Image Texture Analysis Techniques - A Survey

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ABSTRACT

This paper contains a survey of image texture analysis techniques. Three broad classes of methods are discussed: pixel-based, local-feature based and region-based. The pixel-based models include grey level cooccurrence matrices, difference histograms and energy-measures. The local feature-based models mostly rely on edges as local features and include Marr's primal sketch model and a generalization of cooccurrence matrices. Region-based models include a region-growing model and a topographic model which treats the texture image as a digital terrain model.

INTRODUCTION

This paper presents an overview of techniques for image texture analysis, emphasizing methods for describing image textures for the purpose of image classification.

A textured area in an image is characterized by a non-uniform spatial distribution of image intensities. Although color images also contain textures, we will limit our attention to grey scale images. Very little research has been devoted to computational models of color textures which make essential use of color information.

The variation in intensity which characterizes a texture ordinarily reflects some physical variation in the underlying scene. Although it is possible, in principle, to account for the texture by modeling this physical variation, in practice this is quite difficult to do. Horn (1) discusses such image models. Rather, the approaches which we will discuss will treat texture as a two-dimensional pattern of intensities, and will not consider the physical basis of the texture. In fact, we will adopt an intuitive model for image textures in which a texture is composed of pieces: the size, shape, shades, and spatial arrangement of the cells are the critical factors in discriminating between different textures. Notice that the cells might actually form a partition of the image (i.e., form a mosaic) or might be scattered on a homogeneous background (as "bombs" dropped on a field). Although it is possible to develop formal mathematical image models for such patterns (see, e.g., Ahuja (2), Schachter et al (3) or Zucker (4)), this paper will not consider the development of texture analysis procedures based on such models. Rather, the texture description models which we will discuss are more heuristically motivated. They have been applied to a wide variety of practical problems, including, e.g., texture analysis of many biomedical images and satellite images.

Texture description models can be broadly classified into three main classes:

1) pixel-based models, where the texture is described by statistics of the distribution of grey levels, or intensities, in the texture,

2) local feature-based models, where the statistics are computed with respect to the distribution of local features, such as edges or lines, in the texture, and

3) region-based models, where the texture is first <u>segmented</u> into regions, and then statistics on the shape and spatial arrangement of the regions are used to characterize the texture.

Section 2 of this paper reviews pixel-based models; Section 3 deals with local feature-based models, and Section 4 discusses region-based models.

PIXEL-BASED TEXTURE MODELS

Perhaps the most widely used pixel-based texture model is the grey level cooccurrence matrix, or GLCM. GLCM's were first introduced by Haralick et al (5), and are defined as follows. Let f be a digital image and let $D = \{(dx_i, dy_i)\}$ be a set of image displacement vectors. Then the GLCM of f with respect to D, C_D, is:

$$C_D(g_1,g_2) = \#\{((x,y),(x',y')): f(x,y) = g_1,\ f(x',y') = g_2,$$

and for some i,

$$x = x' + dx_i, \text{ and } y = y' + dy_i\}$$

where #S is the size of set S.

Thus, $C_D(g_1,g_2)$ is a count of the number of pairs of points in f which have grey levels g_1 and g_2, respectively, and are separated by one of the displacement vectors in D.

We can intuitively relate the structure of the cooccurrence matrix to the structure of the texture on which it is computed. Suppose, for example, that the set D includes all displacement vectors of length less than 2 (i.e., we consider a point and its eight neighbors in computing the cooccurrence matrix), and that the texture itself is very "busy" - i.e., contains very many small pieces. Then many pairs of adjacent points will have different grey levels, so that the cooccurrence matrix will have large values at positions far from its main diagonal - i.e., where $|g_1-g_2|$ is high. Suppose, on the other hand, that the texture is composed of a relatively few, large pieces. Then most pairs of adjacent pixels will have similar grey levels (they will either both be in one of the pieces or in the background) and therefore the cooccurrence matrix will have high values only on those elements which lie on or near the main diagonal. Any statistic computed from the cooccurrence matrix which is sensitive to the spread of values away from the main diagonal should be helpful in discriminating between such textures. One such statistic is the CONTRAST statistic defined as:

$$\text{CONTRAST} = \sum_{i,j} (i-j)^2 * C_D(i,j)$$

Haralick et al (5) contains a much more extensive list of such statistics.

