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ANALYSIS ON FEATURE EXTRACTION TOWARDS TEXTURE AND NON-TEXTURE CLASSIFICATION

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ABSTRACT
Texture is one of the important characteristics used in identifying objects (or) regions of interest in an image. This can be identified by aerial or satellite photographs, biomedical images and other types of images [1]. In the field of computer vision, texture classification is an important task. Texture classification is used in different pattern recognition application. It retains feature-liked appearance. This paper examines, analyzing the feature extraction towards texture and non-texture classification. In this paper we present texture classification and the feature extraction methods used in the research. Different extraction methods were introduced and used for texture classification problems.

I. INTRODUCTION

Texture is one of the basic attributes of object besides color and shape. It is the structure of the material surface. Texture can be considered to be repeating patterns of local variations of pixel intensities. There are two approaches of textures one can describe texture by tone (based on pixel intensity properties) and structure (describes spatial relationships of primitives).Texture can also be described by the number and types of primitives and by their spatial relationships. The texture field of the appearance node can contain various types of texture nodes like Image textures, Movie textures or pixel textures. There are two approaches of texture Structural Approach and Statistical Approach.

Texture analysis is important in many applications of computer image analysis[12]. It is used for classification or segmentation of images based on local spatial variations of intensity or color. The main task in texture analysis is the texture segmentation of an image. It is used to partition the image into set of sub regions, with homogeneous texture. The goal of texture segmentation is to assign an unknown sample image to one of a set of known texture classes[12].

Texture classification is the process to label or classify various kinds of texture into correct texture groups, which is based on the feature vectors found on them. The goal of texture classification is to view a specific type of texture and hence they can be solved using classification techniques. Texture classification is one of the four problem domains in the field of Texture Analysis, Texture Segmentation, Texture Synthesis and Shape from Texture [2]. There are five techniques in texture classification namely Structural, Statistical, Signal Processing, Model-based, and Morphology-based. The most widely used methods are statistical and signal processing because they can be directly applied onto any type of textures [3].

Texture classification process involves two phases *learning phase*, the target is to build a model for each of the texture content. Texture classes present in the training data, which generally comprises of image with known class labels. Training images is captured

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with the chosen texture analysis method, which yields a set of textural features for each image. These features can be discrete histograms, empirical distribution or scalar number. The textural properties of the images are spatial structure, roughness, contrast, orientation, etc. *Recognition phase*, the texture content of the unknown sample is first described with the same method. The textural features of the sample are compared to those of the training images, with a classification algorithm. Then the sample is assigned to the best match of the category. According to some predefined criteria, if the best match is not sufficiently good, the unknown sample can be rejected instead [2].

II. FEATURE EXTRACTION

Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Transforming the input data into the set of features is called *feature extraction*. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. Different feature extraction methods are used to extract the feature. They are Statistical, Geometrical, Textural and Hybrid features are discussed below.

III. STATISTICAL FEATURE

A statistical approach sees an image texture as quantitative measures of the arrangement of intensities in a region. In general, this approach is easier one to compute and is more widely used, since natural texture is made of patterns irregular sublimates. Many statistical features were calculated to measure different properties of that variable. The main groups of the calculated statistical measures are as follows [6],

Feature (1): Mean or the average, which is defined as:

$$\overline{x} \equiv \frac{1}{N}\sum_{i=1}^{N} x_i$$

Where, $\overline{x}$ is the mean value and N is the total number of data values, x_i.

Feature (2): The standard deviation: The best known measure of the spread of the distribution is the simple variance and it is defined as:

$$\mathrm{var} \equiv \frac{1}{N-1}\sum_{i=1}^{N} (x_i - \overline{x})^2$$

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The standard deviation is a well-known measure of deviation from its mean value and is defined as the square root of the variance.

$$\sigma \equiv \sqrt{var}$$

Feature (3): Smoothness is measured with its second moment as:

$$smoothness = 1 - \frac{1}{(1 + var)}$$

Feature (4): The skewness, or third moment, is a measure of asymmetry of distribution defined as:

$$skew \equiv \frac{1}{N}\sum_{i=1}^{N}\left[\frac{x_i - \bar{x}}{\sigma}\right]^3$$

Feature (5): Energy is calculated as:

$$energy = \sum_i \sum_j P_d^2(i, j)$$

The gray level co-occurrence matrix P_d for a displacement vector d= (d_x, d_y) is defined. The entry (I, j) for P_d is the number of occurrences of the pair of gray levels i, j which are a distance d apart.

