Content Based Color Image Retrieval via Wavelet Transforms

Mrs.Y. M. Latha † **Dr.B.C.Jinaga**† **V.S.K.Reddy**††,

GNITS,JNTU,India *Rector ,JNTU,India* *IIT,Kharagpur.India*

Summary

Content-Based Image Retrieval (CBIR) allows to automatically extracting target images according to objective visual contents of the image itself. Representation of visual features and similarity match are important issues in CBIR. In this paper a novel CBIR method is proposed by exploit the wavelets which represent the visual feature. We use Haar and D4 wavelet to decompose color images into multilevel scale and wavelet coefficients, with which we perform image feature extraction and similarity match by means of F-norm theory. Furthermore, we also provide a progressive image retrieval strategy to achieve flexible CBIR. We tested five categories of color images in the experiments. The retrieval performance of D4 and Haar wavelet is compared with wavelet histograms in terms of recall rate and retrieval speed. Experiment results reflect the importance of wavelets in CBIR and F-norm theory along with progressive retrieval strategy achieves efficient retrieval.

Key words:

F-norm theory , progressive image retrieval strategy.

1. Introduction

Content-Based Image Retrieval (CBIR) is considered as the process of retrieving desired images from huge databases based on extracted features from the image themselves (without resorting to a key word). Features are derived directly from the images and they are extracted and analyzed by means of computer processing[1].CBIR is a bottleneck of the access of multimedia databases that deal with text, audio, video and image data which could provide us with enormous amount of information . Many commercial and research CBIR systems have been built and developed (e.g.: QBIC, Virage, Pichunter, visual *SEEK,* Chabot, Excalibur, photobook, Jacob) [2]. Content based image retrieval [3]-[4], allowing to automatically extract targets according to objective visual contents of image itself(e.g. color, texture and shape) has become increasingly attractive, in Multimedia Information Service System *(MISS).* With appealing time frequency localization and multi-scale properties, wavelet transform proved to be effective in visual feature extraction and representation. It can be used to characterize textures using statistical properties of the gray levels of the points/pixels comprising a surface image.

In CBIR, wavelet approaches mainly include wavelet histogram and wavelet moment of image, etc. [12]. Wavelet transform can be used to characterize textures using statistical properties of the gray levels of the pixels comprising a surface image [13]**.** The wavelet transform is a tool that cuts up data or functions or operators into different frequency components and then studies each component with a resolution matched to its scale.
In this paper, we used D4 and Haar wavelet transforms to decompose color images into multilevel scale and wavelet coefficients, with which we perform image feature extraction and similarity match by means of F-norm theory. We also present a progressive retrieval strategy, which contributes to flexible compromise between the retrieval speed and the recall rate. The retrieval performances are compared with the existing wavelet histogram technique. The efficiency in terms Recall rate and retrieval speed is tested with five types of images and the results reflect the importance of wavelets in CBIR.F-norm theory along with progressive retrieval strategy improves retrieval performance.

The rest of this paper is organized as follows. In section 2, we introduced the general structure of the proposed *CBIR* system. Section 3 provides the image decomposition using wavelets. Section 4 describes Feature Extraction and Similarity criteria. Section 5 presents a progressive CBIR strategy. Section 6 describes the implementation and experimental results. Finally conclusions are offered in section 7.

2. General structure of Proposed CBIR system

Our proposed *CBIR* algorithm is based on decomposition of the database images using Haar and D4 wavelets in the offline as well as in online for query image. With resulting coefficients using F-norm theory we extract the features and perform highly efficient image matching. In the database we used four typical groups of color images namely Sunflowers, Horses, Roses ,Lilies

Manuscript received December 5, 2007
Manuscript revised December 20, 2007

and Fishes as shown in the Fig. 1.

