Performance Comparison of Image Retrieval Using Fractional Coefficients of Transformed Image Using DCT, Walsh, Haar and Kekre's Transform

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Abstract

The thirst of better and faster retrieval techniques has always fuelled to the research in content based image retrieval (CBIR). The paper presents innovative content based image retrieval (CBIR) techniques based on feature vectors as fractional coefficients of transformed images using Discrete Cosine, Walsh, Haar and Kekre's transforms. Here the advantage of energy compaction of transforms in higher coefficients is taken to greatly reduce the feature vector size per image by taking fractional coefficients of transformed image. The feature vectors are extracted in fourteen different ways from the transformed image, with the first being considering all the coefficients of transformed image and then fourteen reduced coefficients sets (as 50%, 25%, 12.5%, 6.25%, 3.125%, 1.5625% ,0.7813%, 0.39%, 0.195%, 0.097%, 0.048%, 0.024%, 0.012% and 0.06% of complete transformed image) are considered as feature vectors. The four transforms are applied on gray image equivalents and the colour components of images to extract Gray and RGB feature sets respectively. Instead of using all coefficients of transformed images as feature vector for image retrieval, these fourteen reduced coefficients sets for gray as well as RGB feature vectors are used, resulting into better performance and lower computations. The proposed CBIR techniques are implemented on a database having 1000 images spread across 11 categories. For each proposed CBIR technique 55 queries (5 per category) are fired on the database and net average precision and recall are computed for all feature sets per transform. The results have shown performance improvement (higher precision and recall values) with fractional coefficients compared to complete transform of image at reduced computations resulting in faster retrieval. Finally Kekre's transform surpasses all other discussed transforms in performance with highest precision and recall values for fractional coefficients (6.25% and 3.125% of all coefficients) and computation are lowered by 94.08% as compared to DCT.

Keywords: CBIR, Discrete Cosine Transform (DCT), Walsh Transform, Haar Transform, Kekre's Transform, Fractional Coefficients, Feature Vector.

1. INTRODUCTION

The computer systems have been posed with large number of challenges to store/transmit and index/manage large numbers of images effectively, which are being generated from a variety of sources. Storage and transmission is taken care by Image compression with significant advancements been made [1,4,5].Image databases deal with the challenge of image indexing and retrieval[2,6,7,10,11], which has become one of the promising and important research area for researchers from a wide range of disciplines like computer vision, image processing and database areas. The thirst of better and faster image retrieval techniques is till appetising to the researchers working in some of important applications for CBIR technology like art galleries [12,14], museums, archaeology [3], architecture design [8,13], geographic information systems [5], weather forecast [5,22], medical imaging [5,18], trademark databases [21,23], criminal investigations [24,25], image search on the Internet [9,19,20].

1.1 Content Based Image Retrieval

In literature the term content based image retrieval (CBIR) has been used for the first time by Kato et.al.[4], to describe his experiments into automatic retrieval of images from a database by colour and shape feature. The typical CBIR system performs two major tasks [16,17]. The first one is feature extraction (FE), where a set of features, called feature vector, is generated to accurately represent the content of each image in the database. The second task is similarity measurement (SM), where a distance between the query image and each image in the database using their feature vectors is used to retrieve the "closest" images [16,17,26]. For CBIR feature extraction the two main approaches are feature extraction in spatial domain [5] and feature extraction in transform domain [1]. The feature extraction in spatial domain includes the CBIR techniques based on histograms [5], BTC [2,16,23], VQ [21,25,26]. The transform domain methods are widely used in image compression, as they give high energy compaction in transformed image[17,24]. So it is obvious to use images in transformed domain for feature extraction in CBIR [1]. Transform domain results in energy compaction in few elements, so large number of the coefficients of transformed image can be neglected to reduce the size of feature vector [1]. Reducing the size feature vector using fractional coefficients of transformed image and till getting the improvement in performance of image retrieval is the theme of the work presented here. Many current CBIR systems use average Euclidean distance [1,2,3,8-14,23]on the extracted feature set as a similarity measure. The direct Average Euclidian Distance (AED) between image P and query image Q can be given as equation 1, where Vpi and Vqi are the feature vectors of image P and Query image Q respectively with size 'n'.

$$AED = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(Vpi - Vqi)^2} \qquad (1)$$

2. DISCRETE COSINE TRANSFORM

The discrete cosine transform (DCT) [1,10,21,22,24] is closely related to the discrete Fourier transform. It is a separable linear transformation; that is, the two-dimensional transform is equivalent to a one-dimensional DCT performed along a single dimension followed by a one-dimensional DCT in the other dimension. The definition of the two-dimensional DCT for an input image A and output image B is

$$B_{pq} = \alpha_p \alpha_q \sum\sum A_{mn} \cos\frac{\pi(2m+1)p}{2M} \cos\frac{\pi(2n+1)q}{2N}, \begin{matrix} 0 \le p \le M-1 \\ 0 \le q \le N-1 \end{matrix} \qquad (2)$$

$$\alpha_p = \begin{cases} 1/\sqrt{M} & , p = 0 \\ \sqrt{2/M} & , 1 \le p \le M-1 \end{cases} \qquad (3)$$

$$\alpha_q = \begin{cases} 1/\sqrt{N} & , q = 0 \\ \sqrt{2/N} & , 1 \le q \le N-1 \end{cases} \qquad (4)$$

where M and N are the row and column size of A, respectively. If you apply the DCT to real data, the result is also real. The DCT tends to concentrate information, making it useful for image compression applications and also helping in minimizing feature vector size in CBIR [23]. For full 2-Dimensional DCT for an NxN image the number of multiplications required are N2(2N) and number of additions required are N2(2N-2).

