Feature Vectors based CBIR in Spatial and Transform Domain

Swapna Borde
Vidyavardhini's College of Engineering and Technology, Vasai (W)

Udhav Bhosle, PhD.
Rajiv Gandhi Institute of Technology, Andheri (W), Mumbai

ABSTRACT

This paper presents Content Based Image Retrieval Techniques based on feature vectors in Spatial Domain and Transform Domain. The feature extraction in spatial domain includes the CBIR techniques based on Gaussian Pyramid, Laplacian Pyramid and Steerable Pyramid. The feature extraction in transform domain includes the CBIR techniques based on Discrete Cosine Transform, Discrete Fourier Transform, Hadamard Transform and Wavelet Transform. Instead of using all the coefficients of images as feature vector for Content Based Image Retrieval, only two feature vectors such as mean and standard deviation are used. The feature vector size in transform domain is less as compared to feature vector size in spatial domain. All the CBIR techniques are implemented on a database having 648 images spread across 9 classes. For each CBIR technique, 27 queries (3 per class) are applied on the Image database and precision & Recall values are computed. The results have shown performance improvement with Discrete Fourier Transform, Wavelet Transform and Gaussian Pyramid as compared to other techniques at reduced computations.

Keywords

Content Based Image Retrieval (CBIR), Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT), Wavelet Transform (WT), Hadamard Transform (HT), Gaussian Pyramid (GP), Laplacian Pyramid (LP), Steerable Pyramid (SP)

1. INTRODUCTION

The large amount of image collections available from a variety of sources (digital camera, digital video, scanner, the Internet, etc.) have posed increasing technical challenges to computer systems to store/transmit and index/manage the image data effectively and efficiently to make such collections easily accessible [1],[2],[3].While manual image annotations can be used to a certain extent to help image Search, the feasibility of such an approach to large databases is a questionable issue.

In some cases, such as face or texture patterns, simple textual descriptions can be ambiguous and often inadequate for database search. This problem can be solved by using Content Based Image Retrieval (CBIR) [5], [6],[10].

The typical CBIR system performs two major tasks. The first one is feature extraction, where a set of features, called feature vector is generated to accurately represent the content of each image in the database. Set of features is called as image signature and size of the image signature is very small as compared to the original image. The second task is similarity measurement, where a distance between the query image and each image in the database is computed so that top closest images can be retrieved from the database [3], [9]. This paper presents Content Based Image Retrieval Techniques based on feature vectors in Spatial Domain and Transform Domain. The feature extraction in spatial domain includes the CBIR techniques based on Gaussian Pyramid, Laplacian Pyramid and Steerable Pyramid. The feature extraction in transform domain includes the CBIR techniques based on Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT), Hadamard Transform (HT) and Wavelet Transform (WT). Normalized Euclidean Distance is used to compare the features of query image with features of images in the database. The normalized Euclidean distance [11] between query image and each image in the database can be given by following equation ,where $w_{i,j}$ and $w_i(q)$ be the feature vector for image I_j and the feature vector for query image q respectively , i=1-------N

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

Where the distance function is

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

2. Discrete Cosine Transform

Discrete Cosine Transform (DCT) is used as key functions in many signal and image processing applications. All JPEG images use the discrete cosine transform as the initial stage of compression. Just as the Fourier transform uses sines and cosines waves to represent a signal, the DCT uses N real basis vectors whose components are cosines. It is shown that DCT can not only be used for compressing images, it can also be conveniently used for Content Based Image Retrieval [7].

3. Discrete Fourier Transform

In Fourier transform, a signal is decomposed into a number of sinusoids of different frequency. The Fast Fourier Transform (FFT) refers to a class of algorithms for efficiently computing the Discrete Fourier Transform (DFT). Hence FFT is not an approximation of the DFT, it is the DFT with a reduced number of computations. DFT is most useful in digital signal processing, Convolution and digital filtering. This paper shows that DFT can also be conveniently used for Content Based Image Retrieval.

4. Hadamard Transform

The Hadamard Transform is faster than sinusoidal transforms, since no multiplications are required. The hadamard transform is based on the hadamard matrix which is a square array having entries of +1 and -1.

The Hadamard matrix of order 2 is given by

$$H(2) = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

Hadamard matrices of order 2^n can be recursively generated using the kronecker product.

