Comprehensive Performance Comparison of Cosine, Walsh, Haar, Kekre, Sine, Slant and Hartley Transforms for CBIR with Fractional Coefficients of Transformed Image

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Abstract

The desire of better and faster retrieval techniques has always fuelled to the research in content based image retrieval (CBIR). The extended comparison of innovative content based image retrieval (CBIR) techniques based on feature vectors as fractional coefficients of transformed images using various orthogonal transforms is presented in the paper. Here the fairly large numbers of popular transforms are considered along with newly introduced transform. The used transforms are Discrete Cosine, Walsh, Haar, Kekre, Discrete Sine, Slant and Discrete Hartley transforms. The benefit of energy compaction of transforms in higher coefficients is taken to reduce the feature vector size per image by taking fractional coefficients of transformed image. Smaller feature vector size results in less time for comparison of feature vectors resulting in faster retrieval of images. The feature vectors are extracted in fourteen different ways from the transformed image, with the first being all the coefficients of transformed image considered and then fourteen reduced coefficients sets are considered as feature vectors (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 coefficients). To extract Gray and RGB feature sets the seven image transforms are applied on gray image equivalents and the color components of images. Then these fourteen reduced coefficients sets for gray as well as RGB feature vectors are used instead of using all coefficients of transformed images as feature vector for image retrieval, resulting into better performance and lower computations. The Wang image database of 1000 images spread across 11 categories is used to test the performance of proposed CBIR techniques. 55 queries (5 per category) are fired on the database o find net average precision and recall values for all feature sets per transform for each proposed CBIR technique. 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 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 Cosine or Sine or Hartlay transforms.

Keywords: CBIR, Image Transform, DCT, Walsh, Haar, Kekre, DST, Slant, Hartley, Fractional Coefficients.

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 [1,4,5,43]. One of the promising and important research area for researchers from a wide range of disciplines like computer vision, image processing and database areas is image indexing and retrieval [2,6,7,10,11]. The desire of better and faster image retrieval techniques is till enticing to the researchers working in some of important applications for CBIR technology like museums, archaeology [3], art galleries [12,14], weather forecast [5,22], architecture design [8,13], geographic information systems [5], criminal investigations [24,25], medical imaging [5,18], trademark databases [21,23], image search on the Internet [9,19,20].

1.1 Content Based Image Retrieval (CBIR)

The interest in CBIR is growing because of the limitations inherent in metadata-based systems, as well as the large range of possible applications for efficient image retrieval. In literature Kato et. al. [4] used the term content based image retrieval (CBIR) for the very first time, to describe his experiments on automatic retrieval of images from a database by colour and shape feature. Textual information about images can be easily searched using existing technology, but requires humans to personally describe every image in the database. This is impractical for very large databases, or for images that are generated automatically, e.g. from surveillance cameras. It is also possible to miss images that use different synonyms in their descriptions. Systems based on categorizing images in semantic classes like "cat" as a subclass of "animal" avoid this problem but still face the same scaling issues [9,19].

Mainly two major tasks are performed by CBIR system [16,17]. Feature extraction (FE) is the first one, where a set of features, called feature vector, is generated to accurately represent the content of each image in the database. Similarity measurement (SM), is the second one 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]. As the transform domain methods are widely used in image compression, as they give high energy compaction in transformed image[17,24], hence images in transformed domain are used for feature extraction in CBIR [1]. The 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].

Using individual image transforms various CBIR techniques have been proposed, but so far comparison of transforms is not being studied thoroughly [41,42]. In the paper the performance of fairly large number of popular transforms for CBIR are compared along with newly introduced Kekre transform. Getting the improvement in the performance of image retrieval technique even with reduced size feature vector using fractional coefficients of transformed image 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’.

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

Here total seven different image transforms are considered which can be listed as discrete cosine transform (DCT) [1,10,21,22,24], Walsh transform matrix [1,11,18,19,26], Haar Transform [28,29], Kekre transform [1,8,12,13,15,22], Discrete Sine Transform (DST) [36,37,40], Slant Transform [38, 39]. A discrete Hartley transform (DHT) [30-33]