3. WALSH TRANSFORM

Walsh transform matrix [1,11,18,19,26,30] is defined as a set of N rows, denoted Wj, for j = 0, 1, ... , N - 1, which have the following properties:

- Wj takes on the values +1 and -1.
- Wj[0] = 1 for all j.
- $W_j x W_k^T = 0$, for $j \neq k$ and $W_j x W_k^T = N$, for j=k.
- Wj has exactly j zero crossings, for j = 0, 1, ..., N-1.
- Each row Wj is even or odd with respect to its midpoint.

Walsh transform matrix is defined using a Hadamard matrix of order N. The Walsh transform matrix row is the row of the Hadamard matrix specified by the Walsh code index, which must be an integer in the range [0, ..., N - 1]. For the Walsh code index equal to an integer j, the respective Hadamard output code has exactly j zero crossings, for j = 0, 1,..., N - 1. The step of the algorithm to generate Walsh matrix from hadamard matrix by reordering hadamard matrix is given below [30].

Step 1 : Let H be the hadamard matix of size NxN and W be the expected Walsh Matrix of same size
Step 2 : Let seq=0, cseq=0, seq(0)=0, seq(1)=1, i=0
Step 3 : Repeat steps 3 to 12 till i <= $\log_2(N)$-2
Step 4 : s=size(seq)
Step 5 : Let j=1, Repeat steps 6 and 7 till j<=s(1)
Step 6 : cseq(j)=2*seq(j)
Step 7 : j=j+1
Step 8 : Let p=1, k=2*s(2) repeat steps 9 to 11 until k<=s(2)+1
Step 9 : cseq(k)=cseq(p)+1
Step 10 : p=p+1 and k=k-1
Step 11 : seq=cseq,
Step 12 : i=i+1
Step 13 : Let seq=seq+1
Step 14 : Let x and y indicate the rows and columns of ‘seq’
Step 15 : Let i=0 Repeat steps 16 and 17 till i<= y-1
Step 16 : q=seq(i)
Step 17 : i=i+1
Step 18 : Let i=0, repeat steps 19 to 22 till i<=s1-1
Step 19 : for j=0, repeat steps 20 and 21 till j<=s1-1
Step 20 : W(i,j)=H(seq(i),j)
Step 21 : j=j+1
Step 22 : i=i+1

For the full 2-Dimensional Walsh transform applied to image of size NxN, the number of additions required are $2N^2(N-1)$ and absolutely no multiplications are needed in Walsh transform [1].

4. HAAR TRANSFORM

This sequence was proposed in 1909 by Alfréd Haar [28]. Haar used these functions to give an example of a countable orthonormal system for the space of square-integral functions on the real line. The study of wavelets, and even the term "wavelet", did not come until much later [29,31].The Haar wavelet is also the simplest possible wavelet. The technical disadvantage of the Haar wavelet is that it is not continuous, and therefore not differentiable. This property can, however, be an advantage for the analysis of signals with sudden transitions, such as monitoring of tool failure in machines. The Haar wavelet's mother wavelet function ψ (t) can be described as:

$$\psi(t) = \begin{cases} 1 & ,0 \leq t < \frac{1}{2} \\ -1 & ,\frac{1}{2} \leq t < 1 \\ 0 & ,\text{otherwise} \end{cases} \tag{5}$$

and its scaling function $\varphi(t)$ can be described as:

$$\varphi(t) = \begin{cases} 1 & ,0 \le t < 1 \\ 0 & ,\text{otherwise} \end{cases} \tag{6}$$

5. KEKRE'S TRANSFORM

Kekre's transform matrix is the generic version of Kekre's LUV color space matrix [1,8,12,13,15,22]. Kekre's transform matrix can be of any size NxN, which need not have to be in powers of 2 (as is the case with most of other transforms). All upper diagonal and diagonal values of Kekre's transform matrix are one, while the lower diagonal part except the values just below diagonal is zero.