$H(2^n) = H(2) \times H(2^{n-1})$

If n=1, $H(2) = H(2)$

n=2, $H(4) = H(2) \times H(2)$

$$H(4) = \begin{bmatrix} H(2) & H(2) \\ H(2) & -H(2) \end{bmatrix}$$

If n=3

$$H(8) = \begin{bmatrix} H(4) & H(4) \\ H(4) & -H(4) \end{bmatrix}$$

Similarly, If n=7

$$H(128) = \begin{bmatrix} H(64) & H(64) \\ H(64) & -H(64) \end{bmatrix}$$

If f is a N ×N image and H (N) is a N ×N transformation matrix then Hadamard transform is given by

$$F = \left[H(N)\, f\, H(N) \right]$$

5. Wavelet Transform

Wavelet is used to decompose a signal. The practical implementation of wavelet compression schemes is similar to subband coding schemes. As in the case of subband coding, we decompose the signal using filter banks. The outputs of the filter banks are down sampled, quantized and encoded. The decoder decodes the coded representations, up samples and recomposes the signal using a synthesis filter bank. Figure.1. shows subband decomposition. We begin with an N×M image. We filter each row and then down sample to obtain two N×M/2 images. We then filter each column and sub sample the filter output to obtain four sub images , the one obtained by low-pass filtering the rows and columns is referred to as the LL image, the one obtained by low – pass filtering the rows and high pass filtering the columns is referred to as the LH image, the one obtained by high-pass filtering the rows and low- pass filtering the columns is called the HL image and the sub image obtained by high-pass filtering the rows and columns is referred to as the HH image. Each of the subimages obtained in this fashion can then be filtered and sub sampled to obtain four more sub images. This process can be continued until the desired subband structure is obtained [3].

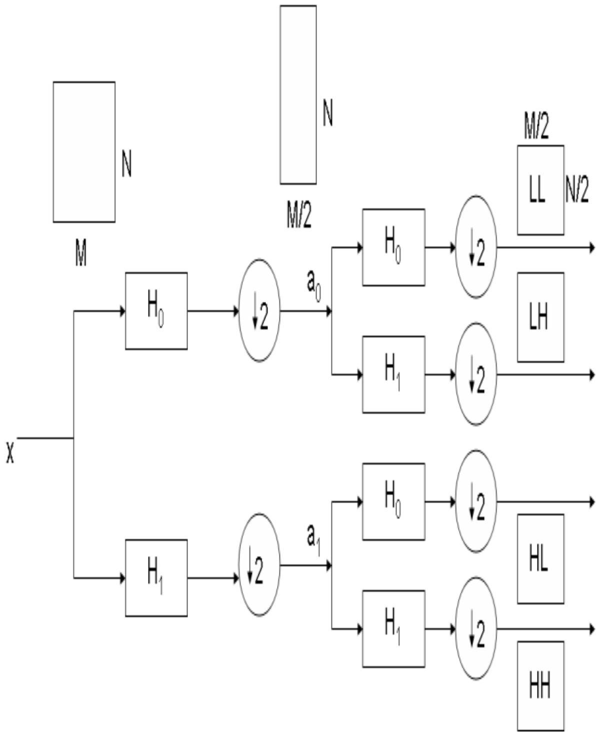

Figure 1: Subband decomposition of an N×M Image

6. Gaussian Pyramid

The Gaussian pyramid is used to decompose images into information at multiple scales, to extract features and to remove noise. The Gaussian pyramid consists of low-pass filtered, downsampled version of the previous level of the pyramid, where the base level is defined as the original image. Figure 2 shows the decomposition of an image into its Gaussian Pyramid representation.

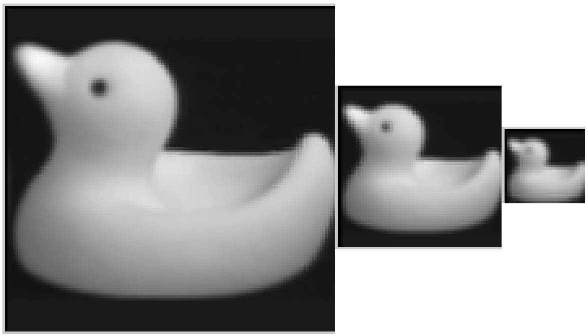

Figure 2 : Gaussian Pyramid Decomposition

7. Laplacian Pyramid

The Laplacian Pyramid is a decomposition of the original image into a hierarchy of images. Figure 3 shows 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. [12].

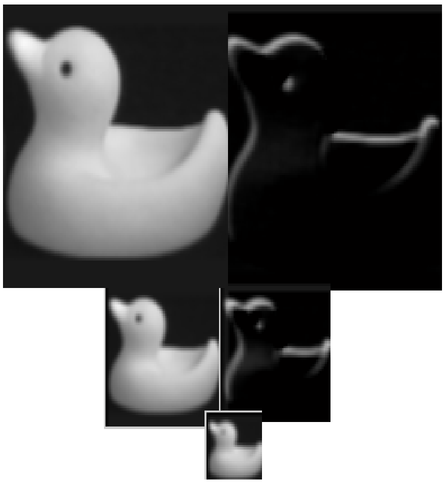

Figure. 3 Laplacian Pyramid Decomposition

8. Steerable Pyramid

The Steerable Pyramid generates a multi-scale, multi-directional representation of the image. The image is decomposed into low-pass sub-band and high-pass sub-band and decomposition is iterated in the low-pass sub-band. The Steerable Pyramid decomposition is similar to the two-dimensional discrete wavelet transform but with directional subbands [13].

