Content Based Image Retrieval using Contourlet Sub-band Decomposition

Ch.Srinivasa Rao and S.Srinivas Kumar

***Abstract*-- Content Based Image Retrieval (CBIR) system using features obtained by sub-band decomposition of Contourlet transform (CT) is proposed in this work. Energy and Standard deviation (SD) computed in each sub-band are used as features of each image in the database. Unique properties of CT, viz., directionality and anisotropy are explored to improve the retrieval efficiency. Improved result in terms of retrieval efficiency is observed over recent work based on Gabor - Zernike features based CBIR system. The results are also compared with our recent work using Contourlet transform based CBIR system, wherein standard deviation computed in each sub-band is used as feature. Computational complexity of this work is compared with Gabor-Zernike features based CBIR system and also with CT based system, wherein standard deviation is used as feature.**

***Index Terms*—CBIR, Contourlet transform, Feature extraction, Image retrieval, Similarity measures.**

I. Introduction

CONTENT Based Image Retrieval (CBIR) finds applications in internet, advertising, medicine, crime detection, entertainment, and digital libraries. High retrieval efficiency and less computational complexity are the desired characteristics of CBIR system and they are the key objectives in the design of CBIR system [1]. However, designing of CBIR system with these objectives becomes difficult as the size of image database increases. CBIR based on color, texture, shape, and edge information are available in the literature [2]-[4]. Features of an image should have a strong relationship with semantic meaning of the image. CBIR system retrieves the relevant images from the image database for the given query image, by comparing the features of the query image and images in the database. Relevant images are retrieved according to minimum distance or maximum similarity [5] between feature of query image and each image in the image database. CBIR systems can be designed based on several features, viz., color, texture, shape and edge information. In [6] color distribution and quantization is used for color image retrieval. Texture contains important information about the structural arrangement of surfaces and their relationship to the surroundings. Various techniques are developed for texture analysis [7], [8]. Most of the textural features are obtained from the application of a local operator, statistical analysis, or measurement in transform domain. Shape features are computed assuming that images contain only one shape. Shape features include: modal matching , histograms of edge directions [9], and matching of shape components such as corners, line segments or circular arcs [10].

Recently, Fu et al., [11] have proposed CBIR system based on features obtained by Gabor - Zernike features (GF+ZM). Gabor wavelets are used for texture feature extraction, and Zernike moments are used for shape feature extraction. The algorithm is tested on Georgia Tech face database [12].

Spatial and spectral features of the images can be explored for image retrieval in CBIR systems. Due to the local nature, it is difficult to detect edge and texture orientations using spatial methods [13]. Spectral methods based on multiscale directional transforms, viz., wavelets have fixed number of directions. They are also inefficient to capture edges and smooth contours in natural images. Discrete wavelet transforms [14] are inherently non-supportive to directionality and anisotropy. The Contourlet Transform (CT) is a directional transform capable of capturing contours and fine details in images. The contourlet expansion is composed of basis functions oriented at variety of directions in multiple scales with flexible aspect ratios. With this rich set of basis functions, the contourlets can effectively capture smooth contours (Edge and Texture orientations) that are the dominant features in images in the database.

In our earlier work, standard deviation (SD) computed in each directional sub-band of contourlet decomposed image is used as feature [15] and compared the results with Gabor – Zernike features based CBIR system.

In the proposed method, an image is represented in the contourlet transform domain. Standard deviation and energy parameters computed in each directional sub-band of the CT decomposed image is used to obtain feature vector to represent every image in the image database. The basic assumption of using energy as a feature is energy distribution in frequency domain identifies a texture [16].Besides

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providing high retrieval performance energy based approaches partly supported by psychological studies of visual cortex [17]. Contourlet transform can effectively represent information in than wavelet transform for the images having more directional information with smooth contours [18] due to its properties, viz., directionality and anisotropy. Hence, the proposed method based on CT is producing improved performance in terms of retrieval efficiency and computational complexity over Gabor-Zernike features based CBIR system. Computation complexity is increasing over our earlier work [15], due to increase in size of the feature vector, improved performance is observed in terms of retrieval efficiency.