Generalized NxN Kekre's transform matrix can be given as:

$$K_{NxN} = \begin{bmatrix} 1 & 1 & 1 & .. & 1 & 1 \\ -N+1 & 1 & 1 & .. & 1 & 1 \\ 0 & -N+2 & 1 & .. & 1 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & .. & 1 & 1 \\ 0 & 0 & 0 & .. & -N+(N-1) & 1 \end{bmatrix} \tag{7}$$

The formula for generating the term K_{xy} of Kekre's transform matrix is:

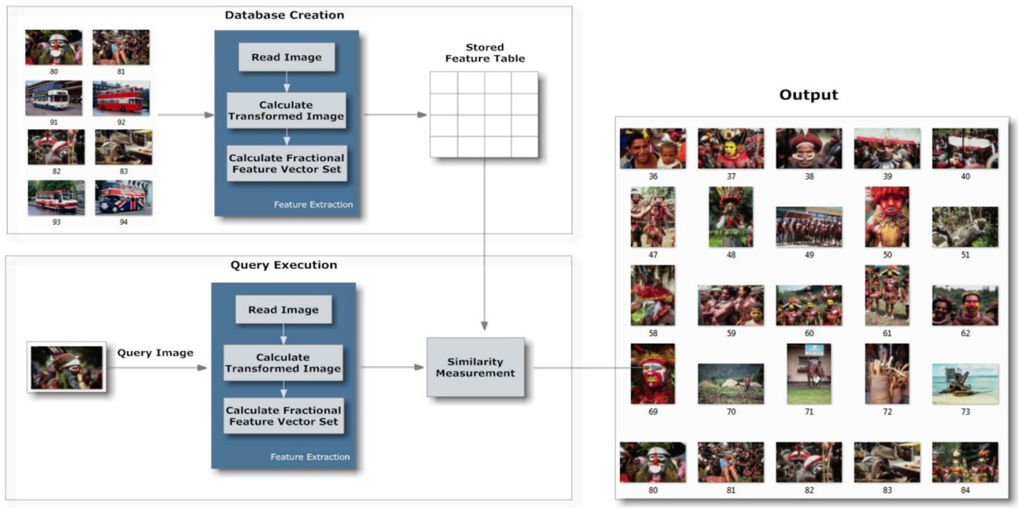
$$K(x,y) = \begin{cases} 1 & ,x \le y \\ -N+(x-1) & ,x = y+1 \\ 0 & ,x > y+1 \end{cases} \tag{8}$$

For taking Kekre's transform of an NxN image, the number of required multiplications are 2N(N-2) and number of additions required are $N(N^2+N-2)$.

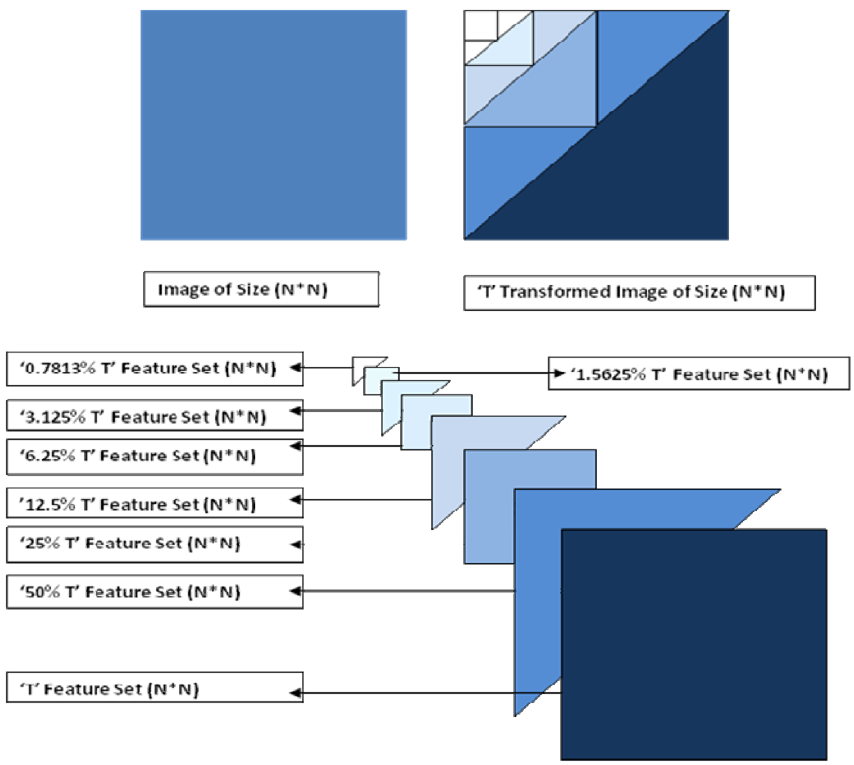
	DCT	Walsh	Haar	Kekre's
Number of Additions	$2N^2(N-1)$	$2N^2(N-1)$	$2N^2\log_2(N)$	N[N(N+1)-2]
Number of Multiplications	$N^2(2N)$	0	0	2N(N-2)
Total Additions for transform of 256x256 image	301,858,816	33,423,360	1,048,576	17,882,624
Computations Comparison For 256x256 image	100 %	11.07%	0.35%	5.92%

[Here one multiplication is considered as eight additions for second last row computations and DCT computations are considered to be 100% for comparison in last row]

TABLE 1: Computational Complexity for applying transforms to image of size NxN [1]



1.a. Flowchart of proposed CBIR Technique



1.b. Feature Extraction for Proposed CBIR Techniques

FIGURE 1: Proposed CBIR Techniques using fractional Coefficients of Transformed Images

6. PROPOSED CBIR-GRAY TECHNIQUES

Figure 1.a gives the flowchart of proposed CBIR technique for feature extraction and query execution. Figure 1.b explains the feature sets extraction used to extract feature sets for proposed CBIR techniques using fractional coefficients of transformed images.