Steps to extract features from a color image by using Steerable Pyramid are as follows:

1. This method first resizes the image to 128 ×128. Then divide the image into R, G, and B components.
2. Apply the low pass filter and high pass filter on each component (R, G, and B).
3. The low frequency content is the most important part of the signal. High frequency component contains less information as compared to low frequency component. Hence, the output of the low pass filter received from the first stage can be down sampled by a factor of 2. The process of filtering and down sampling can be repeated to get a multi-level decomposition.
4. Then directional subbands (8 Nos.) are obtained from the output of low pass filter of each stage.
5. Compute the features such as mean and standard deviation of directional subbands of query image as well as images in the database. Then Normalized Euclidean Distance [11] is used to compute the similarity measure between query image and images from the database.

9. Experimental Results

For evaluating the performance of the algorithms, Coil-100 Image database is used [8]. Image database contains 648 images spread across 9 classes. Some of the sample images which are used as query images are shown in Figure 4.

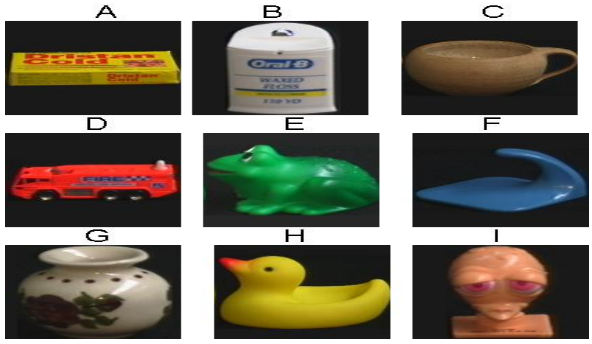

Figure 4. Sample images

Normalized Euclidean Distance is used to compare the features of query image with features of images in the database. The query image was selected from the image database and it would be the first image in the result list. Other images in the result list were retrieved based on the similarity to the query image. The performance of the CBIR system is evaluated using standard bench marks such as Precision, Recall [4], [12].

Figure 6(a) , 6(b) , 6(c) , 6(d) ,6(e) , 6(f) ,6(g) shows the results of Discrete Cosine Transform, Discrete Fourier Transform, Hadamard Transform , Wavelet Transform, Gaussian Pyramid, Laplacian Pyramid and Steerable Pyramid using Normalized Euclidean distance for the query image (Class 'E') shown in Figure.5

Figure 5 Query Image (Class 'E")

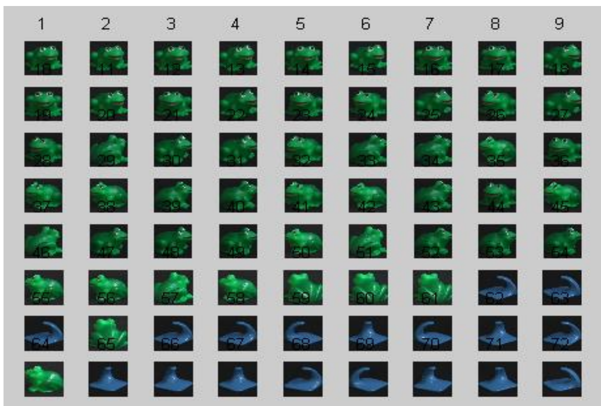

Figure 6(a) Results of Discrete Cosine Transform (Total No. of images retrieved:- 72, Actual no. of relevant images retrieved:-54, Non-relevant images retrieved:-18)

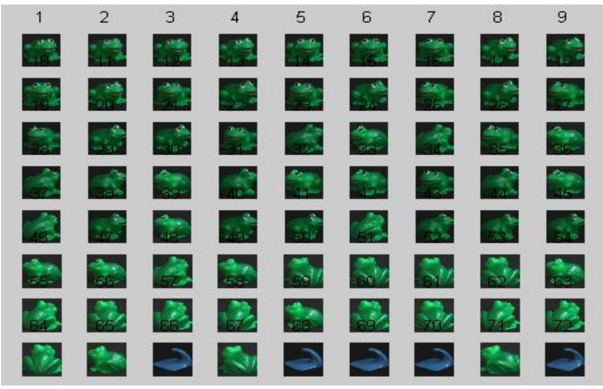

Figure 6(b) Results of Discrete Fourier Transform (Total No. of images retrieved:- 72, Actual no. of relevant images retrieved:-67, Non-relevant images retrieved:-05)

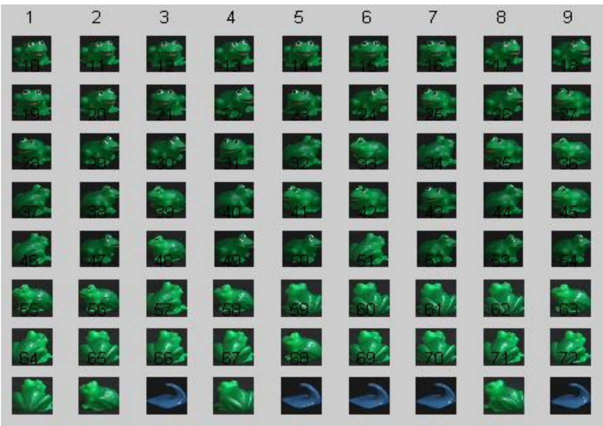

Figure 6(c) Results of Hadamard Transform (Total No. of images retrieved:- 72, Actual no. of relevant images retrieved:-67, Non-relevant images retrieved:-05)