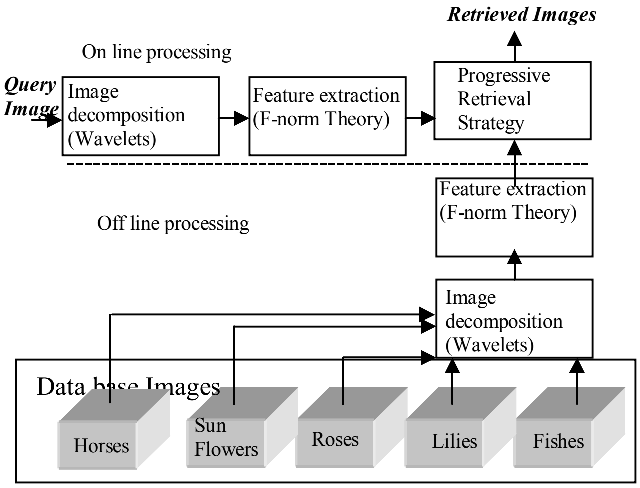


Fig.1.Structure of proposed CBIR system

3. Image decomposition with wavelets

We used two wavelet approaches for color image decomposition, namely Haar, D4 wavelets. These resulting decomposition coefficients are employed to perform image feature extraction and similarity match by virtue of F-norm theory

3.1 Haar Wavelet Transform

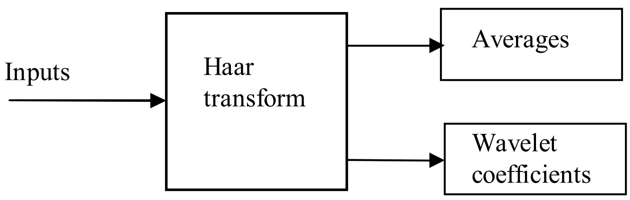


Fig. 2. Haar wavelet forward transform

If a data set S_0, S_1 ….S_{N-1} contains N elements, there will be N/2 averages and N/2 wavelet coefficient values. The averages are stored in the upper half of the N element array and the coefficients are stored in the lower half as shown in the Fig.2. The averages become the input for the next step in the wavelet calculation, where for iteration i+1, $N_{i+1} = N_i/2$. The recursive iterations continue until a single average and a single coefficient are calculated. This replaces the original data set of N elements with an average, followed by a set of coefficients whose size is an increasing power of two (Ex: 2^0, 2^1, 2^2 ... N/2).

The Haar equations to calculate an average a_i and a wavelet coefficient c_i from an odd and even element in the data set are:

$$a_i = \frac{s_i + s_{i+1}}{2} \qquad c_i = \frac{s_i - s_{i+1}}{2} \qquad (1)$$

Forward Haar transform for an eight element signal is shown in the Fig 3. Here signal is multiplied by the forward transform matrix.

$$\begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix} \Leftarrow \begin{bmatrix} a_0 \\ c_0 \\ a_1 \\ c_1 \\ a_2 \\ c_2 \\ a_3 \\ c_3 \end{bmatrix} = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{2} & -\frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{2} & -\frac{1}{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} & -\frac{1}{2} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & -\frac{1}{2} \end{bmatrix} \bullet \begin{bmatrix} s_0 \\ s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \\ s_6 \\ s_7 \end{bmatrix}$$

Fig.3.Haar Forward ward transform for 8 element signal

The arrow represents a split operation that reorders the result so that the average values are in the first half of the vector and the coefficients are in the second half. To complete the forward Haar transform there are two more steps. The next step would multiple the average values a_i by a 4x4 transform matrix, generating two new averages and two new coefficients which would replace the averages in the first step. The last step would multiply these new averages by a 2x2 matrix generating the final average and the final coefficient.

