Statistical Texture Analysis

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***Abstract*—**This paper presents an overview of the methodologies and algorithms for statistical texture analysis of 2D images. Methods for digital-image texture analysis are reviewed based on available literature and research work either carried out or supervised by the authors.

***Keywords*—**Image Texture, Texture Analysis, Statistical Approaches, Structural approaches, spectral approaches, Morphological approaches, Fractals, Fourier Transforms, Gabor Filters, Wavelet transforms.

I. INTRODUCTION

TEXTURE is a property that represents the surface and structure of an Image. Generally speaking, Texture can be defined as a regular repetition of an element or pattern on a surface.

Image textures are complex visual patterns composed of entities or regions with sub-patterns with the characteristics of brightness, color, shape, size, etc. An image region has a constant texture if a set of its characteristics are constant, slowly changing or approximately periodic [1]. Texture can be regarded as a similarity grouping in an image [2].

II. TEXTURE ANALYSIS

Because texture has so many different dimensions, there is no single method of texture representation that is adequate for a variety of textures. Here, we provide a brief description of a number of texture analysis techniques and some examples.

Texture analysis is a major step in texture classification, image segmentation and image shape identification tasks. Image segmentation and shape identification are usually the preprocessing steps for target or object recognition in an image.

Texture analysis refers to a class of mathematical procedures and models that characterize the spatial variations within imagery as a means of extracting information. Texture is an areal construct that defines local spatial organization of spatially varying spectral values that is repeated in a region of larger spatial scale. Thus, the perception of texture is a function of spatial and radiometric scales.

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Descriptors providing measures of properties such as *smoothness, coarseness* and *regularity* are used to quantify the texture content of an object.

Since an image is made up of pixels, texture can be defined as an entity consisting of mutually related pixels and group of pixels. This group of pixels is called as texture primitives or texture elements (texels).

III. APPROACHES TO TEXTURE ANALYSIS

Mathematical procedures to characterize texture fall into two major categories,

1. Statistical and
2. Syntactic

Statistical approaches compute different properties and are suitable if texture primitive sizes are comparable with the pixel sizes. These include Fourier transforms, convolution filters, co-occurrence matrix, spatial autocorrelation, fractals, etc.

Syntactic and hybrid (Combination of statistical and syntactic) methods are suitable for textures where primitives can be described using a larger variety of properties than just tonal properties; for example shape description. Using these properties, the primitives can be identified, defined and assigned a label. For gray-level images, tone can be replaced with brightness.

This papers discusses some of the statistical approaches for texture analysis

IV. STATISTICAL APPROACHES

Statistical methods analyze the spatial distribution of gray values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features [3]. The reason behind this is the fact that the spatial distribution of gray values is one of the defining qualities of texture.

Depending on the number of pixels defining the local feature, statistical methods can be further classified into first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics [3]. The basic difference is that first-order statistics estimate properties (e.g. average and variance) of individual pixel values, ignoring the spatial interaction between image pixels, whereas second- and higher-order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other.

Statistical approaches yield characterizations of textures as fine, coarse etc. Thus one measure of texture is based on the primitive size, which could be the average area of these primitives of relatively constant gray level. The average could be taken over some set of primitives to measure its texture or the average could be about any pixel in the image. If the average is taken within a primitive centered at each pixel in the image, the result can be used to produce a texture image in which a large gray level at a pixel indicates, for example, that the average primitive size is large in a region around that pixel

The average shape measure of these primitives, such as P^2/A, where P is the perimeter and A is the area of the primitive could also be used as texture measure.

4.1 First-order statistics based approach

First order texture measures are statistics calculated from the original image values, like variance, and do not consider pixel neighborhood relationships

Histogram based approach to texture analysis is based on the intensity value concentrations on all or part of an image represented as a histogram. Common features include moments such as mean, variance, dispersion, mean square value or average energy, entropy, skewness and kurtosis.

Variance in the gray level in a region in the neighborhood of a pixel is a measure of the texture. For example in a 5 X 5 region, the variance is

$$\mathrm{T}_v(x,y) = \frac{1}{25}\sum_{s=-2}^{2}\sum_{t=-2}^{2} | g(x+s, y+t) - \bar{g} |^2 \qquad \text{Eq (1)}$$

Where

$$\bar{g} = \frac{1}{25}\sum_{s=-2}^{2}\sum_{t=-2}^{2} g(x+s, y+t) \qquad \text{Eq (2)}$$

Where s and t are the positional differences in the x, y direction However, the Standard Deviation could also be used instead of variance.