IV. GEOMETRICAL FEATURE

Geometric feature learning is the technique combining machine learning and computer vision to solve visual task. The main goal of this method is to find a set of representative features in geometric form, to represent an object by collecting geometric features from image and learning them using machine learning methods[15]. These features can be corner, edges, Blobs and Ridges, Salient point's image texture and so on[17]. In this method, the texture to be composed of texture primitives, attempting to describe the primitives and the rules governing their spatial organization. By the edge detection technique, the primitives may be extracted with a Laplacian-of-Gaussian or Difference-of-Gaussian filter, or by mathematical morphology[2]. A set of eight geometric features is defined which has been used in the literature successfully. Geometric features and their calculation formulas are shown below[4]:

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GEOMETRIC FEATURES

Nr.	Name	Symbol/ Formula	Explanation
G1	Position	$P = h/H$	*H*: width of weld bead *h*:distance of object from middle of weld bead
G2	Aspect ratio	L/e	*L*: the big axis *e*: the small axis
G3	Length/Area Ratio	e/A	*A*: area of the object
G4	Area/bound. rect. Ratio	A/Ar	*Ar*: the area of the minimum rectangle that includes the object
G5	Roundness	$\frac{p^2}{4\pi A}$	*p*: perimeter of the object
G6	Rectangle or 'box' ratio	$\frac{W}{H^*}$	*W/H**: the width/height of minimum rectangle that includes object
G7	Heywood Diameter	d_H	the diameter of a circle having an equivalent area to that of the object
G8	Angle	Θ	Angle of major object axis with line vertical to weld bead

V. TEXTURE FEATURE

The various texture features are helpful to clarify what the terms segmentation, classification and feature measure. Texture segmentation is used to refer to the process of dividing an image up into homogeneous regions according to some homogeneity criteria[14]. Texture classification refers to the process of grouping test samples of texture into classes, where each resulting class

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contains similar samples according to some similarity criterion. Some homogeneity or similarity criterion must be defined in the segmentation or classification. These criteria are normally specified in terms of a set of feature measures, which each provide a quantitative measure of a certain texture characteristic. These feature measures are alternatively referred to here as texture measures. Groups of feature measures assembled for segmentation or classification purposes are often referred to as feature vectors[14]. Note that when the performance of feature measures is compared, it is misleading to compare classification and segmentation accuracies. The former normally refers to the percentage of correctly classified texture samples or regions, while the latter may refer to the number of correctly identified pixels. The features can be calculated along different directions[14]. Texture features correspond to eleven measurements and their calculation formula are shown below [4]:

TEXTURE FEATURES

Nr.	Name	Formula
T1	Angular 2nd moment	$\sum_{i=1}^{N_x}\sum_{j=1}^{N_x}[p(i,j)]^2$
T2	Contrast	$\sum_{n=0}^{N_x-1} n^2 \sum_{i=1}^{N_x}\sum_{j=1,\ \lvert i-j\rvert=n}^{N_x} p(i,j)$
T3	Correlation	$\frac{1}{\alpha x \alpha y}\sum_{i=1}^{N_x}\sum_{j=1}^{N_x}(ij \,.\, p(i,j) - \mu_x\mu_y)^2$
T4	Sum of squares	$\sum_{i=1}^{N_x}\sum_{j=1}^{N_x}(i-j)^2 \,.\, p(i,j)$
T5	Inverse difference moment	$\sum_{i=1}^{N_x}\sum_{j=1}^{N_x}\frac{1}{1+(i-j)^2} \,.\, p(i,j)$
T6	Sum average	$\sum_{i=2}^{2N_x} i \,.\, p_{x+y}(i)$

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T7	Sum variance	$-\sum_{i=2}^{2N_x} p_{x+y}(i) \log[p_{x+y}(i)]$
T8	Sum entropy	$-\sum_{i=2}^{2N_x} (i - T_7)\, p_{x+y}(i)$
T9	Entropy	$-\sum_{i=1}^{N_x} \sum_{j=1}^{N_x} p(i, j) \log p(i, j)$
T10	Difference variance	$\mathrm{var}\,(p_{x+y})$
T11	Difference entropy	$-\sum_{i=0}^{N_x-1} p_{x-y}(i) \log p_{x-y}(i)$

VI. WAVELET FEATURE

Wavelets are mathematical functions that divide data into different frequency components. The study of each component with a resolution matched to its scale [8]. The basic idea behind wavelets to analyze according to scale[8]. Wavelets are functions that satisfy certain mathematical requirements. Wavelets are used for representing data or other functions. The wavelet analysis procedure is to adopt a wavelet prototype function called an Analyzing wavelet or mother wavelet[8].

Wavelet is a powerful tool, which has rich mathematical contents and great application. Wavelet can be employed in lots of fields and applications. Wavelets examples such as, signal processing, image analysis, communication system, time frequency analysis, image compression, etc. Pattern recognitions an important technique. Example, such as recognize systems or security system.

