

A New Content Based Image Retrieval Method Using Contourlet Transform

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Abstract

One of the challenging issues in managing the existing large digital image libraries and databases is Content Based Image Retrieval (CBIR). The accuracy of image retrieval methods in CBIR 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 to index texture of the images. We employ the properties of contourlet coefficients to model the distribution of coefficients in each sub-band using the normal distribution function. The assigned normal distribution functions are used effectively at the next stage to extract the texture feature vector. 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 CBIR method.

Keywords: Content-based image retrieval, Contourlet transform, Feature vector, Texture.

1. Introduction

Digital image libraries and databases have been expanding in recent years due to widespread use of digital images in various applications such as remote sensing, medical imaging and multimedia systems. Hence, management of these databases, which are usually large in content 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 with 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. It is worth noting that most of the wavelet transforms-based image retrieval methods use the mean and variance of the sub-bands coefficients as a representative for the energy of the 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 for representing 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 high performance of the wavelet -based image retrieval methods lead to the use of wavelet based methods in the compressed domain image retrieval applications, especially in the JPEG2000 compressed domain [5, 6]. Another well known filter in texture- based CBIR applications is Gabor filter. The main principles of Gabor filter and its application to extract the texture features of images are discussed in [7]. 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 [8] the mean and standard deviation of Gabor filter coefficients in different scales and orientations of an image are used to produce a texture feature vector.

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The contourlet transform is a 2-D image transform, which has recently been proposed for multi-directional and multi-resolution analysis of digital images [9]. This method overcomes the weakness of conventional wavelets to obtain smooth contours of images with low computational complexity [9]. It means that contourlet transform can be a good candidate for texture description in image retrieval applications. Hence, new feature vectors have been introduced in literature based on contourlet transform. For example, in [10] a texture retrieval method is introduced using the spectral histogram of the contourlet transform coefficients as the feature vector. The proposed method in [11] 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 [12]. This means, even though the distribution of contourlet coefficients in each sub-band is not an exact Gaussian distribution, they have necessary features for modeling them by Gaussian distribution. This property of contourlet transform along with the properties of Gaussian density function can be used for image texture description. Therefore, in this paper, which is an extension of our previous works in [13], 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 for representing the texture of an image. The proposed method remarkably outperforms other traditional texture retrieval methods such as Gabor filter and wavelet based methods. Moreover, 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 the paper is organized as follows. In section 2 we provide a brief overview of the contourlet transform. Statistical evaluations and modeling of contourlet coefficients are discussed in section 3. The proposed image retrieval method is explained in section 4. In section 5 simulation results are presented. Finally the paper concludes in section 6.

2. The Contourlet Transform

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 wavelet transforms, 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 into different multi-scales and a directional filter

bank (DFB), which is applied to reveal the directional details at each scale level.

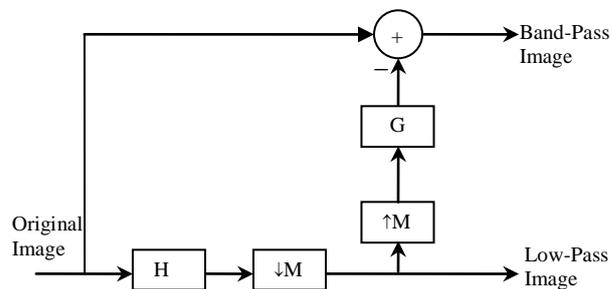


Fig. 1. One level of LP decomposition.

The LP decomposition at each scale level generates a down sampled low-pass version of the original image and the difference between the original and the prediction by low-pass version results in band-pass image. One level of the decomposition process is shown in Figure 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 (Figure 2). The DFB is implemented via l -level binary tree decomposition that leads to 2^l sub-bands with wedge-shaped frequency partitioning.

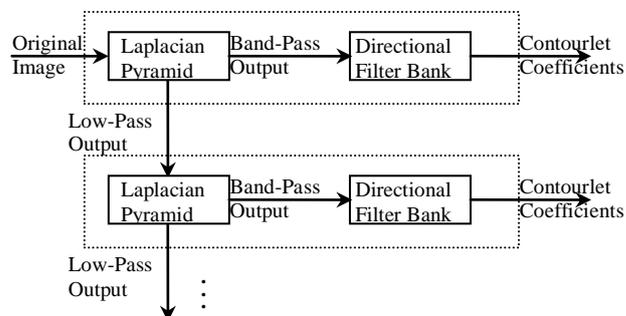


Fig. 2. Block diagram of the contourlet transform.

