

Comparative Evaluation of Transform Based CBIR Using Different Wavelets and Two Different Feature Extraction Methods

¹Omprakash Yadav, ²Vaishali Suryawanshi

¹Computer Department, Xavier Institute of Engineering, Mahim
Mumbai University, India

²Computer Department, Thadomal Shahni Engineering College, Bandra
Mumbai University, India

Abstract— In this paper, evaluation is made on the result of CBIR system based on different types of wavelets from wavelet family like haar, daubechies, coiflet and symlet wavelet transform with Euclidean distance for similarity matching to calculate the deviation from query image. In this paper discrete wavelet transform is used to decompose the image and two different strategies are used for feature extraction. The image is decomposed till sixth level using different wavelets. In this paper two different experiments are carried out for two different methods evaluation. In first experiment the last level approximate component of decomposed image considered as a feature vector while in second experiment all the level approximate component is taken into consideration. All the approximate component is concatenated and used as a feature vector. Experiments results are tabulated. COIL image database is considered. The experiment is performed on different set of images, 720 having 10 different classes, 1440 having 20 different classes and 2160 images having 30 different classes for comparisons purpose. The result is tabulated at the end.

Keywords— CBIR, QBIC, Precision, Recall, Query Image, Distances, Efficiency, HAAR, Chessboard Distance, City Block Distance, Euclidean Distance. **Introduction.**

I. INTRODUCTION

An image retrieval system is effective if it can retrieve an image or a collection of images from an operating database upon being inputted with a single image whose replicas or lookalikes need to be extracted. Database management and Computer vision are two major research communities, which study the subject of image retrieval from different perspectives. Text based image retrieval employs techniques of attaching text or data along with the image to describe it, often termed as 'metadata', while content based techniques use visual features to match images to the query image.

In CBIR, all the images from the database are taken and features of each are extracted and stored in a vector. These features are compared to the extracted features of the query image. A CBIR typically converts images in feature vector representations and uses them to match similar images [1]. IBM was the first research company to take initiative by proposing a system called QBIC (query by image content), which was developed, at the IBM Almaden Research Center.

Unlike keyword based system, visual features are extracted from images itself. Content based image retrieval system

uses contents and extracts features like color, shape and texture. All these are visual contents [2].

Feature extraction based on the color is done taking color histogram of each image. It is nothing but the portion of pixels within an image which has some specific value. This specific value people express as colors. One more benefit of using extraction based on colors is that it does not depend on the size of image. Eventually, color histograms will be taken and compared [3].

Feature extraction based on shape does not refer to the shape of the whole image. Within an image we have certain area of interest. Shape denotes the shape that area of interest. To get the shape first image segmentation is performed or edge detection is done [3].

Feature extraction based on texture measurely concentrates on visual patterns and how they are organized. It is given by texels. Texels are kept into number of different sets ,depending how many of textures detected. The sets determined like this will give complete information about the which patterns and where in the image they got detected. The determination of specific texture can be made by molding texture as a 2D gray level variation. For determination of level of contrast, regularity , directionality and coarseness pixels relative brightness is considered. In this paper texture features are extracted using DWT transform [3].

Figure shows a general description of a standard image retrieval system[7].

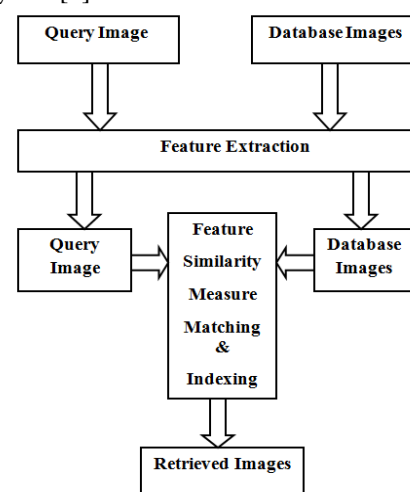


Figure 1. Basic block diagram of CBIR system

As shown in the above diagram, feature extraction is done for both query image as well as database images. First of all, all the databases images will be presented and there feature will be extracted and stored as feature database. Then query image is selected and its features will be extracted. This process will result into query features. After this process, query feature is taken and all the database feature is selected, and depending on criteria similarity measure will be calculated and the retrieved images will be displayed. In this paper, a similarity measurement criterion is taken based on Euclidean distance [3].