Wavelet transforms are a mathematical means for performing signal analysis when signal frequency varies over time. For certain classes of signals and images, wavelet analysis provides more precise information about signal data than other signal analysis techniques.Wavelet Transform is classified into Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), and Fast Wavelet Transform (FWT).Generally, the wavelet transform can be expressed by the following equation [7]:

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\, \psi^*_{(a,b)}(x)\, \mathrm{d}x$$

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where the * is the complex conjugate symbol and function ψ is some function. This function can be chosen arbitrarily provided that obeys certain rules. The texture features are extracted using DWT at different level and co-occurrence matrix of whole image and first level of DWT decomposition.

VII. WAVELET STATISTICAL FEATURES (WSF)

The Wavelet transform provides a multi-resolution approach. It decomposes a signal with a family of basic functions obtain through translation and dilation of a mother wavelet. Based on the available wavelet coefficients, Energy (1) and standard deviation (2) of all the sub-bands up to fifth level of decomposition are calculated as features by using the equation[9]

$$E_k = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} |x_k(i,j)| \qquad (1)$$

$$\sigma_k = \left[\frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} (x_k(i,j) - \mu_k(i,j))^2 \right]^{\frac{1}{2}} \qquad (2)$$

,

where E_k is the energy & σ_k is the standard deviation for the k-th sub-band of dimension NxN and coefficients are $x_k(i\ j)$ & mean value is $\mu_k(i\ j)$. Above features are computed and stored in the data base feature vector as Wavelet Statistical Features (WSF). This feature is used at the time of classification stage.

VIII. WAVELET CO-OCCURRENCE FEATURES (WCF)

The Co-occurrence matrix features are obtained from whole sample image. One level DWT decomposed sub-bands coefficients of sample image. Co-occurrence matrix is derived for distance vector d (i, j). From the Co-occurrence matrix the co-occurrence parameters namely contrast, inverse difference moment, energy, norm entropy, local homogeneity, cluster shade, cluster prominence, & maximum probability[9].

$$Inverse\ difference\ moment = \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{Co(i,j)}{|i-j|^2}, \quad i \neq j$$

$$contrast = \sum_{i=1}^{N} \sum_{j=1}^{N} (i-j)^2\, Co\,(i,j)$$

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$$energy = \sum_{i=1}^{N} \sum_{j=1}^{N} Co^2\,(i,j)$$

$$norm\ entropy = \frac{\sum_{i,j=1}^{N} |Co(i,j)|^{1.5}}{N}$$

$$local\ homogeneity = \sum_{i,j=1}^{N} \frac{1}{1+(i-j)^2} Co(i,j)$$

$$cluster\ shade = \sum_{i,j=1}^{N} (i - Px + j - Py)^3 Co(i,j)$$

$$cluster\ prominence = \sum_{i,j}^{N} (i - Px + j - Py)^4 Co(i,j)$$

$$maximum\ probability \quad Max[Co(i,j)]$$

$$Px = \sum_{i,j=1}^{N} i\,Co(i,j) \quad and \quad Py = \sum_{i,j=1}^{N} j\,Co(i,j)$$

Co (i, j) is the (i, j) the element of the co-occurrence matrix. These parameters are also stored in database feature vector as Wavelet Co-occurrence Features (WCF).

IX. HYBRID FEATURE

The combination of supervised and unsupervised classification is called *hybrid classification* [10]. In texture classification different feature extraction methods are used to extract features from images/scene. Extracted features are trained and tested[16]. The comparative results are proving efficiency of the proposed hybrid feature extraction method. In hybrid feature method, selecting distinguishing features from a set of features and eliminating the irrelevant ones. This results in lower test error, reduces the processing time and can produce better accuracy [18]. For Example, formulas are extracted from various extraction methods given below:

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HYBRID FEATURES

Homogeneity	$\sum_i \sum_j \frac{P_d(i,j)}{1+\lvert i-j\rvert}$
Skewness	$skew \equiv \frac{1}{N}\sum_{i=1}^{N}\left[\frac{x_i-\bar{x}}{\sigma}\right]^3$
Energy	$energy = \sum_i \sum_j P_d^2(i,j)$
Correlation	$r = \frac{\sum(Z_X Z_Y)}{N}$
Aspect ratio	L/e
Angular 2nd moment	$\sum_{i=1}^{N_x}\sum_{j=1}^{N_x}[p(i,j)]^2$
Difference entropy	$-\sum_{i=0}^{N_x-1} p_{x-y}(i)\log p_{x-y}(i)$

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X. CONCLUSION

In this paper, the different feature extraction methods are analyzed for texture classification. We have described about statistical features, geometric features, wavelet features and hybrid features which seem to have general applicability for different kinds of image data. In the recent research, Statistical method, hybrids method and wavelet transform are most popularly used due to their promising accuracy result. Other feature extraction methods are also available for texture classification. But in the current year, that are not popular. Some methods are , Model –Based Stochastic method, Basic Image Feature, and Multiscale Blob Feature(MBF) [3].

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