Due to cascading LP and DFB structures, the multi-scale and directional decompositions are independent of each other. Hence, different scales may decompose to arbitrary power of two numbers of directional sub-bands. As an example, Figure 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. Figure 4 shows “Barbara” image and its corresponding contourlet decomposition. In this contourlet 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 Figure 3.

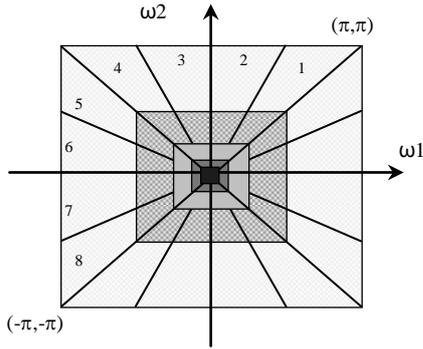


Fig. 3. A typical contourlet frequency partitioning.

3. Statistical Modeling of Contourlet Coefficients

The contourlet transform coefficients have specific properties which make normal (Gaussian) distribution an appropriate model for representing their distribution. In this section we study these properties, based on statistical evaluations of the contourlet coefficients.

We have selected 225 images of the VisTex database [14] and performed contourlet transform on them, which produced 32 sub-bands for each image. We got the coefficient distribution histograms for all the produced contourlet transform sub-bands of the all the images in database (32×225=7200 sub-bands). Figure 5 indicates histograms of two sample sub-bands of an image. Considering their shape, for all the images, the produced histograms were very similar to these two histograms. Observing shapes of the produced histograms, they seem to have the significant properties of normal (Gaussian) distribution. We used the statistical parameters to validate these properties.

There are several parameters for classifying data distributions. Two main parameters for classifying the distributions are skewness and kurtosis:

$$Skewness = \frac{\mu_3}{\sigma^3} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^3}{\left(\sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \right)^3} \quad (1)$$

$$Kurtosis = \frac{\mu_4}{\sigma^4} - 3 = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^4}{\left(\sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \right)^4} - 3 \quad (2)$$

where μ_3 , μ_4 are the third and fourth moments about mean, σ is the standard deviation, n is the total number of values and x_i is the i^{th} value in a distribution.

The skewness value of each distribution is used to evaluate the symmetry property of the distribution. The closer value to zero for this parameter, the higher degree of symmetry is for that distribution. On the other hand, the value of kurtosis is used to approximate the peak value of a distribution. For a normal distribution, skewness should be

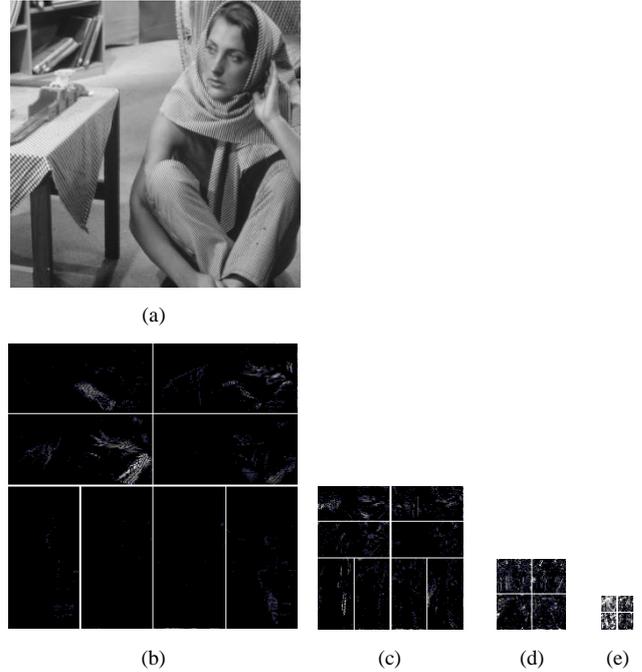


Fig. 4. The “Barbara” image and its contourlet transform. (a) The original image. (b-e) Decomposition result of different scales and orientations.