3.2The Daubechies D4 Wavelet Transform

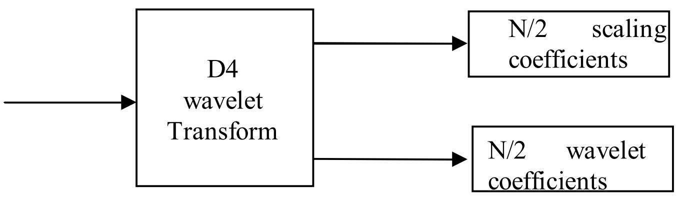


Fig. 4. D4 wavelet forward transform

The D4 transform has four wavelet and scaling function coefficients as shown in the Fig.4.

The scaling function coefficients are:

$$h_0 = \frac{1+\sqrt{3}}{4\sqrt{2}} \quad h_1 = \frac{3+\sqrt{3}}{4\sqrt{2}}$$
$$h_2 = \frac{3-\sqrt{3}}{4\sqrt{2}} \quad h_3 = \frac{1-\sqrt{3}}{4\sqrt{2}} \qquad (2)$$

Each step of the wavelet transform applies the scaling function to the data input. If the original data set has N values, the scaling function will be applied in the wavelet transform step to calculate N/2 smoothed values. In the ordered wavelet transform the smoothed values are stored in the lower half of the N element input vector.

The wavelet function coefficient values are:

$$g_0 = h_3 ; g_1 = -h_2 ; g_2 = h_1 ; g_3 = -h_0 . \qquad (3)$$

Each step of the wavelet transform applies the wavelet function to the input data. If the original data set has N values, the wavelet function will be applied to calculate N/2 differences (reflecting change in the data). In the ordered wavelet transform the wavelet values are stored in the upper half of the N element input vector.

The scaling and wavelet functions are calculated by taking the inner product of the coefficients and four data values. The equations are shown below.

Daubechies D4 scaling function

$$a_i = h_0 s_{2i} + h_1 s_{2i+1} + h_2 s_{2i+2} + h_3 s_{2i+3}$$
$$a[i] = h_0 s[2i] + h_1 s[2i+1] + h_2 s[2i+2] + h_3 s[2i+3]$$

(4)

Daubechies D4 wavelet function

$$c_i = g_0 s_{2i} + g_1 s_{2i+1} + g_2 s_{2i+2} + g_3 s_{2i+3}$$
$$c[i] = g_0 s[2i] + g_1 s[2i+1] + g_2 s[2i+2] + g_3 s[2i+3]$$

(5)

Each iteration in the wavelet transform step calculates a scaling function value and a wavelet function value. The index i is incremented by two with each iteration, and new scaling and wavelet function values are calculated.

D4 forward transform matrix for 8 element signal is shown in the Fig.5.

$$\begin{bmatrix} h_0 & h_1 & h_2 & h_3 & 0 & 0 & 0 & 0 & & \\ g_0 & g_1 & g_2 & g_3 & 0 & 0 & 0 & 0 & & \\ 0 & 0 & h_0 & h_1 & h_2 & h_3 & 0 & 0 & & \\ 0 & 0 & g_0 & g_1 & g_2 & g_3 & 0 & 0 & & \\ 0 & 0 & 0 & 0 & h_0 & h_1 & h_2 & h_3 & & \\ 0 & 0 & 0 & 0 & g_1 & g_2 & g_3 & g_4 & & \\ 0 & 0 & 0 & 0 & 0 & 0 & h_0 & h_1 & h_2 & h_3 \\ 0 & 0 & 0 & 0 & 0 & 0 & g_0 & g_1 & g_2 & g_3 \end{bmatrix} \bullet \begin{bmatrix} s_0 \\ s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \\ s_6 \\ s_7 \end{bmatrix}$$

Fig.5. D4 forward transform matrix for 8 element signal

4. Feature Extraction and Similarity criteria

Our *CBIR* algorithm is based on direct wavelet decomposition of image in *RGB* color space and utilizes the “query by example” method. With approaches mentioned above, database images are decomposed offline into multi-level coefficients from -1 to -J levels, with which, we can generate color feature database and perform similarity match between images. After decomposition, each resulting sub image is in fact a coefficient matrix, where, by special processing, large coefficients with more energy can be distributed in the up-left area, therefore, with F-norm theory[7], we can well decrease the dimension of image feature and perform highly efficient image matching.

