated that larger values of this sum corresponded to textural edges running approximately through the intersection of the four regions. In addition, an edge direction was calculated. Let $D(i,j)$ be the computed dissimilarity between two regions i and j ($D(i,j) \geq 0$ for any two image regions). Then we can define a textural boundary operator at the point in the scene shown in Fig. 1 as

$$T = D(a,d) + D(b,c).$$

To determine the orientation of the edge, observe that

$$\text{ang} = \pm\arctan(D(a,d)/D(b,c)),$$

where ang $= 0 \Rightarrow$ an edge with negative slope at 45° to the x axis.

To see why two angles are possible, notice that $D(a,d) = D(b,c)$ may correspond to either a vertical or horizontal edge. This is a direct consequence of the multiple degrees of freedom possible and the lack of direction implicit in the dissimilarity measure. The ambiguity is straight forwardly resolved by considering $D(a,c)$, $D(b,d)$, $D(a,b)$, and $D(c,d)$.

In the current system, an edge map is first produced by applying the textural boundary operator at selected points in an image. A second edge map is produced by smearing each point in the first map along the direction of edge orientation. This is done to emphasize collinear edges. Finally, binary edge points are isolated by locating "ridge points" in the edge map. A ridge point is defined as an image point sufficiently greater than its neighbors along some direction. Much of the code to process the edge maps was adapted with little modification from a system originally designed to operate only on intensity information [12].

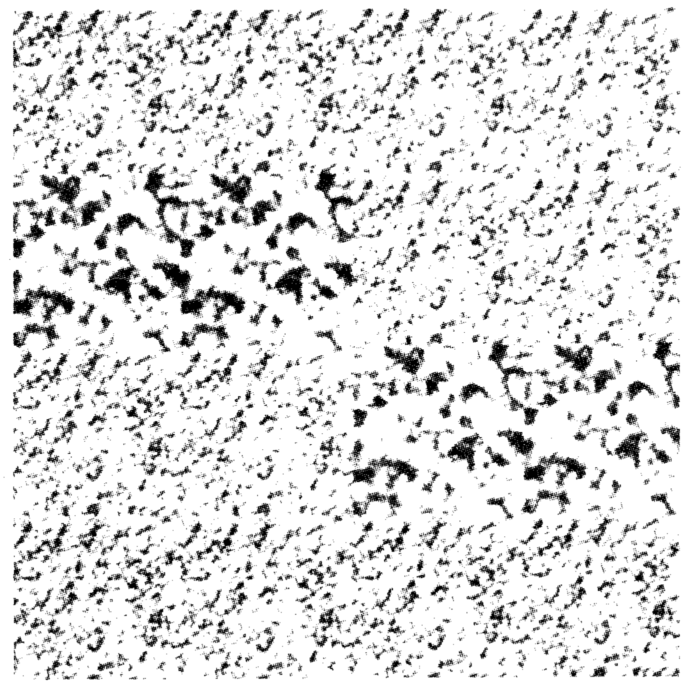

Fig. 2. Textural mosaic 1.

IV. Results

While most analysis systems designed to operate on natural imagery will use texture as only one of a set of multiple cues to determine image organization, some way is needed to evaluate the utility of the textural boundary operator on its own. As a result, this operator was applied to pictures in which the edges could be described as "purely textural." These test images were created as mosaics of textural patterns taken from pictures of natural scenes. Each component of the mosaic was individually normalized such that all components had approximately the same distribution of intensity levels. Thus, it was impossible to distinguish patterns based on average brightness or contrast criteria. The normalization technique used was a histogram mapping procedure with a clipped Gaussian target distribution.

