Texture Analysis Using Statistical and Structural Approaches

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Abstract- In This Survey advocates new methods for the extraction techniques and models to measure image textural properties using statistical and structural approaches which includes Spatial Gray Tone Dependence: Cooccurence Matrix And also deals with extracting Texture Features based on which different Image Textures can be classified by comparing with the original image and the segmented image. Segmentation of texture is done using combinatorial method and Segmentation without using local maximum condition method. Supervised and Unsupervised Texture classification is also projected for classifying the mosaic textures in a graphical way. In the end a Cross-Diagonal Texture Filtering method is applied to filter the image textures.

Keywords – Texture Analysis, Image Texture, Statistical Approaches.

I. INTRODUCTION

Texture refers to properties that represent the surface or structure of an object (in reflective or transmissive image, respectively); it is widely used, and perhaps intuitively obvious, but has no precise definition due to its wide variability. One can define texture as a something consisting of mutually related elements; therefore humans are considering a group of pixels (a *texture primitive* or *texture element*) and the texture described is highly dependent on the number considered (the texture scale).

Texture consists of texture primitives or texture elements, sometimes called texels. Texture description is *scale dependent*. The main aim of texture analysis is texture recognition and texture-based shape analysis. People usually describe texture as fine, coarse, grained, smooth, etc., implying that some more precise features must be defined to make machine recognition possible. Such features can be found in the tone and structure of a texture. Tone is based mostly on pixel intensity properties in the primitive, while structure is the spatial relationship between primitives. Each pixel can be characterized by its location and tonal properties.

Figures show that the same number and the same type of primitives do not necessarily give the same texture. Texture tone and structure are not independent; textures always display both tone and structure even though one or the other usually dominates, and one can usually speak about one or the other only. Tone can be understood as tonal properties of primitives, taking primitive spatial relationships into consideration. Structure refers to spatial relationships of primitives considering their tonal properties as well.

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	Fig(A) Artificial Textures	

If the texture primitives in the image are small and if the tonal differences between neighboring primitives are large, a fine texture results. If the texture primitives are larger and consist of several pixels, a coarse texture results. Again, this is a reason for using both tonal and structural properties in texture description. Note that the fine/coarse texture characteristic depends on scale.

Further, texture can be classified according to their strength-texture strength then influences the choice of texture description method. *Weak* textures have small spatial interactions between primitives, and can be adequately described by frequencies of primitive types appearing in some neighborhood. In strong textures, the spatial interactions between primitives are somewhat regular. To describe strong textures, the frequency of occurrence of primitive pairs in some spatial relationship may be sufficient.

One existing definition claims that 'an image region has a constant texture if a set of its local properties in that region is constant, slowly changing, or approximately periodic'. The set of local properties can be understood as primitive types and their spatial relationships. An important part of the definition is that the properties must be repeated inside the constant texture area. One can see that image resolution (scale) must be a consistent part of the texture description; if the image resolution is appropriate, the texture character does not change for any position in the window.

A. Texture Analysis

In order to improve the quality of an image, a spatial and radiometric filtering can be processed. Usually this filtering makes use of the radiometric and spatial distribution of the spatial and radiometric characteristics of the considered image. The representation of such a distribution corresponds to the concept of "texture".

B. Texture Characteristics

The texture is a property inherent to the surface; various parameters, or textural characters described it: the Granularity, which can be rough or fine, the Evenness which can be more or less good, the Linearity (roads, rivers), the Directivity; possible occurrence of main directions, the Repetitively; possible occurrence of periodicities, the Contrast, the Order, the Convexity; Other characteristics such as the colour, the size and the shape must also be considered. These parameters can be quantified as indices of texture and so can be useful for image processing.

These concepts are useful in order to describe the objects as one can see them and are used to discriminate them. Due to this study there are important correlations between them. It is rather difficult to mathematize these concepts; however, some topologic, geometric and morphology characteristics can be apprehended.

Different types of vegetation induce different textures: forest, savannahs, and rice fields, wheat fields, so the texture of an urban area is finer than the one of its neighboring farming area. The contrast of a town center, due to its dense pattern of streets and its higher buildings (shadow), is more important than the one the suburbs. A farming area can be characterized by specific directions due to the existence of furrows, and by a more or less important homogeneity according the number of crop varieties. A rice field is usually not homogeneous.