II. DWT LITERATURE SURVEYED

DWT is an mathematical tool, it decomposes the image into various parts and decomposition is performed hierarchically. It is very much useful in the processing of non-stationary signals. It uses wavelets. Wavelets are small waves and of limited duration. In Fourier transform we lose the time information after transform is performed. But, In wavelet transform we get both time and frequency information. Different wavelets can be generated by translation and dilations performed on mother wavelet[7]. DWT decomposes the image into components like horizontal denoted by cH, vertical component denoted by cV and diagonal component denoted by cD. Figure below shows the decomposition upto three level. In our project we have used decomposition till sixth level. Major benefit we get by decomposing till sixth level is that feature vector size gets reduced too much [4]. Wavelet transform is very efficient. It can also be implemented using filter banks using convolution. Image processed with wavelet transform gives multi resolution description of image. Image can be viewed at different levels of resolution. In the lowest band LL magnitude is largest level wise. Significantly its good to have more magnitude. Larger the magnitude of wavelet coefficient , it will become more significant [5][6][7].

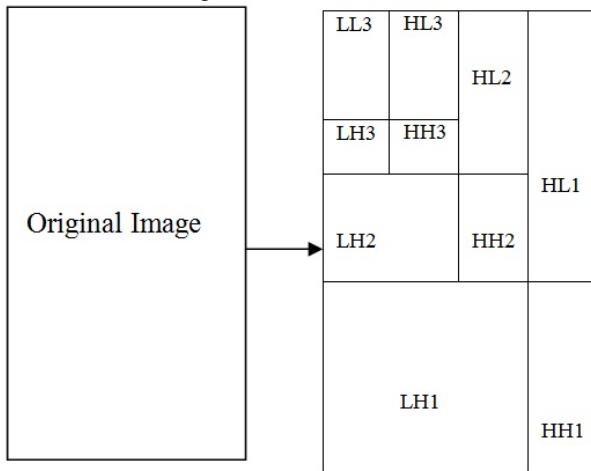


Figure 2: DWT decomposition of image till 3rd level

III. WAVELETS TO BE USED

In this paper the experiment is carried out on the four wavelets Haar, Symlet, Coiflet and Daubechies. Different wavelet posses different properties. Compact support (lead to efficient implementation), symmetry (useful in avoiding dephasing in image processing), orthogonality (allow fast

algorithm), regularity, and degree of smoothness (related to filter order or filter length). Each wavelet family can be parameterized by integer N that determines filter order. Symmetry in wavelets can be obtained only if we are willing to give up either compact support or orthogonality of wavelet (except for Haar wavelet, which is orthogonal, compactly supported, and symmetric). If we want both symmetry and compact support in wavelets, we should relax the orthogonality condition and allow nonorthogonal wavelet functions. An example is the family of biorthogonal wavelets that contains compactly supported and symmetric wavelets [6].

A. COIFLET

The breakdown of any image using COIFLET wavelet transform is different than any other wavelet used. COIFLET belongs to the family of Daubechies Wavelet Transforms. This helps in understanding how this transform works. Coiflet wavelets are families of orthogonal wavelets that are compactly supported. Compactly supported wavelets correspond to finite-impulse response (FIR) filters[6]. So, coiflet has compactly supported, nearly symmetrical, has arbitrary number of vanishing moments, exact reconstruction is possible.

B. SYMLET

SYMLET Transform belongs to the family of Haar wavelet. Symlet has compactly supported, nearly symmetrical, has arbitrary number of vanishing moments, exact reconstruction is possible.

C. HAAR

Any discussion of wavelets begins with Haar wavelet, the first and simplest. Haar wavelet is discontinuous, and resembles a step function. They are a modified version of Daubechies wavelets with increased symmetry. It represents the same wavelet as Daubechies db1. Haar wavelet, is orthogonal, compactly supported, and symmetric and exact reconstruction is possible.

D. DAUBECHIES

Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets -- thus making discrete wavelet analysis practicable. The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. The db1 wavelet, as mentioned above, is the same as Haar wavelet. In our experiment db2 is taken as daubechies wavelet. Daubechies wavelets are families of orthogonal wavelets that are compactly supported. Compactly supported wavelets correspond to finite-impulse response (FIR) filters. Daubechies Wavelet is evaluated on the basis of the same two parameters Average Precision and Average Recall. This wavelet transform, on implementation proved as efficient as Haar Wavelet since the crossover point is the same for both. In this paper db2 is taken as daubechies wavelet.