A second important aspect of texture which can be captured in cooccurrence matrices is directionality - i.e., the differences in grey level correlation as a function of direction. To compute directionally sensitive texture statistics, one can design the set D to include only displacement vectors of a fixed direction, and then compute cooccurrence matrices for a variety of directions, and compare the statistics for each direction. One tool which has been developed to accomplish this is the polarogram which is a polar plot of a directionally sensitive texture statistic (such as the contrast statistic of a directionally specific cooccurrence matrix) as a function of direction (6). Statistics which measure the shape and size of the polarogram are quite sensitive to texture directionality, while at the same time being invariant to the orientation of the texture in the field of view. Figure 1 contains two texture samples, while Figure 2 contains polarograms for the two textures. Notice that they have quite different shapes and sizes.

The utility of statistics computed from GLCM's depends on the choice of the displacement vector set, D. Zucker (7) describes a procedure for choosing good displacement vectors based on measures of statistical independence of the rows and columns of the cooccurrence matrices. Applying this technique to the LANDSAT data set used by Weszka et al (8) in their experimental study described below enabled him to achieve comparable classification rates to those reported in (8) without exhaustively classifying a large training set using many sets of cooccurrence statistics.

A second pixel-based texture analysis tool which is closely related to the cooccurrence matrix is the difference histogram. A difference histogram is a frequency count of the number of pairs of pixels whose grey levels differ by a fixed amount. More specifically, let D be a set of image displacement vectors as defined above. Then the difference histogram of a texture with respect to D, H_D, is defined by:

$$H_D(v) = \#\{((x,y),(x',y')) : |f(x,y) - f(x'y')| = v,$$
$$\text{and for some } i,\ x = x' + dx_i,\ y = y' + dy_i\}$$

Notice that the grey level difference histogram for a set of displacements D can be directly obtained from the GLCM for D by summing along diagonals of the GLCM which are parallel to the main diagonal. Pairs of points which contribute to the main diagonal of the GLCM, e.g., have difference of grey levels 0. Thus, the grey level difference histogram contains strictly less information than the GLCM. If, however, it turns out in practice that texture classifications based on statistics derived from the difference histograms are as high as those based on statistics derived from GLCM's, then the difference histogram would be the preferable tool, since its storage requirements are lower than GLCMs, and it is computationally less costly to compute statistics from difference histograms than it is to compute them from GLCMs.

The structure of difference histograms can also be intuitively related to texture structure. For example, suppose that the set D contains all image displacements vectors of length less than 2, as we did for GLCMs. Then, for a busy texture, since most pairs of points will have different grey levels, we would suppose that the difference histogram will have relatively high values for large differences. For coarse textures, on the other hand, since most pairs of adjacent points will either both be in the same texture element, or both be in the background, we would expect that the difference histogram would have relatively high values for small differences. One statistic defined for difference histograms which can capture such distinctions is the MEAN statistic defined as:

$$MEAN = \sum_{i} i*H_D(i)$$

Weszka et al (8) describe a comparative experimental study where classification results based on statistics derived from GLCMs and difference histograms were compared for several texture discrimination problems. They found that the difference histograms performed just as well on those problems as the GLCMs. That study also investigated statistics derived from the texture's power spectrum, but they resulted in lower overall classification rates.

A texture model which is computationally very similar to difference histograms has recently been introduced by Faugeras and Pratt (9). They propose a texture synthesis model whereby a stochastic texture array is produced by applying some spatial operator to an array of independent identically distributed (i.i.d.) random variables. They suggest, therefore, that to analyze a texture one should attempt to decorrelate the grey levels in the texture to compute an approximation to the i.i.d. field; first-order statistics of the decorrelated texture should, then, be valuable texture statistics. This decorrelation can be achieved by a whitening transformation, but due to the computational cost of applying the whitening transformation, they suggest as an alternative that a gradient operator, such as a Sobel operator (10) or a Laplacian (11) be applied to the texture.

