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Modified Local Binary Pattern for Color Texture Analysis and Classification

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***Abstract*-Texture Analysis is an important process in image analysis and processing. In the recent years, many techniques have been developed for identification and representation of textures. In general, they are classified into Statistical, Geometrical, Model based and Signal processing methods. The aim of this work is to study and design Texture Analysis scheme for color images and to present an overview of statistic methods for color images. Color is the most visually available feature of an image. In this work, Architecture for statistical technique is proposed to analyze the Texture of color images. In order to carry out the texture analysis scheme, co-occurrence statistical technique is deployed. It gives the information about pixels of color image. Further, to ensure the reliability, and to analyze the correlation between color bands of different colors using the features of co-occurrence matrix and color space conversion technique is proposed. The histogram statistics and Modified Local Binary Pattern (LBP) are used to find the color texture and its features. These analyzed texture features are used as input for texture classification, then classifies the texture effectively based on statistical texture features. From the experiments, it is proved that the proposed technique successfully analyzed the texture in color images. Further, to ensure the reliability the texture images are classified by Bayesian classifier based on extracted texture features. From the experimental results, it is evident that the proposed technique successfully analyses the texture in color images and classification accuracy is high.**

Keywords – Texture Analysis, co-occurrence, Statistical Technique, Color, Texture classification.

I. INTRODUCTION

Texture is one of the important characteristics used in identifying objects or region of interest in an image. Texture can be evaluated as being fine, coarse, or smooth, rippled, irregular, or lineated. It is an innate property of virtually all surfaces the grain of wood, the weave of a fabric, the pattern of crops in field, etc [1]. In computer vision literature there are many different definitions of texture. Texture was composed of randomly placed, short, oriented line segments [2]. Texture can be defined as local statistical pattern of texture primitives in observer's domain of interest [3]. Its structure is simply attributed to the repetitive pattern in which elements or primitives are arranged according to a placement rule [4]. An image texture is described by the number and types of its primitives and the spatial organization or layout of its primitives [5].

Texture analysis methods have been traditionally divided into two categories. The first one, called the statistical approach, treats textures as statistical phenomena. The formation of a texture is described with the statistical properties of the intensities and positions of pixel, auto correlation function, optical transforms, digital transforms, textural edge, structural elements, gray level co-occurrence, run lengths, and auto regressive model [6].

The second category, called the structural approach introduces the concept of texture primitives, often called texels or textons. To describe a texture, a vocabulary of texels and a description of their relationships are needed. The goal is to describe complex structures with simpler primitives, for example via graphs. Structural texture models work well with macro textures with clear constructions [6]. Textures can be described structurally, in terms of the individual textural elements and their spatial relationships [7]. In the texture analysis the taxonomy of texture models are following Statistical method, Geometrical method, Model based method, Signal processing method.

II. RELATED WORK

Several problems are identified in the related works. It can be classified into four Categories as shown below.

A. *Statistical Method*

Statistical method is the most traditional way to analyze the spatial distribution of gray levels of an image. The value of single pixel is first order statistics, value of pair pixel is second order statistics, higher order statistics [8]. The co-occurrence matrix, auto correlation features, power spectrum, histograms are the statistical techniques. In statistical approaches, the textures are described by statistical measures. One commonly applied and reference method is co-occurrence method, introduced by Haralick.

In the co-occurrence method, the relative frequencies of gray level pairs of pixels at certain relative displacements are computed and stored in matrix [9]. Gray level co-occurrence matrices (GLCMs) are used to represent the pair wise joint statistics of pixels of an image. A histogram is the distribution of the number of pixels for an

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image. It is based on spatial or frequency representation [10, 11], 12]. The Local Binary Pattern (LBP) approach is based on the assumption that the local differences of the central pixel and its neighbors are independent of central pixel itself [13, 14].

B. Model Based Method

Model based methods rely on the construction of image models that can be used to describe and synthesis texture. The Random field model and fractal model are the techniques to analyze the texture [4]. The Marko Random Field (MRF) [15] and Gibbs Random Field (GRF) [16] are having ability to capture spatial information of image. In the Fractal model [17], it is used to describe the irregular and fragmented pattern of image that appears in nature.