4.1 Feature Vector

Suppose A is a square matrix and A_i is its i^{th} order sub matrix where

$$A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{n1} & \dots & a_{nn} \end{bmatrix}, \quad A_i = \begin{bmatrix} a_{11} & \dots & a_{1i} \\ \dots & \dots & \dots \\ a_{i1} & \dots & a_{ii} \end{bmatrix} \quad (i = 1 \sim n)$$

The F-norm of A_i is given as:

$$\|A_i\|_F = \left(\sum_{k=1}^{i} \sum_{l=1}^{i} |a_{kl}|^2 \right)^{1/2} \qquad (6)$$

Let $\Delta A_i = \| A_i \|_F - \|A_{i-1}\|_F$ and $\|A_0\|_F = 0$, we can define the feature vector of A as:

$$V_{AF} = \{\Delta A_1, \Delta A_2 \ldots \Delta A_n\} \qquad (7)$$

4.2 Similarity criteria

Define the Similarity α_i of ΔA_i and ΔB_i as:

$$\alpha_i = \begin{cases} \min(\Delta A_i, \Delta B_i)/\max(\Delta A_i, \Delta B_i) --- \Delta A_i \neq 0 or \Delta B_i \neq 0 \\ 1 ----------------- \Delta A_i = 0 or \Delta B_i = 0 \end{cases} \quad (8)$$

and we can thus give the similarity α of the matrices A and B as:

$$\alpha = \sum_{i=1}^{n} c_i \alpha_i \quad (9)$$

Where, $C_i = \frac{2i-1}{n^2} (i = 1,2,...,n)$ and

$\sum_{i=1}^{n} C_i = 1$. Obviously, the similarity $0 \leq \alpha \leq 1$.

5. Progressive Retrieval Strategy

We use progressive retrieval strategy in order to balance between computational complexity and retrieval accuracy.

1. Rough filtering:

Starting from the maximal decomposition level –J,

With the resulting LL coefficients, we calculate standard variances vectors of the query image and the database image *as* $(\sigma_r^q, \sigma_g^q, \sigma_b^q)$ and $(\sigma_r^d, \sigma_g^d, \sigma_b^d)$respectively, after which ,we can roughly filter database images as follows

$$F = (\beta\sigma_r^q < \sigma_r^d < \sigma_r^q/\beta) \;\&\&\; (\beta\sigma_g^q < \sigma_g^d < \sigma_g^q/\beta) \;\&\&\; (\beta\sigma_b^q < \sigma_b^d < \sigma_b^q/\beta)$$

Where, the filtering constant β Є (0, 1) is used to adjust the sifted database images. If F is false, then database image can be identified as far apart from Query image and therefore is discarded; else, database image be kept for further match.

2. Progressive rough filtering:

Considering the effect of high frequency components with LH and HL wavelet coefficients in step1.

3. More precise filtering:

With the obtained LL coefficients, which best reflect the general feature of image; we use the similarity criteria (9) to determine more precise images. If α exceeds a given threshold, it means that mismatch occurs and it should be discarded; else, it will be kept for further match.

4. Iteration:

J=J-1, and iterate step 1~ 4 till J = 0. Finally, retrieval results are fed back to users in the order of their similarity values.