One last pixel-based model deserving attention is a recent set of "texture energy" transforms introduced by Laws (12). These transforms are fast since they can be computed by one-dimensional convolutions and simple moving-average techniques. They can also be made invariant to changes in luminance, contrast and orientation without any image preprocessing. Figure 3 contains one set of the one-dimensional convolution masks which Laws describes. The one letter names are mnemonics for Level, Edge, Spot, Wave, Ripple, Undulation and Oscillation. The 1x3 vectors form a basis for the remainder of the vector set. For example, each 1x5 vector can be generated by convolving two 1x3 vectors.

Two-dimensional masks can be produced by convolving a vertical 3-vector with a horizontal 3-vector. Texture information can then be extracted from an image by convolving the 3x3 masks with the texture. The fact that the two-dimensional masks are separable means that they can be computed very fast. A 5x5 convolution, for example, can be achieved by performing two 3x3 convolutions.

Laws described the results of a comparative classification study where statistics derived from his texture energy transforms were compared to grey level cooccurrence statistics. The textures used were digitized version of the textures in Brodatz (13). The texture energy measures gave 87% classification accuracy versus an accuracy rate of only about 70% for the cooccurrence statistics.

LOCAL FEATURE-BASED TEXTURE MODELS

Local feature-based models describe image textures using statistics based on the distribution of local image features, such as edges, in the texture. They are most useful for what are called <u>macro-textures</u>, i.e., textures where the cells, or texture elements, are relatively large, say several pixels in diameter. For such textures, pixel-based statistics depend more on the transitions between grey levels in the texture elements than they do on the size, shape and spatial arrangement of the texture elements.

Perhaps the most salient local feature in textures are edges. Davis (14) contains a survey of edge detection techniques for general image analysis. When we restrict our attention to macro-textures, then it is possible to construct mathematical models which describe the size and spatial arrangement of the texture elements and to use such models to guide the design of optimal edge detection procedures. Davis and Mitiche (15-16) present a minimal error edge detection procedure based on such mathematical models for macro-textures.

The simplest texture model based on edges describes textures using first-order statistics of the distribution of edges. For example, the average contrast of edges, or the variability in their orientations are first-order edge statistics. However, such first-order statistics do not seem to result in very reliable texture discriminations.

Marr (17) suggested that instead of computing first-order statistics of a raw edge map of a texture, one should first construct relatively large segments of edges in those maps by applying certain similarity grouping operators to the edge map. He claims that first-order statistics of such extended edges can be used to account for most texture discriminations which humans can perform. This conjecture is consistent with recent psychophysical results reported in Julesz (18).

In practice, however, the computational cost of Marr's similarity grouping operators might prohibit their application to a texture analysis problem. Davis et al (19) suggested as an alternative that second-order statistics of the raw edge map might be a computationally cost-effective alternative. Such second-order statistics can be collected from cooccurrence matrices computed from the edge map. In order to compute useful cooccurrence matrices, it is necessary to generalize the notion of a cooccurrence matrix. This generalization involves replacing the set of displacement vectors, D, with a spatial predicate, P. The spatial predicate has at its arguments a pair of edges and, based on properties of the edges such as their position, orientation and contrast, returns a value of either TRUE or FALSE. Those pairs of edges which satisfy the spatial predicate (i.e., result in a TRUE value) are used to construct the edge cooccurrence matrix. Figure 4 contains a simple example. Figure 4a contains an edge map where the edges are labeled H (horizontal), V (vertical), L (left diagonal), and r (right diagonal). Figure 4b contains the edge cooccurrence matrix. The spatial predicate assigns value TRUE to the pair of edges (e_1,e_2) if:

1) e_1 and e_2 are neighbors, and

2) e_2 smoothly continues e_1 - i.e., if e_1 is a vertical edge, then e_2 must be a vertical neighbor of e_1.