C. Geometrical Method

Geometrical methods analyze texture by texture elements or primitives. This analysis is made considering the geometrical properties of the primitives like size, shape, area and length. This kind of analysis becomes difficult for natural textures, because primitives and placement rule can be irregular [5, 18].

D. Signal Processing Method

Signal processing methods characterize textures by applying filters over the image. Spatial and frequency domain filters are used in this method [4]. Spatial domain filter: The most direct way to capture image texture properties. Frequency domain filter: Decomposing the image into its frequency and orientation components. Fourier domain filter, Gabor and Wavelet filters are used in frequency domain [9, 19].

III. MODIFIED LOCAL BINARY PATTERN

The LBP operator is a shift invariant complementary measure for local image contrast. It uses the gray level of the center pixel of a sliding window as a threshold for surrounding neighborhood pixels. Its value is given as a weighted sum of thresholded neighboring pixels. Usually, a simple local contrast measurement is calculated as a complement to the LBP value in order to characterize local spatial relationships together called LBP/C. Two-dimensional distributions of the LBP and local contrast measures are used as texture features. The LBP operator is relatively invariant with respect to changes in illumination and image rotation (for example, compared to co-occurrence matrices), and computationally simple. Followings are the steps involved to extract the texture features from the color image. For each pixel in the original image, get its RGB values then these steps performed for each Color channel.

Step1: Divide the image into (3*3) blocks.

Step2: Apply MLBP_C (Contrast) and MLBP_M (Magnitude) on every block.

Step3: Compute the histograms for both MLBP_C and MLBP_M.

Step4: Find the maximum occurring pattern from MLBP_C.

Step5: Find standard deviation and variance from the histograms.

Step6: Multiply maximum occurring pattern and variance to form the feature of the image.

Step7: Input the feature into Bayesian classifier for texture classification.

In MLBP_M, we are calculating the pattern by analyzing the original pixel value, rather than comparing the pixel value with the other. Thus now we have two patterns for the image, one by comparing with the center pixel and the other by analyzing the original pixel value.

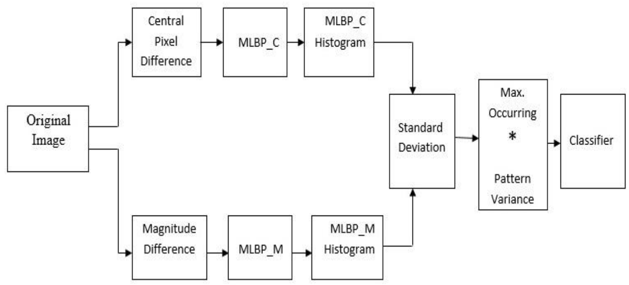


Fig.1 MLBP System Architecture

Histograms are now built separately for both MLBP_C and MLBP_M. A histogram is the distribution of the number of pixels for an image. The number of elements in a histogram depends on the number of bits in each pixel in an image. For example, if we suppose a pixel depth of n bit, the pixel values will be between 0 and 2^n-1, and the histogram will have 2^n elements. Histogram statistics features, such as range, mean, geometric mean, harmonic mean, standard deviation, variance, and median can be computed and used for classification. Histogram comparison statistics, such as Divergence, Histogram intersection, Chi-square, and Normalized correlation coefficient, can also be used as texture features. Despite the simplicity, Histogram techniques are used as low level approach in various applications. These characteristics make them ideal for use in application to tonality discrimination. The accuracy of histogram based methods can be enhanced by using statistics from local image regions. Simple histogram moments, such as mean and standard deviation, from sub blocks were used for defect classification.

From the two histograms computed, the mean and standard deviation of both are calculated using the following formula,

$$\bar{\chi} = \frac{\sum_{i=0}^{255} i * h[i]}{\text{Number of Pixels}} \quad (1)$$

$$\bar{\delta} = \sqrt{\frac{1}{\text{Number of Pixels}} \sum_{i=0}^{255} h[i] * (i - \bar{\chi})^2} \quad (2)$$

Where h is the histogram of the image, $\bar{\chi}$ is mean and $\bar{\delta}$ is standard deviation of the histogram h.

