Improved Efficiency of CBIR using Contourlet Transform

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Abstract - Content-based image retrieval (CBIR) is an impotent research area for manipulating large amount of image database and archives. In this paper we explain the efficiency retrieval rate of content based image retrieval system using contourlet transform, the multiresolution using the Laplacian pyramid (LP). And the directionality can be analyzed by using the Directional Filter bank (DFB). In CBIR system using Contourlet Transform based features directionality and anisotropy are made it powerful. Improved results in terms of retrieval efficiency and less complexity are observed in recent work. The distance measures VIZ., Manhattan distance and minkowski distance are used in similarity measures in the proposed CBIR system.

Keywords: Contourlets, Multiresolution, Laplacian pyramid Directionality, Directional Filter Bank.

I. INTRODUCTION

The function of a content-based image retrieval system [Niblack et al., 1993; Guibas and Tomasi, 1996] is typically to find database images that look similar to a given query image or drawing. Database and query images are usually summarized by their color, shape, and texture content. Here we use the term images in a very broad sense that includes any type of graphical information. Content-based image retrieval Image processing typically relies on simple statistical models to characterize images. Natural images tend to have certain common characteristics that make them look “natural.” The aim of statistical modeling is to capture these defining characteristics in a small number of parameters so that they can be used as prior information in image processing tasks such as compression, denoising, feature extraction, and inverse problems. A simple, accurate and tractable model is an essential element in any successful image processing algorithm. Images have effectively been modeled using the wavelet transform [1], [2], which offers a multiscale and time frequency-Located image representation. Initially, the wavelet transform was considered to be a good decorrelator for images, and thus wavelet coefficients were assumed to be independent and were simply modeled using marginal statistics [3]. Later it was realized that wavelet coefficients of natural images exhibit strong dependencies both across scales and between neighboring coefficients within a subband, especially around image edges. This gave rise to several successful joint statistical models in the wavelet domain [4], [5], [6], [7], [8], [9], as well as improved image compression schemes [10], [11], [12].

The major drawback for wavelets in two-dimensions is their limited ability in capturing directional information. To overcome this deficiency, researchers have recently considered multiscale and directional representations that can capture the intrinsic geometrical structures such as smooth contours in natural images. Some examples include the steerable pyramid [13], brushlets [14], complex wavelets [15], and the curvelet transform [16]. In particular, the curvelet transform, pioneered by Cand`es and Donoho, was shown to be optimal in a certain sense for functions in the continuous domain with curved singularities.

Inspired by curvelets, Do and Vetterli [17], [18] developed the contourlet transform based on an efficient two-dimensional multiscale and directional filter bank that can deal effectively with images having smooth contours. Contourlets not only possess the main features of wavelets (namely, multiscale and time-frequency localization), but also offer a high degree of

Directionality and anisotropy. The main difference between Contourlets and other multiscale directional systems is that the contourlet transform allows for different and flexible number of directions at each scale, while achieving nearly critical sampling. In addition, the contourlet transform uses iterated filter banks, which makes it computationally efficient; specifically, it requires O(N) operations for an N-pixel image.
In this paper we explain how to decompose the image using contourlet transform. In the section 1 we explain multi-resolution by using pyramidal decomposition. In this at each level how the image can be reduced. In section 2 we can explain directionality. This directionality can be alkazied by using directional filter banks. This is the main property of the contourlet transform to which we can prefer this technique.

