Color Texture Classification Using Local Feature Extraction

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Abstract— **This Paper proposes a new approach to extract the features of a color texture image for the purpose of color texture classification by using local feature set. LBP, Gabor & DWT these three methods are used for local features extraction. The DWT decomposition of an image is applied up to three levels to reach some finest details of texture & co-occurrence matrix of that each sub band is measured as feature set. Gabor wavelet is also a better feature set preferred over dyadic wavelets as it conserves maximal information in feature space & mean of Gabor filter with deferent scale & orientation is used as a feature set. LBP is one of the efficient feature sets used in computer vision, which classifies the texture efficiently. The LBP operator is an image operator which transforms an image into an array or image of integer labels describing small-scale appearance of the image & histogram of LBP image, are then used as a texture feature set. The texture classification process is carried out with KNN classifier. The experimental results on the CUReT database shows that the classification rate of LBP is higher as compared with other methods.**

Keywords— **LBP, Gabor Wavelet, DWT, KNN c1assifier**

I. Introduction

Textures are characteristic intensity (or color) variations that typically originate from roughness of object surfaces. For a well-defined texture, intensity variations will normally exhibit both regularity and randomness, and for this reason texture analysis requires careful design of statistical measures. While there are certain quite commonly used approaches to texture analysis, much depends on the actual intensity variations, and methods are still being developed for ever more accurately modelling, classifying and segmenting textures. Texture is defined as spatially homogenous and has repeated visual patterns. Classification of color texture image is a challenging task in image processing and pattern recognition. Over the years numerous methods have been proposed for the classification of color image textures. Texture classification methods are broadly divided into four categories, namely statistical methods, model based methods, structural methods and filter based methods [1].The work based on the analysis of statistical properties of the color texture which deals with the spatial distribution of intensity values. Some statistical methods used are co-occurrence matrix, histogram [2], [3], [4].

In geometrical methods, textures are considered to be composed of primitives and are extracted and analysed [5]. The signal processing techniques are mainly based on texture filtering for analysing the frequency contents in spatial or frequency domain [6]. Filter bank instead of a single filter has been proposed giving rise to several multichannel texture analysis systems such as Gabor filters and wavelet transforms [7], [8]. Wavelet based methods for texture c1assification is divided into two categories. They are feature based and model based methods. In this case image is decomposed using wavelet transforms and features like entropy, energy and standard deviation are extracted from the decomposed sub bands [9]. In addition to these statistical features, co-occurrence features are extracted from the wavelet decomposed sub-bands in order to increase the rate of classification [10].

II. Local Binary Pattern(LBP)

The LBP is one of the efficient feature sets used in computer vision, which classifies the texture efficiently. 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. Initially it was developed for monochrome images and later it has been extended for color images. In this paper the method used [11] as followed. Initially the RGB color texture image was converted into HSV. LBP operator was applied individually on each component and then the histogram response of each component concatenated and this histogram response act as a feature vector for texture classification process.

The original version of the local binary pattern operator works in a 3×3 pixel block of an image. The neighbor pixels in this block are threshold by its center pixel value multiplied by powers of two and then summed to obtain a label for the center pixel. As the neighborhood consists of eight pixels, total 2^8 = 256 different labels can be obtained depending on the relative gray values of the center and the pixels in the neighborhood. The usual formula for LBP is given by

$$LBP_{p,r} = min_{0\leq n<p}\left\{\sum_{p=0}^{p-1} s(g_c - g_p)2^{[(p+n)\ mod\ P]}\right\}$$

Where, g_c is the gray value of the central pixel, g_p is the gray value of its neighboring pixel, p=0,…., P-1, P is the total number of neighbors, and r be the radius of the neighborhood which determines how distant the neighboring pixels are placed away from the center pixel. F is a step function given by,

$$F = \begin{Bmatrix} 1, & f \geq 0 \\ 0, & f < 0 \end{Bmatrix}$$

In this paper we also classify the images with different radius(r).