This paper is organized as follows: In section II, discrete contourlet transform and its advantages over discrete wavelet transform are reviewed. Proposed CBIR system using normalized energy and standard deviation calculated in each sub-band of CT, is discussed in section III. Experimental results are presented in section IV. Concluding remarks and future directions are given in section V.

II. Discrete contourlet transform

Multiscale and time-frequency localization of an image is offered by wavelets. But, wavelets are not effective in representing the images with smooth contours in different directions. Contourlet Transform (CT) addresses this problem by providing two additional properties viz., directionality and anisotropy [19] made it a powerful tool for CBIR.

Contourlet transform is a multiscale and directional image representation that uses first a wavelet like structure for *edge* detection, and then a local directional transform for *contour segment* detection. A double filter bank structure of the contourlet is shown in Fig. 1. In the double filter bank structure, Laplacian Pyramid (LP) [20], [21] is used to capture the point discontinuities, and then followed by a Directional Filter Bank (DFB) [22], which is used to link these point discontinuities into linear structures. The contourlets have elongated supports at various scales, directions and aspect ratios. This allows contourlets to efficiently approximate a smooth contour at multiple resolutions. Contourlet transform is simple and flexible, but it introduces redundancy (up to 33%) due to LP stage.

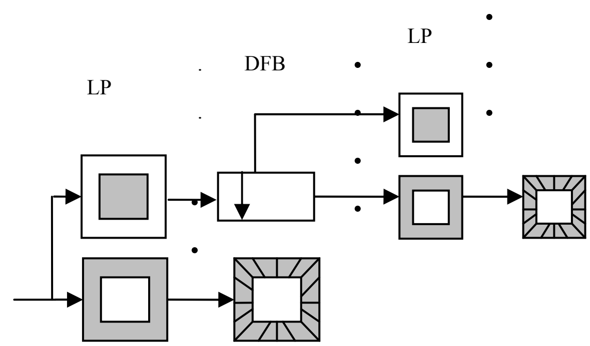


Fig. 1. Double Filter Bank Decomposition of Contourlet Transform.

A. Laplacian Pyramid Decomposition

Laplacian Pyramid is used to obtain multiscale decomposition. LP decomposition at each level generates a down sampled low pass version of the original image and difference between the original and the prediction, results in a band pass image. The LP decomposition is shown in Fig. 2. In the LP decomposition process H, G are one dimensional low pass analysis and synthesis filters, M is the sampling matrix. Here, the band pass image obtained in LP decomposition is then processed by the DFB stage.

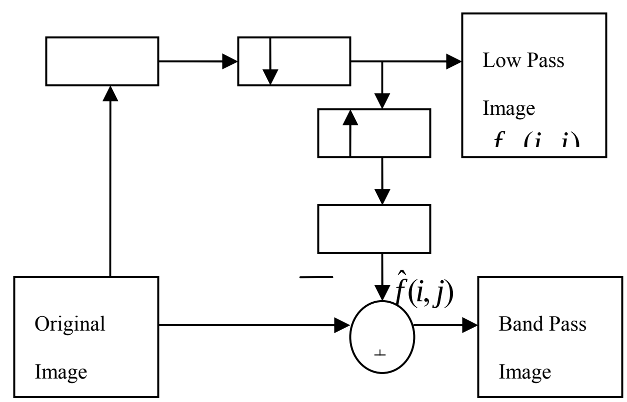


Fig. 2. LP Decomposition (One Level)

In LP decomposition of an image, $f(i,j)$ represent the original image, its low pass filtered version is $f_{lo}(i,j)$ and the prediction is $\hat{f}(i,j)$. The prediction error is given by

$$P_e(i,j) = f(i,j) - \hat{f}(i,j) \tag{1}$$

The directional decomposition is performed on $P_e(i,j)$ as it is largely decorrelated and requires less number of bits than $f(i,j)$.