Davis et al (20) contains a comparative classification study of edge cooccurrence with grey level cooccurrence for a database of natural textures. The classification rates achieved using statistics computed from edge cooccurrence matrices were 20% higher than classification rates achieved using statistics computed from grey level cooccurrence matrices.

One can use a variety of other local features to describe textures. For some textures it might be more appropriate to detect linear features than edges. Or, as another alternative, one can regard the intensity image as an elevation map and describe the spatial distribution of peaks and valleys. Ehrich and Foith (21) develop a hierarchical representation of such peaks and valleys called a relational tree which they have found useful for texture description. Such a structure is invariant to linear transformations of the image grey scale.

REGION-BASED TEXTURE MODELS

All of the previously described texture models attempt to describe the structure of an image texture in relatively indirect ways. Inasmuch as our intuitive texture model describes textures in terms of the size, shape and spatial arrangement of texture elements, a reasonable approach is to model texture by directly computing such factors. Such approaches can be generically referred to as region-based texture models. Ideally, the regions should coincide with the cells which compose the texture.

Although in principle such an approach might be preferable to either pixel-based or local feature-based models, it is important to keep in mind that computing the texture cells on which the description of the texture will be based is an instance of the image segmentation problem (hopefully for non-textured segments). Thus, it might be very difficult to reliably compute the texture cells in practice.

The first region-based texture model was proposed by Maleson et al (22) who suggested that standard region-growing segmentation techniques be applied to a texture to extract the texture cells. Zucker (23) contains a survey of region growing procedures. Each cell is then described by an enclosing ellipse. Properties of the ellipse (such as its eccentricity or size) as well as cooccurrence statistics between ellipses (e.g., how many have parallel axes) can be used to describe texture.

Haralick (24), in an extensive survey paper, suggests as texture regions the reachability sets of local grey level extrema. The reachability set of a local maximum is the set of all pixels reachable by that local maximum by a monotonically decreasing path, and not reachable from any other local maximum by such a path. For the ellipses that Maleson employed elongation was related to eccentricity. For reachability sets, elongation can be more generally defined as the ratio of the larger to smaller eigenvalue of the 2x2 second moment matrix obtained from the coordinates of the boundary pixels of the set (25). It should be pointed out that there has not been a substantial amount of research devoted to applying region-based texture models to the discrimination of different textures.

CONCLUSIONS

This paper has attempted to provide a non-comprehensive survey of techniques for describing image textures. It has concentrated on techniques which have either proved to be of value or which are potentially of value in solving texture discrimination problems. The techniques discussed were classified into three categories - pixel-based, local feature-based and region-based. Pixel-based models have been extensively applied to real texture analysis problems; neither local feature-based nor region-based models have received the extensive testing which will be required to gauge their actual utility in image analysis.

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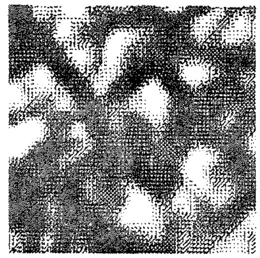

Figure 1b - Scrap metal texture

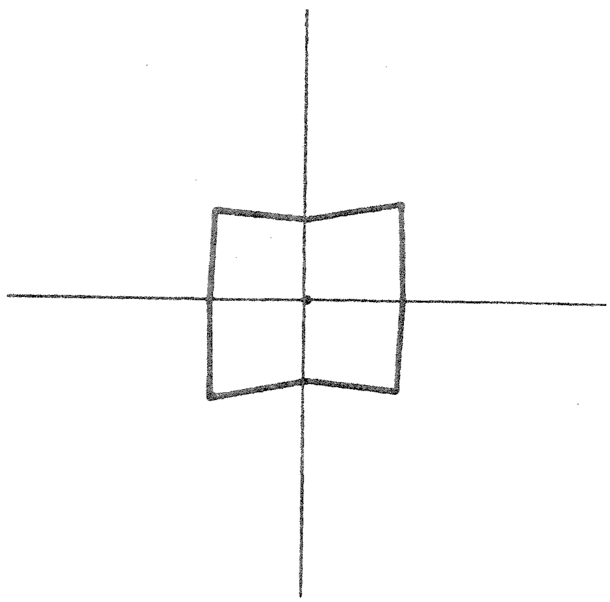

Figure 2b - Polarogram of Figure 1b for distance 5 cooccurrence matrices and the contrast statistic.