0 (or near to 0) and kurtosis should be lower than 3. In Figure 5 these values are shown for two sample sub-bands histograms. Besides these two parameters, a normal distribution should be unimodal, which means there is only one maximum value for the whole distribution and there is no other local maximum.

We obtained skewness, kurtosis, mean, and standard deviation of the sub-bands' coefficients of each image of the VisTex database. Table 1 indicates the resulting mean values for all the produced sub-bands of the database images. It reveals that most of the sub-bands have mean values very close to 0. Also in Table 2 skewness values of all the sub-bands are shown in different ranges and it is obvious that most of the sub-bands' skewness values are near to 0. These two facts indicate that the distributions are symmetric and in each distribution most of the values are accumulated near zero. On the other hand, the sketched histograms of the sub-bands are unimodal. These properties; symmetry and being unimodal, in addition to having mean and skewness approximately near to 0, are the significant properties of normal distributions. Although sub-bands distributions are not exactly normal because the resulted kurtosis values are larger than 3 for many sub-bands (Table 3), the aforementioned properties make normal distribution a suitable tool for modeling these distributions.

Moreover, it is shown in [15] that in image retrieval applications, eliminating the bins with the lowest values improves the histogram matching process and reduces the computational cost. On the other hand, in all the sub-bands there are a large number of coefficients near to zero, therefore it is not necessary to match two sub-bands around

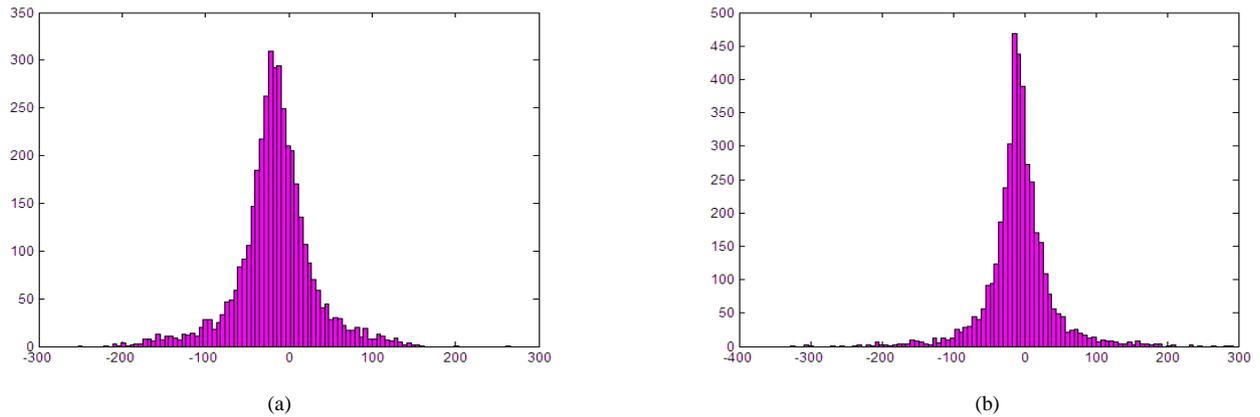


Fig. 5. Distribution histograms of two sub-bands of a sample image and the values of the statistical parameters:
 (a) mean = -16.13, standard deviation=46.44, kurtosis=5.92, skewness=-0.17;
 (b) mean = -8.02, standard deviation=46.34, kurtosis=10.29, skewness = -0.10.

zero bins, since zero bins are similar in all the sub-bands and cannot be used to differentiate the histograms. In fact, the most important advantages of assigning Gaussian Distribution (GD) function to each sub-band are canceling the impact of the noisy shape bins and near to zero bin values of histograms. In this paper we used the mean and standard deviation of the coefficients of each sub-band to model the histogram by GD. Figure 6 indicates a sample histogram and the GD curve, which is used to model it. Even though this model does not exactly fit the distribution, simulation results indicate that it provides a simple way to produce an effective feature vector to describe the image texture.