C. Texture Classification

Texture is composed of one or more spatial primitives organized in some more or less periodic or repeated manner to produce the visual effect of a region that has a high degree of localized variation, but that also appears visually consistent when considered on a more global scale. Classification of texture represents an important area of image processing, as textures describe region properties, when are complementary to edges that describe region boundaries. Central to virtually all aspects of texture classification is the identification of a "texture cell" that defines a local region containing the essence of the repeated structure. Texture classification is used extensively in the analysis of remotely sensed data of the environment as well as in various applications of medical diagnosis from image data.

Techniques capable of analyzing the regular but nondeterministic local image structure of textured regions include simple statistical measures of gray level distribution, measures of local edge density or other gradient features, the use of run lengths, and the computation of various measures of second order statistics in the form of gray level co – occurrence matrices.

The applicability of local spatial frequency domain analysis for the classification of textures has been known for some time, and recently there has been renewed interest in the development of spatial frequency domain filters that can be used to classify texture, much of this interest being generated by the observation that human texture perception effectively uses tuned spatial frequency selective channels. The role of the local spatial frequency domain is important for the present work, which uses a local spatial frequency transform as a feature space in which classification is performed. Although a variety of different approaches to the texture classification problem have been developed, with good classification accuracy, developing a texture classifier still tends to require extensive supervision. The following choices and selections must be made before a classifier can operate: Choice of the "Cell Size" to be used, Selection of an appropriate feature space, and Selection of features to describe particular textures, Classifier design. In addition, the nature of the processing required for texture classification often precludes the use of efficient computational means. The goal of this work is a method of texture classification that relies less on

supervision and that is conducive to efficient implementation. In general, all texture classification techniques are based on the context free analysis of spatially localized, non-overlapping blocks of image data.

II. LITERATURE ON TEXTURE

In This survey, unify, and generalize some of the extraction techniques and models which investigators have been using to measure textural properties. The image texture we consider is nonfigurative and cellular. We think of this kind of texture as an organized area phenomenon. When it is decomposable, it has two basic dimensions on which it may be described. The first dimension is concerned with tonal primitives or local properties, and the second dimension is concerned with the spatial organization of the tonal properties

Tonal primitives are regions with tonal properties. The tonal primitive can be described in terms such as the average tone, or maximum and minimum tone of its region. The region is a maximally connected set of pixels having a given tonal property. The tonal region can be evaluated in terms of its area and shape. The tonal primitive includes both its gray tone and tonal region properties.

An image texture is described by the number and types of its primitives and the spatial organization or layout of its primitives. The spatial organization may be random, may have a pair wise dependence of one primitive on a neighboring primitive, or may have a dependence of n primitives at a time. The dependence may be structural, probabilistic, or functional (like a linear dependence).

Image texture can be qualitatively evaluated as having one or more of the properties of fineness, coarseness, smoothness, granulation, randomness, lineation, or being motled, irregular or hummocky. Each of these adjectives translates to some property of the tonal primitives and the spatial interaction between the tonal primitives. Unfortunately few experiments have been done attempting to map same meaning into precise properties of tonal primitives and the spatial distributional properties.

In summary, to characterize texture, we must characterize the tonal primitive properties as well as the spatial interrelationships between them. This implies that texture-tone really a two-layered structure, the first layer having to do with specifying the local properties which manifest themselves in tonal primitives and the second layer having to do with specifying the organization among the tonal primitives. We therefore, would expect that methods designed to characterize texture would have parts devoted to analyzing each of these aspects of texture.

III. IMPLEMENTATION

Statistical Approach to Texture classification

Suppose the area to be analyzed for texture is rectangular, and has N_c resolution cells in the horizontal direction, N_r resolution cells in the vertical direction, and that the gray tone appearing in each resolution cell is quantized to N_g levels. Let $L_c = \{1, 2, 3, ..., N_c\}$ be the horizontal spatial domain, let $L_r = \{1, 2, 3, ..., N_r\}$ be the vertical spatial domain, and $G = \{1, 2, 3, ..., N_g\}$ be the set of Ng quantized gray tones. The set $L_r X L_c$ is the set of resolution cells of the image ordered by their row-column designations. The image I can be represented as a function which assigns some gray tone in G to each resolution cell or pair of coordinates in $L_r X L_c$; $I : L_r X L_c \rightarrow G$.