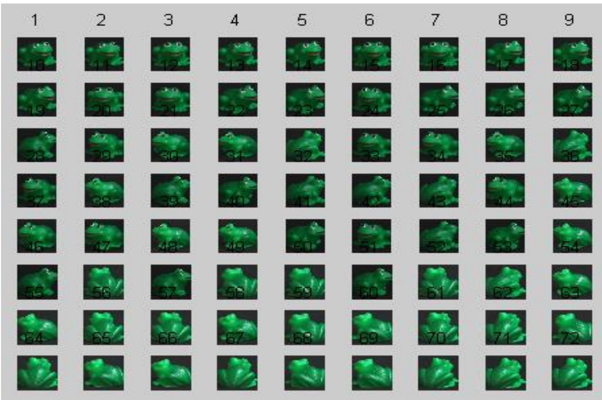

Figure 6(d) Results of Wavelet Transform (Total No. of images retrieved:- 72, Actual no. of relevant images retrieved:-72, Non-relevant images retrieved:-00)

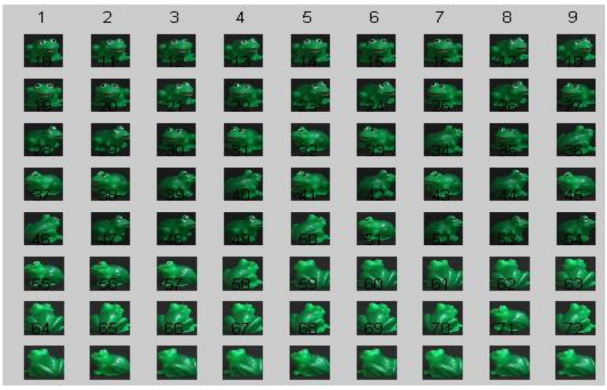

Figure 6(e) Results of Gaussian Pyramid (Total No. of images retrieved:- 72, Actual no. of relevant images retrieved:-72, Non-Relevant images retrieved:-00)

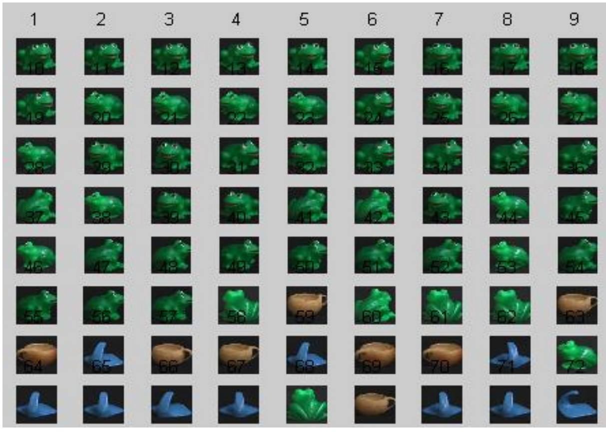

Figure 6(f) Results of Laplacian Pyramid (Total No. of images retrieved:- 72, Actual no. of relevant images retrieved:-54, Non-relevant images retrieved:-18)

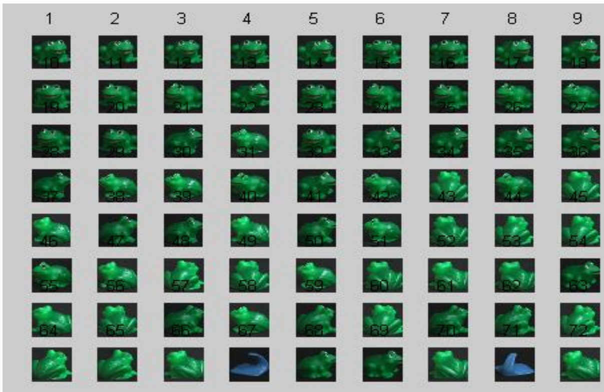

Figure 6(g) Results of Steerable Pyramid (Total No. of images retrieved:- 72, Actual no. of relevant images retrieved:-70, Non-relevant images retrieved:-02)

Table 1 to Table 7 gives Precision and Recall for all 9 classes and 3 queries each for first 72 retrieved images using Discrete Cosine Transform , Discrete Fourier Transform , Hadamard Transform, Wavelet Transform , Gaussian Pyramid, Laplacian Pyramid and Steerable Pyramid. From each category randomly three images are chosen as query image and for every query image precision and recall are computed.

