ISSN:0975-9646

Column wise DCT plane sectorization in CBIR

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***Abstract*—Content Based Image Retrieval (CBIR) is the application of computer vision techniques used to retrieve digital images from a large database. In this paper we have used the concept of sectorization of the plane formed form DCT transformed image. We have proposed an approach which involves augmentation of zero and highest row components of column-wise DCT transformed image for generating the feature vector. Precision-Recall crossover point, LIRS (Length of initial string of relevant images retrieved), LSRR (Length of string to recover all relevant images)and LSRI (Longest string of relevant images retrieved) are used to evaluate the performance of the proposed method. We have introduced a new performance evaluation parameter apart from the above mentioned parameters viz. and LSRI (Longest string of relevant images retrieved). Two similarity measures used to calculate performance evaluation parameters are: 1. Sum of Absolute Distance & 2. Euclidean Distance. The column-wise DCT transformed image is sectorized on the basis of even-odd column components of transformed image with and without augmentation of zero and highest row components. The proposed algorithm is applied to a database of thousand images spread over 10 varying classes. Performance is evaluated and compared for 4, 8, 12 and 16 DCT sectors.**

***Keywords*—CBIR, DCT, Precision-Recall, LIRS, LSRR, Absolute Difference, Euclidean Distance, Longest String of Relevant Retrieved Images.**

I. INTRODUCTION

Content Based Image Retrieval (CBIR) algorithms are a means to access a digital image from a database [1]. In CBIR the actual contents of the image are used to describe and analyse an image. The contents of an image are used to form a set of feature vectors using the method involved. Various techniques are used for extraction of the feature vectors for an image. Some of these techniques involve using attributes like shape, color [15], textures [15] and edge density [15] of an image to extract the feature vector [2]. Feature vectors are unique identities of images which are used to differentiate among images and facilitate better retrieval of relevant images. The feature vector of the query image is compared to that of the feature vectors of the images in the database using the similarity measures which leads to retrieval of the images with feature vectors close to that of the query images. A general model for a CBIR system is shown in Figure 1.

CBIR has attracted research interests of people from various fields. Some of them being Artificial Intelligence, Data Mining, Web Development, Information Theory, Statistics, etc [3].

The shortcomings of CBIR lay in the difference between the high-level image semantics and the low-level image features [3] due to the rich content but subjective semantics of an image.

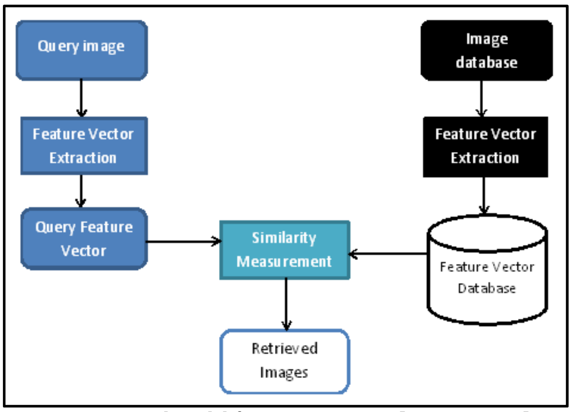


Fig. 1: General model for a CBIR system [11, 14, 16, 22]

Nonetheless good CBIR systems have already being developed. These systems help in improving the existing methods as well as propose new methods which improve results to get a better match with lesser complexity [2]. The various applications of CBIR are fingerprint recognition [4], iris recognition [5], face recognition [6], etc. Feature vector extraction using Region of Interest [7], FFT sectors [19 - 20], Walsh Transform [2], DCT [3], DCT-DST [8], Gaussian Mixtures [9], Haar and Kekre Wavelet [10], feature vector extraction using color histograms [14, 16], bit truncation coding [17, 18], etc. has been implemented earlier. This paper proposes the use of sectorization of column-wise DCT transformed images on the basis of even-odd column components of transformed image with augmentation of zero and highest row components for feature vector extraction.