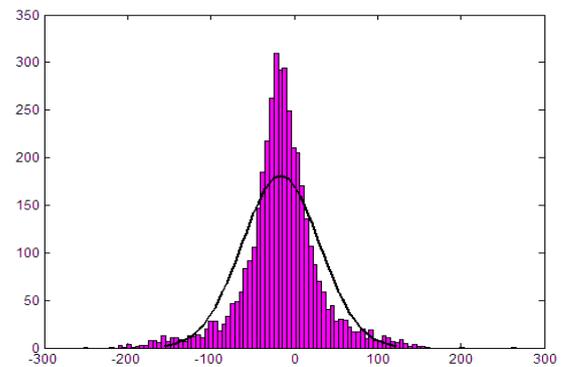


Fig. 6. A sample sub-band and its assigned GD function curve.

Table 1

Number of sub-bands for different mean ranges of all the 7200 sub-bands of VisTex database.

Range of Mean Values	[-5, +5]	[-10, -5] & (+5, +10]	[-20, -10] & (+10, +20]	[-59.2, -20] & (+20, +2956.5]	[-59.2, 2956.5]
Number of Sub-bands	4498	1434	685	583	7200

Table 2

Number of sub-bands for different skewness ranges of all the 7200 sub-bands of VisTex database.

Range of Skewness Values	[-1, +1]	[-2, -1] & (+1, 2]	[-2, -5] & [+2, +5]	(-5, -9.3] & (+5, +16.3]	[-9.3, +16.3]
Number of Sub-bands	6799	115	61	225	7200

Table 3

Number of sub-bands for different kurtosis ranges of all the 7200 sub-bands of VisTex database.

Range of Kurtosis Values	[1, 3]	(3, 6]	[6, 12)	(12, 620.11]	[1, 620.11]
Number of Sub-bands	231	3914	1979	1076	7200

4. The Proposed Image Retrieval Method

The sub-bands of contourlet transform have texture information due to the fact that contourlet transform has coarse to fine property and includes directional details of the image. Hence, analysis of sub-bands coefficient characteristics provides valuable information about image texture. Besides, the distribution of the coefficients in each sub-band is symmetric and unimodal with mean and skewness near to zero, which makes GD function an appropriate tool for modeling the coefficients distribution. We used these prominent properties of contourlet transform 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.

4.1. Texture Feature Extraction

Since the unimodal and symmetric distribution of the contourlet coefficients makes the GD function a good candidate for modeling the distribution of contourlet coefficients, we used the GD function to model each sub-band coefficients. Although the coefficients distribution is not exactly Gaussian, the normal distribution function can be used as a suitable model of each sub-band. It is because coefficients distribution is perfectly symmetric, unimodal and has skewness about zero. Moreover, the modeling GD function for each sub-band can be estimated by low complexity calculations:

$$n(X, \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{X-\mu}{\sigma}\right)^2}; -\infty < X < +\infty \quad (3)$$

where μ and σ are the mean and standard deviation value of all the coefficients of the 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 Figure 4, there are 24 GD functions because the contourlet transform generate 24 sub-bands. Each GD function can be represented by only two parameters: μ and σ . In order to reduce the computational load of the next step we add the range of the values of each sub-band's coefficients, $[Mx_{sb}, Mn_{sb}]$ to the feature vector. Therefore, the size of the feature vector is confined to few numbers including 4 values for each sub-band.

4.2. 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, which are modeled by GD function. We calculate the distance of two GD functions to find their similarity using (4):

$$D_{sb}(I, J) = \sum_{i=b_l}^{b_h} |n_{sb_l}(X_i, \mu_I, \sigma_I) - n_{sb_j}(X_i, \mu_J, \sigma_J)| \quad (4)$$

where n_{sb_l} and n_{sb_j} are the GD functions of corresponding sub-bands (sb) in the images I and J , respectively. The range $[b_l, b_h]$, where $b_l = \min(Mn_{sb_l}, Mn_{sb_j})$ and $b_h = \max(Mx_{sb_l}, Mx_{sb_j})$, represents the range of coefficients values in sub-band sb at two images I and J . In fact, the resulting value in (4) is the sum of difference of two probability functions n_{sb_l} and n_{sb_j} , where x ranges from $-\infty$ to $+\infty$ in the GD function. To reduce the computational complexity in (4), 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:

$$D(I, J) = \sum_{sb=1}^{N_{sb}} D_{sb}(I, J) \quad (5)$$

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.

