Analysis of Texture Features for Image Processing Applications

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Abstract—*Digital Images are the effective means of communicating information because a picture speaks more than 1000 words. Many of the digital image processing applications require images to be further processed in order to enhance, segment or to extract features from it. For specific applications like CBIR, object recognition and image Forgery detection texture features plays a key role. Texture can be characterized into two types: Statistical and Structural. In this paper, we analyze both statistical and structural texture features.*

Keywords—*Texture Feature, Gabor Transform, LBP, GLCM, Order statistics*

I. INTRODUCTION

The feature is defined as a function of one or more measurements, each of which specifies some quantifiable property of an object, and is computed such that it quantifies some significant characteristics of the object. We classify the various features currently employed as follows [1]:

• General features: Application independent features such as color, texture, and shape. According to the abstraction level, they can be further divided into:

- Pixel-level features: Features calculated at each pixel, e.g. color, location.
- Local features: Features calculated over the results of subdivision of the image band on image segmentation or edge detection.
- Global features: Features calculated over the entire image or just regular sub-area of an image.

• Domain-specific features: Application dependent features such as human faces, fingerprints, and conceptual features. These features are often a synthesis of low-level features for a specific domain. Among them, texture is the main feature used in image processing and computer vision to characterize the surface and structure of a given object [2]. Textures are complex, visual patterns composed of entities, or sub-patterns, that have characteristic brightness, color, slope, size, etc. Thus texture can be treated as a similarity grouping in an image [3]. The local sub-pattern properties give rise to the perceived lightness, uniformity, density, roughness, regularity, linearity, frequency, phase, directionality, coarseness, randomness, fineness, smoothness, granulation, etc of the texture as a whole [4]. There are four major issues in texture analysis [5]:

i. Feature extraction: To compute a characteristic of a digital image able to numerically describe its texture properties.
ii. Texture discrimination: To partition a textured image into regions, each corresponding to a perceptually homogenous texture.
iii. Texture classification: To determine to which of a finite number of physically defined classes a homogenous texture region belongs.
iv. Shape from texture: To reconstruct 3D surface geometry from texture information.

First order & Second order statistics, Local Binary Pattern (LBP), Gray Level Co-occurrence Matrix (GLCM) falls under Statistical texture methods.

II. STRUCTURAL TEXTURE FEATURES

Structural approaches represent texture by well-defined primitives (micro-texture) and a hierarchy of spatial arrangements (macro-texture) of those primitives [4]. The advantage of the structural approach is that it provides a good symbolic description of the image; however, this feature is more useful for synthesis than analysis tasks. The abstract descriptions can be ill defined for natural textures because of the variability of both micro- and macrostructure and no clear distinction between them. Structural texture features can be obtained using Gabor Transform and 2D Wavelet.

A. Gabor Transform

Gabor filters are a group of wavelets. A set of Gabor filters with different frequencies and orientationsmay be helpful for extracting useful features from an image. Gabor filters have been widely used in Pattern recognition applications [6].For a given image I(x, y) with size M×N, its discrete Gabor wavelet transform is given by the following formula. Prior to any processing, the images are converted to gray-scale format and are resized to a 256 x 256 size. The general functional form of 2D Gabor filters is [7].

$$h(x,y,f,\theta) = \frac{1}{\sqrt{\pi}\sigma_1\sigma_2} e^{\left(-\frac{1}{2}\left(\frac{R_1^2}{\sigma_1^2}+\frac{R_2^2}{\sigma_2^2}\right)\right)} . e^{(i(f_x x + f_y y))} \quad (1)$$

Where,

$$R_1 = x\cos\theta + y\sin\theta \ , \quad R_2 = -x\cos\theta + y\sin\theta \ ,$$

$$f_x = f\cos\theta \ , \quad f_y = f\cos\theta \ , \quad \sigma_1 = \frac{c_1}{f} , \quad \sigma_2 = \frac{c_2}{f}$$

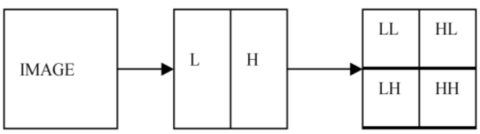
Gabor filters have sinusoidal shape in the spatial domain and are limited by a Gaussian window. They may be said to be frequency sensitive and orientation sensitive band-pass filters. The central frequency is f, the orientation is $\theta$and $\sigma_1$and σ_2 are the standard deviations of the two dimensional Gaussian window. Here c_1 and c_2 are constants. The input image is convoluted with Gabor function as per equation (2).

$$G(x,y,f_k,\theta_m) = \sum_m \sum_n f(x-m,y-n)h(m,n;f_k,\theta_m) \quad (2)$$

A Gabor Kernel is defined and is convoluted with the image. We then have a 256 x 256 output matrix whose column wise mean is calculated and these 'means' are our feature vectors. Total number of feature vectors generated is thus equal to 256. However Gabor Filter is orientation sensitive. Hence we obtain features by rotation from 0^o to 360^o in steps of 10^o to make the calculated feature vectors rotation independent.