Table 1.:----- Average Precision/Recall for all 9 classes for first 72 top images using Discrete Cosine Transform

	A	B	C	D	E	F	G	H	I
Query Image 1 Precision/Recall	86.11	100	86.11	95.83	81.94	100	98.61	100	95.83
Query Image 2 Precision/Recall	81.94	93.05	62.5	95.83	52.77	100	100	100	98.61
Query Image 3 Precision/Recall	87.5	100	86.11	75	75	100	100	98.61	100
Average Precision/Recall	85.18	97.68	78.24	88.88	69.90	100	99.53	99.53	98.14

Table 2.:----- Average Precision/Recall for all 9 classes for first 72 top images using Discrete Fourier Transform

	A	B	C	D	E	F	G	H	I
Query Image 1 Precision/Recall	86.11	100	87.5	97.22	83.33	100	98.61	100	88.88
Query Image 2 Precision/Recall	83.33	97.22	63.88	97.22	51.38	100	100	100	97.22
Query Image 3 Precision/Recall	87.5	100	87.5	75	93.05	100	100	100	100
Average Precision/Recall	85.64	99.07	79.62	89.81	75.92	100	99.53	100	95.36

Table 3.:----- Average Precision/Recall for all 9 classes for first 72 top images using Hadamard Transform

	A	B	C	D	E	F	G	H	I
Query Image 1 Precision/Recall	86.11	100	87.5	97.22	83.33	100	98.61	100	88.88
Query Image 2 Precision/Recall	83.33	97.22	63.88	97.22	48.61	100	100	100	97.22
Query Image 3 Precision/Recall	87.5	100	87.5	75.00	93.05	100	100	100	100
Average Precision/Recall	85.64	99.07	79.62	89.81	74.99	100	99.53	100	95.36

Table 4.:----- Average Precision/Recall for all 9 classes for first 72 top images using Wavelet Transform

	A	B	C	D	E	F	G	H	I
Query Image 1 Precision/Recall	94.44	100	86.11	100	100	100	97.22	100	93.05
Query Image 2 Precision/Recall	100	100	75	100	90.27	100	100	100	93.05
Query Image 3 Precision/Recall	98.61	95.83	86.11	87.5	100	100	100	100	88.88
Average Precision/Recall	97.68	98.61	82.40	95.83	96.75	100	99.07	100	91.66

Table 5.:----- Average Precision/Recall for all 9 classes for first 72 top images using Gaussian Pyramid

	A	B	C	D	E	F	G	H	I
Query Image 1 Precision/Recall	86.11	100	87.5	98.61	95.83	100	98.61	100	90.27
Query Image 2 Precision/Recall	88.88	100	72.22	98.61	70.83	100	100	100	98.61
Query Image 3 Precision/Recall	87.5	100	87.5	75.00	100	100	100	100	100
Average Precision/Recall	87.49	100	82.40	90.74	88.88	100	99.53	100	96.29

Table 6.:----Average Precision/Recall for all 9 classes for first 72 top images using Laplacian Pyramid

	A	B	C	D	E	F	G	H	I
Query Image 1 Precision/Recall	75.00	100	87.5	97.22	87.5	100	100	80.55	100
Query Image 2 Precision/Recall	86.11	54.16	91.66	86.11	79.16	100	100	100	97.22
Query Image 3 Precision/Recall	90.27	76.38	88.88	76.38	75	100	100	97.22	100
Average Precision/Recall	83.79	76.84	89.34	86.57	80.55	100	100	92.59	99.07

Table 7.:----- Average Precision/Recall for all 9 classes for first 72 top images using Steerable Pyramid

	A	B	C	D	E	F	G	H	I
Query Image 1 Precision/Recall	30.55	100	61.11	83.33	86.11	83.33	100	95.83	98.61
Query Image 2 Precision/Recall	73.61	100	81.94	86.11	66.66	79.16	100	100	100
Query Image 3 Precision/Recall	75	100	90.27	30.55	97.22	90.27	100	93.05	100
Average Precision/Recall	59.72	100	77.77	66.66	83.33	84.25	100	96.29	99.53

Figure.7a, 7b, 7c, 7d, 7e, 7f, 7g Shows the bar chart of Precision/Recall for all 9 classes using Discrete Cosine Transform, Discrete Fourier Transform, Hadamard Transform, Wavelet Transform, Gaussian Pyramid, Laplacian Pyramid and Steerable Pyramid.