In equation (1), $P_e(i,j)$ represents a band pass image. Further decomposition can be carried by applying equation (1) on $f_{lo}(i,j)$ iteratively to get

$f_{l1}(i,j)$, $f_{l2}(i,j)$,. . . . . . $f_{ln}(i,j)$, where, 'n' represents the number of pyramidal levels. In LP reconstruction, the image is obtained by simply adding back the difference to the prediction from the coarse image.

B. Directional Filter Bank Decomposition

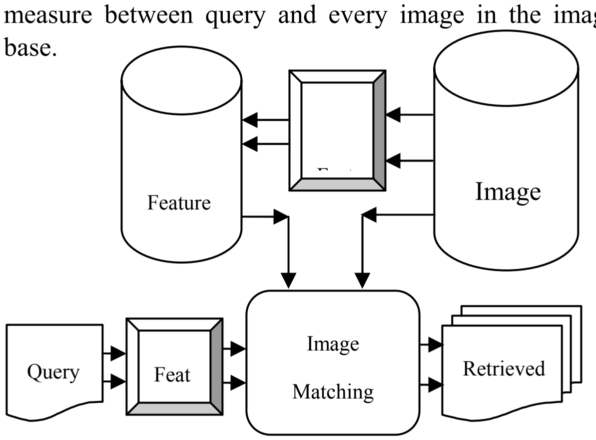
DFB is designed to capture the high frequency content like smooth contours and directional edges [23]. The DFB is implemented by using a *k*-level binary tree decomposition that leads to 2^k directional sub-bands with wedge shaped frequency partitioning. But, the DFB used in this work is a simplified DFB [24], which is constructed from two building blocks. The first one is a two-channel quincunx filter bank with fan filters. It divides a 2-D spectrum into two directions, horizontal and vertical. The second one is a shearing operator, which amounts to the reordering of image pixels. Due to these two operations, directional information is preserved. This is the desirable characteristic in CBIR system to improve retrieval efficiency.

Combination of a LP and DFB gives a double filter bank structure known as contourlet filter bank. Band pass images from the LP are fed to DFB so that directional information can be captured. The scheme can be iterated on the coarse image. This combination of LP and DFB stages result in a double iterated filter bank structure known as contourlet filter bank, which decomposes the given image into directional sub-bands at multiple scales.

III. CBIR ARCHITECTURE

The objective of the proposed work is to study the use of edge and texture orientations as image features in image retrieval. The basic architecture of CBIR system is shown in Fig. 3. An improved method based on contourlet transform for CBIR system is proposed in this work. There are two issues in building a CBIR system.

1. Every image in the image data base is to be represented efficiently by extracting significant features.
2. Relevant images are to be retrieved using similarity measure between query and every image in the image data base.



(Feat Ext. - Feature Extraction)

Fig. 3. CBIR System Architecture

A. Proposed Algorithm

The steps involved in the proposed CBIR system with combined energy and standard deviation features includes database processing and resizing, creation and normalization of feature database, comparison and image retrieval. Steps of the proposed algorithm are as follows.

1. Decompose each image in the Contourlet domain

2. Compute the standard deviation (SD) and energy (E) of the CT decomposed image on each directional sub-band.

   Standard deviation (σ_k) and Energy (E_K) of k th sub-band are given as

$$\sigma_k = \sqrt{\frac{1}{MxN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(W_k(i,j)-\mu_k\right)^2} \tag{2}$$

$$E_k = \frac{1}{MxN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|W_k(i,j)\right| \tag{3}$$

   where,
   W_k = Co-efficient of k th CT decomposed sub- band
   μ_k = Mean value of k th sub-band
   $M \; x \; N$ = Size of the CT decomposed sub- band

   The resulting combined standard deviation with energy feature vector is given as

$$\bar{f}_{\sigma E} = [\sigma_1\sigma_2\sigma_3.....\sigma_n E_1 E_2 E_3.....E_n] \tag{4}$$

   where, n is number of sub-bands

3. Normalize the feature vector to the range [0 1] for every image in the database.

$$\bar{f}_{CT} = \frac{\bar{f}_{\sigma E} - \mu_{\bar{f}}}{\sigma_{\bar{f}}} \tag{5}$$

   where,
   $\mu_{\bar{f}}, \sigma_{\bar{f}}$ are the mean and standard deviation of $\bar{f}_{\sigma E}$.