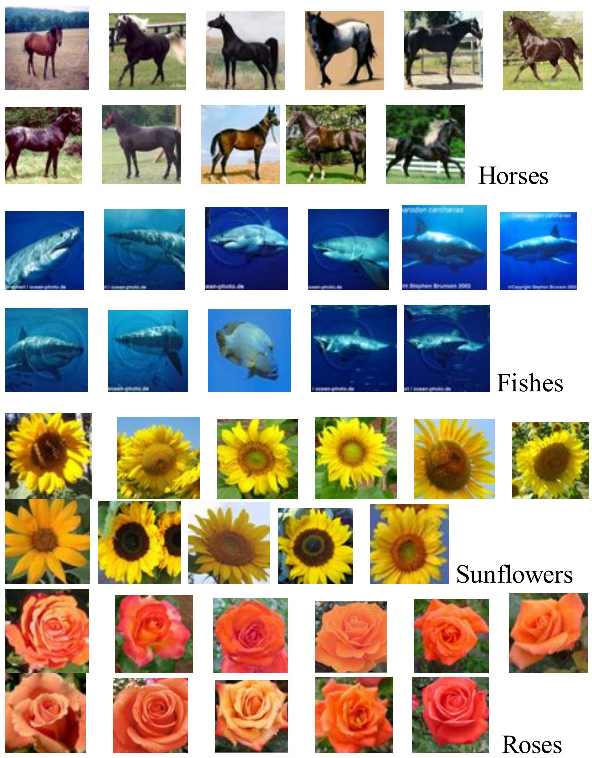
6. Experimental Results

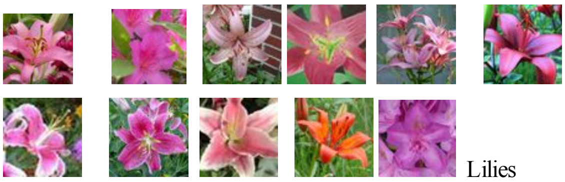
The general flow of the experiments starts with the decomposition of data base image using Haar and D4 wavelet in offline. The maximal decomposition level J = 4. We repeated the same decomposition in online for query image. With F-norm theory we extracted the image feature vector and performed highly efficient image matching. We used progressive retrieval strategy to balance between computational complexity and retrieval accuracy. We focus on the comparison of two important retrieval indices, namely retrieval accuracy and the speed. The test image database contains over 2400 images of 24 bits true color. They are divided into 4 groups each containing 600 images. The four groups are Horses, Fishes, Sunflowers, and Roses. For simplicity, all images are pre processed to be 256x256 sizes before decomposition. Sample data base images for each category are shown in the Fig.6.

The Recall rate is defined as the ratio of the number of relevant (same category) retrieved images to the number of relevant items in collection [8].

$$\text{Recall rate} = \frac{\text{Number of relevant items retrieved}}{\text{Total number of relevant items in collection}}$$

SAMPLE DATA BASE IMAGES





Lilies

Fig. 6. Sample data base images of four categories

Sample retrieved images for the given query image using Haar and D4 wavelets are shown in the Fig.6 and 7. The number at the foot of each image indicates its similarity (α) to the example image.α values indicate the similarity between the Query image and the images in the database .For similar images, α value is 1.Greater the α value greater is the similarity between the Query image and the database image. Retrieved images are sorted according to their alpha values (degree of similarity).

RETRIEVED IMAGES BASED ON HAAR WAVELET

Query Image

Retrieved Images:

1.0000 0.8413 0.8356 0.8257 0.8061 0.7956

0.7926 0.7927 0.7919 0.7901 0.7759 0.7680

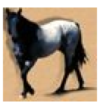
Query Image

Retrieved Images

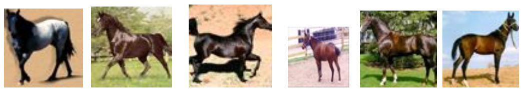
.0000 0.8940 0.8665 0.8549 0.8538 0.8530