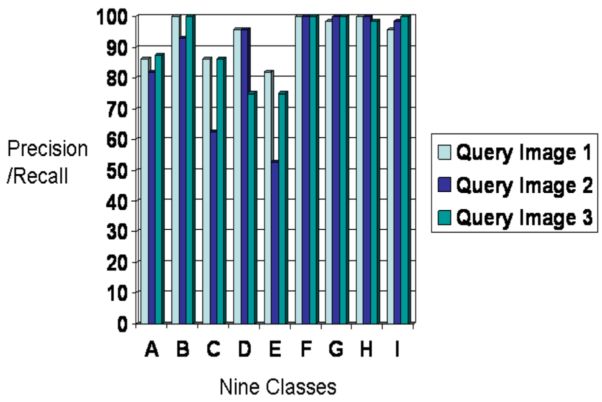

Figure 7(a) Discrete Cosine Transform based CBIR

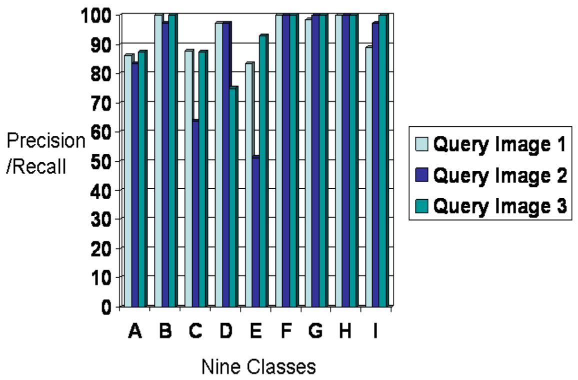

Figure 7(b) Discrete Fourier Transform based CBIR

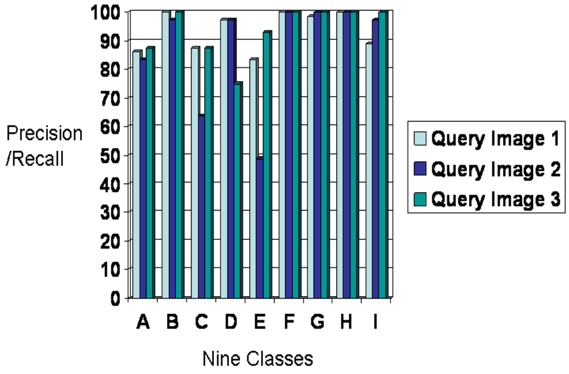

Figure 7(c) Hadamard Transform based CBIR

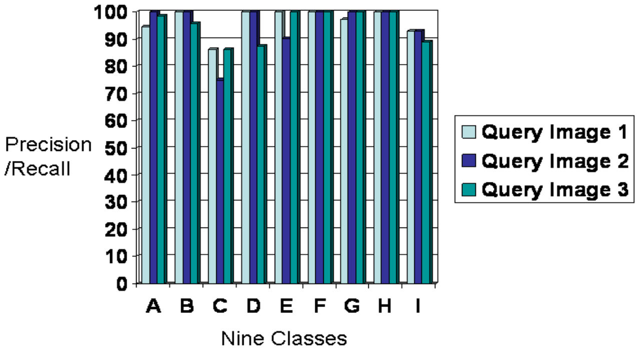

Figure 7(d) Wavelet Transform based CBIR

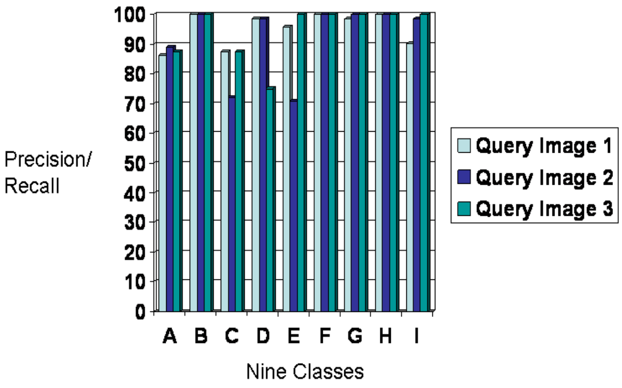

Figure 7(e) Gaussian Pyramid based CBIR

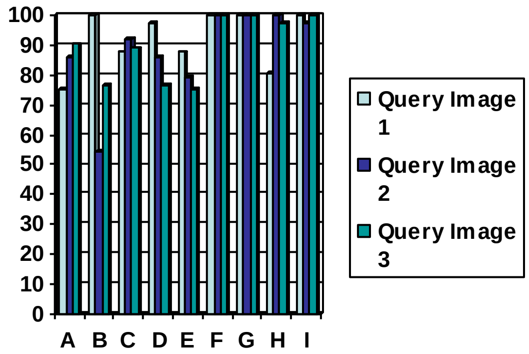

Figure 7(f) Laplacian Pyramid based CBIR

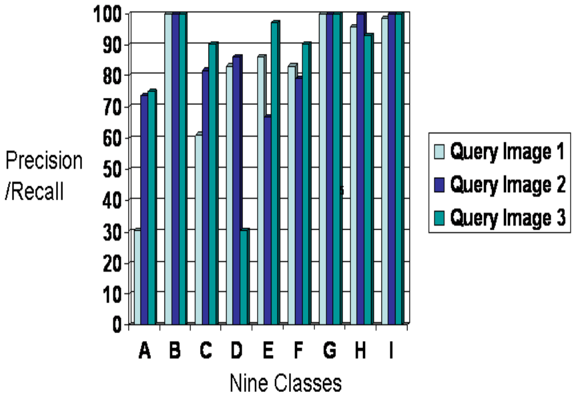

Figure 7(g) Steerable Pyramid based CBIR

From Table 1 to Table 7 and Figure 7 (a) to Figure 7 (g), it is clear that average Precision and Recall of Discrete Cosine Transform varies from 69.90 (Approximately 70%) to 100%. Average Precision and Recall of Discrete Fourier Transform varies from 75.92 to 100%. Average Precision and Recall of Hadamard Transform varies from 74.99% to 100%. Average Precision and Recall of Wavelet Transform varies from 82.40% to 100%. Average Precision and Recall of Gaussian Pyramid Varies from 82.40 to 100%. Average Precision and Recall of Laplacian Pyramid varies from 76.84 to 100%. Average Precision and Recall of Steerable Pyramid Varies from 59.72 (Approximately 60%) to 100%.

Table 8 and Table 9 gives computational complexity of CBIR Techniques based on Transform Domain and Spatial Domain

Table 8. Computational complexity for applying Transform Domain Techniques to R-component of the image of size N ×N

Technique	Discrete Cosine Transform (DCT)	Discrete Fourier Transform(DFT)	Hadamard Transform	Wavelet Transform
No.of additions For Query Image	$2N^2(N-1)$	$2N^2Log_2N$	$2N^2(N-1)$	$4N(N-1)$
No. of multiplications for Query Image	$N^2(2N)$	$2N^2Log_2N$	0	$8N^2$
No.of additions for Images in the database	$2PN^2(N-1)$	$2PN^2Log_2N$	$2PN^2(N-1)$	$4NP(N-1)$
No.of multiplications for Images in the database	$PN^2(2N)$	$2PN^2Log_2N$	0	$8PN^2$
No. of additions for Feature-1 of Query Image	$N^2 - 1$	$N^2 - 1$	$N^2 - 1$	$S(N^2 - 1)$
No. of additions for Feature-2 of Query Image	$2N^2 - 1$	$2N^2 - 1$	$2N^2 - 1$	$S(2N^2 - 1)$
No. of multiplications for Feature-2 of Query Image	N^2	N^2	N^2	SN^2
No. of additions for Feature-1 of Images in the database	$P(N^2 - 1)$	$P(N^2 - 1)$	$P(N^2 - 1)$	$SP(N^2 - 1)$
No. of additions for Feature-2 of Images in the database	$P(2N^2 - 1)$	$P(2N^2 - 1)$	$P(2N^2 - 1)$	$SP(2N^2 - 1)$