6.1 Feature Extraction for feature vector 'T-Gray'

Here the feature vector space of the image of size NxN has NxN number of elements. This is obtained using following steps of T-Gray

Extract Red, Green and Blue components of the colour image.

i. Take average of Red, Green and Blue components of respective pixels to get gray image.

ii. Apply the Transform 'T' on gray image to extract feature vector.
iii. The result is stored as the complete feature vector 'T-Gray' for the respective image.

Thus the feature vector database for DCT, Walsh, Haar and Kekre's transform are generated as DCT-Gray, Walsh-Gray, Haar-Gray, Kekre's-Gray respectively. Here the size of feature vector is NxN for every transform.

6.2 Feature Vector Database 'Fractional T-Gray'

The fractional coefficients of transformed image as shown in figure 1, are considered to form 'fractional T-Gray' feature vector databases. Here first 50% of coefficients from upper triangular part of feature vector 'T-Gray' are considered to prepare the feature vector database '50%-T-Gray' for every image as shown in figure 1. Thus DCT-Gray, Walsh-Gray, Haar-Gray, Kekre's-Gray feature databases are used to obtain new feature vector databases as 50%-DCT-Gray, 50%-Walsh-Gray, 50%-Haar-Gray, 50%-Kekre's-Gray respectively. Then per image first 25% number of coefficients (as shown in figure 1) form the feature vectors database DCT-Gray, Walsh-Gray, Haar-Gray, Kekre's-Gray are stored separately as feature vector databases as 25%-DCT-Gray, 25%-Walsh-Gray, 25%-Haar-Gray, 25%-Kekre's-Gray respectively. Then for each image in the database as shown in figure 1, fractional feature vector set for DCT-Gray, Walsh-Gray, Haar-Gray, Kekre's-Gray using 25%, 12.5%, 6.25%, 3.125%, 1.5625% ,0.7813%, 0.39%, 0.195%, 0.097%, 0.048%, 0.024%, 0.012% and 0.06% of total coefficients are formed.

6.3 Query Execution for 'T-Gray' CBIR

Here the feature set of size NxN for the query image is extracted using transform 'T'. This feature set is compared with each entry from the feature database using Euclidian distance as similarity measure. Thus DCT, Walsh, Haar, Kekre's transform based feature sets are extracted from query image and are compared respectively with DCT-Gray and Walsh-Gray feature sets using average Euclidian distance to find the best match in the database.

6.4 Query Execution for 'Fractional T-Gray' CBIR

For 50%-T-Gray query execution, only 50% number of coefficients of upper triangular part of 'T' transformed query image (with NxN coefficients) are considered for the CBIR and are compared with '50%-T-Gray' database feature set for Euclidian distance computations. Thus DCT, Walsh, Haar, Kekre's transform based feature sets are extracted from the query image and are compared respectively with 50%-DCT-Gray, 50%-Walsh-Gray, 50%-Haar-Gray, 50%-Kekre's-Gray feature sets to find average Euclidian distances. For 25%, 12.5%, 6.25%, 3.125%, 1.5625% ,0.7813%, 0.39%, 0.195%, 0.097%, 0.048%, 0.024%, 0.012% and 0.06% T-Gray based query execution, the feature set of the respective percentages are considered from the 'T' transformed NxN image as shown in figure 1, to be compared with the respective percentage T-Gray feature set database to find average Euclidian distance.

7. PROPOSED CBIR-RGB TECHNIQUES

7.1 Feature Extraction for feature vector 'T-RGB'

Here the feature vector space of the image of size NxNx3 has NxNx3 number of elements. This is obtained using following steps of T-RGB

i. Extract Red, Green and Blue components of the color image.
ii. Apply the Transform 'T' on individual color planes of image to extract feature vector.
iii. The result is stored as the complete feature vector 'T-RGB' for the respective image.

Thus the feature vector database for DCT, Walsh, Haar, Kekre's transform is generated as DCT-RGB, Walsh-RGB, Haar-RGB, Kekre's-RGB respectively. Here the size of feature database is NxNx3.

7.2 Query Execution for 'T-RGB' CBIR

Here the feature set of NxNx3 for the query image is extracted using transform 'T' applied on the red, green and blue planes of query image. This feature set is compared with other feature sets in feature database using Euclidian distance as similarity measure. Thus DCT, Walsh, Haar, Kekre's transform based feature sets are extracted for query image and are compared respectively with DCT-RGB, Walsh-RGB, Haar-RGB, Kekre's-RGB feature sets to find Euclidian distance.

7.3 CBIR using 'Fractional-T-RGB'

As explained in section 6- 6.4 and section 7 – 7.2 the 'T-RGB' feature extraction and query execution are extended to get 50%,25%, 12.5%, 6.25%, 3.125%, 1.5625% ,0.7813%, 0.39%, 0.195%, 0.097%, 0.048%, 0.024%, 0.012% and 0.006% of T-RGB image retrieval techniques.