The gray tone co occurrence can be specified in a matrix of relative frequencies P_{ij} with which two neighboring resolution cells separated by distance by distance *d* occur on the image, one with gray tone i and the other with gray tone *j*. Such matrices of spatial gray tone dependence frequencies are symmetric and a function of the angular relationship between the neighboring resolution cells as well as a function of the distance between them. For a 0° angular relationship, they explicitly average the probability of a left-right transition of gray tone *i* to gray tone *j* within the right-left transition probability. Fig 2.1 illustrates the set of all horizontal neighboring resolution cells separated by distance 1. This set, along with the image gray tones, would be used to calculate a distance 1 horizontal spatial gray tone dependence matrix.

(1,1)	(1,2)	(1,3)	(1,4)
(2,1)	(2,2)	(2,3)	(2,4)
(3,1)	(3,2)	(3,3)	(3,4)
(4,1)	(4,2)	(4,3)	(4,4)

$$L_{Y} = \{1, 2, 3, 4\}$$
$$L_{X} = \{1, 2, 3, 4\}$$

$$R_{H=} \{ ((k,l), (m,n)) \in (L_Y x L_X) x (L_Y x L_X) | k-m = 0, |l-n| = l \}$$

Fig (B) The set of all distance 1 horizontal neighboring resolution cells on a 4 X 4 image Formally, for angles quantized to 45° intervals, the un-normalized frequencies are defined by:

$$\begin{split} P(i,j,d,0^0) &= \# \left\{ ((k,l),(m,n)) \in (Lr \ X \ Lc) \ X \ (Lr \ X \ Lc) \ | \\ & k-m=0, \qquad |I-n| = d, \\ P(i,j,d,45^0) &= \# \left\{ ((k,l),(m,n)) \in (Lr \ X \ Lc) \ X \ (Lr \ X \ Lc) \ | \\ & (k-m=d, \qquad I-n = -d), \\ Or \ (k-m= -d, \qquad I-n = d), \\ I(k,1) &= i, \qquad I(m,n) = j \ \right\} \\ P(i,j,d,90^0) &= \# \left\{ ((k,l),(m,n)) \in (Lr \ X \ Lc) \ X \ (Lr \ X \ Lc) \ | \\ & |k-m| = 0, \qquad I-n = 0, \\ I(k,1) &= I, \qquad I(m,n) = j \ \right\} \\ P(i,j,d,135^0) &= \# \left\{ ((k,l),(m,n)) \in (Lr \ X \ Lc) \ X \ (Lr \ X \ Lc) \ | \\ & k-m = d, \qquad I-n = d \), \\ Or \ (k-m = -d, \qquad I-n = d \), \\ Or \ (k-m = -d, \qquad I-n = -d \), \\ I(k,1) &= i, \qquad I(m,n) = j \ \right\} \end{split}$$

 $\sum P_{ij}^{2}$

Statistical Parameters

Parameter

Uniformity or Energy (Related to the Variance of $\{P_{i1},...,P_{ij},...,P_{NN}\}$)

Entropy

Maximum Probability

Formula

i , j

i , j

 $\max P_{ij}$

 $\sum P_{ij} \log P_{ij}$

i , j

Contrast

 $\sum |\mathbf{I} - \mathbf{j}|^{k} (\mathbf{P}_{ij})^{l}$ assuming k=2,l=1

Inverse Difference Moment (Homogeneity)

$$\sum_{\substack{i,j \\ i \neq j}} (\mathbf{P}_{ij})^l$$

Correlation

$$\Sigma \frac{(i-u)(j-u)P_{ij}}{i_{ij}\sigma^2}$$

Probability of a Run of Length 'n' for Gray Tone i

$$\frac{(P_{i} - P_{ii})^{2} (P_{ii})^{n-1}}{P_{i}^{n}}$$

Texture features Based on Texture Spectrum For Image Texture Classification

Texture Units & Texture Spectrum

In a square raster digital image, each pixel is surrounded by eight neighboring pixels. The local texture information for a pixel can be extracted from a neighborhood of 3 X 3 pixels, which represents the smallest complete unit (in the sense of having eight directions surrounding the pixel). Given a neighbourhood of 3 X 3 pixels, which will be denoted by a set of containing nine elements: $V = \{V_0, V_1 \dots V_8\}$, where V_0 represents the intensity value of the central pixel and V_i {i = 1,2,...,8}, is the intensity value of the neighbouring pixel i, we define the corresponding texture unit (TU) by a set containing eight elements. $TU = \{E_1, E_2, \dots, E_8\}$, where E_i (i=1,2,....8) is determined by the formula :

0 if
$$V_i < V_o$$

E $_i = 1$ if $V_i = V_o$ for : i=1,2,.....8
2 if $V_i > V_o$

and the element E_i occupies the same position as the pixel i.