No. of multiplications for Feature-2 of Images in the database	$P N^2$	$P N^2$	$P N^2$	$SP N^2$
Number of additions for normalized Euclidean distance	$4F_rP$	$4F_rP$	$4F_rP$	$4Ph$

Whereas, P is the number of images in the database, S is the number of sub-images and Fr & h are the number of features

Table 9. Computational complexity for applying Spatial Domain Techniques to R-component of the image of size N ×N

Technique	Gaussian Pyramid (GP)	Laplacian Pyramid (LP)	Steerable Pyramid (SP)
No.of additions For Query Image	$M(N-2)^2$	$(FM+1)(N-2)^2$	$RM(N-2)^2$
No.of additions For L-level pyramid of Query Image	$M((N/2^L)-2)^2$	$(FM+1)((N/2^L)-2)^2$	$RM((N/2^L)-2)^2$
No. of multiplications for Query Image	0	$(M+1)(N-2)^2$	0
No. of multiplications for L-level pyramid of Query Image	0	$(M+1)((N/2^L)-2)^2$	0
No.of additions for Images in the database	$MP(N-2)^2$	$P(FM+1)(N-2)^2$	$RMP(N-2)^2$
No.of additions For L-level pyramid of Images in the database	$PM((N/2^L)-2)^2$	$P(FM+1)((N/2^L)-2)^2$	$PRM((N/2^L)-2)^2$
No.of multiplications for Images in the database	0	$(M+1)P(N-2)^2$	0
No. of multiplications for L-level pyramid of Images in the database	0	$P(M+1)((N/2^L)-2)^2$	0
No. of additions for Feature-1 of Query Image	N^2-1	N^2-1	$D(N^2-1)$
No. of additions for Feature-1 of L-level pyramid of Query Image	$((N/2^L)^2-1)$	$((N/2^L)^2-1)$	$D((N/2^L)^2-1)$
No. of additions for Feature-2 of Query Image	$2N^2-1$	$2N^2-1$	$D(2N^2-1)$
No. of additions for Feature-2 of L-level pyramid of Query Image	$(2(N/2^L)^2-1)$	$(2(N/2^L)^2-1)$	$D(2(N/2^L)^2-1)$
No. of multiplications for Feature-2 of Query Image	N^2	N^2	DN^2
No. of multiplications for Feature-2 of L-level pyramid of Query Image	$(N/2^L)^2$	$(N/2^L)^2$	$D(N/2^L)^2$
No. of additions for Feature-1 of Images in the database	$P(N^2-1)$	$P(N^2-1)$	$PD(N^2-1)$
No. of additions for Feature-1 of L-level pyramid of Images in the database	$P((N/2^L)^2-1)$	$P((N/2^L)^2-1)$	$PD((N/2^L)^2-1)$
No. of additions for Feature-2 of Images in the database	$P(2N^2-1)$	$P(2N^2-1)$	$PD(2N^2-1)$
No. of additions for Feature-2 of L-level pyramid of Images in the database	$P(2(N/2^L)^2-1)$	$P(2(N/2^L)^2-1)$	$PD(2(N/2^L)^2-1)$
No. of multiplications for Feature-2 of Images in the database	PN^2	PN^2	PDN^2
No. of multiplications for Feature-2 of L-level pyramid of Images in the database	$P(N/2^L)^2$	$P(N/2^L)^2$	$PD(N/2^L)^2$
Number of additions for normalized Euclidean distance	$4E_rP$	$4E_rP$	$4Pd$