II. DISCRETE COSINE TRANSFORM

DCT transforms an image in the spatial domain into frequency domain. DCT is made up of cosine functions taken over half the interval and dividing this half interval into N equal parts and sampling each function at the center of these parts. The discrete cosine transform matrix is formed by arranging thesesequences row wise. On applying DCT to an image, most of visually significant data is concentrated in a few coefficients of DCT and also many of the DCT coefficients are close to zero. The most common DCT definition of 1D Sequence of Length N is:

$$C(u) = \alpha(u) \sum_{x=o}^{N-1} \left(\mathrm{f}(x) \cos \frac{\pi(2x+1)u}{2N} \right) \qquad \ldots(1)$$

For u=0, 1, 2,…, N-1.

Similarly inverse transform is given as:

$$f(x) = \sum_{u=0}^{N-1} \alpha(u) C(u) \cos \frac{\pi(2x+1)u}{2N} \qquad \ldots(2)$$

For x=0, 1, 2,…, N-1and $\alpha(u)$ for both the above equations is given as:

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}} & for\ u = 0 \\ \sqrt{\frac{2}{N}} & for\ u \neq 0 \end{cases} \qquad \ldots(3)$$

III. FEATURE VECTOR GENERATION

In our proposed method, we apply DCT transform column-wise to the image. Then, this DCT transformed image is divided into various sectors based on the even-odd column components of the transformed image. The rows in the above transformed image have an increasing sequency, i.e. all the even numbered rows have even sequency whereas the odd numbered rows have an odd sequency. The proposed algorithm takes into consideration a combination of even-odd co-efficient pair to sectorize the DCT transformed image putting even co-efficient on X-axis and odd co-efficient on the Y-axis. Considering these components as co-ordinates, we get a point in X-Y plane as shown in Figure 2. We will be sectorizing the transformed image into 4, 8, 12 and 16 sectors based on values of co-efficient.

This proposed even-odd plane is used for feature vector generation. We have proposed the use of the following method to extract the feature vector in our proposed algorithm:

The average of all the co-efficient placed in a sector for every plane is taken. Also the zeroth and highest row components are augmented to the feature vector for every plane. For 4 DCT sectors, there are four components in the feature vector per plane, 1 for each sector and 2 components for the augmented rows. Thus for 4 DCT sectors, the size of the feature vector is 6*3=18. Similarly, for 8, 12 and 16 DCT sectors, the sizes of the database are 30, 42 and 54 respectively.

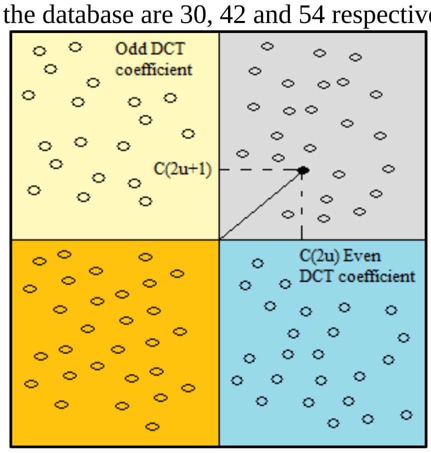


Fig. 2: DCT even-odd plane used sectorization [3, 8].

The results for a given query image are computed for this feature vector using the similarity measures Sum of Absolute Distance [2, 3, 8, 10] and Euclidean Distance [2, 3, 8, 10]. Comparison of the results obtained for both the similarity measures and for 4, 8, 12 and 16 sectors is done.

A. DCT 4 Sectors

To get the sector in which an even-odd co-efficient pair is to be placed, the conditions mentioned in Table 1 are used.

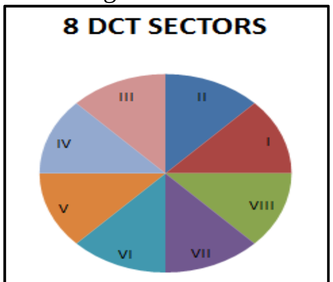
Table 1: Formation of four DCT sectors.

Sign of Even column	Sign of Odd column	Sector Assigned
+	+	I quadrant
+	-	II quadrant
-	-	III quadrant
-	+	IV quadrant

All planes in the image are DCT transformed. Then the even column co-efficient and odd column co-efficient are checked for their signs. The even and odd DCT co-efficient are then placed in respective sector in accordance with the above table. The similarity measures Sum of Absolute Difference and Euclidean Distance are used to check the closeness of the query image to the images in the database and performance evaluation parameters are calculated to measure the overall performance of the algorithm.

