Abstract— Content based image retrieval is a challenging issue in management of existing large digital image libraries and databases. The accuracy of image retrieval methods is subject to effective extraction of image features such as color, texture, and shape. In this paper we propose a new image retrieval method using contourlet transform coefficients. We use the properties of contourlet coefficients to assign the normal distribution function to the distribution of coefficients in each sub-band. The assigned normal distribution functions are used to extract the texture feature vector at the next stage. Simulation results indicate that the proposed method outperforms other conventional texture image retrieval methods such as, Gabor filter and wavelet transform. Moreover, this method shows a noticeable higher performance compared to another contourlet based method.

I. INTRODUCTION

Digital image libraries and databases have been expanding in recent years due to wide spread use of digital images in various applications such as remote sensing, medical imaging and multimedia systems. Hence, management of these databases that are usually large in contents is a challenging issue. Content Based Image Retrieval (CBIR) is introduced for effective search and access to the huge amount of available data in image libraries. In CBIR the visual information of the image is used for indexing and retrieval of visual contents. Texture is among the typical visual features that are used for image indexing in CBIR.

There are various methods in the literature to extract texture features of digital images based on different transforms or filtering techniques, which achieved considerable outcomes. In [1] and [2], the texture feature of an image is extracted from sub-bands of image wavelet transform. The texture feature vectors obtained by these two methods represent sub-bands’ energy of an image. The wavelet transform based image retrieval methods use the mean and variance of the sub-bands’ coefficients as an indication of the energy of sub-bands. The proposed method in [3] uses the mean and variance of the coefficients of each sub-band to estimate a generalized Gaussian density function to represent the distribution of the coefficients in each sub-band of the wavelet transform and consequently creates a texture feature vector based on the assigned coefficient density functions. The texture feature vector in [4], also, is produced based on the mean and standard deviation of the wavelet transform sub-bands’ coefficients. The main principles of Gabor filter and its application to extract the texture features of images are discussed in [5]. Gabor filter can be applied through different scales and orientations to an image and the filtering results in a set of scales and orientations that can be used as a texture feature vector. For instance, in [6] the means and standard deviations of Gabor filter coefficients of an image are used to produce a texture feature vector.

The contourlet transform is a 2-D image transform, which is recently proposed for multi-directional and multi-resolution analysis of digital images [7]. This method overcomes the weaknesses of conventional wavelets to obtain smooth contours of images with low computational complexity [7]. Therefore it can be very suitable for texture description applications. Hence, new feature vectors have been introduced in literature based on contourlet transform. For example, in [8] a texture retrieval method is introduced using the spectral histogram of the contourlet transform coefficients as the texture feature vector. The proposed method in [9] simply applies the mean and standard deviation of each sub-band to create a feature vector and uses the Euclidean distance to find the similarity of images based on this feature vector.

The sub-band coefficients in contourlet transform of an image have a symmetric and near to unimodal distribution with a mean and skewness about zero, though they have not exactly Gaussian distribution [10]. This means, even though the distribution of contourlet coefficients in each sub-band is not an exact Gaussian distribution, they have special characteristics, which make them suitable for modeling by Gaussian distribution. This property of contourlet transform can be used for image texture description. Therefore, in this paper we propose an efficient texture retrieval method in which we assign a simple normal distribution function to each sub-band. By this means we employ the aforementioned properties of contourlet coefficients efficiently, for representing the texture of an image. The proposed method remarkably outperforms other traditional texture retrieval methods such as Gabor filter and wavelet transform methods. Besides, the simulation results indicate that using the normal distribution function to extract texture of images is more effective than another contourlet based texture retrieval method.

The rest of this paper is organized as follows. In section II we provide a brief overview of the contourlet transform. The proposed retrieval method is explained in section III. In section IV simulation results are presented. Finally the paper concludes in section V.

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Texture Image Retrieval Using Contourlet Transform

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The contourlet transform is a technique recently developed for image representation and analysis. This transform has multi-resolution and frequency localization properties of the conventional wavelets, and also shows a very precise directionality. The contourlet consists of two different filter banks. The Laplacian pyramid (LP), which is used in contourlet transform to decompose an image to different multi-scales and a directional filter bank (DFB), which applies to reveal the directional details at each scale level.