8. IMPLEMENTATION

The implementation of the three CBIR techniques is done in MATLAB 7.0 using a computer with Intel Core 2 Duo Processor T8100 (2.1GHz) and 2 GB RAM. The CBIR techniques are tested on the image database [15] of 1000 variable size images spread across 11 categories of human being, animals, natural scenery and manmade things. The categories and distribution of the images is shown in table 2.

Category	Tribes	Buses	Beaches	Dinosaurs	Elephants	Roses
No.of Images	85	99	99	99	99	99
Category	Horses	Mountains	Airplanes	Monuments	Sunrise	
No.of Images	99	61	100	99	61	

TABLE 2: Image Database: Category-wise Distribution

FIGURE 2: Sample Database Images
[Image database contains total 1000 images with 11 categories]

Figure 2 gives the sample database images from all categories of images including scenery, flowers, buses, animals, aeroplanes, monuments, and tribal people. To assess the retrieval effectiveness, we have used the precision and recall as statistical comparison parameters [1,2] for the proposed CBIR techniques. The standard definitions of these two measures are given by following equations.

(5)

$$\Pr ecision = \frac{Number\_of\_relevant\_images\_retrieved}{Total\_number\_of\_images\_retrieved}$$

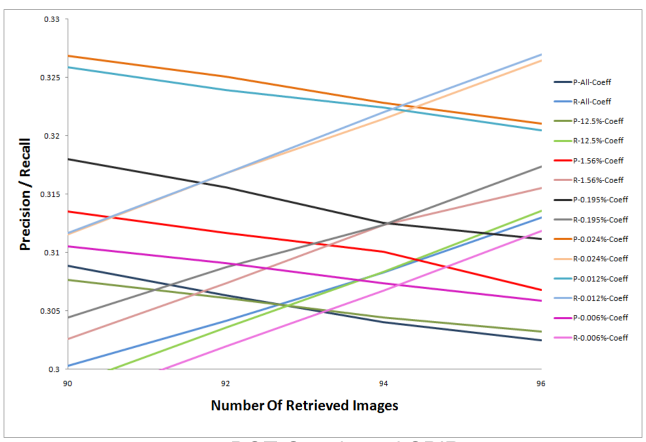
$$\text{Re}\, call = \frac{Number\_of\_relevant\_images\_retrieved}{Total\_number\_of\_relevent\_images\_in\_database} \quad (6)$$

9. RESULTS AND DISCUSSION

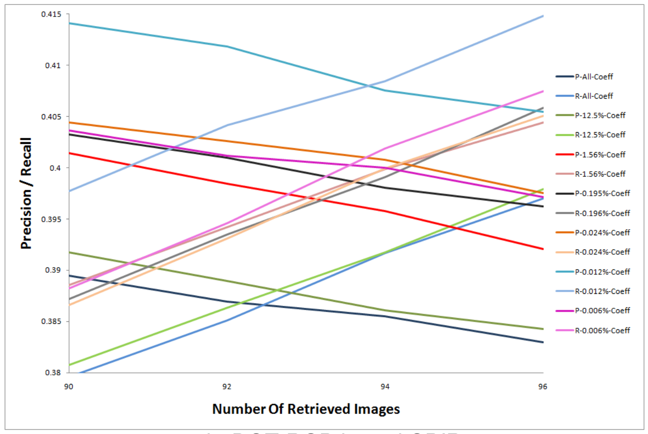
For testing the performance of each proposed CBIR technique, per technique 55 queries (5 from each category) are fired on the database of 1000variable size generic images spread across 11 categories. The query and database image matching is done using average Euclidian distance. The average precision and average recall are computed by grouping the number of retrieved images sorted according to ascending average Euclidian distances with the query image. In all transforms, the average precision and average recall values for CBIR using fractional coefficients are higher than CBIR using full set of coefficients. The CBIR-RGB techniques are giving higher values of crossover points than CBIR-Gray techniques indicating better performance. The crossover point of precision and recall of the CBIR techniques acts as one of the important parameters to judge their performance [1,2,19,20].

Figure 3 shows the precision-recall crossover points plotted against number of retrieved images for proposed image retrieval techniques using DCT. Uniformly in all image retrieval techniques based on gray DCT and colour DCT features 0.012% fractional feature set ($1/8192^{th}$ of total coefficients) based image retrieval gives highest precision and recall values. Figure 3.a gives average precision/recall values plotted against number of retrieved images for all DCT-Gray image retrieval techniques. Precision/recall values for DCT-RGB image retrieval techniques are plotted in figure 3.b.

Figures 4.a and 4.b respectively shows the graphs of precision/recall values plotted against number of retrieved images for Walsh-Gray and Walsh-RGB based image retrieval techniques. Here $1/4096^{th}$ fractional coefficients (0.024% of total Walsh transformed coefficients) based image retrieval gives the highest precision/recall crossover values specifying the best performance using Walsh transform.