III. Gabor Wavelet Transform

To Gabor wavelet [7] is also a better feature set preferred over dyadic wavelets as it conserves maximal information in feature space. The two dimensional Gabor function $g(x,y)$ is expressed as

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right) exp\left(\frac{-1}{2}\left(\frac{x^2}{\sigma_u^2} + \frac{y^2}{{\sigma_v}^2}\right) + 2\pi j w_x\right)$$

Where $\sigma_u = \frac{1}{2\pi\sigma_x}$ and $\sigma_v = \frac{1}{2\pi\sigma_y}$

Gabor functions form a complete but non orthogonal basis set. Expanding a signal using this basis provides a localized frequency description. A class of self-similar Gabor functions is referred to as Gabor wavelets. Here we have developed 24 filters with 4 scales & 6 orientations as shown in figure 1. These each filter convolves with HSV component of the texture image separately & mean of each convolved filter is used as a feature set for classification.

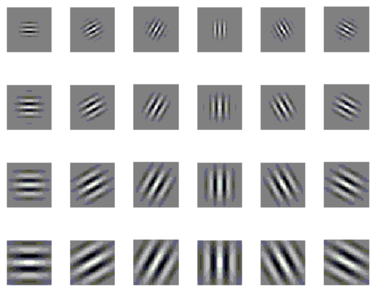

Fig.1Gabor filters with 4 scales & 6 orientations

IV. Discrete Wavelet Transform

Another form of representing a signal is called as transform of a signal [12]. The wavelet transform provides time frequency representation of the signal wave is an oscillating function of time or space and is periodic whereas wavelets are localized waves. The information content present in the signal does not get changed. In this paper discrete wavelet transform is applied on the HSV plane of color texture images separately and the level of decomposition was extended up to three sub-bands to reach some finest scale and from each sub-band, co-occurrence matrix are used as a feature vector for further texture classification process.

V. K-nn Classifier

K nearest neighbours is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions). KNN has been used in statistical estimation and pattern recognition already in the beginning of 1970's as a non-parametric technique. We utilize the K-nearest-neighbor (K-NN) with K=1 as the default classifier due to its simplicity, effectiveness, and suitability for the adopted fusion method. Therefore, a certain input texture image will be assigned to the class corresponding to the nearest (most similar) training model

VI. Experimental Results And Discussions

Experiments are carried out with fifty color texture classes of CUReT database. The size of the texture images in each class is 128×128.The samples of fifty texture classes are shown in Figure 3. From each class randomly selected twenty five color texture images are trained. Texture classification is done with thirty color texture images other than trained images per class.