B. DCT 8 Sectors

Each sector obtained in the previous section is divided into 2 equal sectors, each of 45^0. In all we have 8 sectors for each plane. For one plane the sectors are divided as shown in Figure 3.



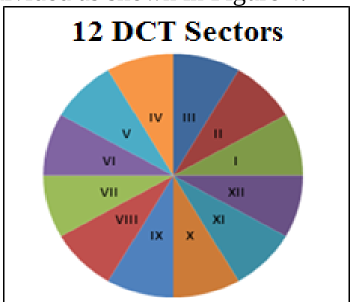
Sectors	Conditions
I, IV, V, VIII	|A| >= |B|
II, III, VI, VII	|B| >= |A|

Where
A=Even Row of Transfromed image
B=Odd Row of Transfromed image

Fig. 3: Formation of 8 DCT sectors

C. DCT 12 Sectors

Each sector obtained in the previous section of 4 sectors is divided into 3 equal sectors, each of 30^0. In all we have 12 sectors for each plane. For one plane the sectors are divided as shown in Figure 4.



Sectors	Conditions
I, VI, VII, XII	|A| >= √3 * |B|
II,V,VIII,XI	1/√3 * |A| <= |B| <= √3*|A|
III, IV, IX, X	Otherwise

Where
A=Even Row of Transformed image
B=Odd Row of Transformed image

Fig. 4: Formation of 12 DCT Sectors

D. DCT 16 Sectors

Sixteen sectors are obtained by dividing each one of eight sectors into two equal parts each of 22.5^0.

IV. RESULTS AND DISCUSSIONS

The database[12, 13] used by us to evaluate the performance of our proposed algorithm consisted of 1000 images of ten different classes such as Tribal, Beaches, Monuments, Buses, Dinosaurs, Elephants, Flowers, Horses, Mountains, and Food dishes. The figure below shows the sample images from the database.

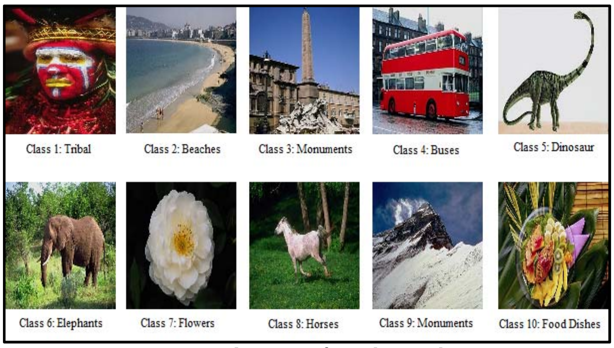


Fig. 5: Sample images from the Database.

These images are displayed class-wise i.e. Class 1 has images of tribal and so on. Also each class consist of 100 images. Feature vector for all the images in the database is generated and feature database is formed. Five images are randomly selected from every class as query images to evaluate the performance. Similarity measures Euclidean Distance and Absolute Distance are used to compare the feature vector of the query images to that of the feature vectors in the feature database. The smaller the value of the similarity measures for the query image better is the match with the respective image in the database. To check the effectiveness of the algorithm with respect to the retrieval of relevant images we have made use of precision and recall using the equations given below:

$$Precision = \frac{\text{Number of Relevant Images Retrieved}}{\text{Total Number of Images Retrieved}} \quad \ldots(4)$$

$$Recall = \frac{\text{Number of Relevant Images Retrieved}}{\text{Total Number of Relevant Images in Database}} \quad \ldots(5)$$

We have also made use of two more performance evaluation parameters: Length of Initial Relevant retrieval String (LIRS) and Length of String to Recover all Relevant images in the database (LSRR) given by the equations below:

$$LIRS = \frac{\text{Length of Initial Relevant String of Images}}{\text{Total Number of Relevant Images Retrieved}} \quad \ldots(6)$$

$$LSRR = \frac{\text{Length of String to Recover all Relevant Images}}{\text{Total Number of Images in the Database}} \quad \ldots(7)$$

Higher the precision-recall crossover point better is the performance. Similarly higher the value of LIRS better is the performance of the proposed algorithm, whereas lower the value of LSRR better is the performance.