0.8529 0.8478 0.8448 0.8363 0.8319 0.8218

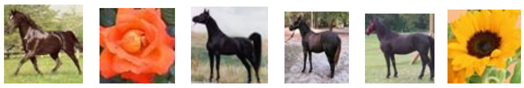
Query Image



Retrieved Images



1.0000 0.8998 0.8764 0.8589 0.8567 0.8542

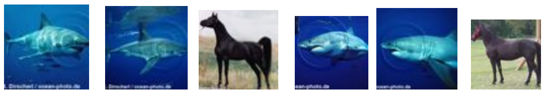


0.8509 0.8489 0.8462 0.8453 0.8446 0.8438

Query Image

Retrieved Images

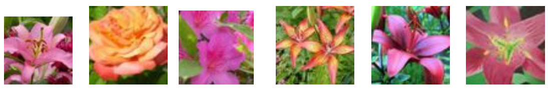
1.0000 0.8998 0.8764 0.8589 0.8567 0.8542



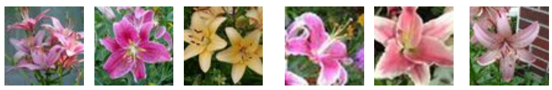
0.8509 0.8489 0.8462 0.8453 0.8446 0.8438

Query Image

Retrieved Images:



1.0000 0.8799 0.8775 0.8498 0.8471 0.8461



0.8415 0.8348 0.8291 0.8125 0.8096 0.8092

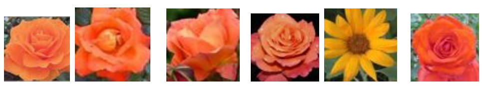
Fig.7.Retrieved Images based on Haar wavelet

RETRIEVED IMAGES BASED ON D4 WAVELET

Query Image

Retrieved Images

1.0000 0.9108 0.8964 0.8899 0.8853 0.8754



0.8748 0.8569 0.8533 0.8513 0.8446 0.8421

Query Image

Retrieved Images:

1.0000 0.8415 0.8357 0.8256 0.8060 0.7954

0.7934 0.7929 0.7922 0.7901 0.7761 0.7679

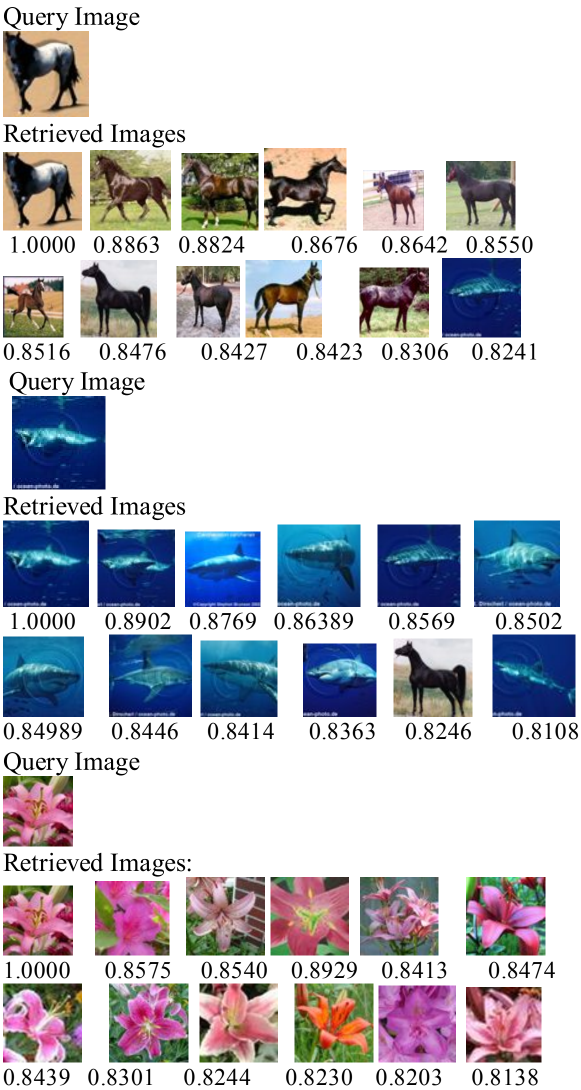
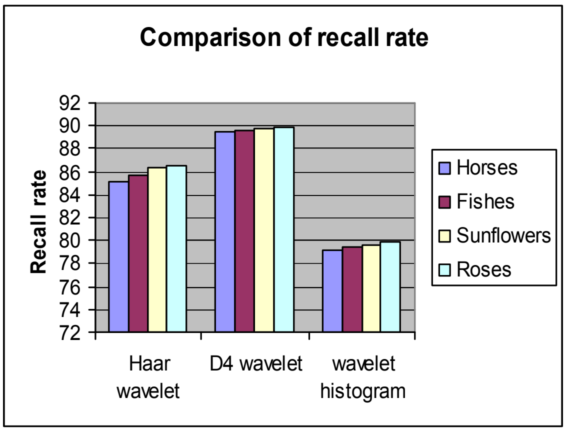