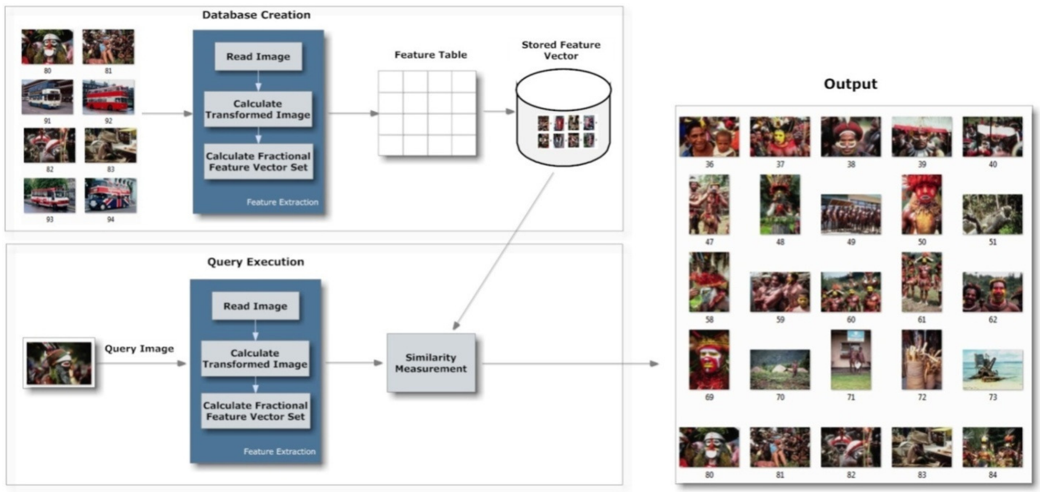

FIGURE 1.a. Flowchart of proposed CBIR Technique

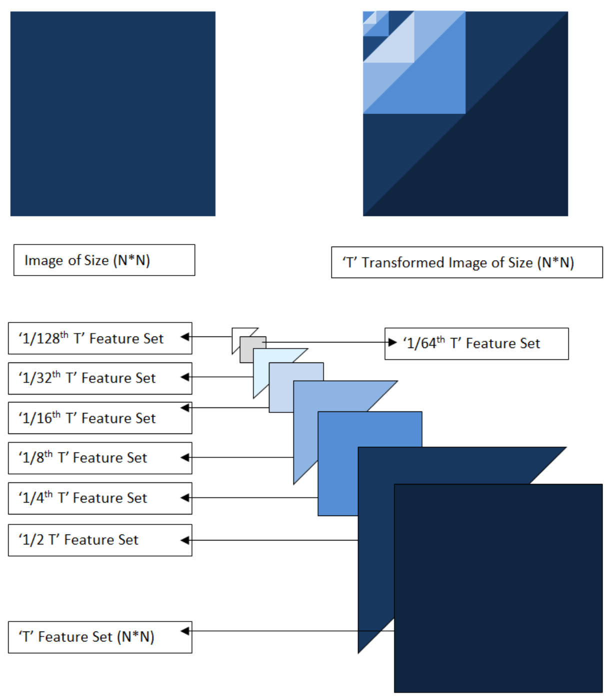

FIGURE 1b. Feature Extraction for Proposed CBIR Techniques

FIGURE 1. Proposed CBIR Techniques using fractional Coefficients of Transformed Images [43]

TABLE 1. Computational Complexity for applying transforms to image of size NxN [1,43]

Transform	Number of Additions	Number of Multiplications	Total Additions for transform of 256x256 image	Computations Comparison (For 256x256 image)
	For NxN image			
DCT	$2N^2(N-1)$	$N^2(2N)$	301858816	100
Walsh	$2N^2(N-1)$	0	33423360	11.07
Haar	$2N^2\log_2(N)$	0	1048576	0.35
Kekre	$N[N(N+1)-2]$	$2N(N-2)$	17882624	5.92
DST	$2N^2(N-1)$	$N^2(2N)$	301858816	100
Slant	$2N^2(N-1)$	$N^2(N)$	167641088	55.54
Hartley	$2N^2(N-1)$	$N^2(2N)$	301858816	100

[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]

2. PROPOSED CBIR-GRAY TECHNIQUES

The flowchart of proposed CBIT technique is given in figure 1.a 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.

2.1 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

(i). Extract Red, Green and Blue components of the colour image.
(ii). Take average of Red, Green and Blue components of respective pixels to get gray image.
(iii). Apply the Transform 'T' on gray image to extract feature vector.
(iv). The result is stored as the complete feature vector 'T-Gray' for the respective image.

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

2.2 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-Gray, DST-Gray, Slant-Gray, DHT-Gray feature databases are used to obtain new feature vector databases as 50%-DCT-Gray, 50%-Walsh-Gray, 50%-Haar-Gray, 50%-Kekre-Gray, 50%-DST-Gray, 50%-Slant-Gray, 50%-DHT-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-Gray, DST-Gray, Slant-Gray, DHT-Gray are stored separately as feature vector databases as 25%-DCT-Gray, 25%-Walsh-Gray, 25%-Haar-Gray, 25%-Kekre-Gray, 25%-DST-Gray, 25%-Slant-Gray, 25%-DHT-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-Gray, DST-Gray, Slant-Gray, DHT-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.

2.3 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, DST, Slant, DHT transform based feature sets are extracted from query image and are compared respectively with DCT-Gray, Walsh-Gray, Haar-Gray, Kekre-Gray, DST-Gray, Slant-Gray, DHT-Gray feature sets using average Euclidian distance to find the best match in the database.

2.4 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, DST, Slant, DHT 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-Gray, 50%-DST-Gray, 50%-Slant-Gray, 50%-DHT-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.

