TEXTURAL RESOLUTION

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Abstract

Texture is a property of a region. Thus, it is necessary to specify an optimal region over which textural properties are to be measured. Small regions will lead to higher spatial resolution in determining boundaries. Measurement regions which are too small, however, lead to inaccurate detection of textural differences. The limits of human textural resolutions are investigated. Statistical characterizations of image regions are found which correlate well with the perceptual ability to detect distinct textures over small areas.

I. Introduction

Textural properties of imagery must be sampled over a region. This concept is particularly important in any system which analyzes spatial variations in textural characteristics. The need to specify the range of region sizes for textural measurements arises both in procedures for detecting textural edges or gradients and in region merger systems utilizing textural information.

Several authors have recognized a similar problem for simple gray scale edges. Derivative operators dependent only on adjacent picture points display an extreme noise sensitivity. Furthermore, a boundary might separate two areas of significantly differing average brightness and yet the intensity transition across the edge may be relatively gradual. One successful edge operator, developed by Hueckel, locates the "best" edge over a relatively large, fixed size region in the image.[1] Another approach is to interpret an edge as two adjacent regions differing significantly in average brightness. Rosenfeld and Thurston use this formulation to develop an operator which evaluates average brightness over a number of region sizes.[2] A decision procedure is then applied at each point to determine which (if any) region size best measures a possible "conspicuous edge" running through that point.

Textural boundaries may be located by finding adjacent image regions differing significantly in perceived textural properties.[3] Here too, it is necessary to determine the regions over which measurements are to be calculated. The computation of textural features is a complex task. It would therefore be advantageous to limit the range of region sizes as much as possible.

An additional problem arises for very small region sizes. The digital measurement of texture is essentially a statistical process. For small regions, the digital estimate of the textures present is apt to be highly imprecise. Thus, if the region size is too small, the estimate of textural edges will be quite inaccurate. As a result, we need a lower bound on the region size over which to compute textural measurements.

II. Background

Minimal region sizes for texture analysis have usually been selected somewhat arbitrarily. This is often done by trial on the domain of imagery on which a given system is expected to perform. For example, Bajcsy uses a variety of region sizes, the smallest of which is a square region 8 sample points on a side.[4] The penalty of choosing a minimal size which is too large is a lack of resolution. Visually distinct detail may not be recognized by the system. The problems of choosing a size which is too small are more severe. As with brightness edge approaches, if the size of the area over which textural statistics are sampled is insufficient to accurately characterize the texture, then the accuracy of any processing dependent on those measurements will be severely limited.

A number of approaches are possible for investigating this problem. One possibility is to look at the effect of region size on pattern classification procedures. Another technique is to search for statistical characterizations of texture which correlate well with minimal size for detectability. Alternately, it is possible to determine the textural resolution of the human visual system for a given domain of textures. This is of particular value for systems searching for visually distinct textural boundaries.

Ausherman studies the problem of determining minimum region sizes from a classification view point.[5] Images are divided into disjoint fixed size regions and textural measurements made on each region. Based on these measurements, a region is assigned to one of a fixed set of classes. A major problem is to balance the finer resolution inherent in smaller region sizes against the resulting degradation of classification accuracy. Several experimental plots of the effects of varying region sizes on classification results are presented. Thus, if a particular classification accuracy is desired, a particular region size may be specified.

Several other statistically motivated approaches are possible. If we view texture as described by a replicated basic pattern,[6] then as that base pattern is made larger, it is reasonable to assume that larger regions must be employed for correct evaluation of the texture. (It would presumably be necessary that the region be large enough to both estimate the nature of the basic pattern and the characteristics of the replacement rule.) Thus, for proper identification, coarser patterns should be measured over larger regions than are necessary for finer textures. A number of authors have suggested that the auto-correlation function of an image region is a good indicator of the coarseness of the texture in the region.[7] Specifically, the sharper the drop off in the auto-correlation function from its maximum, the finer the texture. It might therefore be possible to analytically estimate the region size required for correct analysis of a given texture pattern.