B. *Wavelet Transform*

Wavelet transform represents a function as a superposition of a family of basis functions called wavelets. Translating and dilating the mother wavelet corresponding to a particular basis can generate a set of basis functions. The signal is passed through a low pass and high pass filter, and the filters output is decimated by two. Thus, wavelet transforms extract information from signal at different scales. For reconstruction, the coefficients are up sampled and passed through another set of low pass and high pass filters.



DWT on Rows DWT on Columns

For a one level decomposition, the discrete two dimensional wavelet transform of the image function f(x,y) can be written as [11],

$$LL = [(f(x,y)^* \emptyset(-x)\,\emptyset(-y))(2n,2m)],\ (n,m) \in z^2 \quad (3)$$

$$LH = [(f(x,y)^* \emptyset(-x)\Psi(-y))(2n,2m)],\ (n,m) \in z^2 \quad (4)$$

$$HL = [(f(x,y)^* \Psi(-x)\,\emptyset(-y))(2n,2m)],\ (n,m) \in z^2 \quad (5)$$

$$HH = [(f(x,y)^* \Psi(-x)\Psi(-y))(2n,2m)],\ (n,m) \in z^2 \quad (6)$$

where $\emptyset(t)$ is a low pass scaling function and $\Psi(t)$ is the associated band pass wavelet function.

III. STATISTICAL TEXTURE FEATURES

Statistical methods characterize texture by the statistical distribution of the image intensity. Spatial distribution of gray values is one of the defining qualities of texture. 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 [10].

A. *Local Binary Pattern*

Local Binary Pattern (LBP) is a powerful technique for texture classification. The local binary pattern operator is an image operator which transforms an image into an array or image of integer labels describing small-scale appearance of the image. These labels or their statistics, most commonly the histogram, are then used for further image analysis [8]. Consider a gray-scale image. Let $g_c$denote the gray level of the center pixel. Let $g_p$denote the gray level of a sampling point in an evenly spaced circular neighborhood of P pixels of radius R around the center pixel.

$$g_p = f(x_p, y_p) (7)$$

where

$$x_p = x_c + R\cos\left(\frac{2\pi p}{P}\right),\ y_p = y_c - R\sin\left(\frac{2\pi p}{P}\right)$$

The texture in a local neighborhood of a gray image can be assumed to be a joint distribution of gray-scale values of its P neighbors [7].

$$T = t(g_c g_0 \ldots \ldots g_{P-1}) \quad (8)$$

Subtracting the value of $g_c$we get,

$$T = t(g_c g_0 \ldots \ldots g_{P-1}) \quad (9)$$

$$T = t(g_c, g_0 - g_c, \ldots\ldots g_{P-1} - g_c) \quad (10)$$

We can write the above equation safely without any loss of information. Assuming that the values of $g_i - g_c$ are independent of g_c, the above equation can be approximated as,

$$T \approx t(g_c)t(g_0 - g_c, \ldots\ldots g_{P-1} - g_c) \quad (11)$$

The function $t(g_0 - g_c, \ldots\ldots g_{P-1} - g_c)$ can be used to model the local texture data. The term $t(g_c)$ does not contain any useful local texture information. To reduce some complications in the computation and to better its invariance, only the signs of the differences are considered. Let s (z) be the unit step function. The LBP operator is defined as [9]:

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{n} s(g_p - g_p)\, 2^p \quad (12)$$

We can interpret the signs of the differences as a P bit binary pattern. This means that a total of 2^p distinct values are plausible for the LBP code. The local texture description can thus be described as a 2^p-bin discrete distribution of LBP codes. A LBP code for each center pixel is calculated by the operator mentioned above. The distribution of these LBP codes is used for calculation of the feature vector, say S.

For obtaining the feature vector, the image is first converted in to gray-scale format. Next, a circular neighborhood cell with P=8,16,24 and radius R=1,2,3 is chosen respectively. The value of the center pixel is compared with its neighbors. If the value of the neighboring pixel is less than that of center pixel, 1 is written there, else 0 is written. A binary pattern is thus generated. Usually for convenience, this binary pattern is converted to decimal format. Histogram over the cell is then computed and normalized. The feature vector is obtained by concatenating all the normalized histograms.