Whereas, P is the number of images in the database, M is the number of neighborhood pixels, F is the number of filters in laplacian pyramid , R is the number of filters in Steerable Pyramid , D is the number of directional subbands in Steerable pyramid, L is the number of levels and E_r & d are the number of features

10. Conclusion

Content Based Image Retrieval (CBIR) is used to retrieve relevant images from the large image database. In a CBIR system, features are used to represent the image content (Color, Texture and Shape). Features are extracted automatically and there is no manual annotation. This paper presents Content Based Image Retrieval Techniques based on feature vectors (mean and standard deviation) in Spatial domain and Transform domain. The experimental results on a database of 648 rotated images indicate that Performance of CBIR is improved using Spatial Domain and Transform Domain Techniques considering 60% average Precision and Recall as acceptable norms. But feature extraction using Discrete Fourier Transform, Wavelet Transform (From Table 8) as compared to Discrete Cosine Transform, Hadamard Transform in transform domain and feature extraction using Gaussian Pyramid (From Table 9) as compared to Laplacian Pyramid and Steerable Pyramid in spatial domain is computationally lighter. Hence feature extraction using Discrete Fourier Transform, Wavelet Transform and Gaussian Pyramid in lesser time is possible with increased performance.

11. References

[1] Guoping Qiu," Color Image Indexing Using BTC,"IEEE Transactions on Image Processing, VOL.12, NO.1, pp.93-101, January 2003.

[2] B.G.Prasad, K.K. Biswas, and S. K.Gupta," Region – based image retrieval using integrated color, shape, and location index," computer vision an d image understanding, October 2003.

[3] Minh N. Do, Member, IEEE, and Martin Vetterli, Fellow, IEEE," Wavelet-Based Texture Retrieval Using Generalized Gaussian Density and Kullback-Leibler Distance," IEEE Transactions On Image Processing, VOL.11, NO.2, February 2002.

[4] Dr. Fuhui Long, Dr. Hongjiang Zhang and Prof. David Dagan Feng," Fundamentals of Content-Based Image Retrieval,"

[5] Michael Eziashi Osadebey ," Integrated content -based image retrieval using texture , shape and spatial information ",Master Thesis Report in Media Signal Processing , Department of Applied Physics and Electronics, Umea University, Umea Sweden .

[6] Rajashekhara," Novel Image Retrieval Techniques: domain specific approaches," Ph.D. Thesis Department of Electrical Engineering Indian Institute of Technology – Bombay, 2006.

[7] Guojun Lu and Shyhwei Teng," A Novel Image Retrieval Technique based on Vector Quantization," Technical Report, Gippsland School of computing and Information Technology, Monash University, Gippsland Campus, Churchill, Vic 3842.

[8] Sameer A. Nene, Shree K. Nayar and Hiroshi Murase,"Columbia Object Image Library(COIL-100)", Technical Report

[9] Stian Edvardsen,"Classification of Images using color, CBIR Distance Measures and Genetic Programming, "Ph.D. Thesis , Master of science in Informatics, Norwegian university of science and Technology, Department of computer and Information science, June 2006.

[10] Rami Al-Tayeche & Ahmed Khalil,"CBIR: Content Based Image Retrieval," Project Report, Department of systems and computer Engineering, Faculty of Engineering, Carleton University, April 4, 2003.

[11]Lei Zhu, Chun Tang, Aibing Rao and Aidong Zhang,"Using Thesaurus To Model Keyblock-Based Image Retrieval ," Technical Report, Department of Computer Science and Engineering , State University of New York At Buffalo,Buffalo,NY 14260,USA.

[12] Swapna Borde , Dr. Udhav Bhosle ," Image Retrieval Using Contourlet Transform," International Journal of Computer Applications

[13] Swapna Borde , Dr. Udhav Bhosle ," Image Retrieval Using Steerable Pyramid," International Journal of Computer Applications