One interpretation of an auto-correlation function is that an image region is compared to a shifted version of itself. If the structures in the region are large, small shifts will produce little difference in the comparison. If the basic structures are smaller, however, only a small shifting is needed to produce a great difference in the point by point comparison. It will be convenient to define an auto-correlation function c(a,d) with the shifting specified in terms of angle and displacement rather than distance in x and y. Furthermore, a measure c(d) without angular dependence may be computed by averaging c(a,d) over several angles for a fixed displacement. Displacement is specified in terms of the spacing between sample points. In the experiments to be described, auto-correlations were not normalized. Thus in general, $c(0) \neq 1$.

To demonstrate the relationship between auto-correlation drop-offs and the intuitive notion of textural coarseness, a sequence of texture patterns was ordered based on auto-correlation ratios of the form $x(l)/c(m)$, $l < m$. Most of the ratio measures agree with perceived rankings of coarseness. Figure 1 shows a set of patterns ranked by $c(0)/c(1)$. (This measure is in effect a normalized auto-correlation for a one pixel shift.) Clearly, the coarseness of the patterns increases from left to right.

III. Perceived Textural Resolution

Accurate simulation of human perception represents a desirable (and ambitious) goal for many scene segmentation systems. To effectively analyze "perceived boundaries", an understanding is needed of the powers and limitations of human visual processing. This understanding may suggest the performance to be expected from automated simulations. In order to gain information about the perception of textural effects, a procedure was developed for experimentally determining the smallest region over which a textural pattern can be resolved by a human observer. The procedure was formulated such that both the effects of the nature of the central texture and the effects of surrounding image regions could be investigated.

A simple set of experiments was created to investigate the smallest region over which a distinct textural pattern could be recognized. First, "eye chart" templates were created (see figure 2). The characters in the charts were distinguished by having either a vertical or a horizontal orientation. Each row of the charts contained characters smaller than the row above. The charts were represented as a digital image array of 256 by 256 elements. Character height ranged in five steps from 48 to 8 pixels. The individual strips in the characters ranged from 12 to 2 pixels in width.

These charts were used as templates for creating a series of textural resolution tests. Two digital images representative of different, naturally occurring textures were merged according to the pattern of a particular chart. The output image was identical to the first textural image in those areas corresponding to background on the chart. In those areas corresponding to the characters, the second textural pattern was inserted.

A series of such textural charts were created corresponding to different pairs of natural textures. For the current experiment, only intensity normalized samples were used as it was desired to measure purely textural effects. The normalized patterns all had the same distribution of intensity levels and thus no differences existed in either contrast or average brightness. The technique used was a histogram mapping procedure with a clipped Gaussian target distribution. (Quantization errors in the normalization procedure resulted in a slight variation in $c(0)$ between samples.) For each pair, two charts were created. A given texture would be used first as background, and then as characters. A sample chart is given in figure 3.

Subjects were placed at a specified distance from a digital image display. Each was given a fixed time to correctly identify the characters on a given line. Successive lines were read until an error occurred. Efforts were made to hold constant pattern illumination and ambient lighting. The same presentation sequence was used for all subjects. The testing procedure proved to be quite tiring. As a result, testing sessions for a given subject were limited and appropriately spaced to minimize visual fatigue.

IV. Results

A prime intent of the textural resolution experiments was to find if any of the standard characterization of texture in digital imagery correlated well with actual observer performance. A large number of resolution experiments were conducted. Each experiment was defined by a foreground and a background textural pattern. Each experiment yielded an average value for the smallest resolvable textural area. The actual metric values for region size of course were dependent on the nature and resolution of the scanning and display devices. The next step was to see if it was possible to compute functions of the two textured regions which correlated well with the observed minimal resolution size.

The structural interpretation of textural patterns suggests that resolution size may be related to intuitive impressions of coarseness or fineness. As demonstrated above, it is possible to estimate visual coarseness by using auto-correlation measures. We might expect the size of the smallest resolvable textured region to vary directly with the coarseness of the pattern (and thus with the size of the elementary texture elements). If these assumptions are true, then the size of the smallest readable characters in the resolution experiments should vary inversely to the ratio $c(0)/c(1)$ for the central texture. In fact, this does not happen. The correlation coefficient between the width of the smallest readable character and the auto-correlation ratio is less than -0.1. Other auto-correlation ratio measures performed even worse. Figure 4 shows a plot of average minimal width versus $c(0)/c(1)$.