3. PROPOSED CBIR-RGB TECHNIQUES

3.1 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, DST, Slant, DHT transform is generated as DCT-RGB, Walsh-RGB, Haar-RGB, Kekre-RGB, DST-RGB, Slant-RGB, DHT-RGB respectively. Here the size of feature database is NxNx3.

3.2 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, DST, Slant, DHT transform based feature sets are extracted for query image and are compared respectively with DCT-RGB, Walsh-RGB, Haar-RGB, Kekre-RGB, DST-RGB, Slant-RGB, DHT-RGB feature sets to find Euclidian distance.

3.3 CBIR using 'Fractional-T-RGB'

As explained in section 2.1 to 2.4 and section 3.1 – 3.3 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.

4. IMPLEMENTATION

The proposed CBIR methods are tested using a test bed of 1000 variable size images spread across 11 categories and taken from Wang image database [15]. The categories and distribution of the images is shown in table 2. Programming is done in MATLAB 7.0 using a computer with Intel Core 2 Duo Processor T8100 (2.1GHz) and 2 GB RAM.

TABLE 2. Image DatabaseCategory-Wise Distribution

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

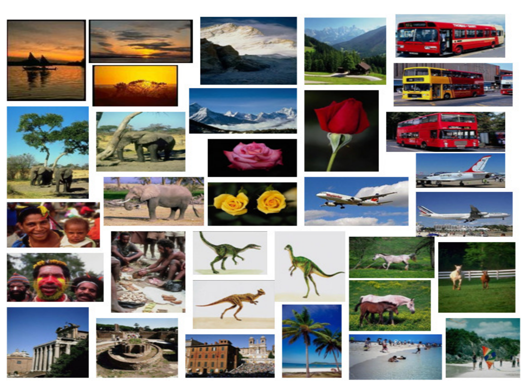

FIGURE 2. Sample Database Images
[Image database contains total 1000 images with 11 categories]

Figure 2 gives the sample database images from all categories of images considered in test bed image database. Precision and recall are used as statistical comparison parameters [1,2] for the proposed CBIR techniques. The standard definitions of these two measures are given by following equations.

$$\Pr ecision = \frac{Number\_of\_relevant\_images\_retrieved}{Total\_number\_of\_images\_retrieved} \quad (2)$$

$$\mathrm{Re}\, call = \frac{Number\_of\_relevant\_images\_retrieved}{Total\_number\_of\_relevent\_images\_in\_database} \quad (3)$$

5. RESULTS AND DISCUSSION

The performance of each proposed CBIR technique is tested by firing 55 queries (5 from each category) per technique on the database of 1000 variable size generic images spread across 11 categories. Average Euclidian distance is used as similarity measure. 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].

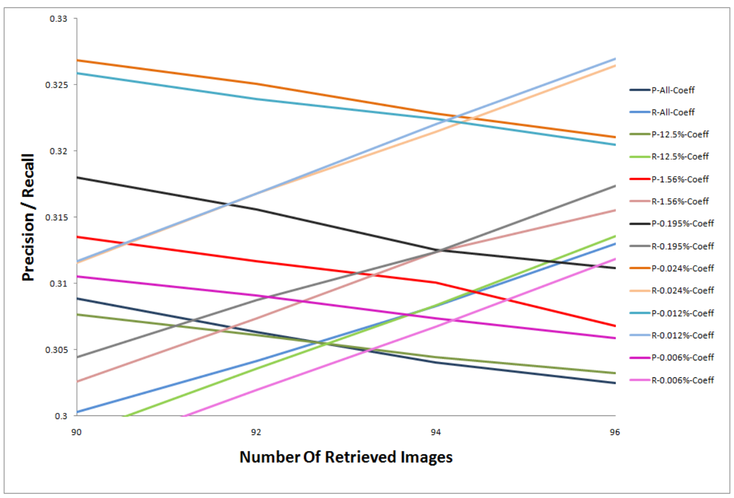

FIGURE 3.a. DCT-Gray based CBIR

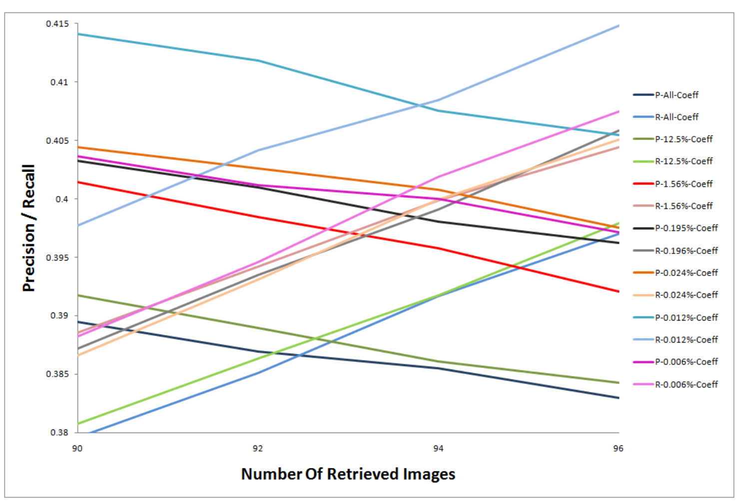

FIGURE 3.b. DCT-RGB based CBIR

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

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 color DCT features 0.012% fractional feature set (1/8192th 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 1/4096thfractional coefficients (0.024% of total Walsh transformed coefficients) based image retrieval gives the highest precision/recall crossover values.