The LP decomposition at each scale level generates a downsampled low-pass version of the original image and the difference between the original and the prediction, resulting in band-pass image. One level of this decomposition process is demonstrated in Fig. 1. The process can be iterated on the low-pass signal to generate different scales. The generated sub-bands from multi-scale decomposition stage (LP) are followed by a DFB to reveal the directional details (Fig. 2). The DFB is implemented via an \( l \)-level binary tree decomposition that leads to \( 2^l \) sub-bands with wedge-shaped frequency partitioning.

Due to cascading LP and DFB structures, the multi-scale and directional decompositions are independent of each other. Hence, one can decompose each scale into any arbitrary power of two numbers in orientations and different scales can be divided into different number of orientations. Fig. 3 illustrates a typical frequency division of the contourlet transform in which the four scales are divided into four, four, eight and eight directional sub-bands. Fig. 4 shows “Lena” image and its corresponding contourlet decomposition. In this decomposition the original image is divided into four detail scales and each scale is partitioned into directional sub-bands based on the scales and orientations shown in Fig. 3.

III. THE PROPOSED METHOD

The coefficients in the produced sub-bands of contourlet transformed image are very appropriate to obtain the texture feature due to coarse to fine and directional details of the image in these sub-bands. Besides, the distribution of the coefficients in each sub-band is symmetric and unimodal with mean and skewness of approximately near to zero that eases the modeling of their distribution. We used these prominent properties of contourlet transform of the images to introduce an image retrieval scheme. In the first step of the proposed retrieval process, the sub-bands are processed to extract the required features. Then, the extracted features of the images are used for calculating the similarity among various images. The calculated similarity values provide the necessary information for comparing images. In the following subsections these two stages of the proposed method are described in more details.

A. Texture Feature Extraction

The symmetric and unimodal distribution of contourlet coefficients can be used to represent efficiently the texture feature of digital images. Hence, we used the Gaussian density (GD) function to represent each sub-band’s coefficients. Although the distribution is not exactly Gaussian, the normal distribution function can be used as a proper representative of each sub-band since it is perfectly symmetric, unimodal and has skewness of zero. Moreover, the suitable GD function can be estimated by low complexity calculations.
\[ n(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \quad -\infty < x < \infty \]  

where \( \mu \) and \( \sigma \) are the mean and standard deviation value of all the coefficients of a sub-band, respectively.

The texture feature vector of an image can be constructed using all the GD functions of all the sub-bands. Hence, for each sub-band, the GD function is generated and all the GD functions are used as the texture feature vector of the image. As an example, for the image in Fig. 4, 24 GD functions will be obtained because the contourlet transform generated 24 sub-bands. Each GD function can be represented by only two parameters: \( \mu \) and \( \sigma \). In addition, the maximum (\( M_{xsb} \)) and minimum (\( M_{nsb} \)) values of each sub-band are required to calculate the similarity metric. Therefore, the size of the feature vector is confined to few numbers (4 values for each sub-band).

### B. Similarity Measure

Similarity metrics are used as a measure for comparing the feature vectors of the images. For each sub-band there is a GD function in the proposed feature vector. Hence, in the first step we estimate the similarity of two corresponding sub-bands. We calculate the distance of two GD functions to find their similarity using (2):

\[ D_{sb}(I,J) = \sum_{sb} \left[ n_{sb}(x_i;\mu_i,\sigma_i) - n_{sb}(x_j;\mu_j,\sigma_j) \right] \]

where \( n_{sb} \) and \( n_{sb} \) are the GD functions of corresponding sub-bands \( sb \) in the images \( I \) and \( J \), respectively. The range \([b_l, b_h]\), where \( b_l = \min (M_{nsb}, M_{nsb}) \) and \( b_h = \max (M_{xsb}, M_{xsb}) \), represents the range of coefficients values in sub-band \( sb \) at two images \( I \) and \( J \). In fact, the resulted value in (2) is the sum of difference of two probability functions \( n_{sb} \) and \( n_{sb} \) where \( x \) ranges from \(-\infty \) to \( \infty \) in the GD function. To reduce the computational complexity in (2), we used the range \([b_l, b_h]\) for both GD functions.