The histogram of intensity levels is thus a concise and simple summary of the statistical information contained in the image. Calculation of the grey-level histogram involves single pixels. Thus the histogram contains the first-order statistical information about the image (or its fragment). Dividing the values $h(i)$ by the total number of pixels in the image one obtains the approximate probability density of occurrence of the intensity levels.

The histogram can be easily computed from the image. The shape of the histogram provides many clues to the characteristics of the image. For example, a narrowly distributed histogram indicated the low-contrast image. A bimodal histogram often suggests that the image contained an object with a narrow intensity range against a background of differing intensity. Different useful parameters (image features) can be worked out from the histogram to quantitatively describe the first-order statistical properties of the image.

Texture analysis based solely on the gray level histogram suffers from the limitation that it provides no information about the relative position of pixels to each other. For example, 2 completely different images each with a 50% black and 50% white pixels (such as a checkerboard and a Salt & Pepper noise pattern) may produce the same gray level histogram. Therefore we cannot distinguish between them using first order statistical analysis.

4.2 Spatial frequencies based Texture Analysis

Image texture can also be represented as a function of the tonal and structural relationships between the primitives. Tone is based mainly on pixel intensity (gray values) properties in the primitives while the structure is the spatial (location) relationship between the primitives.

Each pixel can be characterized by its tonal and location properties. A texture primitive is a contiguous set of pixels with some tone and/or local property and can be described by its average intensity, maximum and minimum intensity, size, shape etc. The spatial relationship between the primitives can be random or can be pair wise dependent or some number of primitives can be mutually dependent. Image texture is thus defined as the number and types of primitives (texels) and their spatial relationships. Texture always displays both tone and structure. Texture tone and structure are not independent. Tone can be considered as tonal properties of primitives considering primitive spatial relationship also. Similarly Structure refers to spatial relationship considering their tonal properties as well.

However, it is to be noted that the same number and same type of primitives does not necessarily give the same texture (Fig 1a and 1b). Similarly, the same spatial relationship does not guarantee same texture (Fig 1a and 1c).

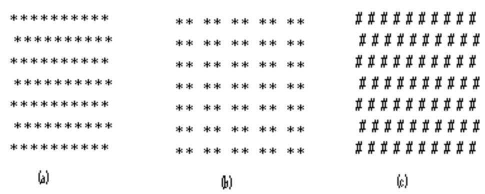

Fig 1. Artificial Structures

Depending on the primitive's tonal and structure characteristics textures can be classified as Fine texture and coarse texture.

A fine texture characteristic is that the primitives in the image are small and the tonal difference between neighboring primitives is large such as a mixture of salt and pepper. A coarse texture results when the texture primitives are larger and consist of several pixels. However, coarse/fine texture characteristics are relative terms.

The strength of a texture can be described by the frequency of primitives appearing in the neighborhood. A weak texture is one with small spatial interaction between primitives and can be described by the low frequency pattern of primitives appearing in some neighborhood. In strong textures, the spatial relationship between primitives is usually regular

Another measure of texture is based on run length. For this, the number of intensity levels in an image needs to be limited using one or more thresholds. Then the image is scanned line by line. The length of line in pixels is noted. Then the relationship between the run lengths is identified. The relationship and the statistical parameters of all these run length gives a pattern. This pattern is a measure of the texture. For example, the average of all the line lengths (in pixels) in a region is a measure of coarseness of the texture. The Statistical distributions, like variance in the length of lines of a specific threshold could be used to detect subtle differences in the texture. The relative sequences such as frequency of appearance of line length of threshold 2 followed by a line length of threshold 5 could also be used depending on how these features vary amongst the texture classes to be discriminated or identified.

An extension of the above process into two dimensions, i.e. from line measure to an area measure will give spatial frequency of gray values. Spatial frequency is a measure of the repetitive placement of identical texture elements (texels) in the image. Spatial frequency gives spatial distribution of gray values.

One method of measuring spatial frequency is to evaluate the autocorrelation function of a texture. The autocorrelation function of an image can be used to assess the amount of regularity as well as the fineness/coarseness of the texture present in the image.