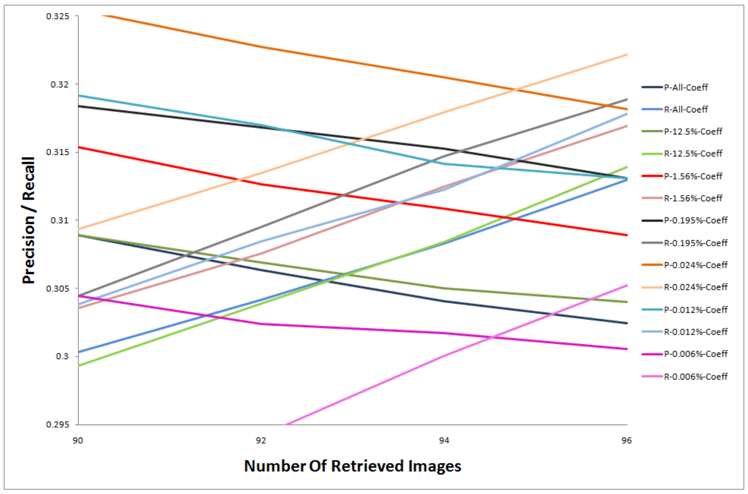

FIGURE 4.a. Walsh-Gray based CBIR

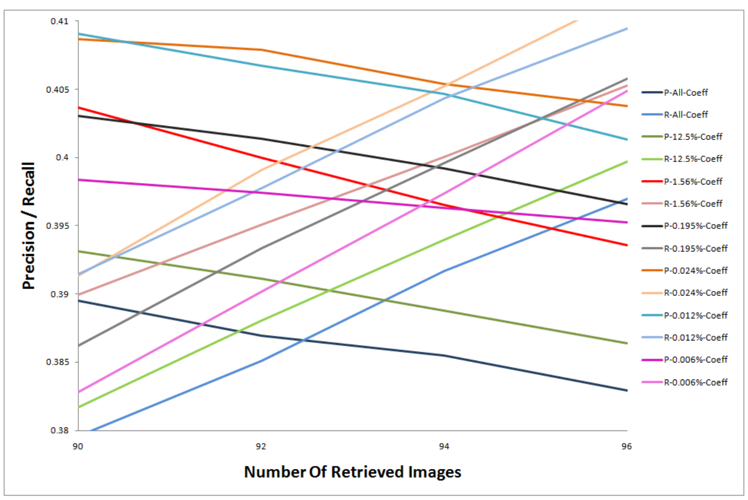

FIGURE 4.b. Walsh-RGB based CBIR
FIGURE. 4. Crossover Point of Precision and Recall for Walsh Transform based CBIR

Figure 5 shows the precision-recall crossover points plotted against number of retrieved images for proposed image retrieval techniques using Haar Transform. Uniformly in all image retrieval techniques based on gray Haar and color Haar features 0.024% fractional feature set (1/4096th of total coefficients) based image retrieval gives highest precision and recall values. Figures 5.a and 5.b give average precision/recall values plotted against number of retrieved images for all Haar-Gray and Haar-RGB image retrieval techniques respectively. Figure 6.a gives average precision/recall values plotted against number of retrieved images for all Kekre-Gray image retrieval techniques. Precision/recall values for Kekre-RGB image retrieval techniques are plotted in figure 6.b. Here 1/32th fractional coefficients (3.125% of total Kekre transformed coefficients) based image retrieval gives the highest precision/recall crossover values specifying the best performance.