   This normalized feature vector $\bar{f}_{CT}$ is used to create the feature database.

4. Apply query image and calculate the feature vector as given in steps 2 to 5.

5. Calculate the similarity using Manhattan Distance measure

$$D_{qi}^{M} = \left|\bar{f}_q - \bar{f}_i\right| \tag{6}$$

   where, D_{qi}^{M} is the Manhattan distance between the feature vector of query image and every image in the database. $\bar{f}_q$, $\bar{f}_i$ are the normalized feature vectors of the query image and database image respectively.

6. Retrieve all relevant images to query image based on minimum 'Manhattan distance'.

■

A query image may be any one of the database images. This query is then processed to compute the feature vector as in equations (4) and (5). The distance D_{qi}^{M} (where 'q' is the query image and 'i' is an image from database) is computed. The distances are then sorted in increasing order and the closest sets of images are then retrieved. The top 'N' retrieved images are used for computing the performance of the proposed method. The retrieval efficiency is measured by counting the number of matches.

IV. Experimental results

Retrieval performance in terms of average retrieval rate and retrieval time of the proposed CBIR system is tested by conducting an experiment on GT face database.

Fig. 4. Sample images from GT Face database of five different subjects

GT face database consists of 750 colorful face images of size 640x480 with 50 subjects and 15 images per subject. These images in the database are considered by allowing for strong variation in size, illumination, facial expression, and rotation both in the image plane and perpendicular to the image plane. In this work, all images in the database are converted to gray level images. Some sample images in this database are shown in Fig. 4. All the images in the database are scaled to a size of 256x256. For creating the feature database, each image is decomposed in the contourlet domain. The feature vector is computed using equations (2), (3) and (4) on each directional sub band of CT decomposed image. This feature vector is then normalized to the range [0, 1] as given in equation (5).

A. Feature Selection

Edge and texture orientations are captured by using CT decomposition with a 4 – level (0, 2, 3, 4) LP decomposition. At each level, the number of directional sub-bands are 3, 4, 8 and 16 respectively. For LP decomposition and directional sub-band decomposition 'pkva' filters [25] are used. Standard deviation with Energy vector is used as image feature, which is computed on each directional sub-band of the CT decomposed image and normalized [26] to range [0 1]. These parameters results in a 64-dimentional feature vector . This normalized feature vector is used for the creation of the feature database.

Fig. 5. Sample image from GT face database (Image no. 210)

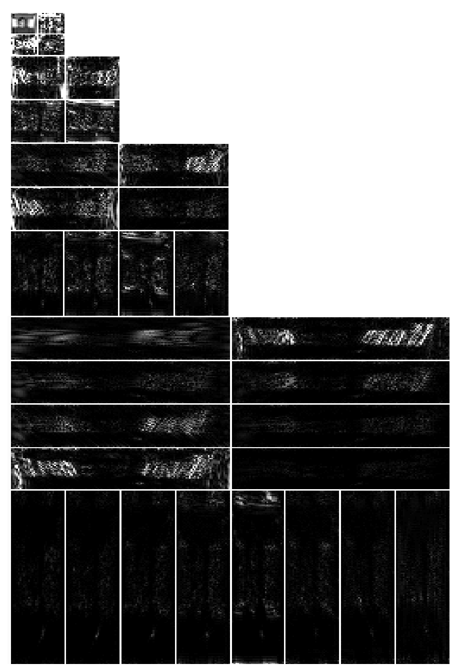


Fig. 6. CT decomposed image using 4-level LP & 'pkva' filter)

A sample image from GT Face database (sample image 210 in the database) and the corresponding CT decomposition with a 4-level LP decomposition i.e.(0, 2, 3, 4) are shown in

Fig. 5 & 6 respectively. Some of the retrieved results when 10 images (N=10) in one subject of the image database are retrieved are shown in Fig. 7.