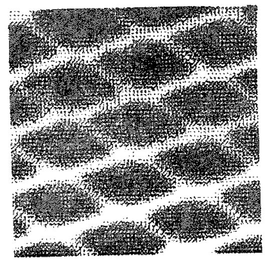

Figure 1a - A grating texture.

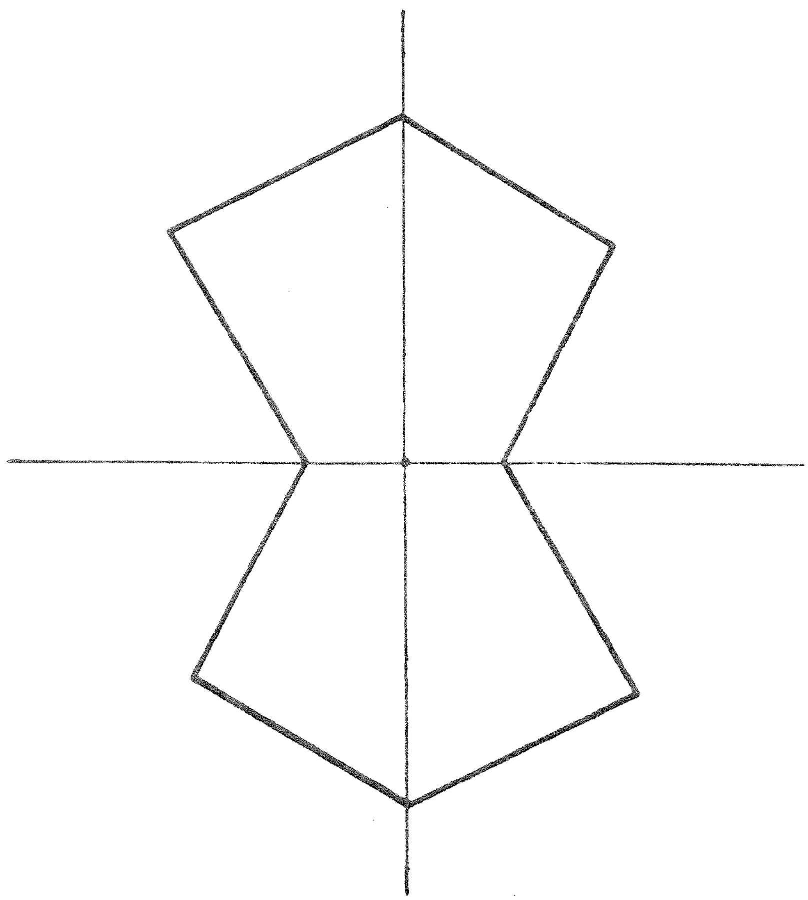

Figure 2a- Polarogram of Figure 1a for distance 3 cooccurrence matrices and the contrast statistic.

Level mask L3	=	1	2	1				
Edge mask E3	=	-1	0	1				
Spot mask S3	=	-1	2	-1				
Wave mask W5	=	-1	2	0	-2	1		
Ripple mask R5	=	1	-4	6	-4	1		
Oscillation mask 07	=	-1	6	-15	20	-15	6	-1

Figure 3 - One-dimensional convolution masks.

			L		
	H	L	R		
	V			R	
	V				V
		R	H		V
	V				H

a) edge map H(-), V(1), L(/), R(\)

	H	V	L	R
H	0	0	1	1
V	2	4	0	0
L	0	1	2	0
R	0	2	0	2

b) GCM of (a)

Figure 4 - A simple example of a GCM.