Figs. 2 and 3 show a representative mosaic pattern. Note that to a human observer, there are several quite prominent edges. Thus, it is clear that human perception can identify boundaries on criteria other than differences in average brightness. Fig. 4 is another mosaic pattern. Fig. 5 indicates the different textural regions present in Fig. 4. In Fig. 4, a very prominent boundary exists between patterns a and b. The boundary between b and d is relatively noticeable while the edge between a and d is hardly detectable. Region c may be viewed at one level as a uniform textural region. On another level, however, the region may be thought of as being composed of many smaller regions corresponding to the predominantly light and predominantly dark areas in the pattern.

The textural edge operator was applied to these and several other mosaic patterns using several different sizes for the basic blocks in the operator (i.e., the blocks in Fig. 1). The original mosaics were 256 by 256 picture elements in size. Fig. 6 is an edge map for Fig. 4 using a basic block size of 16 by 16 picture elements. An effective job has been done of identifying the visually prominent boundaries in the mosaic.

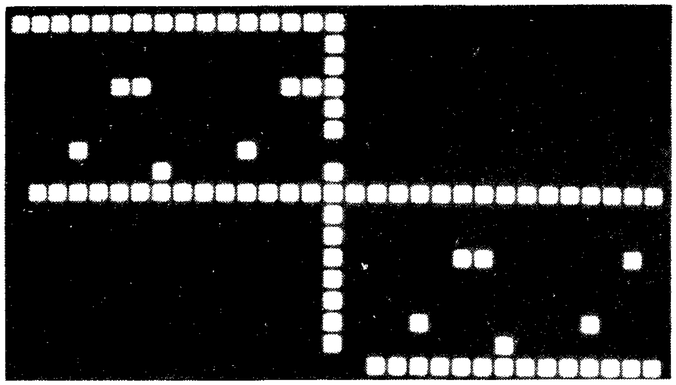

Fig. 3. Edge map for Fig. 2 using 8 by 8 regions.

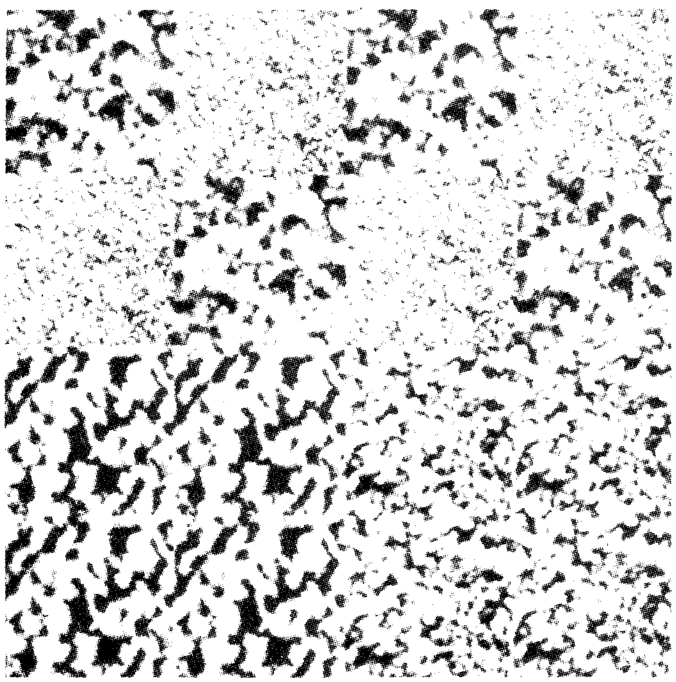

Fig. 4. Textural mosaic 2.

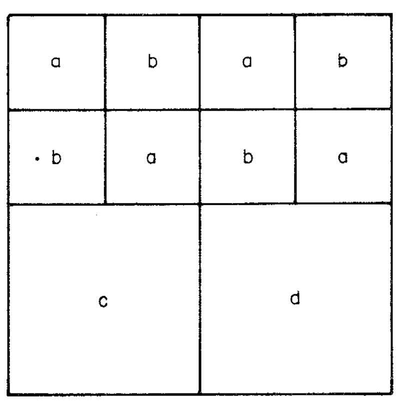

Fig. 5. Identification of regions in mosaic 2.