In an autocorrelation model, texture spatial organization is described by the correlation coefficient that evaluates linear spatial relationship between primitives.

In the following, we will use

$$\{I(x,y), 0 \le x \le N, 0 \le y \le N-1$$

to denote an N X N image with G gray levels. Formally, the autocorrelation function of an image I(x, y) is defined as in Eq (3)

$$\rho(x,y) = \frac{\sum_{u=0}^{N}\sum_{v=0}^{N} I(u,v)I(u+x,v+y)}{\sum_{u=0}^{N}\sum_{v=0}^{N} I^2(u,v)} \qquad \text{Eq (3)}$$

Where x, y is the positional differences in the u, v direction. If the texture primitives are relatively large, the autocorrelation function value decreases slowly with increasing distance, while it decreases rapidly if texture consists of small primitives. If primitives are placed periodically in a texture, the autocorrelation increases and decreases periodically with distance.

4.3 Co-occurrence matrices

Spatial gray level co-occurrence estimates image properties related to second-order statistics which considers the relationship among pixels or groups of pixels (usually two).

Haralick [4] suggested the use of gray level co-occurrence matrices (GLCM) which have become one of the most well-known and widely used texture features. This method is based on the joint probability distributions of pairs of pixels. GLCM show how often each gray level occurs at a pixel located at a fixed geometric position relative to each other pixel, as a function of the gray level. The (1,3) entry in a matrix for right neighbors, for example, would show the frequency or probability of finding gray level 3 immediately to the right of pixel with gray level 1.

Fig 2 shows 3 X 3 image and its 4 gray level co-occurrence matrices. The number of threshold levels is 4. The 2 in the co-occurrence matrix indicates that there are two occurrences of a pixel with gray level 3 immediately to the right of pixel with gray level 1.

i	j

(a) Template

1	3	2
3	1	3
2	1	4

(b) Original image

	1	**2**	**3**	**4**
1	0	0	2	1
2	1	0	0	0
3	1	0	0	0
4	0	1	0	0

(c) Co-occurrence matrix

Fig 2

The size of co-occurrence matrix will be the number of threshold levels. When we consider neighboring pixels, the distance between the pair of pixels is 1. However, each different relative position between the two pixels to be compared creates a different co-occurrence matrix.

If the edges between the neighboring elements (texels) are slightly blurred, nearby neighbors may be very similar in gray level, even near the edges of the texels. In such cases it will be better to base the co-occurrence matrix on more distant neighbors. For example, the matrix entry m_{ij} could represent the number of times gray level j was found 3 pixels to the right of gray level i in the region.

Rather than using gray level co-occurrence matrix directly to measure the textures of images and regions, the matrices can be converted into simpler scalar measures of texture. For example, in an image where the gray level varies gradually, most of the non-zero entries for the right neighbors will be near the main diagonal because the gray levels of neighboring pixels will be nearly equal. A way of quantifying the lack of smoothness in an image is to measure the weighted average absolute distance d of the matrix entries from the diagonal of the matrix.

The example in Fig 3 is for a gradually changing vertical edge and hence all the non-zero entries tend to concentrate towards the diagonal with the result |i-j| = 0 for each entry and d = 0 for all the entries.

$$d = \frac{1}{M}\sum_{i,j} |i-j|\, m_{ij} \qquad \text{Eq (4)}$$

Where

$$M = \sum_{i,j} m_{ij}$$

Where i, j are the size (No. of rows and columns) of the co-occurrence matrix and d is the absolute distance of the matrix entries from the diagonal of the matrix.

If the neighbors tend to have very different gray levels, most of the entries will be far from the diagonal and the value of d will be large, which indicates an uneven edge which can be used to represent a terrain (Haralick)

0	1	2	3	4

Fig 3a : Original Matrix (Picture) with Gradual Variation in horizontal gray level

	0	1	2	3	4
0	0	1	0	0	0
1	0	0	1	0	0
2	0	0	0	1	0
3	0	0	0	0	1
4	0	0	0	0	0

Fig 3b : Co-occurrence matrix; Non-Zero entries concentrated near the main diagonal