To get a measure of similarity for two images based on the proposed feature vector, the total summation of all the distances of sub-bands’ GD functions are calculated:

\[ D(I,J) = \sum_{sb=1}^{Nsb} D_{sb}(I,J) \]

where \( N_{sb} \) is the total number of sub-bands and \( D_{sb}(I,J) \) is the distance between sub-band \( sb \) of two images \( I \) and \( J \). Since in the proposed method we used the distance between GD functions as a measure for comparing two images, the lower value of \( D(I,J) \) indicates higher similarity for images.

### IV. EXPERIMENTAL EVALUATIONS

We used the query by example method to compare the performance of the proposed contourlet based image retrieval method using Matlab with a number of image retrieval methods. In these experiments we used VisTex [11] image database, which includes 225 color images of the size 512×512. All the images in the database were converted to gray scale format in order to deal only with texture of the images. We applied contourlet transform on all the database images. In this transform stage, we used four scales and 3, 4, 8 and 16 orientations for the scales 1 to 4 respectively. Then, the GD functions of all the sub-bands of each image in the database were calculated as the texture feature vector of each image.

In order to evaluate the performance of the proposed technique in a query by example image retrieval method, we used a sample query image set of 25 randomly selected images from the VisTex database. The distance of each image in the database with a query image was calculated using (3). Then ten images with the lowest distance from the query image were retrieved from the database. Fig. 5 shows the ranked six retrieved images for three sample query images. As expected, the first retrieved image in all cases is the query image that has a distance value of zero.

We implemented the Gabor filter texture retrieval method [5] of 13×13 mask size, with 6 orientations and 4 scales. These parameters are the optimal parameter set for the Gabor filter [12]. Hence, for each image there will be 4×6=24 output filtered images and mean (\( \mu \)) and standard deviation (\( \sigma \)) of these images made a feature vector of 48 elements. We implemented an effective texture image retrieval method based on conventional wavelet transform [2]. This method uses the tree structure wavelet transform to decompose an image into sub-bands then mean and variance of each sub-band are calculated. The mean and variance of all the sub-bands make a texture feature vector. One of the new methods which apply contourlet coefficients for CBIR purposes is the one introduced in [9]. We also implemented this method and in implementation of this method we used four scales and 3, 4, 8, 16 directions respectively [9], which are the same as the number of scales and directions for the proposed method. We applied Gabor filter, wavelet transform, and contourlet based methods, in addition to our proposed method for image retrieval on the same query set.

For each query image we also found relevant images by inspecting the whole VisTex database. There were at most ten and at least two relevant images for each image in the sample query image set. Each of the retrieved images, by the four retrieval methods marked as relevant or irrelevant using the images found in this step. The Precision (4) and Recall (5) parameters [13] were used for evaluating the performance of the retrieval methods:

\[ \text{Precision} = \frac{\text{No. of retrieved relevant images}}{\text{Total of retrieved images}} \]

\[ \text{Recall} = \frac{\text{No. of retrieved relevant images}}{\text{Total of relevant images}} \]
We used the marked relevant images, found in the previous step to calculate the Precision and Recall values of the retrieved images for each query image. In this way, we calculated the 11-point interpolated Precision-Recall graphs [13] for each query and then by averaging [13] all the graphs we get the averaged Precision-Recall graph (Fig. 6) for each of the tested retrieval methods. The averaged Precision-Recall graphs are used to compare the performance of the four image retrieval methods. The Precision-Recall graph of the proposed method is higher than the Precision-Recall graph of all the other methods; hence, the proposed method has a superior performance compared to the Gabor filter, wavelet transform, and also the contourlet based method, which uses the mean and variance value of the sub-bands as texture feature vector.

V. CONCLUSION

In this work, an efficient CBIR method based on texture of images is proposed. Since the contourlet transform decomposes an image to directional and multi-resolution detail sub-bands, we used contourlet coefficients to obtain images’ texture feature. The distribution of contourlet transform coefficients is symmetric and unimodal with skewness near to zero and the proposed method applies these properties of contourlet transform coefficients by assigning the Gaussian density function, which is symmetric, unimodal and has a low complexity computation, to each sub-band for obtaining the texture feature efficiently. Simulation results indicate that our proposed retrieval method outperforms the other traditional texture retrieval techniques such as Gabor filter and wavelet transform. Moreover, our method has higher performance compared to another contourlet based method. Hence, the proposed contourlet based image retrieval method is a very effective image retrieval method.

REFERENCES