Fig.8.Retrieved Images based on D4 wavelet scheme

The following graphs and Table.1 shows the Recall rate achieved by the two schemes namely D4 ,Haar Wavelet Transform and existing wavelet histogram for each category of color images. D4 wavelet transform achieves the best Recall rate. Table 2 illustrate the retrieval speed. Different average retrieval times of the two approaches in Table.2, mainly caused by decomposition approaches, could roughly reflect their quantitative computational complexity.

According to the experimental results we obtain:

- In CBIR, representing image using Haar and D4 wavelets achieves efficient recall rate. This is also the most apparent advantage of the wavelets in real time applications.
- The progressive retrieval strategy contributes to flexible compromise between the retrieval speed and the accuracy.



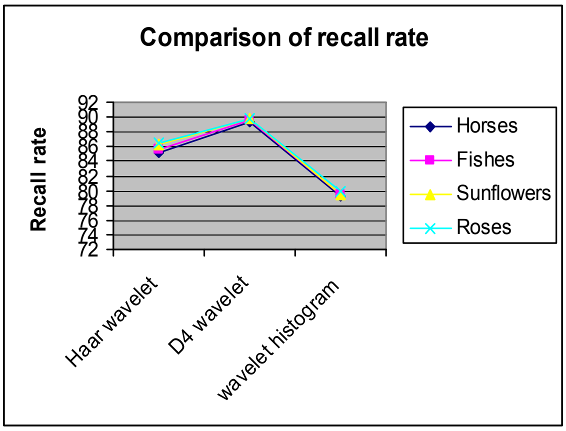
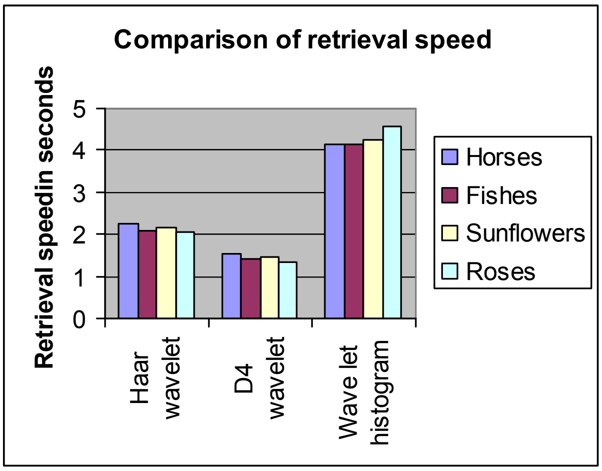


Table.1.Comparison of Recall rate

	D4 wavelet	D4 lifting
Horses	85.12	89.45
Fishes	85.68	89.67
Sunflowers	86.39	89.78
Roses	86.52	89.89

Table.2.Comparison of Retrieval speed(S)

	Haar wavelet	D4 wavelet
Horses	2.25	1.55
Fishes	2.10	1.43
Sunflowers	2.15	1.45
Roses	2.05	1.35



7. Conclusions

In this paper we introduced a novel *CBIR* approach via wavelet decomposition of images, followed by feature extraction and similarity match under F-norm theory. We compared the retrieval performance of D4 wavelet , Haar wavelet schemes with the existing technique wavelet histograms. It turns out that D4 wavelet has greatly speeded retrieval as well as ensured enough recall rate comparable with its Haar wavelet and wavelet histogram. In addition, the progressive retrieval strategy helps to achieve flexible compromise among retrieval indices. Finally we conclude from the results that wavelets achieve high retrieval performance in real time CBIR systems.

