Image Retrieval using Contourlet Transform

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ABSTRACT
The image retrieval problem has recently become more important and necessary because of the rapid growth of multimedia databases and digital libraries. Different search engines use different features to retrieve images from the database. In this paper, the Contourlet Transform is developed to retrieve similar images from the image database. By combining the Laplacian pyramid and the Directional Filter Bank (DFB), a new image representation is obtained. The direction subbands coefficients are used to form a feature vector for classification. The performance of the Contourlet Transform is evaluated using standard bench marks such as Precision and Recall. An experiment shows that the Contourlet Transform (CT) features provide the best results in Image Retrieval.

Keywords
Content Based Image Retrieval (CBIR), Contourlet Transform (CT), Laplacian Pyramid (LP), Directional Filter Bank (DFB)

1. INTRODUCTION
The image retrieval system is to retrieve a set of images from a collection of images such that this set meets the user's requirements. The user's requirements can be specified in terms of similarity to some other image or a sketch, or in terms of keywords. An image retrieval system provides the user with a way to access, browse and retrieve efficiently and possibly in real time, from these databases [6], [7],[9].

Image retrieval systems can be divided into two main types: Text Based Image Retrieval and Content Based Image Retrieval. In the early years Text Based Image Retrieval was popular, but nowadays Content Based Image Retrieval has been a topic of intensive research in the recent years [10]. Manual Annotation or text based image retrieval system is the traditional image retrieval system. In traditional retrieval systems features are added by adding text strings describing the content of an image. The annotation of each image with its corresponding keywords is manually performed. The annotation of images is a tedious process and in case of very large databases, it is not feasible for a person to annotate all the images. Additionally, it is a slow and time consuming process to annotate a large database. This problem can be solved by using CBIR [12]. Content Based Image Retrieval (CBIR) attracted many researchers of various fields in effort to automate data analysis and indexing. CBIR is like filter information Process and it is used to provide a high percentage of relevant images in response to the query image. In a CBIR system, features are used to represent the image content. The features are extracted automatically and there is no manual intervention, thus eliminating the dependency on humans in the feature extraction stage [4], [5].

We consider a simple architecture of a typical Content Based Image Retrieval (CBIR) (Fig. 1), where there are two major tasks. The first one is feature extraction (FE), where a set of features, called image signatures, is generated to accurately represent the content of each image in the database. A signature is much smaller in size than the original image, typically of the order of hundreds of elements (rather than millions). The second task is similarity measurement (SM), where a distance between the query image and each image in the database using their signatures is computed so that the top "closest" images can be retrieved [1], [2], [3]. Recent CBIR systems are used to retrieve images based on visual properties such as color, shape, texture, etc.

One particularly promising approach to image database indexing and retrieval is the query by image content (QBIC) method. Whereby the visual contents of the images such as color distribution (color histogram), [10] texture attributes and other image features are extracted from the image using computer vision/image processing techniques and used as indexing keys.

In an image database, these visual keys are stored along with the actual imagery data and image retrieval from the database is based on the matching of the models visual keys with those of the query images. Because extra information has to be stored with the images, traditional approach to QBIC is not efficient in terms of data storage. Not only it is inefficient it is also inflexible in the sense that image matching / retrieval can only based on the pre-computed set of image features [1].

