COLOR TEXTURE CLASSIFICATION USING LOCAL & GLOBAL METHOD 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 texture classification by using global and local feature set. Four feature sets are involved. Dominant Neighbourhood Structure (DNS) is the new feature set that has been used for color texture image classification. In this feature a global map is generated which represents measured intensity similarity between a given image pixel and its surrounding neighbours within a certain window. Addition to the above generated feature set, features obtained from DWT, LBP or Gabor are added together with DNS to obtain an efficient texture classification. Also the proposed feature sets are compared with that of Gabor wavelet, LBP and DWT. The texture classification process is carried out with the KNN classifier. The experimental results on the CUReT database shows that the classification rate of DNS gets improved by combining Local & Global features

Keywords **--DNS, DWT, Gabor,KNN C1assifier, LBP**

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-

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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

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

Where, is the gray value of the central pixel, is the gray value of its neighboring pixel, *p*=0… *P*-1, *P* is the total number of neighbors, and *r* is 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,

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

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 $g(x,$ 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 $\sigma_u = \frac{}{2\pi}$ and $\sigma_v = \frac{}{2\pi}$

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 Fig 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.

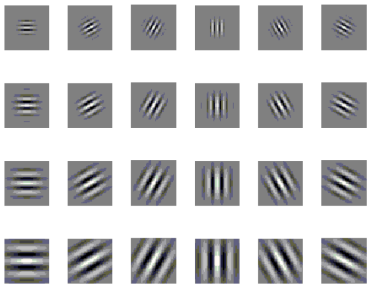

Fig.1Gabor filters with 4 scales & 6 orientations

IV. DISCRETE WAVELET TRANSFORM

Anotherform 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. DOMINANT NEIGHBORHOOD STRUCTURE

The proposed new feature extraction method is based on exploiting the high redundancy that exists in texture images in general and inhomogeneous texture images with repetitive patterns specifically. Naturally, the available high redundancy implies high-intensity similarity between various pixels. In addition, if one considers the intensity similarity of a given image pixel to its surrounding pixels within a certain local image neighborhood called search window, then the high texture redundancy implies that the pixel neighborhood similarity will be the same for most, if not all, image pixels. In order to compute the intensity similarity between a given image pixel and any of its neighboring pixels within the square search window, we apply the distance metric used in [13], which was also applied for image de-noising. The similarity between any two given image pixels i and j is computed using the Euclidean distance between two square local neighborhoods N_i and N_j centered on pixels i and j of predefined size r × r and is given by

$$d^2(i,j)= \|v(N_i)–v(N_j)\|^2 \qquad (1)$$

Where i is the pixel under examination located at the center of the search window $S_i$and j denotes all other pixels neighboring pixel i within its search window. The finding the Euclidean distance between the neighborhood intensities instead of individual pixel values, results in efficient texture classification. Thus applying this DNS feature set on CUReT database results in higher classification accuracy

DNS Map

Based on the redundancy in texture image neighborhoods,feature vectors for such images were extracted from theirrepresentative neighborhood structure map. The image representativeneighborhood structure map is built by the followingsimple procedure. First, the similarity between all pixels enclosedin the search window $S_i$and a selected image pixeli which is located at the center of the search window is computed using equation (1). Theadopted optimal sizefor both the search window and the neighborhood is 21 × 21 and13 × 13, respectively.

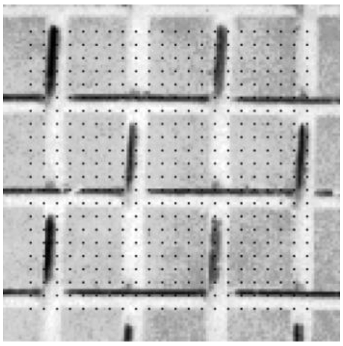

Fig.2. Illustration ofpixelpositions usedtocompute theDNSmapfora texturesampleof size128×128

To determine an optimal value of the spacing interval and hence the size of the necessary subset of image pixels, a range of intervals were selected and the resulting texture features extracted from obtained representative neighborhood structure map were used in classification experiments on CUReT textures. The tests were applied on color texture image samples of size 128 × 128. The minimum skip interval adequate to capture distinctive global texture characteristics was observed to be five pixels. Therefore, neighborhood structure maps are computed at intervals of five pixels horizontally and vertically. This is demonstrated in Fig. 2, where the positions of the selected pixels for computing the neighborhood structure maps are superimposed on the texture image.In case of a texture image ofsize 128×128 and a search window of size 21×21, the totalnumber of pixels is 484. This implies that 484 neighborhood structure maps will be computed & the standard deviation of respective search window is used as a feature vector.

The RGB texture image is initially converted into HSV components and in each component DNS feature set is applied and finally the results are concatenated for further classification.

VI. 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 suitabilityfortheadoptedfusionmethod.Therefore,acertaininput texture image will be assigned to the class corresponding to the nearest (most similar) training model

VII. 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 Fig.3from each class randomly selected twenty five color texture images are used for training of classifier. Texture classification is done with thirty color texture images other than trained images per class.