References

[1] Christopher C. Yang, "Content-based image retrieval: a comparison between query by example and image browsing map approaches ", Journal of Information Science, pp. 254-267, 2004.

[2] Rui Y. & Huang T. *S.,* Chang S. F. "Image retrieval: current techniques, promising directions, and open issues". Journal of Visual Communication and Image Representation, 10, 39-62, 1999.

[3] Vishal Chitkara, "Color-Based image Retrieval Using Binary Signatures". Technical Report TR 01-08, University of Ulberta, Canada, May 2001.

[4] Qasim Iqbal and J. K. Aggarwal, "Combining Structure, Color, and Texture for Image Retrieval: A performance Evaluation".16th International Conference on Pattern Recognition (ICPR), Quebec City, Canada, August 11-15. 2002, vol. 2, pp. 438-443

[5] R. Calderbank, I. Daubechies, W. Sweldens and Y.Boon-Lock, "Wavelet transform that map integers to integers",Appl. Comut. Harmon. Anal., 5(3), 332-369, 1998

[6] [13] M.G. Mostafa, M.F. Tolba, T.F. Gharib, M.A. Megeed, Medical ImageSegmentation Using Wavelet based Multiresolution EM Algorithm". IEEE International Conference on Industrial Electronics, Technology, &Automation., Cairo IETA'2001.

[7] Huihui Huang; Wei Huang; Zhigang Liu; Weirong Chen; Qingquan Qian; "Content-based color image retrieval via lifting scheme" Autonomous Decentralized Systems, 2005. ISADS Proceedings 2005. 4-8 April 2005 Page(s): 378 – 383.

[8] Henning Muller, Wolfgang Muller, David McG. Squire and Thierry Pun, "Performance Evaluation in Content-Based Image Retrieval: Overview and Proposals". Computing Science Center, University of Geneva, Switzerland, 2000.

Y.Madhaveelatha, born on January, 1972, completed her graduation and post graduation from JNT University, Hyderabad. She has been working at G.Narayanamma Institute of Science and Technology, JNT University ,Hyderabad. Her research interest includes Image and Video processing ,Multimedia Systems Design. She is Life Member of Institute of Electronics and Telecommunication Engineers and Life Member of ISTE.

Dr.B.C. Jinaga, born on June, 1950, graduation from Karnataka University, Dharwad**,** Post Graduation from Regional Engineering, Warangal and Ph. D. from Indian Institute of Technology, Delhi. He has been with JNTUniversity since 21 years. Prof. Jinaga was occupied various key positions at JNT University and presently Rector at JNT University. His research interest includes signal Processing and Coding Techniques. He received Best Teacher Award for the year 2002 - Awarded by Government of Andhra Pradesh. He is fellow of Institute of Engineers(India)and Fellow of Institute of Electronics and Telecommunication Engineers

V.S.K.Reddy, born on June 1967, graduated from S.V. University, Tirupati, India, and Post Graduation from JNT University, Hyderabad. His Doctoral Research from IIT Kharagpur in the area of VLSI Signal Processing. He has been working at Srinidhi Institute of Science and Technology since 1998. His specialized fields are Image and Video Processing, TCP/IP Networks and Protocols, VLSI Architectures Signal Processing and DSP Processors. He is fellow of Institute of Electronics and Telecommunication Engineers and Member of IEEE.