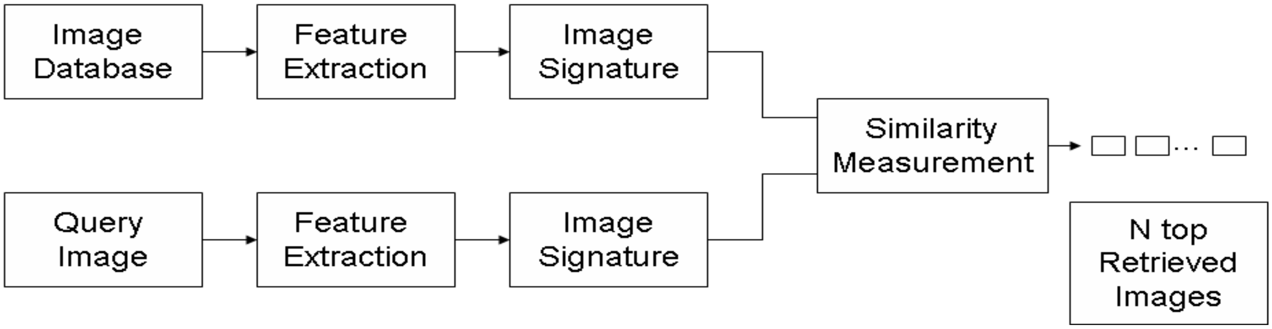

Fig 1: Content Based Image Retrieval Architecture

Texture refers to visual patterns with properties of homogeneity that do not result from the presence of only a single color or intensity. Texture analysis or retrieval is one of the most difficult problems in the area of vision and pattern recognition. There is a wide variety of features used for texture analysis such as coarseness, contrast and directionality, Line likeness measures, Regularity, Roughness. One of the popular representations of the texture is the wavelet [13]. Although this method allow for a multiresolution decomposition, they are limited in directional selectivity and not able to capture directional information. The focus of this paper is to retrieve the texture information for retrieval of images by using contourlet Transform (CT). The contourlet transform provides a multi-scale, multi-directional decomposition of an image.

2. CONTOURLET TRANSFORM

Contourlet Transform is a combination of a Laplacian pyramid and a Directional Filter Bank (DFB). The Contourlet Transform provides a multi-scale, multi-directional decomposition of an image. Figure 2 illustrates the decomposition of an image into its Laplacian Pyramid representation. The original image is at the upper left corner. The images immediately below and to the right of the original image are the coarse and detail signal respectively resulting from the first level of decomposition of the original image. The images adjacent to and below the coarse signal of the first level of decomposition are the detail and coarse signals respectively of the second level of decomposition. The Laplacian Pyramid consists of all the detail signals of each level of decomposition and the final coarse signal [8].Detail images from the Laplacian pyramid are fed into the Directional Filter Bank (DFB) so that directional information can be captured. The scheme can be iterated on the coarse image. The combined result is a double filter bank structure, named Contourlet filter bank, which decomposes images into directional sub-bands at multiple scales [11],[15],[8]. A double filter bank structure of the contourlet is shown in Fig.3 In the experiment, we use a Contourlet Transform with 3 scales and 8 orientations for feature extraction [15].

Fig. 2: LP Decomposition

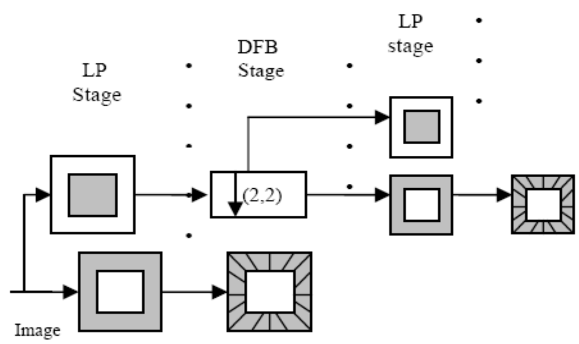

Fig.3.: Double Filter Bank Decomposition of contourlet Transform.

3. EXPERIMENTAL RESULTS

For evaluating the performance of the algorithms, we used an experimental database which consists of 445 images with five different classes. The Classes and distribution of the images is shown in table 1. Fig.4 shows a sample database of 25 images by randomly selecting five images from each category.

Class	A	B	C	D	E
No.of Images	132	80	109	70	54

Table 1: Image database: Class-wise Distribution

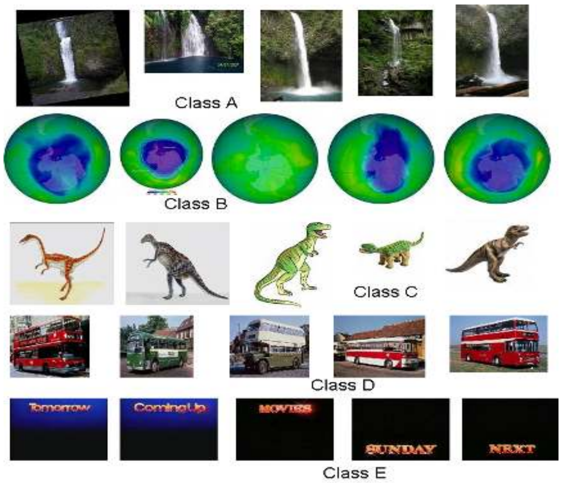

Fig.4: Sample database of 25 Images, the database has 5 classes, for a total of 445 images.