We have also introduced a new evaluation parameter: LSRI (Longest string of relevant images retrieved) as given in equation (8). This is the measure of length of the longest string of relevant images retrieved at any point during the process of retrieval. The value of this parameter lies between 0 to the maximum number of images of the relevant class.

$$LSRI = \frac{\text{Longest string of relevant images retrieved}}{\text{Total Number of relevant Images in the Database}} \quad \ldots(8)$$

These all performance evaluation parameter values are in the range of 0-1 and these can be represented in the percentage.

Figure 6 and Figure 7 show the plot for average crossover point of Precision - Recall DCT Transform (column-wise) sectorization using 4, 8, 12 & 16 sectors and the algorithm proposed to generate the feature vector. As mentioned earlier, 5 images are randomly selected per class to evaluate the performance of the algorithm. The average of the precision - recall crossover point is considered for the purpose of generating the plot. Euclidean Distance and Sum of Absolute Distance are used as similarity measures.

For 4 sectors the performance of the algorithm with respect to retrieval rate is 40% with Euclidian Distance as similarity measure and 41% with Sum of Absolute Distance as similarity measure. For 8 sectors the performance of the algorithm with respect to retrieval rate is 40% with Euclidian Distance as similarity measure and 43% with Sum of Absolute Distance as similarity measure. For 12 sectors the performance of the algorithm with respect to retrieval rate is 40% with Euclidian Distance as similarity measure and 43% with Sum of Absolute Distance as similarity measure. For 16 sectors the performance of the algorithm with respect to retrieval rate is 40% with Euclidian Distance as similarity measure and 43% with Sum of Absolute Distance as similarity measure. We infer that the proposed algorithm performs better when 16 sectors are used to sectorize the image and when using Sum of Absolute Distance as the similarity measure.

From Figure 6 and Figure 7 we conclude that the performance of the proposed algorithm varies from class to class based on the use the similarity measure. Contrary to the overall performance classes 1, 3 and 9 yield better results when Euclidean Distance is used as the similarity measure. Also, when Sum of Absolute Distance is used as the similarity measure, classes 3, 9 and 10 have a decline in the retrieval rate with the increase in the number of sectors which again opposes the conclusion based on the overall performance of the algorithm.

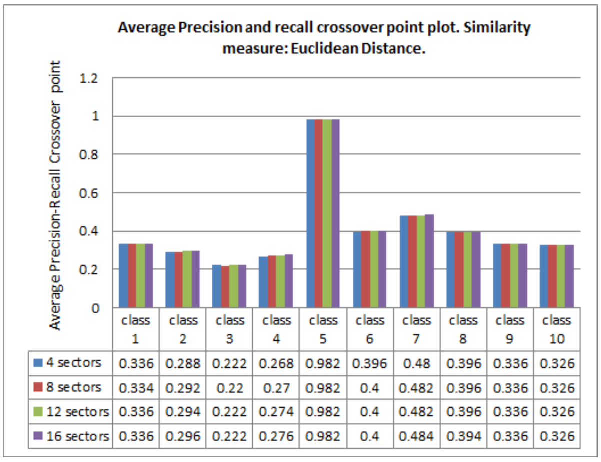


Fig. 6: Plot for Precision - Recall Crossover point using Euclidean Distance as similarity measure

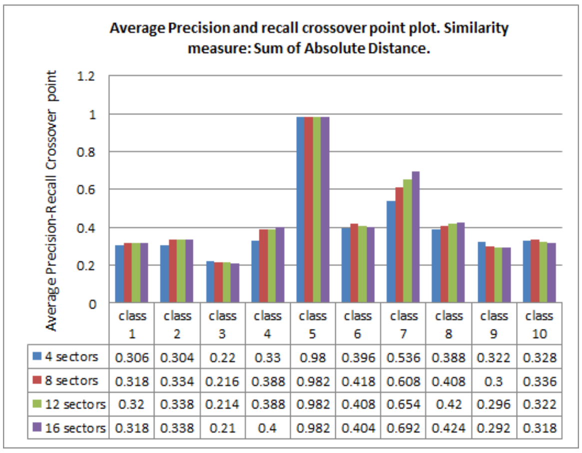


Fig. 7: Plot for Precision – Recall Crossover point using Sum of Absolute Distance as similarity measure