4.4 Edge frequency based Texture Analysis

The total length of all the edges in a region could also be used as a measure of the coarseness or complexity of a texture. Edges can be detected either as micro edges using small edge operator masks or as micro edges using large masks [5]. Operators like Robert's operator or sobel's operator can be used for this purpose. Using gradient as a function of distance between pixels is another option [6]. The distance dependent texture description function g(d) can be computed for any sub-image f defined in a neighborhood N for a variable distance d is

$$g(d) = |F_0-F_1| + |F_0-F_2| + |F_0-F_3| + |F_0-F_4| \qquad \text{Eq(5)}$$

Where $F_0 = f(i, j)$, $F_1 = f(i+d, j)$

$F_2 = f(i-d, j)$, $F_3 = f(i, j+d)$ and

$F_4 = f(i, j-d)$

The function g(d) is similar to the negative autocorrelation function, its minimum corresponds to the maximum of the autocorrelation function and its maximum corresponds to the autocorrelation minimum.

Dimensionality of the texture description feature space is given by the number of distance values d used to compute the edge gradient.

Several edge properties may be derived from first order and second-order statistics of edge distributions [7]. They are

Coarseness : Edge density is a measure of coarseness. The finer the texture, the higher the number of edges present in the texture edge image.

Contrast : High-Contrast textures are characterized by large edge magnitude.

Randomness : Randomness may be measured as entropy of the edge magnitude histogram.

Directivity : An approximate measure of directivity may be determined as entropy of the edge direction histogram. Directional textures have a significant number of histogram peaks, directionless textures have a uniform edge direction histogram.

Linearity : Texture linearity is indicated by co-occurrence of edge pairs with the same edge direction at constant distances and edges are positioned in the edge directions

Periodicity : Texture periodicity can be measured by co-occurrence of edge pairs of the same direction at constant distance in a direction perpendicular to the edge directions

Size : Texture size measure may be based on co-occurrences of edge pairs with opposite edge directions at constant distance in a direction perpendicular to the edge directions

The first three measures are derived from first order statistics and the last three are derived from the second order statistics.

Another approach to texture recognition involves detection of borders between homogeneous textured regions. A hierarchical algorithm for textured image segmentation is described in [8] and a two-stage contextual classification and segmentation of texture, based on a coarse-to-fine principle of edge detection is given in [9]

4.5 primitive length texture analysis

A texture can be described by the features of gray level, length and direction of the pixels and primitives. The direction in the above can be described as the continuous probabilities of length and the gray-level of primitives in the texture.

Thus the texture description features can be based on the continuous probabilities of length and the gray-level of primitives in the texture. [10]. The steps are as below,

1. Find primitives of all gray levels, all lengths and all directions in the texture image.
2. Compute the texture features

4.6 law's texture energy measures

Image texture has a number of perceived qualities which play an important role in describing texture. Laws [11] identified the following properties as playing an important role in describing texture: uniformity, density, coarseness, roughness, regularity, linearity, directionality, direction, frequency, and phase.

Laws texture energy measures determine texture properties by assessing Average Gray Level, Edges, Spots, Ripples and Waves in texture. The measures are derived from three simple vectors. $L_3 = (1,2,3)$ which represents averaging; E3 = (-1,0,1) calculating first difference (edges); and S3 = (-1,2,-1) corresponding to the second difference (spots). After convolution of these vectors with themselves and each other, five vectors result:

Level	$L_5 =$	[1, 4, 6, 4, 1]
Edge	$E_5 =$	[-1,-2, 0, 2, 1]
Spots	$S_5 =$	[-1, 0, 2, 0,-1]
Ripples	$R_5 =$	[1, -4, 6,-4, 1]
Waves	$W_5 =$	[-1, 2, 0,-2,-1]

Mutual Multiplying of these vectors, considering the first term as a column vector and the second term as row vector, results in 5 X 5 Matrix known as Law's Masks.

By convoluting the Law's Mask with Texture image and calculating energy statistics, a feature vector is derived that can be used for texture description.

4.7 Fractal based texture analysis

Fractal based texture analysis was introduced in [12]. Fractals measure geometric complexity, which could be used to describe many spatial patterns of textures [13]. Conceptually, the word `fractal' refers to complex patterns that recur at various scales but are independent of scales. Since most textures involve patterns with certain degree of self-similarity at different scales, fractal metrics could provide measures of these patterns for texture description. Fractal dimension is the defining property in the study of textual analysis.