5. Experimental Evaluations

We used the query by example method to compare the performance of the proposed contourlet based image retrieval method with a number of other image retrieval methods. In these experiments we used VisTex 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, 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 (5). Then ten images with the lowest distance from the query image were retrieved from the database. Figure 7 shows the ranked six retrieved images for three sample query images. As expected, the first retrieved image (the most left image in each row) in all the cases is the query image that has a distance value of zero.

We implemented the Gabor filter texture retrieval method [7] of 13×13 mask size, with 6 orientations and 4 scales. These parameters are the optimal parameter set for the Gabor filter [16]. Hence, for each image there will be $4 \times 6 = 24$ output filtered images and mean (μ) and standard deviation (σ) of these images made a feature vector of 48 elements. For comparing the feature vectors, the same similarity metric as the one in [16] is used, which is, in fact, the Euclidian distance of the two feature vectors. We implemented also 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 [11]. We also implemented this method and in implementation of this method we used four scales and 3, 4, 8, 16 directions respectively [11], which are the same scale and direction number as used in the proposed method. In this method and also the aforementioned wavelet-based method, similarity of two images is estimated based on Euclidian distance of their feature vectors. 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 (6) and Recall (7) parameters [17] were used for evaluating the performance of the retrieval methods:

$$\text{Precision} = \frac{\text{No. of retrieved relevant images}}{\text{Total of retrieved images}} \quad (6)$$

$$\text{Recall} = \frac{\text{No. of retrieved relevant images}}{\text{Total of relevant images}} \quad (7)$$

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 [17] for each query and then by averaging all the graphs [17] we got the averaged Precision-Recall graph for each of the tested retrieval methods (Figure 8). The averaged Precision-Recall graphs are used to compare the performance of the four image retrieval methods. Figure 8 indicates that 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 superior performance compared to the realized Gabor filter, wavelet transform, and also the contourlet based image retrieval methods.

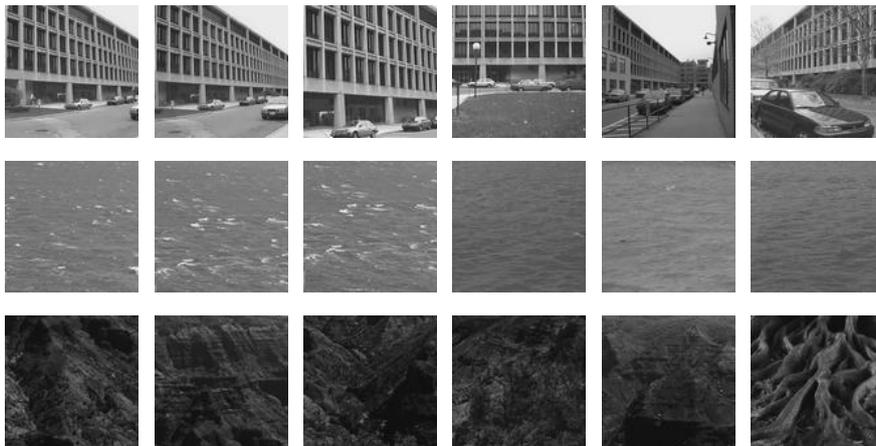


Fig. 7. The top six retrieved images for three sample query images from the VisTex database (left to right). The first retrieved image is the query image.

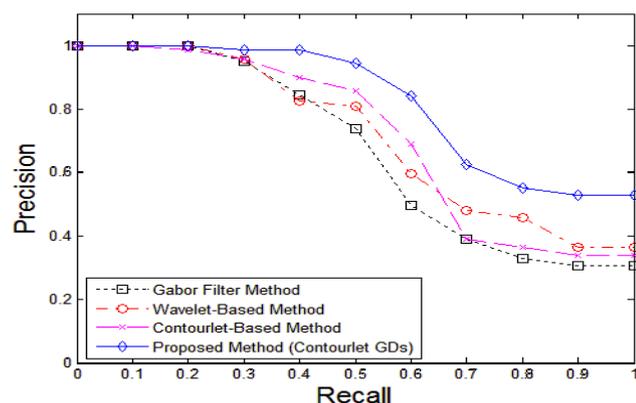


Fig. 8. Performance graphs of the four tested retrieval methods on a sample query set including 25 images.