The best performance class-wise with respect to Precision – Recall Crossover point for the proposed algorithm using the similarity measures Euclidean Distance and Sum of Absolute Distance is shown in Table 2 and Table 3. The worst performance of the algorithm with respect to Precision – Recall crossover point is for class 3 i.e. images of monumentswith an average of 22% using Euclidean Distance and 21% using Sum of Absolute Distance.

Table 2: Top 3 class-wise performance w.r.t. Precision-Recall crossover point using Euclidean Distance

Class	Average Precision – Recall Crossover Point for sectors 4, 8, 12 & 16
5	98%
7	48%
6	39%

Table 3: Top 3 class-wise performance w.r.t. Precision-Recall crossover point using Sum of Absolute Distance as similarity measure.

Class	Average Precision – Recall Crossover Point for sectors 4, 8, 12 & 16
5	98%
7	62%
8	41%

The performance of the evaluation parameter LIRS is shown in Figure 8 and Figure 9 for both the similarity measures Euclidean Distance and Sum of Absolute Distance. Performance of LIRS is compared for all different sectors i.e. 4, 8, 12 & 16 sectors.

From Equation 6, it is evident that higher the value of LIRS better is the performance of the algorithm. For 4 sectors the performance of the algorithm with respect to LIRS is 12% with Euclidian Distance as similarity measure and 13% with Sum of Absolute Distance as similarity measure. For 8 sectors the performance of the algorithm with respect to LIRS is 12% with Euclidian Distance as similarity measure and 13% with Sum of Absolute Distance as similarity measure. For 12 sectors the performance of the algorithm with respect to LIRS is 12% with Euclidian Distance as similarity measure and 13% with Sum of Absolute Distance as similarity measure. For 16 sectors the performance of the algorithm with respect to LIRS is 13% with Euclidian Distance as similarity measure and 14% with Sum of Absolute Distance as similarity measure. We infer that the proposed algorithm performs better when 16 sectors are used to sectorize the image and when using Sum of Absolute Distance as the similarity measure the only exception being the performance of the algorithm when the column-wise DCT transformed image is sectorized using 16 sectors and Sum of Absolute Distance is used as the similarity measure.