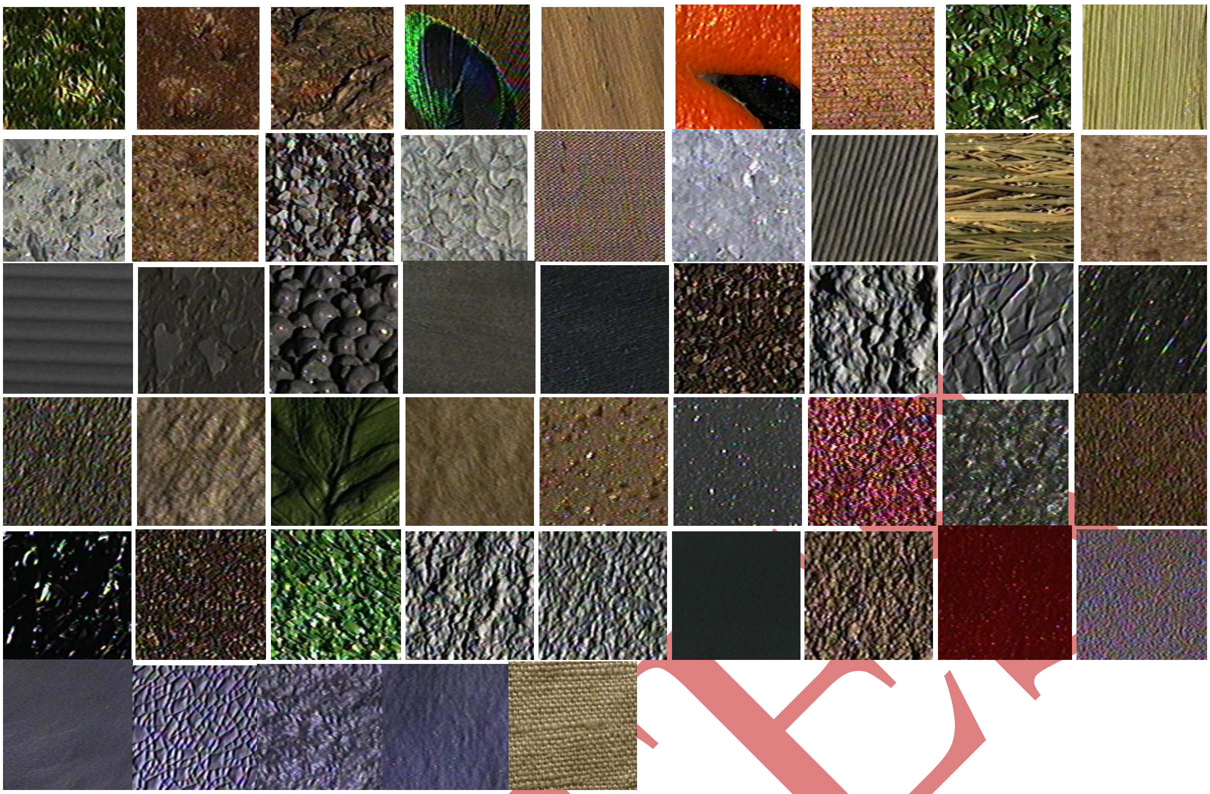

Fig.3 Fifty Color Texture Samples of CUReT Database

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, DWT and DNS are applied individually and features like mean, histogram, co-occurrence matrix and standard deviation are extracted respectively and stored in the feature vector library. The steps in training phase are given in Fig. 4.

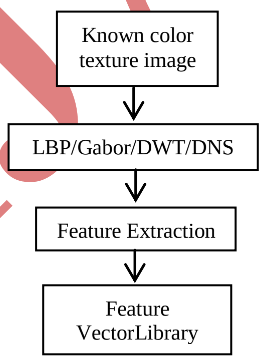

Fig.4 Texture Training Phase

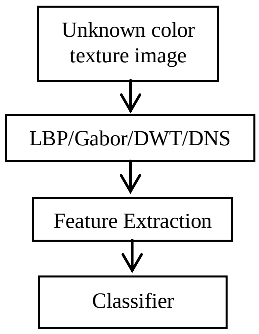

Fig.5 Texture Testing Phase

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 testing phase is shown in Fig.5. 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 (2).

Classification Accuracy= (M/N) × 100 (2)

Where, M – Number of images correctly classified

N – Total number of images used for classification

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%
6	DWT+Gabor+LBP	93.33%
7	DNS	50.60%
8	DNS+DWT+LBP	89.40%
9	DNS+Gabor+LBP	92.06%

VIII. CONCLUSION

From the experimental analysis, it is inferred that LBP produces higher classification rate as compared with that other feature sets. The 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 success rate of DNS is very low; this can be improved by adding local & global features. The above experimental results are obtained by performing the analysis on CUReT database using KNN classifier.

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