Intuitively, the fractal dimension is a statistical quantity that gives a global description of how complex or how irregular a geometric object is. The fractal dimension D of any object in 2D space is in the range of 0 - D - 2. A point has a fractal dimension of 0, any smooth curve has a fractal dimension of 1, and a completely filled rectangle has a fractal dimension of 2, which are the same as their integer topological dimensions. Irregular sets have a fractional dimension between 0 and 2. Most man-made geometric objects have an integer fractal dimension D, while most objects in nature have a fractional fractal dimension. It has been found that textures in nature do encode fractal dimension, information which reflects the irregularity of textures. Hence the fractal dimension gives a measure of the roughness of a surface. Intuitively, the larger the fractal dimension, the rougher the texture is.

4.8 Other statistical methods

A powerful tool for structural texture analysis is provided by mathematical morphology. The mathematical morphology approach looks for spatial repetitiveness of shapes in a binary image using structure primitives. Thus this approach stresses the shape properties of the texture primitives. Due to the assumption of the binary textured images, this approach is often successful for granulated materials, which can be segmented by thresholding.

The texture transform represents another approach for texture analysis. The general idea is to construct an image I where the pixels I(x,y) describe a texture in some neighborhood of the pixel f(i, j) in the original textured image f. In addition, a priori knowledge can be used to guide the transformation and subsequent texture recognition and segmentation.

Another method used for texture analysis is Auto regression Method. In this method, Linear estimates of gray levels in texture pixels are used for texture description. Pixel gray levels are estimated from gray-levels in their neighborhood. The model give consistent results for coarse structures though it may vary substantially for fine structures [14].

The peak and Valley Method is based on detection of local extrema of the brightness function in vertical and horizontal scans of a texture image. Fine structures have a large number of small sized extrema , coarse textures have a smaller number of larger sized local extrema – Higher peaks and deeper valleys.

A modified peak and valley approach is to consider the sequence of peaks and valleys above as a Markov Chain in which the transition probabilities of an m^{th} order chain represent $(m-1)^{th}$ order Statistics of textures [15]

Texture description is highly scale dependant. To decrease the scale sensitivity, a texture may be described in multiple resolutions and an appropriate scale may be chosen to achieve the maximum texture discrimination.

For calculating multiscale features, various time-frequency methods known as spectral methods are adopted. The most commonly used are Fourier, Gabor functions, and wavelet transforms.

Fourier [16], Gabor [17], [18] and wavelet transforms [19], [20], [21] represent an image in a space whose co-ordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size).

Methods based on the Fourier transform perform poorly in practice, due to its lack of spatial localization. Gabor filters provide means for better spatial localization; however, their usefulness is limited in practice because there is usually no single filter resolution at which one can localize a spatial structure in natural textures. Compared with the Gabor transform, the wavelet transforms feature several advantages make the wavelet transform attractive for texture segmentation. They are:

– Varying the spatial resolution allows it to represent textures at the most suitable scale,

– There is a wide range of choices for the wavelet function, so one is able to choose wavelets best suited for texture analysis in a specific application.

Many of the texture description methods mentioned above are interrelated. The Fourier, Gabor, Wavelet transforms, auto-regression and auto-correlation models represent the same subset of second order statistics.

Though identical second order statistics do not guarantee identical textures, higher than second order statistics contain little information that can be used for texture discrimination.

V. CONCLUSION

This article mainly discussed various statistical approaches of image texture description and analysis. There are 3 principal statistical approaches used in image processing to describe the texture of a region: Basic or First Order, structural or Second Order and spectral approaches.

The Basic Statistical approaches yield characterizations of textures as smooth, coarse, grainy, and so on. One of the simplest approaches for describing texture is to use moments of the gray-level histogram of an image or region.

Structural approaches deal with the arrangement of image primitives. They use a set of predefined texture primitives and a set of construction rules to define how a texture region is constructed with the primitives and the rules.

Spectral approaches to texture analysis techniques are based on properties of the Fourier spectrum, Gabor and wavelet based and are used primarily to detect global periodicity in an image by identifying high energy, narrow peaks in the spectrum. Spectral techniques are ideally suited for describing the directionality of periodic or almost periodic 2-D Patterns in an image.

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