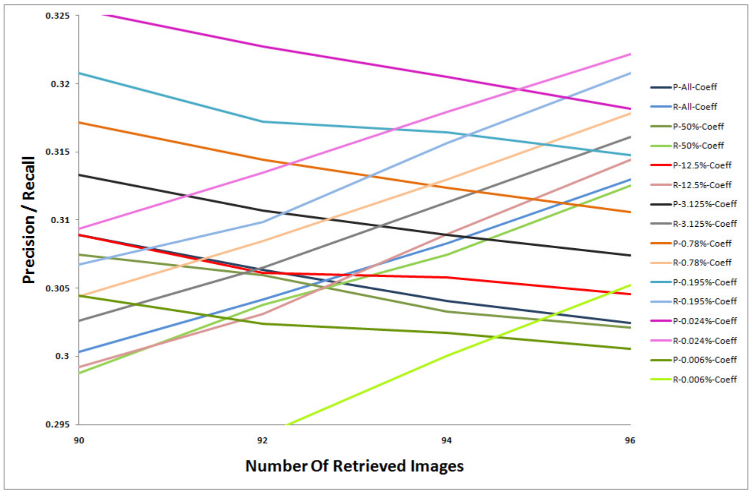

FIGURE 5.a. Haar-Gray based CBIR

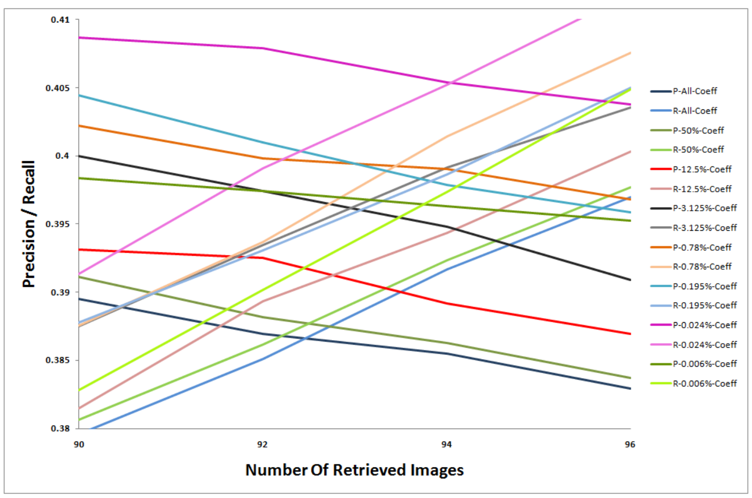

FIGURE 5.b. Haar-RGB based CBIR

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

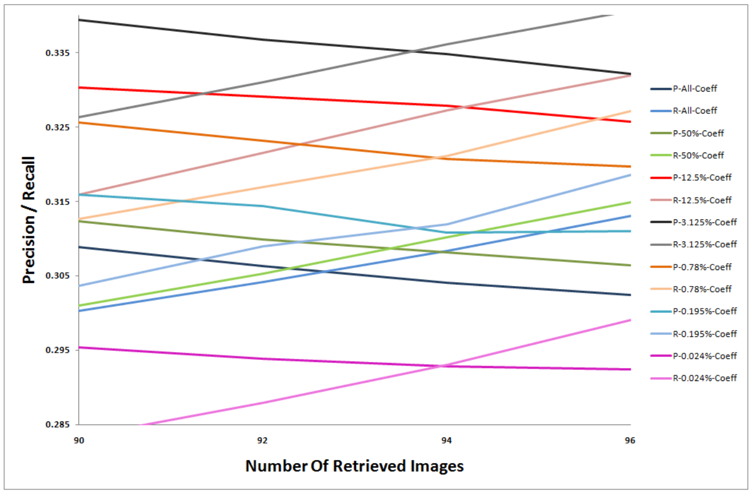

FIGURE 6.a. Kekre-Gray based CBIR

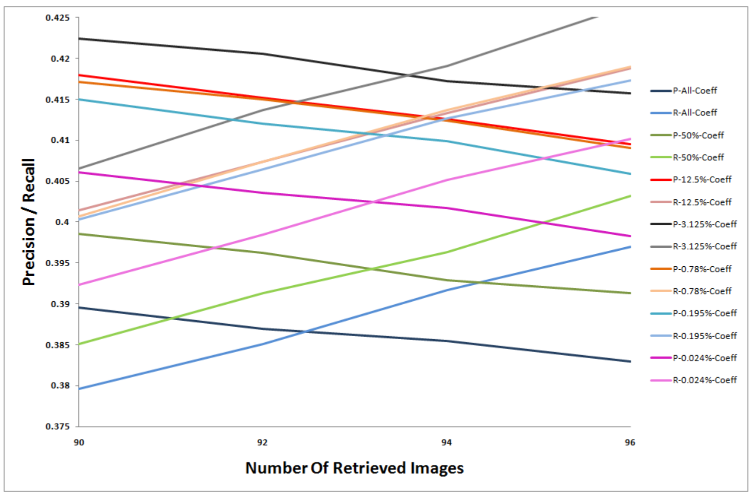

FIGURE 6.b. Kekre-RGB based CBIR

FIGURE 6. Crossover Point of Precision and Recall for Kekre Transform based CBIR

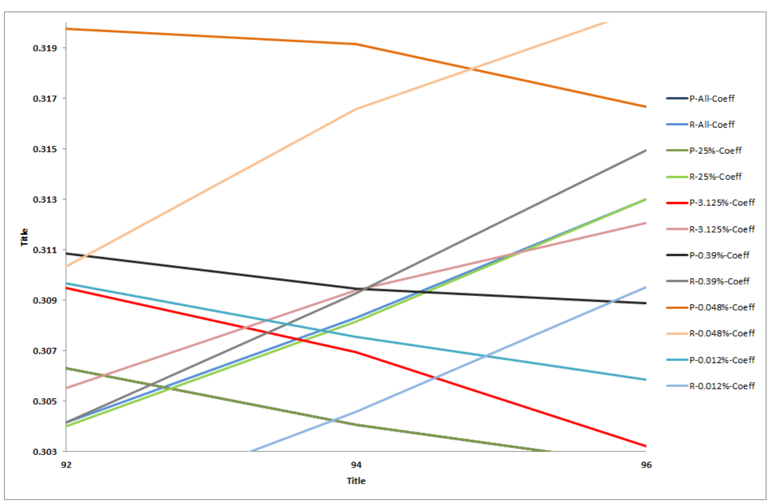

FIGURE 7.a. DST-Gray based CBIR

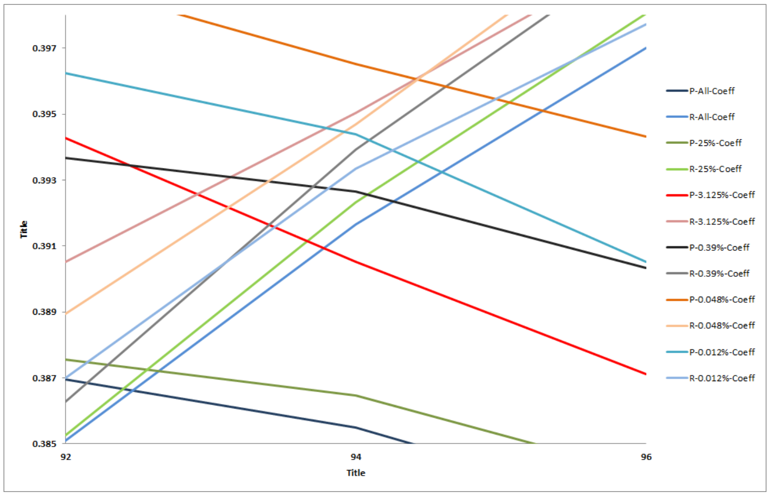

FIGURE 7.b. DST-RGB based CBIR

FIGURE 7. Crossover Point of Precision and Recall for DST based CBIR

Figure 7.a gives average precision/recall values plotted against number of retrieved images for all DST-Gray image retrieval techniques. Precision/recall values for DST-RGB image retrieval techniques are plotted in figure 7.b. Here 1/2048th fractional coefficients (0.048% of total DST transformed coefficients) based image retrieval gives the highest precision/recall crossover values specifying the best performance when using Discrete Sine Transform.

Figure 8.a gives average precision/recall values plotted against number of retrieved images for all Slant-Gray image retrieval techniques. Precision/recall values for Slant-RGB image retrieval techniques are plotted in figure 8.b. Here 1/4th fractional coefficients (25% of total Slant transformed coefficients) based image retrieval gives the highest precision/recall crossover values specifying the best performance when using Slant Transform on a gray image and 1/8th fractional coefficients (12.5% of total Slant transformed coefficients) based image retrieval gives the highest precision/recall crossover values specifying the best performance when using Slant Transform on a color image.

Figure 9.a gives average precision/recall values plotted against number of retrieved images for all DHT-Gray image retrieval techniques. Precision/recall values for DHT-RGB image retrieval techniques are plotted in figure 9.b. Here 1/2 fractional coefficients (0.50% of total DHT transformed coefficients) based image retrieval gives the highest precision/recall crossover values specifying the best performance when using Discrete Hartley Transform.