One of the difficulties with estimating minimal resolution sizes using a statistical characterization of the central textured region is that it ignores the effects of the surrounding image areas. This contextual information may often constitute a dominant influence on perception. A previous paper describes a technique for numerically quantifying the perceived dissimilarity between two textured regions.[8] A set of image statistics characterizing <u>differences</u> between the regions is computed. Unfortunately, none of the commonly used textural measures taken alone is capable of predicting perceived textural differences, even over a limited domain of imagery. However, a properly chosen linear combination of simple difference measures is quite successful in simulating the perception of textural differences.

This composite dissimilarity measure is computed for central and background textures in each chart and the value compared to the experimental resolution results. The correlation coefficient between the dissimilarity value and the size of the smallest readable character is -0.72. This is not surprising as it indicates that the greater the dissimilarity between a region and its surroundings, the easier it is to recognize the region as being defined by a distinct pattern. What is important to note is how much more significant this effect is than the nature of the central texture itself. Figure 5 is a plot of average minimal region width versus computed textural dissimilarity.

It is interesting to investigate the results when the experiments considered consist only of textural pattern pairs lying in some specified range of dissimilarity. For example, a fair number of the texture pairs have dissimilarity measures in the range between 1.0 and 2.0. If only these samples are considered, then the measure $c(0)/c(2)$ correlates with character size with a coefficient of -0.37. If samples in the range 2.0 to 3.0 are considered, the correlation coefficient for the same ratio improves to -0.79. (Note, however, that this represents a relatively small portion of the total samples.)

The results of the resolution experiments appear to carry over into actual textural boundary detection systems. Reference [3] describes a boundary operator capable of locating pairs of adjacent image regions with significant textural differences. It is possible to examine the performance of the system as a function of the size of the regions being compared. A close correspondence is found between the smallest region size yielding effective boundary detection and the experimentally determined minimal perceptual resolution size.

V. Conclusion

The size of the region over which a textural pattern is measured has a significant effect on how well that texture can be characterized. Experimental results show that a dominant influence on human textural resolution is the nature of the patterns surrounding the region of interest. There is a well defined trade off between spatial resolution of a textural boundary and the ability to distinguish between visually similar textures. The structural interpretation of textural patterns suggests several additional methods for estimating minimal resolution regions. Unfortunately, at least one of these measures (an auto-correlation ratio) is not supported experimentally.

The most reasonable conclusions to draw from the above results seem to be that in attempting to predict the perceptual effects of textural patterns, contextual considerations are of great importance. The textural dissimilarity function provides a useful tool for this analysis. If the nature of the textural edges being searched for (or at least an estimate of the edge strengths) is available, then an adequate guess can be made as to the region size required. Measures of textural properties which do not consider context may also often be of value, but they are sometimes dominated by other effects.

References

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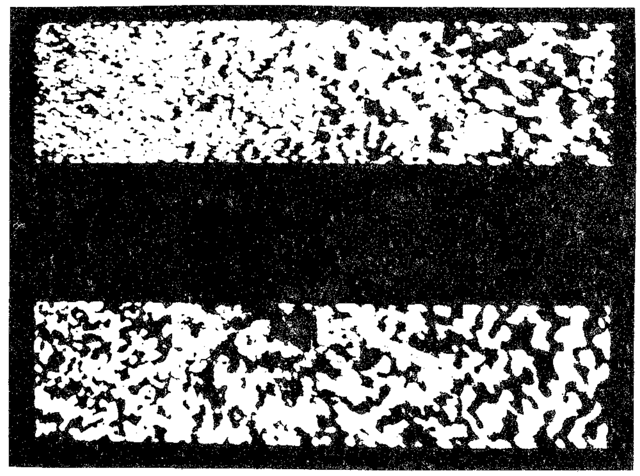