IV. SIMILARITY MEASUREMENT

The parameters being used for calculation of efficiency of the CBIR system designed, namely Average Precision and Average Recall are the ones being used to compare the results of different Distance Types being employed to

retrieve images in the proposed system. Precision and recall can be calculated as follows[7]:

$$\text{Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}}$$

$$\text{Recall} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in the database}}$$

A. EUCLIDEAN DISTANCE

Euclidean distance metric was initially used by CANDID. He used this for the comparison of global signatures. Euclidean distance can be calculate as follows: If A(x,y) and B(p,q) are two pixels then euclidean distance can be given as[7],

$$\text{Distance} = \sqrt{(|x-p|^2 \oplus |y-q|^2)}$$

V. SCHEME OF IMPLEMENTATION

We aim to extract texture from an image. Texture is a pattern on image, which can be smooth, rough, etc. The wavelet transformations transform the images into a multi-scale representation with both spatial and frequency characteristics. In this paper experiment is carried out on different set of images with the different way of extracting features. The image sets are images with 10 different class having total 720 images, images with 20 different classes total 1440 images and images with 30 different classes having total 2160 images.

In the first experiment image is decomposed till 6th level. Last level approximate component is used as a feature vector. Following procedure is followed for experiment 1. To check the performance of proposed technique two measures are used i.e. precision and Recall [1].

$$\text{Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images}}$$

$$\text{Recall} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images in database}}$$

A. FEATURE EXTRACTION OF DATABASE IMAGES FOR FIRST EXPERIMENT

Step1: Apply first level decomposition and decompose image into 4 subparts i.e. cA1, cH1, cV1 and cD1.

Step2: Apply second level decomposition and again decompose cA1 into four subparts i.e. cA2, cH2, cV2 and cD2.

Step3: Apply third level decomposition and again decompose cA2 into its 4 subparts cA3, cH3, cV3 and cD3.

Step4: Apply fourth level decomposition and again decompose cA3 into its 4 subparts cA4, cH4, cV4 and cD4.

Step5: Apply fifth level decomposition and again decompose cA4 into its 4 subparts cA5, cH5, cV5 and cD5.

Step6: Apply sixth level decomposition and again decompose cA5 into its 4 subparts cA6, cH6, cV6 and cD6.

Step7: Save the cA6 as a feature vector.

Where,

cA = Approximate coefficient matrix

cH = Horizontal component

cV = Vertical component

cD = Diagonal component

B. FEATURE EXTRACTION OF QUERY IMAGE FOR FIRST EXPERIMENT

Step 1: Five query images selected from one type of class

Step 2: Each query image is taken one by one and decomposed using dwt till sixth level and query image feature vector extracted

Step 3: Similarity measurement is done using Euclidean distance

Step 4: Step 1 to 3 is repeated till all the classes are covered.

Step 5: Precision and recall calculated for each query image class wise

Step 6: Average precision and recall calculated for all the classes

Results of the experiment 1 is tabulated below.

Table 1. Results without concatenation (using 6th level approximate component only)

Different wavelets	720	1440	2160
Daubechies	0.8408	0.8009	0.7595
Coiflet	0.8461	0.7933	0.7492
haar	0.6397	0.6884	0.6726
symlet	0.6397	0.6884	0.6726

In the second experiment image is decomposed till 6th level. Each level approximate component is stored. Last level approximate component is used as a feature vector. Following procedure is followed for experiment 2.

C. FEATURE EXTRACTION OF DATABASE IMAGES FOR SECOND EXPERIMENT THAT IS WITH PROPOSED METHOD

Step 1: Apply first level decomposition and decompose image into 4 subparts i.e. cA1, cH1, cV1 and cD1 and Store the approximate component cA1 of first level

Step 2: Apply second level decomposition and again decompose cA1 into four subparts i.e. cA2, cH2, cV2 and cD2 and Store the approximate component cA2 of second level

Step 3: Apply third level decomposition and again decompose cA2 into its 4 subparts cA3, cH3, cV3 and cD3 and Store the approximate component cA3 of third level

Step 4: Apply fourth level decomposition and again decompose cA3 into its 4 subparts cA4, cH4, cV4 and cD4 and Store the approximate component cA4 of fourth level

Step 5: Apply fifth level decomposition and again decompose cA4 into its 4 subparts cA5, cH5, cV5 and cD5 and Store the approximate component cA5 of fifth level