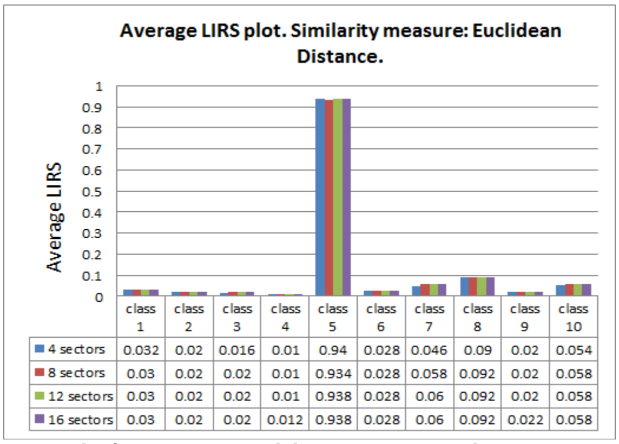


Fig. 8: Plot for LIRS using Euclidean Distance as similarity measure

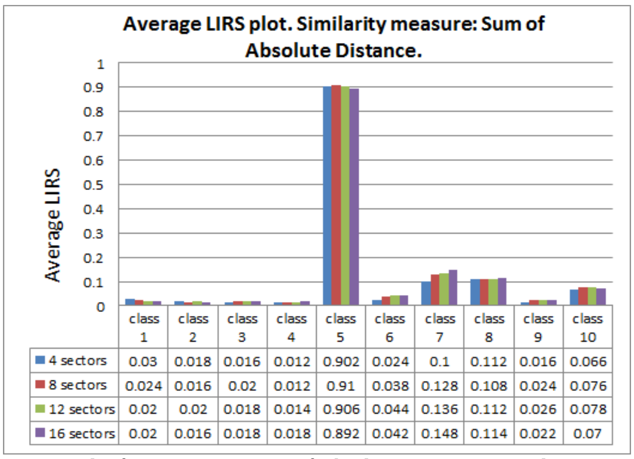


Fig. 9: Plot for LIRS using Sum of Absolute Distance as similarity measure

Contrary to the overall performance, only classes 1, 2, 3 and 5 yield better results when Euclidean Distance is used as the similarity measure. Classes 1 and 5 show a decline in performance in both the cases. For all the 50 query images taken into to check the performance of the algorithm using both Euclidean Distance and Sum of Absolute Distance, the value of LIRS is at least 0.01 i.e. the first image that is retrieved for all the query image is of the relevant class or same class as that of the query image.

The best performance class-wise with respect to LIRS for the proposed algorithm using the similarity measures Euclidean Distance and Sum of Absolute Distance is shown in Table 4 and Table 5. The worst performance of the algorithm with respect to LIRS using Euclidean Distance and Sum of Absolute Distance as the similarity measures is that of class of 4 i.e. busesclass.

Table 4: Top 3 class-wise performance w.r.t.LIRS using Euclidean Distance as similarity measure.

Class	Average LIRS for sectors 4, 8, 12 & 16
5	94%
8	7%
7	10%

Table 5: Top 3 class-wise performance w.r.t.LIRS using Sum of Absolute Distance as similarity measure.

Class	Average LIRS for sectors 4, 8, 12 & 16
5	94%
7	13%
8	11%

The performance of the evaluation parameter LSRR is shown in Figure 10 and Figure 11 for both the similarity measures Euclidean Distance and Sum of Absolute Distance. Performance of LSRR is compared for all different sectors i.e. 4, 8, 12 & 16 sectors.

We can conclude from Equation 7 that lower the value of LSRR better is the performance of the proposed algorithm. For 4 sectors the performance of the algorithm with respect to LSRR is 75% with Euclidian Distance as similarity measure and 74% with Sum of Absolute Distance as similarity measure. For 8 sectors the performance of the algorithm with respect to LSRR is 75% with Euclidian Distance as similarity measure and 73% with Sum of Absolute Distance as similarity measure. For 12 sectors the performance of the algorithm with respect to LSRR is 75% with Euclidian Distance as similarity measure and 73% with Sum of Absolute Distance as similarity measure. For 16 sectors the performance of the algorithm with respect to LSRR is 75% with Euclidian Distance as similarity measure and 72% with Sum of Absolute Distance as similarity measure. We infer that the proposed algorithm performs better when 16 sectors are used to sectorize the image and when using Sum of Absolute Distance as the similarity measure.

We observe that contrary to the overall performance classes 1, 2, 5 and 9 perform better when Euclidean Distance is used as the similarity measure.

The best performance class-wise with respect to LSRR for the proposed algorithm using the similarity measures Euclidean Distance and Sum of Absolute Distance is shown in Table 6 and Table 7. The worst performance of the algorithm with respect to LSRR using both Euclidean Distance and Absolute Distance as similarity measures is that of class 3 i.e. images of monuments with an average of 92% using Euclidean Distance and 92% using Sum of Absolute Distance.

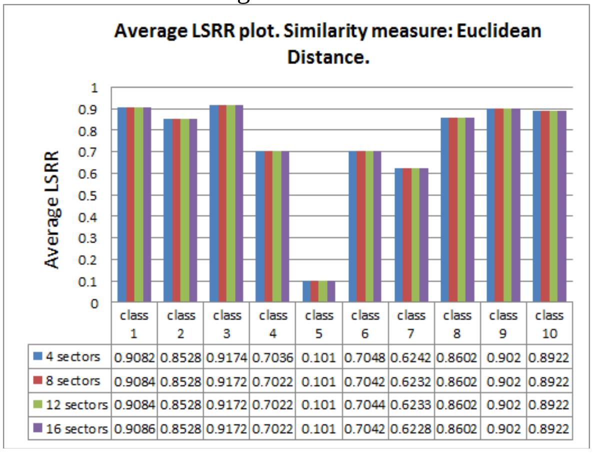


Fig. 10: Plot for LSRR using Euclidean Distance as similarity measure

The performance of the proposed algorithm with respect to LRSI is shown in Figure 12 and Figure 13 for both the similarity measures Euclidean Distance and Sum of Absolute Distance. Performance of Longest String of Relevant Retrieved Images is compared for all different sectors i.e. 4, 8, 12 & 16 sectors.