Fig. 1. Texture patterns ranked by auto-correlation ratio

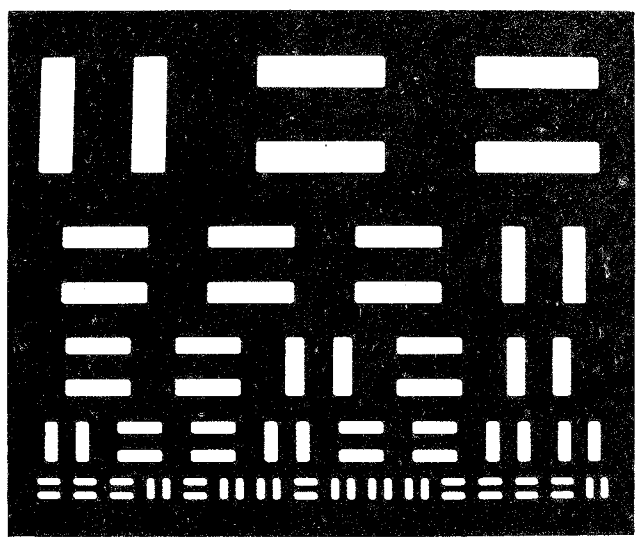

Fig. 2. Eye chart template

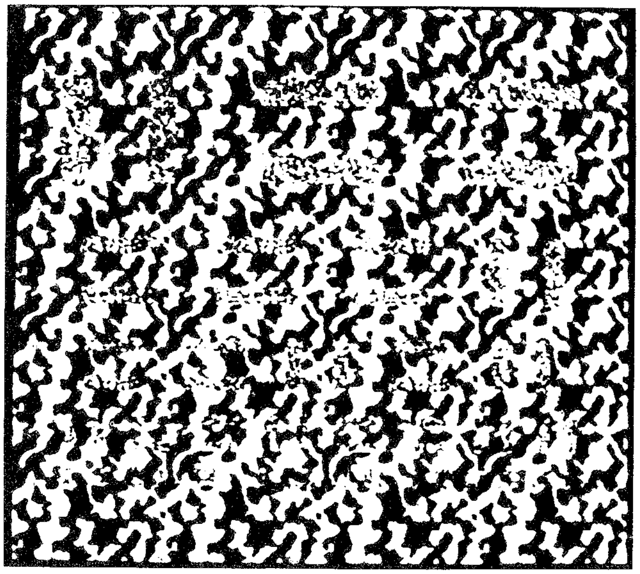

Fig. 3. Sample textural resolution chart

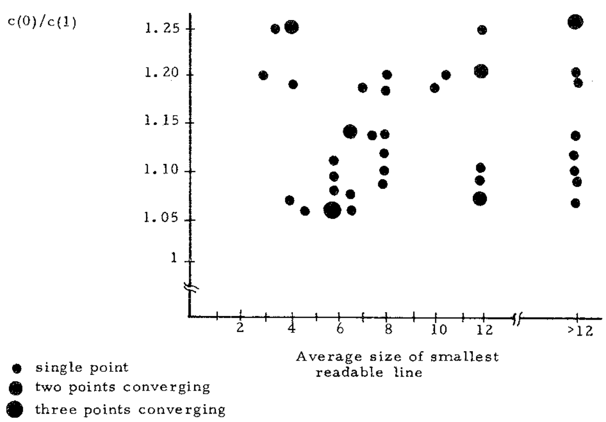

Fig. 4. Minimal visible character width vs. c(0)/c(1)

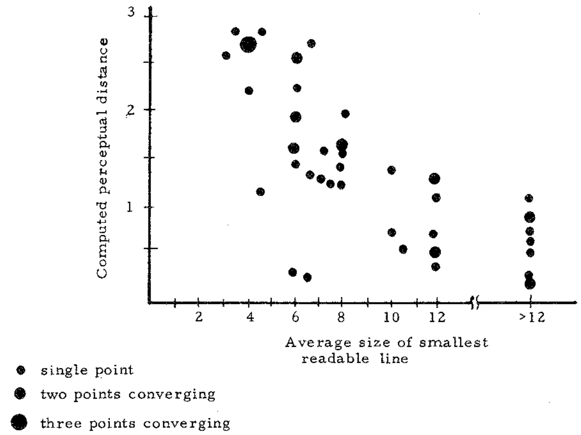

Fig. 5. Minimal visible character width vs. textural dissimilarity