As each element of TU has one of three possible values, the combination of all the eight elements results in $3^8 = 6561$ possible texture units in total. There is no unique way to label and order the 6561 texture units. In our study, the 6561 texture units are labeled by using the following formula:

$$N_{TU} = \sum E_i X 3^{i-1}$$
, $N_{TU} \in \{0, 1, 2, \dots, (N^{8-1})\}$

where N_{TU} represents the texture unit number and E_i is the ith element of texture unit set $TU = \{E_1, E_2, \dots, E_8\}$.

А	В	С
Н	E ₀	D
G	F	Е

Fig(C) Eight clockwise successive ordering ways of the eight elements of a texture unit: the first element may take eight possible positions from a to h.

	0					
31	88	10	0	2	0	
78	44	83	 2		2	
27	44	19	0	1	0	1

Fig(D) Example of Transforming a neighborhood to a Texture Unit.

Texture Features

Based on the concepts of texture units and texture spectrum, several features can be defined as follows.

- Black-white symmetry
- Geometric symmetry
- Degree of direction
- Orientational features
- Central symmetry

Unsupervised Texture Classification

A clustering algorithm has been designed to perform an unsupervised texture classification. Consider a cluster as an aggregation of points in the test space such that the distance between any point in the cluster is less than the distance between any point in the cluster and any point not in it. In this project, this minimum distance precision rule was employed and the integrated absolute difference between two texture spectra has been taken as the distance between them. The user will first supply the number of clusters desired (K) and an initial threshold T. The algorithm will then determine, through an iterative process, the best value of D, which would be the minimum between-cluster distance, such that a new cluster will be created once the minimum distance between a pattern and all cluster centres is greater than T, and that the final number of clusters will be close or equal to the user-defined number (K). In practice, this can be realized as the procedure described as follows:

Unsupervised Texture Classification Algorithm

(1). Transform the original image into a texture unit image: that is, scan the whole image using a 3 X 3 matrix. The central pixel of the matrix will be assigned by the corresponding texture unit number (NTU) calculated through the method described in section above. This results into a new image in which the value of the pixel represents the

corresponding NTU of the pixel. All the remaining processes will be realized in this NTU image instead of the original image.

(2). Input initial parameters, including the desired number of classes (K), a threshold value (T) and a step value (DS). The choice of these values will be discussed at the end of this section

(3). Set the number of effective classes NC to zero (NC=0) (here, an effective classification means a not-empty classification) and scan the whole image using a window of M pixels X M pixels:

(a)The first window will be chosen as the sample subimage of the first classification and let NC=1. The second windows will be :

- Either classified to the first classification if the distance between the second window and the sample sub-image of the first class is less than or equal to the threshold value *T* or
- Chosen as the sample subimage of the second class if the distance is greater than T and let NC=2.

(b) The integrated absolute difference between the texture spectrum of the window and the spectrum of the sample sub image is considered as the distance between them:

$$D(i) = \sum_{j=1}^{6561} |W(j) - S(i, j)|$$

Where D(i) denotes the distance between the window W and the sample subimage of class i; W(j) represents the occurrence value of the texture unit j in the window considered; S(i,j) represents the occurrence value of the texture unit j in the sample subimage of class i.

(c) The algorithm continues by scanning the rest of the image. For a window encountered, the distances between this window and the sample subimage of each effective class will be calculated. Three possible situations will be considered:

- The central pixel of the window will be assigned to the class L such that D(L) is minimum among all the D(i), for i = 1,2,...,NC (where NC represents the number of effective classes), under the condition that D(L)<= T. The algorithm will continue by considering the next windows.
- The window will be chosen as the sample subimage of the (NC+1)th class if D(L) > T and (NC+1)<= K. Then, let NC = NC + 1 and the algorithm will continue by considering the next windows.
- If D(L) > T and (NC+1) > K, let T = T + DS and the algorithm will go back to the beginning of the scan, that is back to step (3).