6. 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 image texture features. The distribution of contourlet transform coefficients is symmetric and unimodal with skewness near to zero and the proposed method employs these properties of contourlet transform coefficients by assigning the Gaussian density function to each sub-band for obtaining the texture feature efficiently. Simulation results indicate that the proposed retrieval method outperforms the other traditional texture retrieval techniques such as Gabor filter and wavelet transform. Moreover, our method has also higher performance compared to another contourlet based method. Hence we deduce that, the proposed contourlet based image retrieval method is a very effective texture- based image retrieval method.

References

- [1] A. Laine, and J. Fan, Texture classification by wavelet packet signatures. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 15, no. 11, pp. 1186-1191, 1993.
- [2] T. Chang and C.C.J. Kuo, Texture analysis and classification with tree-structured wavelet transform. *IEEE Trans. on Image Processing*, vol. 2, no. 4, pp. 429-441, 1993.
- [3] M. N. Do and M. Vetterli, Wavelet-based texture retrieval using generalized Gaussian density and Kullback-Leibler distance. *IEEE Trans. on Image Processing*, vol. 11, no. 2, pp. 146-158, 2002.
- [4] L. Brigale, M. Kokare and D. Doye, Colour and texture features for content based image retrieval. in *Proc. of Int. Conf. on Computer Graphics, Imaging and Visualisation, Sydney*, pp. 146-149, 2006.
- [5] M. K. Mandal and C. Liu, Efficient image indexing techniques in the JPEG2000 domain. *Journal of Electronic Imaging*, vol. 13, pp. 182-187, 2004.
- [6] F. Zargari, A. Mosleh and M. Ghanbari, A fast and efficient compressed domain JPEG2000 image retrieval method. *IEEE Trans. on Consumer Electronics*, vol. 54, no. 4, pp. 1886-1893, 2008.
- [7] B. S. Manjunath and W. Y. Ma, Texture features for browsing and retrieval of image data. *IEEE T-PAMI special issue on Digital Libraries*, vol. 18, no. 8, pp. 837-842, 1996.
- [8] D. Zhang and G. Lu, Content-based image retrieval using Gabor texture features. *Proc. of First IEEE Pacific-rim Conf. on Multimedia (PCM'00)*, Fargo, ND, USA, pp.1-9, 2001.
- [9] M. N. Do and M. Vetterli, The contourlet transform: An efficient directional multiresolution image representation. *IEEE Trans. on Image Processing*, vol. 14, no. 12, pp. 2091-2106, 2005.
- [10] Z. Longa and N. H. Younana, Contourlet spectral histogram for texture classification. *Proc. of 2006 IEEE Southwest Symp. on Image Analysis and Interpretation*, pp. 31-35, 2006.
- [11] R. Romdhane, H. Mahersia and K. Hamrouni, A novel content image retrieval method based on contourlet. *Proc. of 3rd International Conf. on Information and Communication Technologies: From Theory to Applications*, pp. 1-5, 2008.
- [12] M. N. Do and M. Vetterli, Directional multiscale modeling of images using the contourlet transform. *IEEE Trans. on Image Processing*, vol. 15, no. 6, pp. 1610-1620, 2006.
- [13] A. Mosleh and F. Zargari, Texture image retrieval using contourlet transform. Accepted for Publication in *Proc. of 9th International Symposium on Signals, Circuits and Systems, Romania*, 2009.
- [14] <http://vismod.media.mit.edu/vismod/imagery/VisionTexture>
- [15] Y. Gong, H. J. Zhang and T. C. Chua, An image database system with content capturing and fast image indexing abilities. *Proc. IEEE Int. Conf. on Multimedia Computing and Systems, Boston*, pp.121-130, 14-19 May 1994.
- [16] L. Chen, G. Lu and D. S. Zhang, Effects of different Gabor filter parameters on image retrieval by texture. *Proc. of IEEE Int. Conf. on Multi-Media Modeling*, pp. 273-278, 2004.
- [17] C. D. Manning, P. Raghavan and H. Schütze, *Introduction to Information Retrieval*. Cambridge University Press, 2008.