II. CONTOURLETS

Do and Vetterli developed Contourlets in [18]–[20]. Their primary aim was to construct a sparse efficient decomposition for two-dimensional signals that are piecewise smooth away from smooth contours. Such signals resemble natural images of ordinary objects and scenes, with the discontinuities as boundaries of objects. These discontinuities, referred to as edges, are gathered along one-dimensional smooth contours. Two-dimensional wavelets, with basis functions shown in Figure 1(a), lack directionality and are only good at catching zero-dimensional or point discontinuities, resulting in largely inefficient decompositions. For example, as shown in Figure 1(c), it would take many wavelet coefficients to accurately represent even one simple one-dimensional curve. Contourlets were developed as an improvement over wavelets in terms of this inefficiency. The resulting transform has the multi-resolution and time-frequency localization properties of wavelets, but also shows a very high degree of directionality and anisotropy. Precisely, contourlet transform involves basis functions that are oriented at any power of two's number of directions with flexible aspect ratios, with some examples shown in Figure 1(b). With such richness in the choice of basis functions, Contourlets can represent any one-dimensional smooth edges with close to optimal efficiency. For instance, Figure 1(d) shows that compared with wavelets, Contourlets can represent a smooth contour with much fewer coefficients we proposed a double filter bank approach for obtaining sparse expansions for typical images having smooth contours. We called this a pyramidal directional filter bank (PDFB) [25], where the Laplacian pyramid [26] is first used to capture the point discontinuities, then followed by a directional filter bank [27] to link point discontinuities into linear structures. The overall result is an image expansion using basic elements like contour segments, and thus named Contourlets Contourlet transform (CT) can be implemented by using Pyramidal directional decomposition (PDFB). PDFB which is a combination of Laplacian-Pyramid (LP) and Directional Filter bank (DFB).

Properties provided by contourlet transform were given by

1. Multi-resolution. The representation should allow images to be successively approximated, from coarse to fine resolutions.
2) Localization. The basis elements in the representation should be localized in both the spatial and the frequency domains.
3) Critical sampling. For some applications (e.g., compression), the representation should form a basis, or a frame with small redundancy.
4) Directionality. The representation should contain basis elements oriented at a variety of directions, much more than the few directions that are offered by separable wavelets.
5) Anisotropy. To capture smooth contours in images, the representation should contain basis elements using a variety of elongated shapes with different aspect ratios.

The Pyramidal directional filter bank block diagram was given in the figure(a). In order to achieve a multiple resolution with multiple directional feature analysis, a Laplacian pyramid is combined with directional filter bank. In this multi-resolution analysis was done by using the laplacian pyramid. Directionality can be implemented by using directional filter bank

![Flow Graph Of PDFB](image)

Fig 2: Flow Graph Of PDFB
In the above figure when the image is given to the PDFB, first the image is decomposed by using Laplacian pyramid and then that image is given to the directional filter bank for directional decomposition. Here in Laplacian pyramid at every level the image is halved and the sampling rate was doubled. Depending upon the given image we can choose the number of level in LP stage and DFB stage.

## 2.1 MultiResolution

**MULTIRESOLUTION** data representation is a powerful idea. It captures data in a hierarchical manner where each level corresponds to a reduced-resolution approximation. One of the early examples of such a scheme is the Laplacian pyramid (LP) proposed by Burt and Adelson [1] for image Coding. The basic idea of the LP is the following. First, derive a coarse approximation of the original signal by low pass filtering and down sampling. Based on this coarse version, predict the original (by up sampling and filtering) and then calculate the difference as the prediction error. Usually, for reconstruction, the signal is obtained by simply adding back the difference to the prediction from the coarse signal.

### 2.1.1 Laplacian decomposition:

For the given image we can choose the number of levels for decomposition. At every level the laplacian pyramid gives the one down sampled low pass filtered image and one band pass image which can passed through DFB. For multiscale purpose we use laplacian pyramid. In this Laplacian pyramid, The laplacian Pyramid shown in the below.

In LP, the filters and H are low pass analysis and synthesis filters is a sampling matrix, the original image is passed through the low pass filter in which the low frequencies are separated. Here we are using the Low pass analysis filter. The low pass filters in the Laplacian pyramid serves two purposes. First, it is used to separate out the low pass content in an image so that it would not spread across multiple directions. Second, it is used to induce a multiple resolution analysis. At every level of decomposition LP generates the down sampled version of original image and the difference between the original and the prediction. In this the scale of the laplacian pyramid doubles at every level. The center frequencies of pass band reduced by half. Laplacian pyramid iteratively produces the low pass and high pass sub bands. In LP we use up sampling to reduce the aliasing effect.