The structural models of texture assume that textures are composed of texture primitives. The texture is produced by the placement of these primitives according to certain placement rules. This class of algorithms, in general, is limited in power unless one is dealing with very regular textures. It can also be stated that if we can find the texture primitive we can assess the image quite easily. From MLBP_C, the maximum occurring pattern of the image is found out. Now the feature vector of the image is formed by taking maximum occurring pattern and multiplying the maximum occurring pattern with variance (square of standard deviation). Thus we have the feature to represent the image.

IV. TEXTURE CLASSIFICATION

Classification refers to as assigning a physical object or incident into one of a set of predefined categories. In texture classification the goal is to assign an unknown sample image to one of a set of known texture classes. Texture classification is one of the four problem domains in the field of texture analysis. Texture classification is basically the problem of classifying pixels in an image according to their textural cues. This is different from conventional image segmentation as the texture is characterized using both the gray value for a given pixel and the gray-level pattern in the neighborhood surrounding the pixel. Crucial to the success of texture classification are: the identification of features that differentiate textures in an image and developing their representations for further classification and the construction of classification paradigms that operate on the above representations and discriminate between texture features associated with different texture classes [20].

In order to classify the texture images, Bayesian Classifier is used. It gives good reports both categorical and continuous values. The feature vector of the image is formed by taking maximum occurring pattern and multiplying the maximum occurring pattern with variance (square of standard deviation).

(a)

(b)

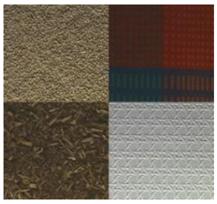
(c)

(d)

Fig.2 Sample Color Single Texture images (a) Barley rice (b) Canvas (c) Chips (d) Wallpaper

Thus we have the feature to represent the image. The feature vector which is extracted from texture analysis phase and used as input for texture classification process. The Fig.2 shows the Sample Color single texture images. The Fig.3 shows the Sample Color multiple texture images.

(a)



(b)

Fig.3 Sample Color Multi Texture images (a) BWWB (b) BCCW

A. *Bayesian Classification*

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The Bayesian Classifier is,

$$p(h \mid d) = \frac{P(d \mid h)P(h)}{P(d)} \tag{3}$$

Let x_1, x_2… x_n be the values of a numerical attribute in the training data set. The mean (μ), standard deviation (σ) are show shown below, where p (h|d) =f (w).

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

$$\sigma = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2 \tag{5}$$

$$f(w) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(w-\mu)^2}{2\sigma^2}} \tag{6}$$

V. EXPERIMENTS AND RESULTS

In this section, the experimental results of Color texture classification are discussed. The input samples are taken from OUTEX texture database. The input images are the size of (256 X 256).In this work we consider four texture classes like Barley rice, Canvas, Chips, Wallpaper from OUTEX texture database are considered. Classification between these four texture classes was done successfully in this experiments. The four texture class images are trained then perform the classification using test images. . In the MLBP F= [Max.Occure pattern* Standard Deviation] is extracted from texture analysis phase in the MLBP and used as input for texture classification process. The result of single texture test images in MLBP are shown in Table 1 and Table 2 shows the result of Multi texture test images in MLBP.

Image Name	Classification Result
Barleyrice008	Classified
Barleyrice010	Classified
Canvas017	Classified
Canvas019	Classified
Canvas036	Classified
Chips008	Miss Classified
Chips012	Classified
Chips016	Classified
Wallpaper004	Classified
Wallpaper009	Classified
Wallpaper012	Classified
Wallpaper015	Classified

Table 2 Result of single texture test images in MLBP

Image Name	Classification Result
BCCW.jpg	Classified
CBCW.jpg	Classified
CCBW.jpg	Classified
CCWB.jpg	Classified
BCCW2.jpg	Classified
BWWB.jpg	Classified

Table 2 Result of multi texture test images in MLBP

VI. CONCLUSION

Statistical features for color texture classification was analyzed and found that OUTEX data provides excellent result which is obtained by the Modified Local Binary Pattern. The success rate of statistical feature was compared and also provides a comparative study of various texture analysis scheme in this work. In future statistical feature will analyze for various color space with other texture databases using many other classification methods.

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