To Test the Proposed System four queries are selected from each category of images, so in all 20 queries for Contourlet Transform (CT) are fired on the database. The query image was selected from the database and it would be the first image in the result list. Other images in the result list were retrieved based on similarity to the query image.

To compare the similarity of two images, we use Normalized Euclidean Distance [14]. Let $w_{i,j}$ and $w_i(q)$ be the feature vector for image I_j and the feature vector for query image q respectively ,where i=1-------N

Then the similarity measure is defined as

$$d(q, I_j) = \frac{1}{1 + dis\ (q, I_j)}$$

Where the distance function is

$$dis\ (q, I_j) = \sum_{i=1}^{N} \frac{| w_{i,j} - w_i(q) |}{1 + w_{i,j} + w_i(q)}$$

The performance is evaluated using standard bench marks such as Precision, Recall. Precision is defined as the ratio of number of relevant images retrieved to total number of retrieved images from the database. And Recall is defined as the ratio of number of relevant images retrieved to total number of relevant images in the database. To find the computational efficiency we measure retrieval time. The retrieval time primarily depends on the size of the image database, the software and the hardware versions that system runs on, size of the feature vector and the similarity measure used. Fig.6 shows the results of Contoulet transform using Normalized Euclidean distance for the query image (Class D) shown in Fig.5. From Fig. 6 it is clear that 68 images retrieved are of same class (Bus Class i, e Class D) among first 70 images retrieved and the first image is the query image itself.

Fig.5: Query Image (Class D)