B. First Order Statistics

First-order texture measures are calculated from the original image values. They do not consider the relationships with neighborhood pixel. Histogram-based approach to texture analysis is based on the intensity value concentrations on all or part of an image represented as a histogram. Features derived from this approach include moments such as mean, standard deviation, average energy, entropy, skewness and kurtosis [10]. The most frequently used central moments are Variance, Skewness and Kurtosis given below. The Variance is a measure of the histogram width that measures the deviation of gray levels from the Mean. Skewness is a measure of the degree of histogram asymmetry around the Mean and Kurtosis is a measure of the histogram sharpness.

$$mean(\mu_i) = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I_i(x,y)}{MXN} \quad (13)$$

$$standardDeviation(\sigma_i) = \sqrt{\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(I_i(x,y)-\mu)^2}{MXN}} \quad (14)$$

$$Energy(e_i) = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I_i^2(x,y) \quad (15)$$

$$Entropy = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I_i(x,y)(-\ln I_i(x,y)) \quad (16)$$

$$Skewness = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(I_i(x,y)-\mu)^3}{MN\sigma^2} \quad (17)$$

$$Kurtosis(k) = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(I_i(x,y)-\mu)^4}{MN\sigma^4} - 3 \quad (18)$$

C. Second Order Statistics

The features generated from the first-order statistics provide information related to the gray-level distribution of the image. However they do not give any information about the relative positions of the various gray levels within the image. These features will not be able to measure whether all low-value gray levels are positioned together, or they are interchanged with the high-value gray levels. The popular one among the second order statistics is Gray Level Co-occurrence Matrix (GLCM).

D. Gray Level Co-occurrence Matrix (GLCM)

The gray-level co-occurrence matrix (GLCM) or gray-level spatial dependence matrix based calculations belongs to the category of second-order statistics. A gray level co-occurrence matrix (GLCM) contains information about the positions of pixels having similar gray level values. Haralick et. al. [16] suggested a set of 14 textual features which can be extracted from the co-occurrence matrix, and which contain information about image textural characteristics such as homogeneity, contrast and entropy.

In a two-dimensional array, $p(i,j)$, represent the relativefrequency by which two pixels with grey levels "i" and "j", thatare at a distance “d” in a given direction, are in the image or neighborhood. It is a symmetrical matrix, and its elements areexpressed by

$$p(i,j) = \frac{P(i,j)}{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} P(i,j)} \quad (19)$$

where Ng represents the total number of grey levels. Using thismatrix, Haralick (1973) proposed several statistical featuresrepresenting texture properties, like contrast, uniformity, mean,variance, inertia moments, etc.

$$Contrast = \sum_{i,j=1}^{n} P_d(i-j)^2 \quad (20)$$

$$Dissimilarity = \sum_{i,j=1}^{n} P_d|i-j| \quad (21)$$

$$Homogeneity = \sum_{i,j=1}^{n} \frac{P_d}{1+|i-j|} \quad (22)$$

$$ASM\ (Energy) = \sum_{i,j=1}^{n} {P_d}^2 \quad (23)$$

$$Entropy = \sum_{i,j=1}^{n} P_d\ (-lnP_d) \quad (24)$$

$$GLCMmean = \begin{cases} \mu_i = \sum_{i,j=1}^{n} i(P_d) \\ \mu_j = \sum_{i,j=1}^{n} j(P_d) \end{cases} \quad (25)$$

$$GLCMStand.Devi. = \begin{cases} \sigma_i = (\sum_{i,j=1}^{n} P_d(i-\mu_i)^2)^{1/2} \\ \sigma_j = (\sum_{i,j=1}^{n} P_d(i-\mu_j)^2)^{1/2} \end{cases} (26)$$

$$InverseDifferenceMoment = \sum_{i,j=1}^{n} \frac{P_d}{|i-j|^2}\ i \neq j (27)$$

IV. ANALYSIS OF TEXTURE METHODS

Compared with the Gabor transform, the wavelet transforms provide several advantages:

- 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.

They make the wavelet transform attractive for texture segmentation. But, the response of Gabor Wavelet transform is close to the human visual system.

The most important property of the LBP operator in real world applications is its invariance against monotonic gray level changes caused, for example by illumination variations. Another very important is its computational simplicity which makes it possible to challenging real time applications. A drawback of the LBP method is that they are not robust in the sense that a small change in the input image would always cause a small change in the output. LBP may not work properly for noisy images or on flat image areas of constant gray level. This is due to the thresholding scheme of the operator.

GLCM texture descriptions of the texture features are not so detail, that it is not good enough to extract the features by this method [12]. In order to make full use of the advantages of GLCM and multiresolution transformations, better to use multi-scale GLCM.

V. CONCLUSION

The textural features can be extracted using Wavelets due to its varying spatial resolution. At the same time, Gabor Wavelets can also be used whose response is very close to human visual system but it is computationally high. LBP operator can be used in real time applications due its invariance to illumination changes. But LBP may not work effectively on noisy images and flat surfaces.

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