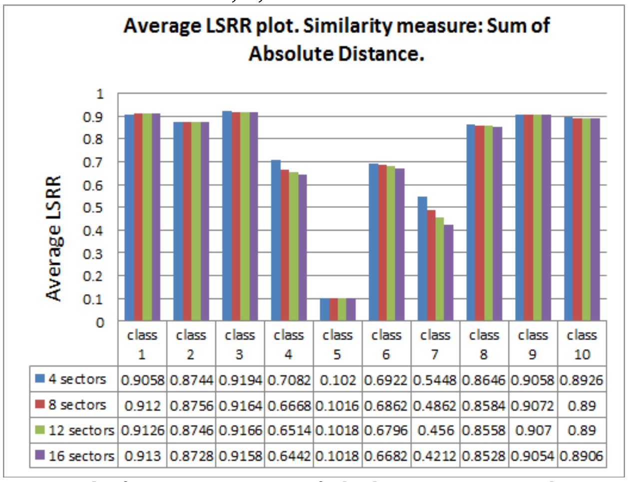


Fig. 11: Plot for LSRR using Sum of Absolute Distance as similarity measure

Table 6: Top 3 class-wise performance w.r.t.LSRR using Euclidean Distance as similarity measure.

Class	Average LSRR for sectors 4, 8, 12 & 16
5	10%
7	62%
4	70%

Table 7: Top 3 class-wise performance w.r.t.LSRR using Sum of Absolute Distance as similarity measure.

Class	Average LSRR for sectors 4, 8, 12 & 16
5	10%
7	47%
4	66%

Higher the value of the above parameter better is the performance. The overall average performance of the algorithm with respect to LSRI is 14% with Euclidian Distance and 15% with Sum of Absolute Distance for all number of sectors. We infer that the proposed algorithm performs better when 16 sectors are used to sectorize the image and when using Sum of Absolute Distance as the similarity measure.the only exception being the performance of the algorithm when the column-wise DCT transformed image is sectorized using 16 sectors and Sum of Absolute Distance is used as the similarity measure.

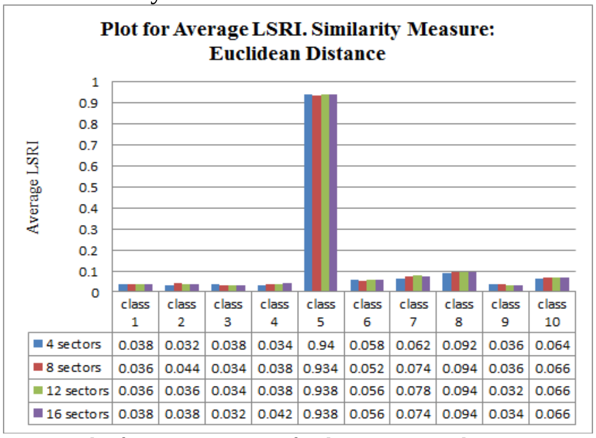


Fig. 12: Plot for Longest String of Relevant Retrieved Images using Euclidean Distance as similarity measure

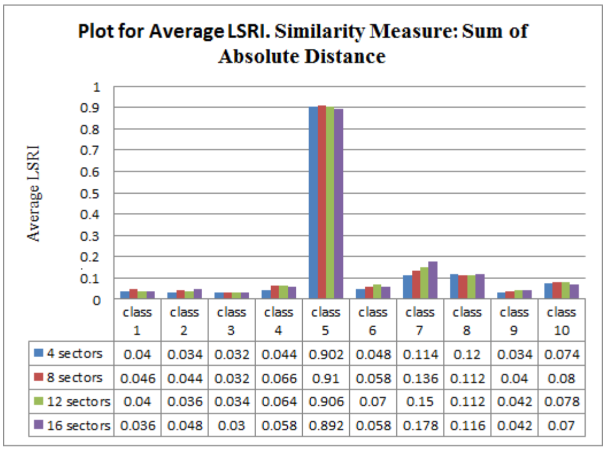


Fig. 13: Plot for Longest String of Relevant Retrieved Images using Sum of AbsoluteDistance as similarity measure