Pass version of the original and the difference between the original and the prediction, results in a band pass image. A drawback of the LP is the implicit over sampling. However, in contrast with the critically sampled wavelet scheme, the LP has the distinguishing feature that each pyramid level generates only one band pass image (even for multidimensional cases) which does not have “scrambled” frequencies. This frequency scrambling happens in the wavelet filter bank when a high pass channel, after down sampling, is folded back into the low frequency, and thus its spectrum is reflected. In the LP, this effect is avoided by only down sampling the low pass channel.

In LP decomposition of an image \( f(i, j) \) represent original image when it is passed through Low pass analysis filter and then down sampled represent the low pass filtered version of original image which is given by \( f_{lo}(i, j) \) and the \( \hat{f}(i, j) \) represents the prediction of the low pass filtered version. The prediction error \( L_{p0}(i, j) \) which is given by

\[
L_{p0}(i, j) = f(i, j) - \hat{f}(i, j)
\]  

![Laplacian Pyramid Decomposition (one level).](image)

Fig2. Laplacian Pyramid Decomposition (one level).

Here the directional decomposition is performed on \( L_{p0}(i, j) \) because here we calculate the directionality on prediction instead of original image because of \( L_{p0}(i, j) \) is largely decor related and it requires less number of bits than \( f(i, j) \).

\( L_{p0}(i, j) \) represents the band pass image. Further decomposition can be performed on \( f_{lo}(i, j) \) by applying equation (1) iteratively to get
Improved Efficiency of CBIR using Contourlet Transform


\[ f_{1n}(i, j), f_{12}(i, j), f_{13}(i, j) \ldots \ldots f_{ln}(i, j), \] where \( n \) represents the number of levels. For reconstruction of image by simply adding back the differences to the prediction from the coarse image. LP with orthogonal filters provide with tile frame bounds equals to 119

2.2 DIRECTIONALITY

The main property of contourlet transform is directionality. This Directionality can be analyzed using directional filter bank (DFB). By its nature, the DFB is designed to capture the high frequency components (representing directionality) of images. Therefore, low frequency components are handed poorly by the DFB.

\[ \text{Fig 3. DFB frequency partitioning} \]

The DFB can be implemented by using a \( k \)-level binary tree decomposition that leads \( 2^k \) directional sub bands with edge shaped frequency partitioning. The based building blocks of DFB are quincx filter bank and shearing operators.

Quincx filter bank with fan filters is used to divide 2-d spectrum into two directions i.e., horizontal and vertical. Resampling metrics which is used to reassembled the pixels. Due to these operations the directional information was preserved. From the figure it is noticed that the band pass image which is passed through the low pass and high pass filters. Then decomposed into horizontal and vertical directional information. In this the properties of CT are i.e. directionality and anisotropy was done in Directional Filter Bank. The applications of directionality in image Enhancement, Denoising, Edge detection Segmentation. The properties of directionality are exact reconstruction, reduced redundancy, high computational complexity and they are able to decompose a multidimensional signal into directional sub bands, that are non redundant. In quincx filter bank Here we are using a simplified [20]

DFB Several implementations of DFBs are available in the literature[21].

III. PROPOSED ALOGORITHM

The basic steps involved in the proposed CBIR system includes database processing and resizing, creation and normalization of feature database, and then compare the query image with the database and finally that image can be retrieved. Proposed algorithm will be given in the steps wise.

Step 1: By using Contourlet Transform we can decompose each image in the Contourlet Domain.

**Step 2:** Compute the standard deviation (SD) of the CT decomposed image on each directional sub band.

Standard deviation is given as

\[
\sigma_k = \sqrt{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (W_k(i, j) - \mu_k)^2}
\]

Where

- \( W_k \) = Co-efficient of \( k^{th} \) CT decomposed sub band.
- \( \mu_k \) = Mean value of \( k^{th} \) sub band.
- \( M \times N \) = Size of the CT decomposed sub band.