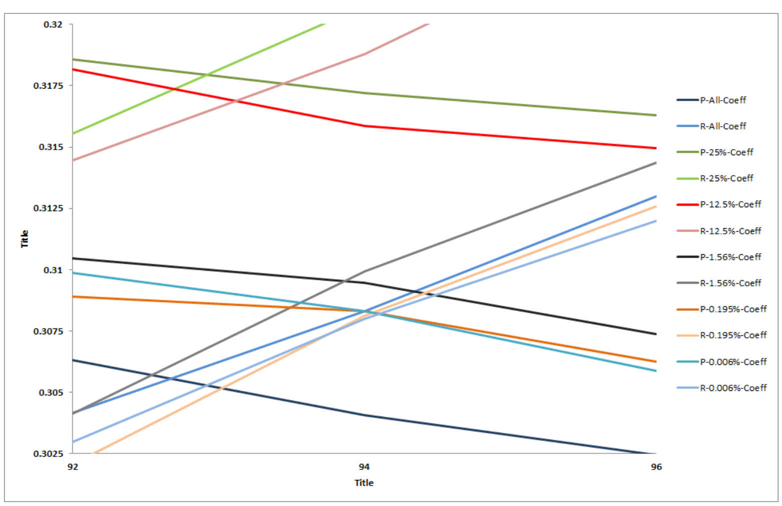

FIGURE 8.a. Slant-Gray based CBIR

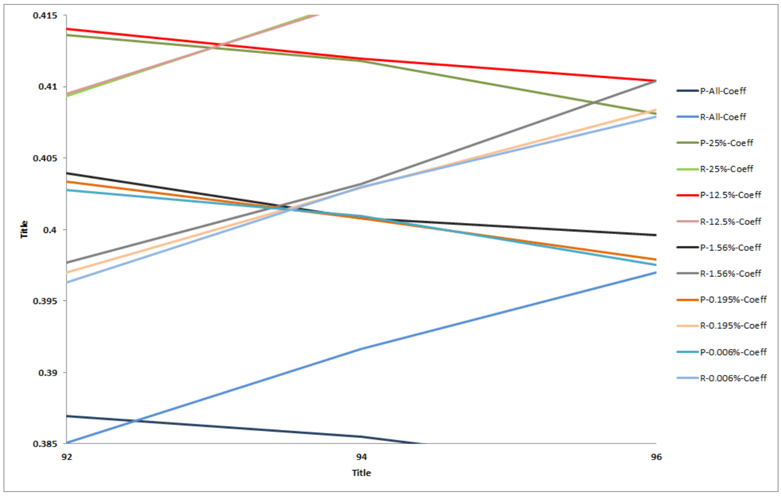

FIGURE 8.b. Slant-RGB based CBIR

FIGURE 8. Crossover Point of Precision and Recall for Slant Transform based CBIR

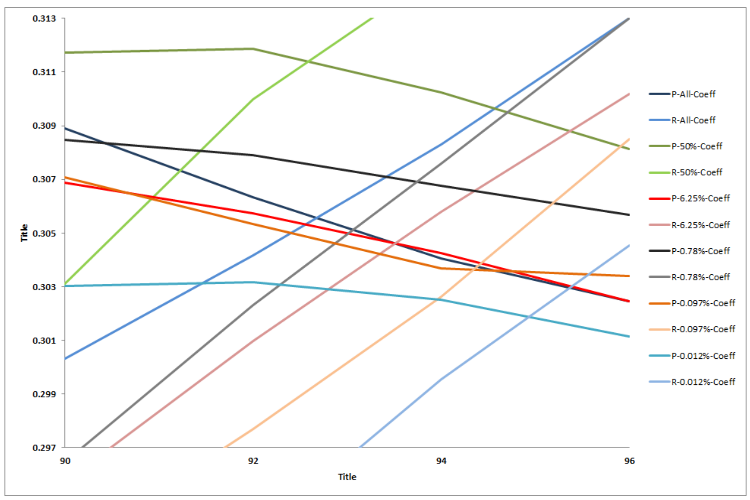

FIGURE 9.a. DHT-Gray based CBIR

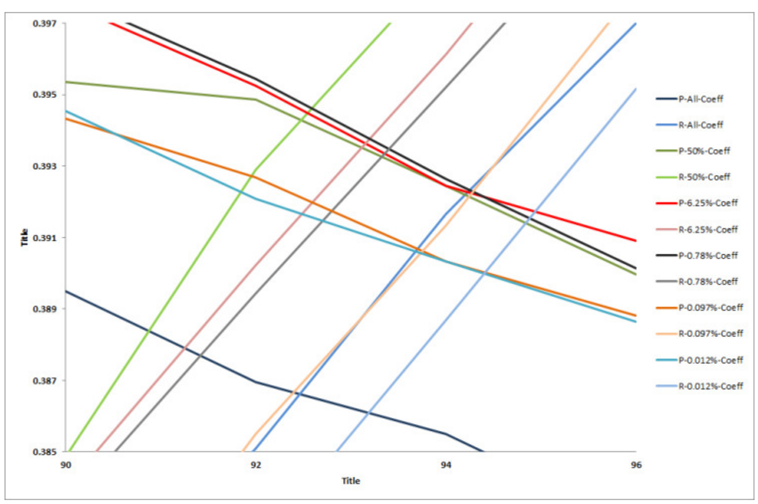

FIGURE 9.b. DHT-RGB based CBIR

FIGURE 9. Crossover Point of Precision and Recall for DHT based CBIR

Figure 10 shows the performance comparison of all the seven transforms for proposed CBIR techniques. Figure 10.a is indicating the crossover points of DCT-Gray, Walsh-Gray, Haar-Gray, Kekre-Gray, DST-Gray, Slant-Gray, and DHT-Gray CBIR for all considered feature vectors (percentage of coefficients of transformed gray images). Here for upto 25% of coefficients Slant transform performs better than all discussed transforms then till0.78 % of coefficients Kekre transform performs better than all discussed transforms after which Haar transform outperforms other transforms up to 0.012 % of coefficients and finally for 0.006 % of coefficients DCT gives highest crossover point value, as energy compaction in Haar and DCT transform is better than other discussed transforms. For Kekre-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 transform with 3.125 % of fractional coefficients gives the best performance for Gray-CBIR techniques discussed here.Figure 10.b indicates the performance comparison of DCT-RGB, Walsh- RGB, Haar- RGB, Kekre- RGB, DST-Gray, Slant-Gray, and DHT-Gray CBIR with different percentage of fractional coefficients. Here Slant-RGB CBIR outperforms all other transforms till 12.5% of coefficients as feature vector then Kekre-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 transform gives the best performance when 6.25% of coefficients are considered. In all, CBIR using Kekre transform with 6.25 % of fractional coefficients gives the best performance for RGB-CBIR techniques discussed here.