Contrary to the overall performance, classes 3 and 5 yield better results when Euclidean Distance is used as the similarity measure. Also, classes 1 and 10 show a decline in the value of Longest String of Relevant Retrieved Images when Sum of Absolute Distance is used the similarity measure. For all the query images used by us, the value of Longest String of Relevant Retrieved Images is always greater than 1. From this we can conclude that the proposed algorithm can retrieve relevant image in a sequence at least once during the process of retrieval.

The best performance class-wise with respect to Longest String of Relevant Retrieved Images for the proposed algorithm using the similarity measures Euclidean Distance and Sum of Absolute Distance is shown in Table 8 and Table 9. The worst performance of the algorithm with respect to Longest String of Relevant Retrieved Images using both Euclidean Distance and Absolute Distance as similarity measures is that of class 3 i.e. images of monuments with an average of 3% using Euclidean Distance and Sum of Absolute Distance.

Table 8: Top 3 class-wise performance w.r.t.LRSI using Euclidean Distance as similarity measure.

Class	Average Longest String of Relevant Retrieved Images for sectors 4, 8, 12 & 16
5	94%
8	9%
7	7%

Table 9: Top 3 class-wise performance w.r.t. LRSI using Sum of Absolute Distance as similarity measure.

Class	Average Longest String of Relevant Retrieved Images for sectors 4, 8, 12 & 16
5	90%
7	14%
8	11%

V. CONCLUSION

An algorithm of sectorization of column-wise DCT transformed planes of images into 4, 8, 12 and 16 sectors to generate the feature vector is proposed. Performance evaluation parameters like Precision – Recall crossover point, LIRS, LSRR and **and LSRI (Longest string of relevant images retrieved)** are used for similarity measures Euclidean Distance and Sum of Absolute Distance. The proposed algorithm is testedover even-odd row DCT component planes of column-wise DCT transformed image.The average value of zeroeth and last row are augmented into the feature vector. Performance of the algorithm is evaluated for the mentioned evaluation parameters and compared for similarity measures Euclidean Distance and Sum of Absolute Distance. We observe that the overall retrieval rate of the algorithm when Euclidean Distance is used as the Similarity measure is 40% and 43% when Sum of Absolute Distance is used as the similarity measure.With respect to LIRS, the performance of the algorithm when Euclidean Distance is used as the similarity measure is 12% and 13% when Sum of Absolute Distance is used as the similarity measure. With respect to LSRR, the performance of the algorithm when Euclidean Distance is used as the similarity measure is 75% and 73% when Sum of Absolute Distance is used as the similarity measure. With respect to Longest String of Relevant Retrieved Images, the performance of the algorithm when Euclidean Distance is used as the similarity measure is 14% and 15% when Sum of Absolute Distance is used as the similarity measure.Thus, we can conclude that the proposed algorithm yields a better result when Sum of Absolute Distance is used the similarity measure. From the other results, we can also conclude that when the image is sectorized into 16 sectors, the overall performance of the algorithm is the best with respect to all the performance evaluation parameters for the given image database. Also, since the value of LIRS for the entire 50 query images is at least 0.01, the performance of the algorithm is good since the first image to be retrieved is always from the relevant class. From the values of Longest String of Relevant Retrieved Images for the entire 50 query images which are greater than 1, we can conclude that the algorithm is capable of retrieving several images of the relevant class together. Furthermore we can conclude that class 5 i.e. class with images of dinosaurs performs the best with respect all the performance evaluation parameters and similarity measures since the intra-class redundancy is the least. From the Precision – Recall crossover point plots for all the query images we can also conclude that the crossover point is always generated when the number of retrieved images is equal to the number of images in the relevant class which in our case is 100 for all classes.

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