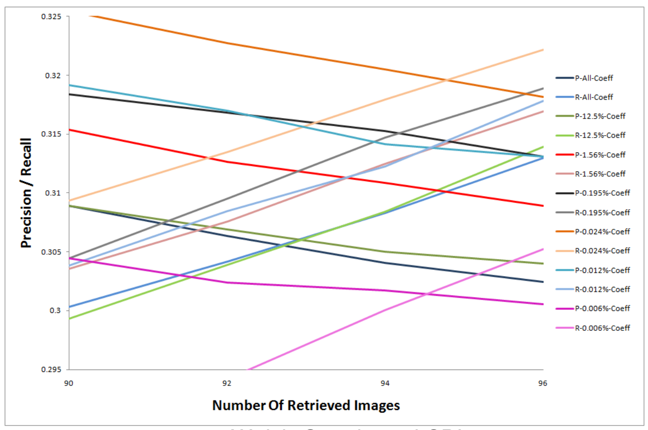


3.a. DCT-Gray based CBIR

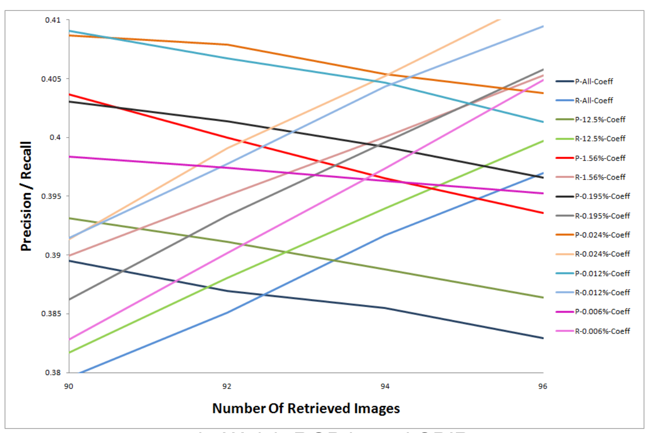


3.b. DCT-RGB based CBIR

FIGURE 3: Crossover Point of Precision and Recall for DCT based CBIR.



4.a. Walsh-Gray based CBI



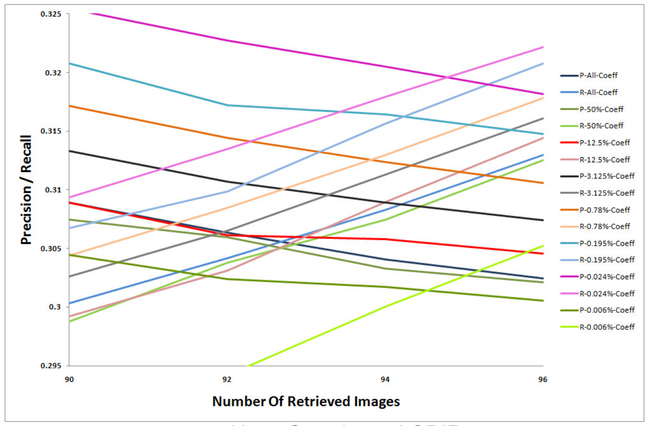
4.b. Walsh-RGB based CBIR

FIGURE 4: Crossover Point of Precision and Recall for Walsh T. based CBIR

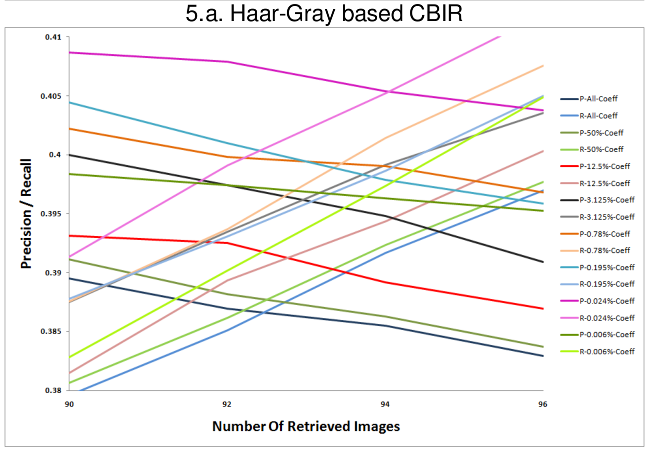
Figures 5.a and 5.b respectively shows the graphs of precision/recall values plotted against number of retrieved images for Haar-Gray and Haar-RGB based image retrieval techniques. Here $1/4096^{th}$ fractional coefficients (0.024% of total Haar transformed coefficients) based image retrieval gives the highest precision/recall crossover values specifying the best performance when using Haar transform.

Figure 6.a gives average precision/recall values plotted against number of retrieved images for all DCT-Gray image retrieval techniques. Precision/recall values for DCT-RGB image retrieval techniques are plotted in figure 6.b. Here $1/32^{th}$ fractional coefficients (3.125% of

total Kekre's transformed coefficients) based image retrieval gives the highest precision/recall crossover values specifying the best performance when using Kekre's transform.