Step 6: Apply sixth level decomposition and again decompose cA5 into its 4 subparts cA6, cH6, cV6 and cD6 and Store the approximate component cA6 of sixth level

Step 7: Calculate the mean of all stored approximate component of each level and concatenate them in 2 dimensions

Step 8: Store the result of seventh step as feature vector

Step 9: Repeat the step from 1 to 8 for all the images in the database and store their feature vector

D. FEATURE EXTRACTION OF QUERY IMAGE FOR SECOND EXPERIMENT

- Step 1:** Five query images selected from one type of class
- Step 2:** Each query image is taken one by one and above mentioned proposed methods steps from 1 to 8 are performed to get feature vector
- Step 3:** Similarity measurement is done using Euclidean distance
- Step 4:** Step 1 to 3 is repeated till all the classes are covered.
- Step 5:** Precision and recall calculated for each query image class wise
- Step 6:** Average precision and recall calculated for all the classes

Results of experiment 2 are tabulated below.

Table 2. Results of proposed method (with concatenation using all level approximate component)

Different wavelets	720	1440	2160
Coiflet	0.8258	0.7681	0.7134
Daubechies	0.8227	0.7704	0.7036
Symlet	0.8077	0.7635	0.6878
Haar	0.8077	0.7635	0.6878

VI. FIGURES/CAPTIONS

Precision/Recall figure is shown only for two best cases one from experiment 1 and other from experiment 2 i.e. from proposed method.

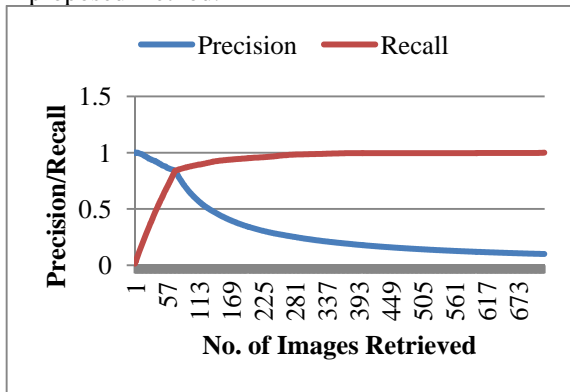


Figure 3. Precision/Recall using Daubechies on 720 images(0.8408) without concatenation

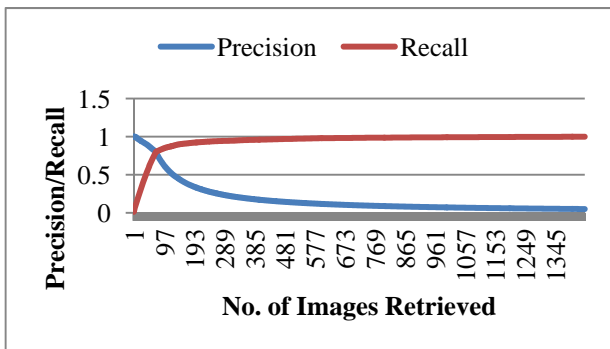


Figure 4. Precision/Recall using Daubechies on 1440 images(8009) without concatenation

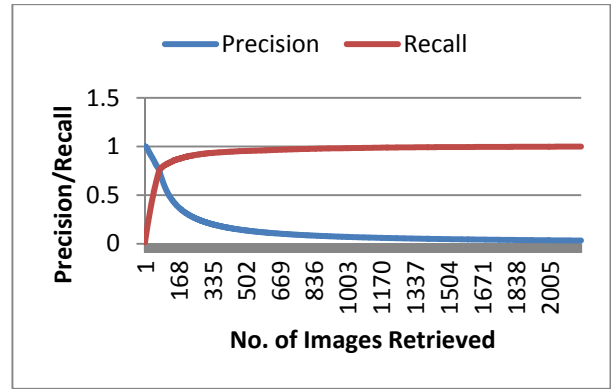


Figure 5. Precision/Recall using Daubechies on 2160 images(0.7595) without concatenation