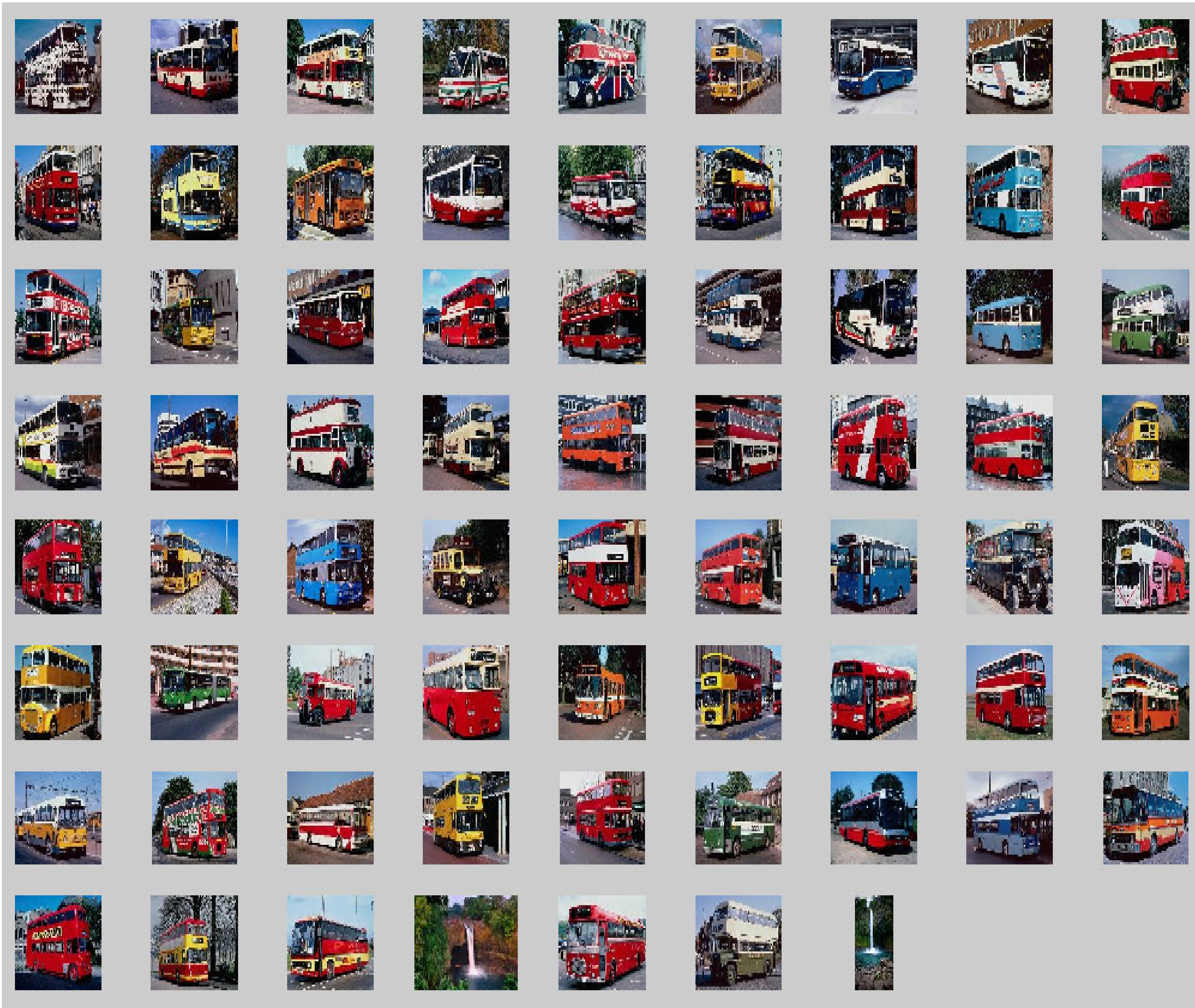

Fig. 6: Results of Contourlet Transform (CT) Based Image Retrieval (Total No. of images retrieved:- 70, Actual no. of relevant images retrieved:-68, Non-relevant images retrieved:-02)

Fig. 7 shows the Bar chart of Precision /Recall for all 5 classes and 4 queries each using Contourlet Transform. Details of Precision and Recall are shown in Table 2. From each category randomly four images are chosen as query image, so in all 20 queries for Contourlet Transform (CT) are fired on the database and for every query image precision and recall are computed. It is observed that average precision and Recall varies from 84.31% to 99.06%.The graphs (Fig 8 to Fig. 12) show precision and recall plotted against number of retrieved images. The graphs are plotted by randomly selecting a one query image from each class.

	A	B	C	D	E
Query Image 1 Precision/Recall	90	98.75	95.41	90	100
Query Image 2 Precision/Recall	86	98.75	95.41	97.14	92.59
Query Image 3 Precision/Recall	87.77	98.75	88.99	82.85	100
Query Image 4 Precision/Recall	73.48	100	97.24	85.71	98.14
Average Precision/Recall	84.31	99.06	94.26	88.92	97.68

Table 2.:--- Precision/Recall for all 5 classes and 4 queries each using Contourlet Transform (CT)

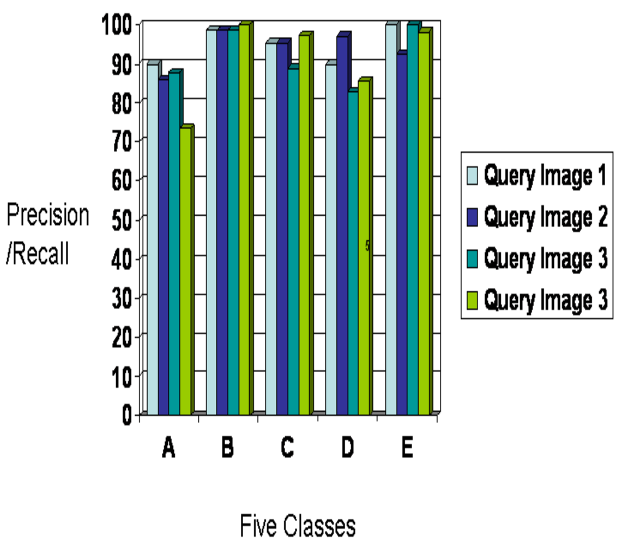

Fig.7: Precision/ Recall Performance for Contourlet Transform (CT)