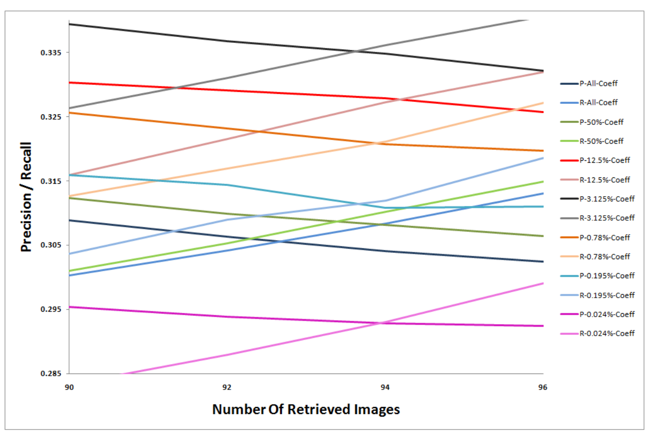


5.a. Haar-Gray based CBIR

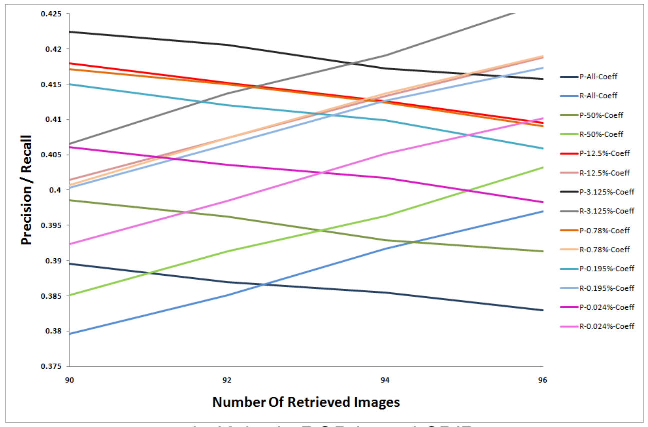


5.b. Haar-RGB based CBIR

FIGURE 5: Crossover Point of Precision and Recall for Haar T. based CBIR



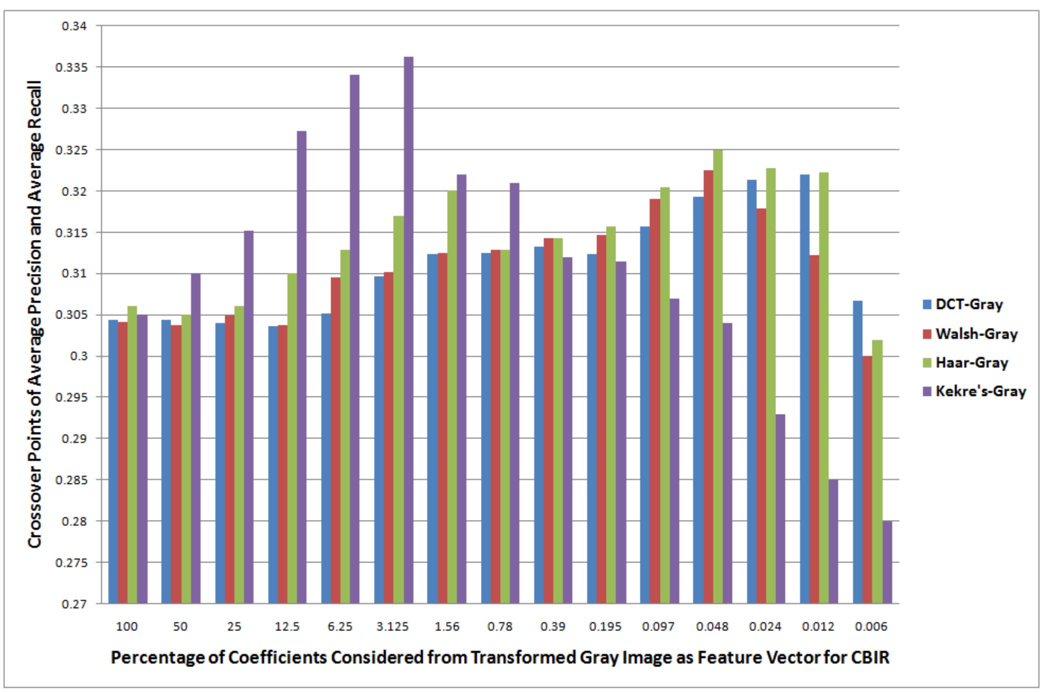
6.a. Kekre's-Gray based CBIR



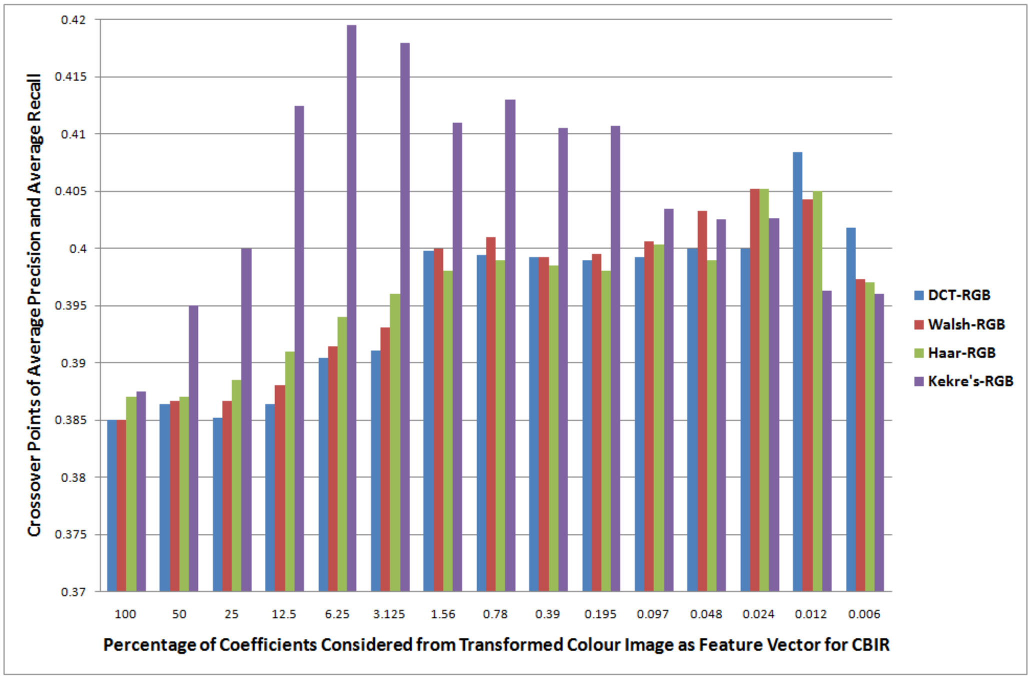
6.b. Kekre's-RGB based CBIR

FIGURE 6: Crossover Point of Precision and Recall for Kekre's T. based CBIR

Figure 7 shows the performance comparison of all the four transformsfor proposed CBIR techniques. Figure 7.a is indicating the crossover points of DCT-Gray, Walsh-Gray, Haar-Gray, Kekre's-Gray CBIR for all considered feature vectors (percentage of coefficients of transformed gray images). Herefor upto 0.78 % of coefficients Kekre's transform performs better than all discussed transforms after which Haar transform outperforms other transformsupto 0.012 % ofcoefficients and finally for 0.006 % of coefficients DCT gives highest crossover point value, as the energy compaction in Haar and DCT transform is better than other transform. For Kekre's-Gray CBIR the performance improves with decreasing feature vector size from 100% to 0.195% and then drops indicating 0.195% as best fractional coefficients. In DCT-Gray CBIR the performance is improved till 0.012% and then drops. Overall in all, CBIR using Kekre's transform with 3.125 % of fractional coefficients gives the best performance for Gray-CBIR techniques discussed here.



7.a. Transform Comparison in Gray based CBIR



7.b. Transform Comparison in Color based CBIR
FIGURE 7: Performance Comparison of Fractional Walsh-CBIR and Fractional DCT-CBIR

Figure 7.b indicates the performance comparison of DCT-RGB, Walsh- RGB, Haar- RGB, Kekre's- RGB CBIR with different percentage of fractional coefficients. Here Kekre's-RGB CBIR outperforms all other transforms till 0.097% of coefficients as feature vector then Walsh-RGB CBIR takes over till 0.024% then DCT-RGB performs best for 0.012% of coefficients. In Walsh-RGB and Haar-RGB CBIR