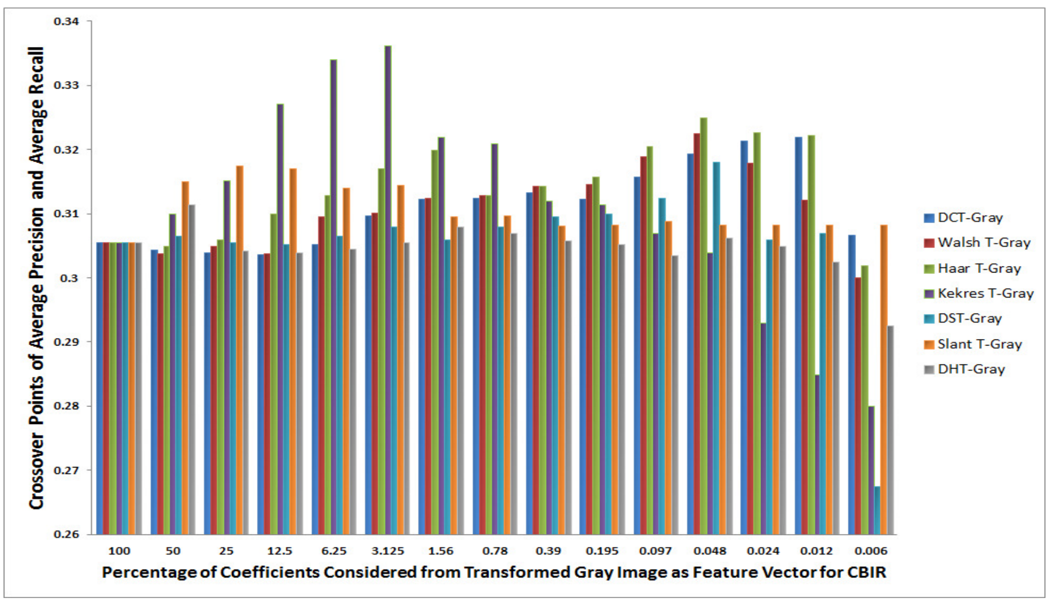

FIGURE 10.a. Transform Comparison in Gray based CBIR

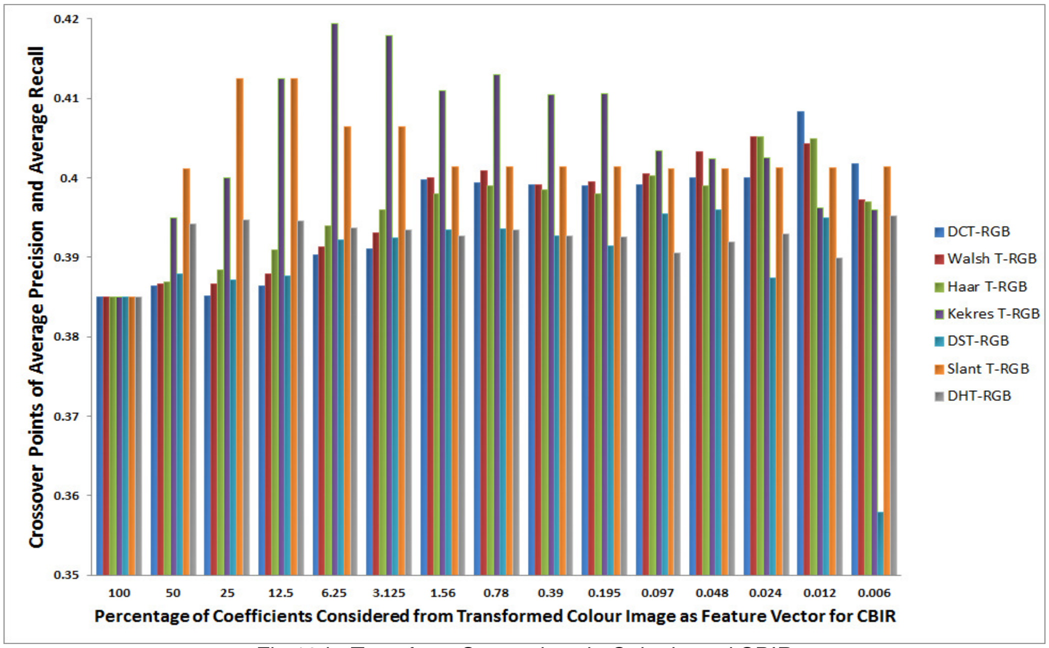

Fig.10.b. Transform Comparison in Color based CBIR

FIGURE 10. Performance Comparison Using Fractional Coefficients across all discussed Transforms

6. 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. Fairly large numbers of popular image transforms are considered here with newly introduced Kekre transform. In all transforms (DCT, Walsh, Haar, Kekre, DST, Slant and DHT), 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 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 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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