(4) After certain iterations, this process becomes stable and the algorithm stops with the current value of NC and T. All the pixels will be classified to one of the NC classes.

Supervised Texture Classification

The four textures are classified for four classes using the minimum distance decision rule. The procedure of the classification is described as follows:

Supervised Texture Classification Algorithm

- (1) Select randomly a sample subimage of 30 X 30 pixels from each texture image (one sample per texture);
- (2) Calculate Texture Spectrum for each sample subimage, by moving the 3 X 3 matrix across the sample with overlap;
- (3) Scan the four textures of Fig (...) by a window of 30 X 30 pixels with a step of two pixels in the row and column directions, and calculate the Texture Spectrum for each window;
- (4) Calculate the absolute difference between the Texture Spectrum of each window and one of each sample:

$$\mathbf{D}(i) = \sum_{j=1} |\mathbf{W}(j) - \mathbf{S}(i, j)|, i=1,2,3,4$$

Where :

D(i) denotes the absolute difference between the Texture Spectrum of a window and the Texture Spectrum of a sample sub image I; W(j) represents the occurrence value of Texture Unit j in the Texture Spectrum of the window considered; S(i,j) represents the occurrence value of Texture Unit j in the Texture Spectrum of the sample sub image i.

(5) The central pixel of the window considered will be assigned to class K such that D(K) is minimum among all the D(i), for i = 1,2,3,4.

Cross Diagonal Texture Filtering Technique For Image Texture Texture Spectrum

The basic concept of textural spectrum method for analysis was introduced by He and Wang (1990, 1991a and 1991b) is that a texture can be extracted from a neighborhood of 3X3 window, which constitute the smallest unit

called 'texture unit'. In the neighborhood of 3x3 window comprising of nine elements respectively as V = [V1, V2, V2]V3, V4, V0, V5, V6, V7, V8] where V0 is the central pixel value and V1... V8 are the values of neighboring pixels within the window (Figure 1). The corresponding texture unit for this window is then a set containing eight elements surrounding the central pixel, represented as TU= {E1, E2, E3, E4, E5, E6, E7, E8} where Ei is defined as,

$$E_{i} = \begin{array}{c} 0 \text{ if } V_{i} < V_{o} \\ 1 \text{ if } V_{i} = V_{o} \\ 2 \text{ if } V_{i} > V_{o} \end{array}$$

and the element Ei occupies the corresponding Vi pixel. Since each of the eight elements of the texture unit has any of these three values (0,1 or 2), the texture unit value TU, can range from 0 to 6560 (3 *, i.e, 6561 possible values). The texture units are labeled by using the relation.

$$N_{TU} - \sum_{i=1}^{\infty} E_i 3^{i-1}$$
(1)

Where NTU is the texture unit value.



Cross Texture Unit

Diagonal Texture Unit

Fig(E) Formation of Cross and Diagonal Texture Unit

Cross Texture Unit (CTU) and Diagonal Texture Unit(DTU) can be defined as:

$$N_{DTU} = \sum_{i=1}^{4} E_{di} 3^{i-1}$$
(3)

Where NCTU and NDTU are the cross texture and diagonal texture unit numbers respectively; ECi and Edi are the ith element of the texture unit.



(a)Teak Scanned Image (b)After Calculating Entropy Filt (c)After Segmentation

(d)After Segmentation Without Using Local Maximum Condition

(e)Scanned Grass Image (f) Grass image After Segmentation

(g) Segmentation Without Using local Maximum Condition

V.CONCLUSION

We have surveyed the image processing literature on the **various** approaches **and** models investigators have used for texture Analysis. For micro textures, the statistical approach seems to work. The statistical approaches have included structural element, gray tone co occurrence and autoregressive models. Here we are extracting Texture Features based on which different Image Textures can be classified by comparing with the original image and the segmented image. Segmentation of texture is done using combinatorial method and Segmentation Without using local maximum condition method. Supervised and Unsupervised Texture classification is also processed for classifying the mosaic textures in a graphical way. In the end a Cross-Diagonal Texture Filtering method is applied to filter the image textures.

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