The resulting SD vector is

\[ f = [\sigma_1, \sigma_2, \sigma_3, \ldots \ldots \sigma_n] \] (3)

**Step 3:**

Normalize the standard deviation vector to the range \([0,1]\) for every image in the database.

\[ \overline{f}_{CT} = \frac{f - \mu_T}{\sigma_T} \] (4)

Where

- \( \mu_T, \sigma_T \) are the mean and the standard deviation of \( \overline{f} \).

The normalized standard deviation vector \( \overline{f}_{CT} \) is used to create the feature database.

**Step 4:**

Apply query image and calculate the feature vector as given in step 2 to 3.

**Step 5:**

Calculate the similarity measure Minkowski’s distance which is given by the formula
\[ d = \left( \sum_{k=1}^{n} |p_k - q_k|^r \right)^{\frac{1}{r}} \] (5)

Where

- \( r \) is a parameter,
- \( n \) is the number of dimensions (attributes) and \( p_k \) and \( q_k \) are, respectively, the kth attributes (components) or data objects \( p \) and \( q \).

Where \( d \) is the Minkowski’s distance between the feature vector of the query image and every image in the database. \( \bar{f}_q \) and \( \bar{f}_i \) are the normalized standard deviation vectors of query image and database image, respectively.

**Step 6:**
Retrieve all relevant images to the query image based on maximum Minkowski’s distance.

A query image may be any one of the database images. This query is then proposed to compute the feature vector as in equation (3) and (4). The distance where ‘\( q \)’ is the query image and ‘\( i \)’ is an image from database is computed. The distances are sorted in increasing order and the closest sets of images are then retrieved. The top ‘\( n \)’ preference of the proposed method. The retrieval efficiency is measured by counting the number of matches.

Spatial and spectral features of the images can be explored for images retrieved in CBIR systems. Due to the local nature, it is difficult to detect edge and texture orientations using spatial methods. Spatial methods based on multiscale directions. They are also inefficient to capture edge and smooth contours in natural images. The contourlet transform (Ct) is a directional transform capable of capturing contours and the 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 efficiently capture smooth contours (edge and texture orientations) that are the dominant feature in image in the database.

**IV. EXPERIMENTAL RESULTS:**

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

**4.1 Feature Extraction**

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. ’Pkva’ filters [25] are used for LP decomposition and directional sub-band decomposition. These parameters results in a 32-directional feature vector \( n=32 \). Standard deviation (SD) 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]. The normalized feature vector is used for the creation of the feature database.

**Fig: Sample image from gale face database (image no.11)**

A sample image from face database (sample image is used in the database) and the corresponding CT decomposition with 4-level LP decomposition i.e. (0, 2, 3, 4) are shown in the figure.
In this work, retrieval performance of the proposed method is computed using Manhattan distance and Minkowaskhi distance as similarity measures. Manhattan distance takes the sum of the absolute differences but in our approach we can take the Minkowaskhi distance in CBIR system in improved retrieval performance. The superiority of proposed method is also observed in all cases i.e., when N is considered as 1, 2, 3, 5, 7, 10 (N is the number of retrieved images). When all the images in a class are retrieved (N=10) proposed method with Minkowaskhi distance is able to produce an improved average retrieval rate of 29.25% (i.e., from 38% to 67.25%).

V. CONCLUSIONS:

The feature vector that represents the image in the database can affect the performance of the CBIR system. Important characteristics of Contourlet transform viz., directionality and anisotropy are explored in this work. The Contourlet transform decomposes the image into sub-bands and calculates the normalized standard deviation for each sub-band which is used as the features in the feature vector representing the image. Superiority of this work is observed in terms of retrieval rate. The performance of retrieval system can be further improved by considering the energy of each sub-band in CT decomposed image. The feature vector can be varied if the database consists of images with different rotations.

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Improved Efficiency of CBIR using Contourlet Transform