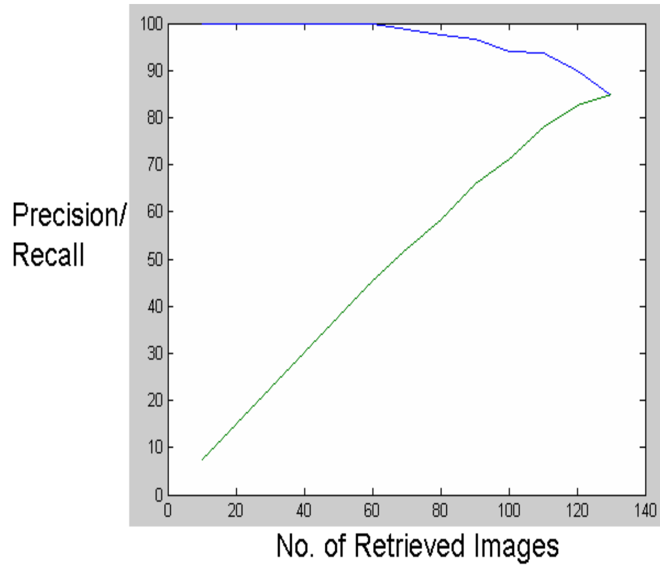

Fig.8: Precision (Blue Line) and Recall (Green Line) performance for query image in Class 'A'

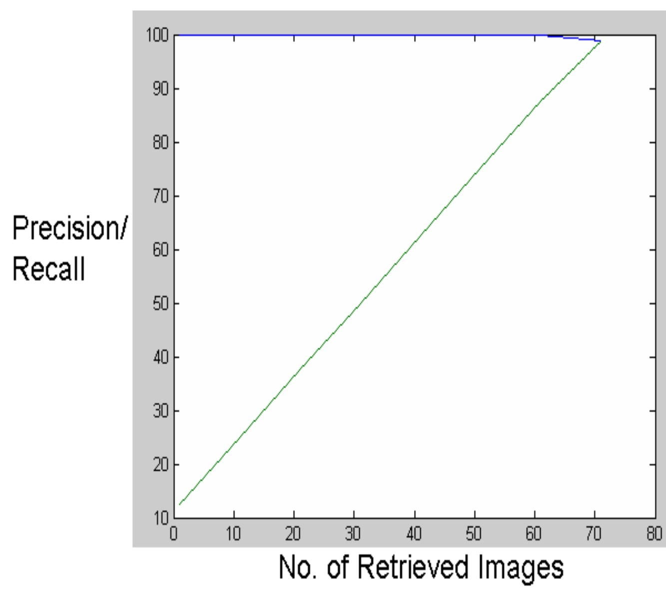

Fig. 9: Precision (Blue Line) and Recall (Green Line) performance for query image in Class 'B'

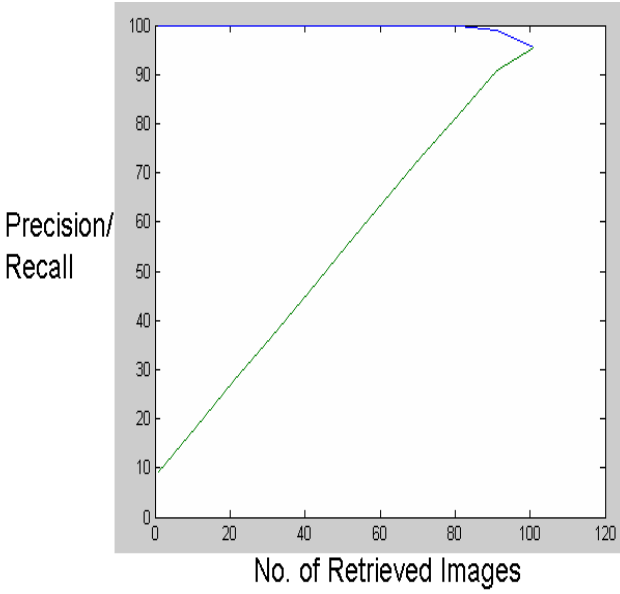

Fig. 10: Precision (Blue Line) and Recall (Green Line) performance for query image in Class 'C'