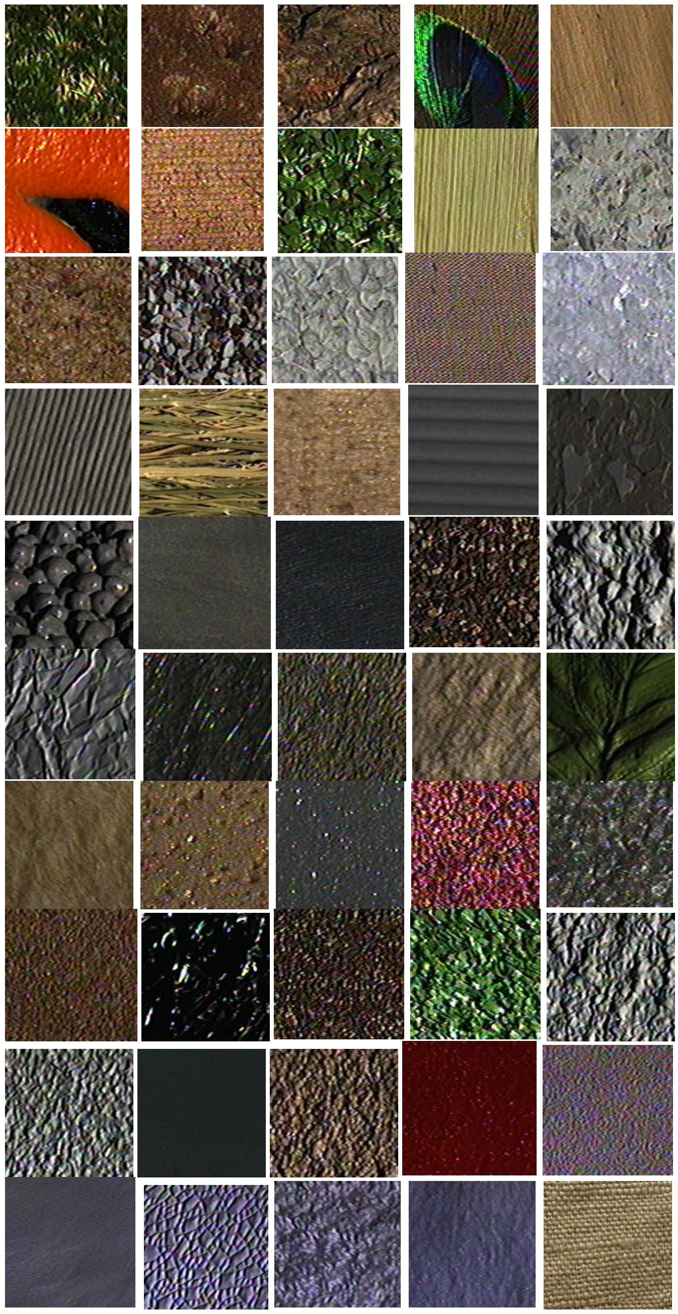

Fig.2 Fifty Color Texture Samples of CUReT Database

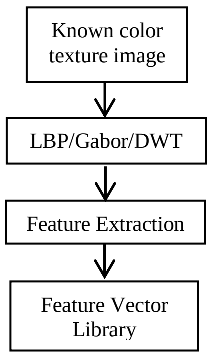

Fig.3 Texture Training Phase

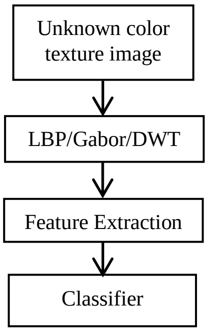

Fig.4 Texture Testing Phase

A) Texture Training Phase.

During the training phase any random twenty five images from each class of CUReT texture album is taken. The size of each texture image is 128×128. Then Gabor wavelet transform, LBP with different radius and DWT are applied individually and features like mean, histogram & co-occurrence matrix are extracted respectively and stored in the feature vector library. The steps in training phase are given in Figure 2.

B) Texture Testing Phase.

In the testing phase thirty color textures per class of CUReT texture album other than training database is considered. The size of the each texture image is 128×128. The procedure followed in training phase is shown in figure3. Then the extracted features are given to the KNN classifier which efficiently classifies the texture. The success of the texture classification is measured by the formula given in equation (1).

$$\text{Classification Accuracy} = (M/N) \times 100 \qquad (1)$$

Where, M – Number of images correctly classified
N – Total number of images used for classification

The steps in testing phase are shown in Figure 3. The results of texture classification for individual feature sets are listed in the TABLE-I.

TABLE I

RESULTS OF TEXTURE CLASSIFICATION

Sr. No.	Feature Sets	Success Rate
1	Gabor wavelet	92.60%
2	LBP(8, 1)	94.10%
3	LBP(16, 2)	96.33%
4	LBP(32, 3)	95.67%
5	DWT	90.67%

VII. CONCLUSION

From the experimental analysis, it is inferred that LBP produces higher c1assification rate as compared with that other feature sets. The mean success rate achieved by using LBP feature is 96.33% and by using the Gabor and DWT features is 92.60% & 90.67% respectively. The above experimental results are obtained by performing the analysis on CUReT database using KNN c1assifier. Further, the work can be extended by introducing Global feature set & combining this local & global feature we can enhance the c1assification performance better than the above.

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