Fig. 7. Retrieved images with (image no. 210) top left image as query image

B. Average Retrieval Rate

The average retrieval rate for the query image is measured by counting the number of images from the same category which are found in the top 'N' matches [27]. Comparative retrieval performance of the proposed CBIR system on the GT face database using CT features is shown in Table I.

TABLE I

AVERAGE RETRIEVAL RATES

(1, 3, 5, 8, 10 are the top 'N' Retrieved Images)

	Number of top matches				
Methods	1	3	5	8	10
GF	100	98.81	96.71	90.27	84.75
ZM(10)	100	98.66	95.37	88.50	82.71
GF+ZM(4)	100	98.96	96.88	90.22	85.11
CT with SD	100	99.99	99.25	98.03	96.78
CT with SD+Energy	**100**	**99.99**	**99.76**	**98.59**	**97.62**

From Table I, it is observed that the proposed CBIR system with SD+Energy features is providing improved retrieval performance over Fu et al., method and CT based CBIR System with standard deviation features. The superiority of the proposed method is also observed in all the cases, i.e., when N is considered as 1, 3, 5, 8, 10 (N is the number of top retrieved images). Comparative retrieval performances in terms of average retrieval rate is shown in Fig. 8.

C. Retrieval Time

Computational complexity for CBIR system (with N=10) using different features, i.e. for the GF, ZM, GF+ZM, CT with SD, CT with SD+energy is shown in Table II.

TABLE II

AVERAGE RETRIEVAL TIME

GF	ZM(10)	GF+ZM(4)	CT(SD)	CT(Energy+SD)
3.24s	4.35s	5.34s	0.846s	1.32s

The proposed method is superior in terms of retrieval time over GF+ZM based CBIR system. Increased size of the feature vector improves the retrieval time in the proposed method when compared to the CBIR system with only standard deviation features. Experiments are conducted using MATLAB version 7.2.0 with Pentium-4, 3.00 GHz.

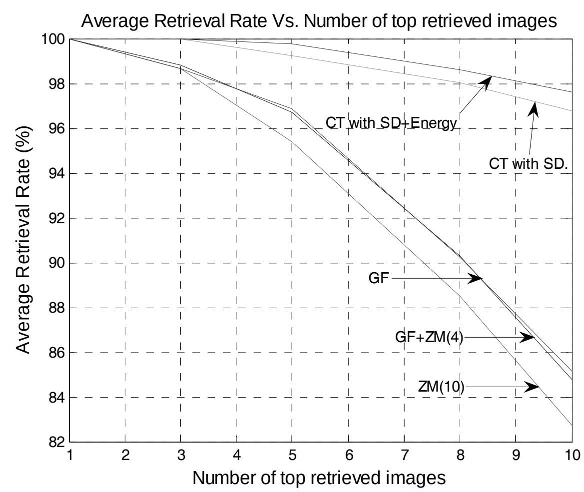


Fig. 8. Comparative average retrieval rates.

V. CONCLUSIONS

The performance of the CBIR system is dependent on the feature vector that represents the image in the database. Important characteristics of contourlet transform viz., directionality and anisotropy are explored in this work. Normalized energy and standard deviation calculated in each sub-band of the CT decomposed image are used as features in the feature vector representing the image. Superiority of this work is observed in terms of retrieval efficiency & retrieval time over Gabor-Zernike features used by Fu et al. The retrieval efficiency of the proposed is increased when compared with our earlier work [15]. However, the computation time of the proposed algorithm increases over our earlier work due to the increase in size of feature vector. The feature vector of the CT decomposed image varies if the database consists of images with different rotations. Hence, a CBIR system with rotational invariance is to be explored.

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VII. Biographies

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