the feature vector with 0.024% of coefficients gives best performance, in DCT-RGB CBIR 0.012% of coefficients shows highest crossover value of average precision and average recall and Kekre's transform gives the best performance when 6.25% of coefficients are considered. In all, CBIR using Kekre's transform with 6.25 % of fractional coefficients gives the best performance for RGB-CBIR techniques discussed here.

10. CONCLUSION

In the information age where the size of image databases is growing exponentially more precise retrieval techniques are needed, for finding relatively similar images. Computational complexity and retrieval efficiency are the key objectives in the image retrieval system. Nevertheless it is very difficult to reduce the computations and improve the performance of image retrieval technique.

Here the performance of image retrieval is improved using fractional coefficients of transformed images at reduced computational complexity. In all transforms (DCT, Walsh, Haar and Kekre's), the average precision and average recall values for CBIR using fractional coefficients are higher than CBIR using full set of coefficients. Hence the feature vector size for image retrieval could be greatly reduced, which ultimately will result in faster query execution in CBIR with better performance. In all Kekre's transform with fractional coefficients (3.125 % in Gray and 6.25 % in RGB) gives best performance with highest crossover points of average precision and average recall. Feature extraction using Kekre's transform is also computationally lighter as compared to DCT or Walsh transform. Thus feature extraction in lesser time is possible with increased performance.

Finally the conclusion that the fractional coefficients gives better discrimination capability in CBIR than the complete set of transformed coefficients and image retrieval with better performance at much faster rate can be done from the proposed techniques and experimentation done.

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