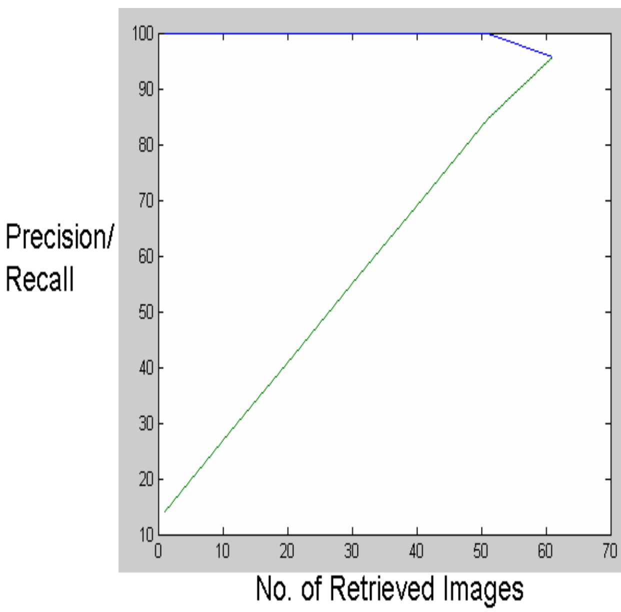

Fig. 11: Precision (Blue Line) and Recall (Green Line) performance for query image in Class 'D'

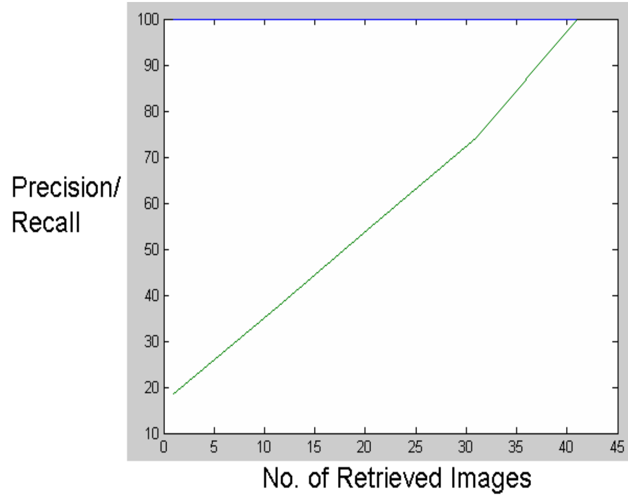

Fig. 12: Precision (Blue Line) and Recall (Green Line) performance for query image in Class 'E'

From Fig. 8 to Fig. 12 it is clear that recall increases as the number of retrieved items increases and precision is constant (i,e 100% for query image in class 'B' and 'E') and it slightly decreases for query image in class 'A','C' and 'D' as the number of retrieved item increases. Usually, a tradeoff must be made between these two measures since improving one will sacrifice the other. In typical retrieval systems, recall tends to increase as the number of retrieved items increases; while at the same time the precision is likely to decrease.

4. CONCLUSION

We have presented the contourlet transform for image retrieval in this paper. The contourlet transform provides a multi-scale, multi-directional decomposition of an image. It is a combination of a Laplacian pyramid and a Directional Filter Bank (DFB). For evaluating the performance of the Contourlet Transform Based Image Retrieval, we used an experimental database which consists of 445 images of size 128x128x3 with five different classes. From each class randomly four images are chosen as query image, so in all 20 queries for Contourlet Transform (CT) are fired on the database and for every query image precision and recall are computed. It is observed that average precision and Recall varies from 84.31% to 99.06%. From these results, it is clear that Contourlet Transform features provide a high percentage of relevant images in response to the query image.

5. REFERENCES

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