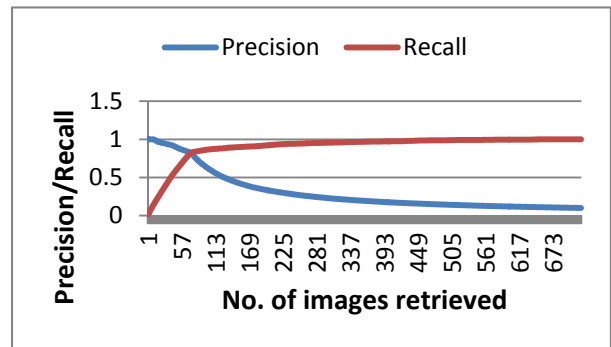


Figure 6. Precision/Recall using Coiflet on 720 images(0.8258) with proposed method

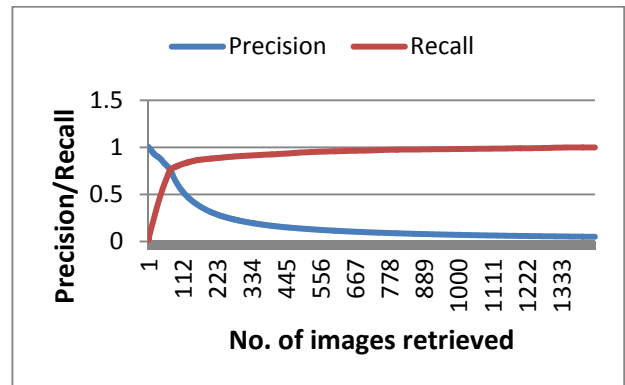


Figure 7. Precision/Recall using Coiflet on 1440 images(0.7681) with proposed method

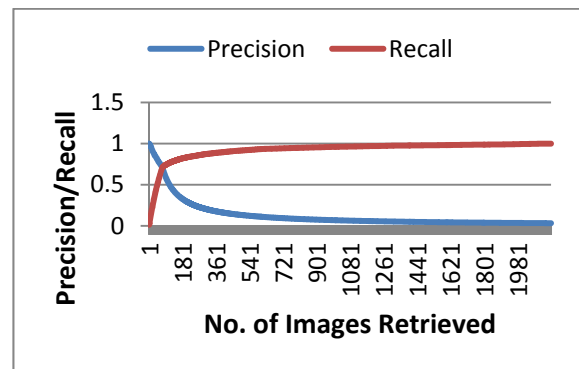


Figure 8. Precision/Recall using Coiflet on 2160 images(0.7134) with proposed method

VII. CONCLUSIONS

From the table1 i.e. with experiment 1 its clear that Daubechies gives better precision/recall values when first method is used. Haar and symlet results are same. Coiflet results are approximately same as daubechies.

From the table2 results that is with proposed method its clear that coiflet results are better and approximately equal to Daubechies results. Symlet and Haar results are same.

By observation of results of both table 1 and 2, results of table 2 i.e. using proposed method are more consistent. If we increase the number of images there is not much drastic change in the Precision/Recall values as compared to the experiment 1.

REFERENCES

- [1] Lidia Xavier, Thusnavis Bella Mary.I and Newton David Raj.W, "Content Based Image Retrieval Using Textural Features based on Pyramid structure wavelet transform", 2011 IEEE.
- [2] Priyanka P. Buch, Madhuri V. Vaghasia and Sahista M. Machchhar, "Comparative analysis of content based image retrieval using both color and texture", International conference on Current Trends in Technology,2, NUiCONE, 2011 IEEE.
- [3] Swapnalini Pattanaik and prof.D.G. Bhalke, "Beginners to Content Based Image Retrieval", International Journal of Scientific Research Engineering & Technology, Volume 1 Issue2 pp 040-044 May 2012.
- [4] Arnold W.M. Smeulders, Marcel Worring, Simone Santini, "Content-based image retrieval at the end of the early years".IEEE Transactions on Pattern analysis and machine intelligence, vol 22, No 12, December 2000.
- [5] N S T Sai , R C Patil, "Image Retrieval using 2D Dual-Tree Discrete Wavelet Transform",. International Journal of Computer Applications (0975 – 8887), Volume 14 – No.6, February 2011.
- [6] Vinay U. Kale & Nikkoo N. Khalsa, "Performance Evaluation of Various Wavelets for Image Compression of Natural and Artificial Images", International Journal of Computer Science & Communication, Vol. 1, No. 1, January-June 2010, , pp. 179-184.
- [7] Omprakash Yadav and Vaishali Suryawanshi, "CBIR Evaluation using Different Distances and DWT", International Journal of Computer Applications 93(16):36-40, May 2014.