Testing data indicated that humans can differentiate between the textural patterns in Figs. 2 and 4 over regions as small as 6 to 8 pixels on a side [13]. Fig. 7 is an edge map for Fig. 4 using an 8 by 8 basic block size and the perceived boundaries have been well located. Fig. 7 is an edge map for the mosaic in Fig. 4 using the same 8 by 8 block size. Again, the boundaries are well identified. The operator completely degenerates in region *c*, however. A look at the original picture will show that many of the elementary light and dark areas are of comparable size to the 8 by 8 basic blocks. Thus, at this resolution, the microedges are a dominant effect. This is another example of the importance of realizing that per-

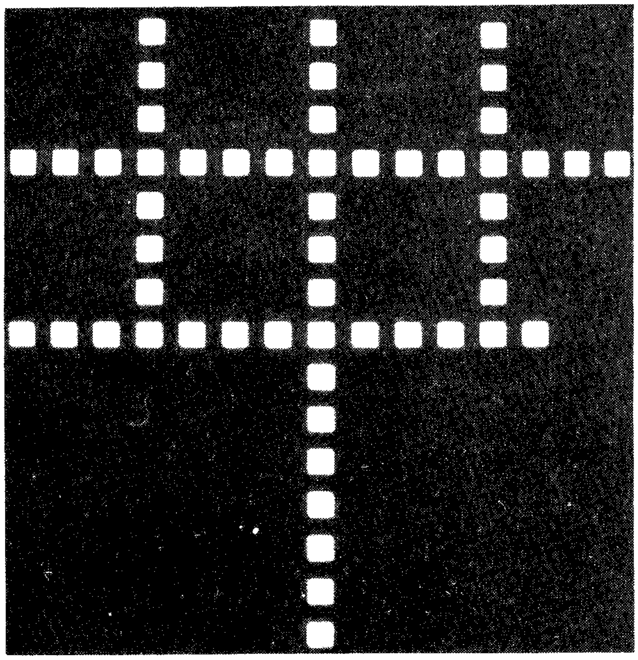

Fig. 6. Edge map for Fig. 4 using 16 by 16 regions.

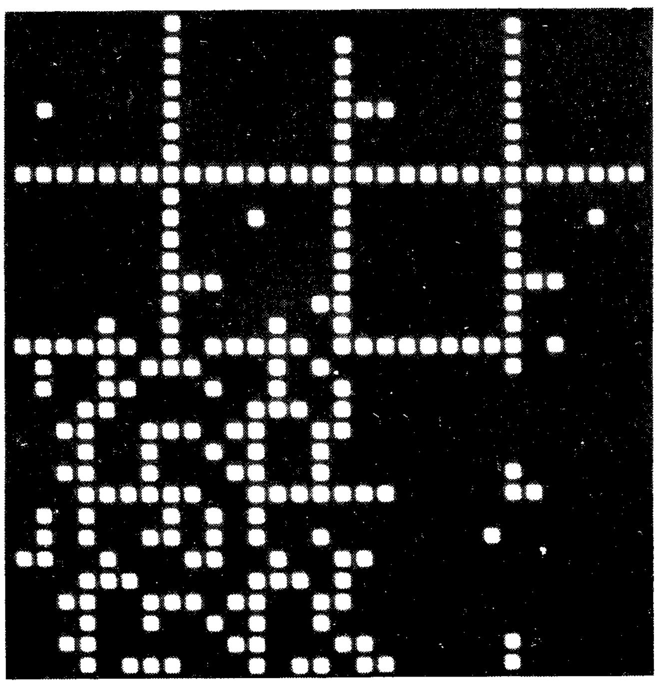

Fig. 7. Edge map for Fig. 4 using 8 by 8 regions.

ceived edges have a "size" associated with them that is a function of the size of the objects being searched for. Comparable results were obtained on the other mosaic test patterns.

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