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Histogram Partitioning for Feature Vector Dimension Reduction in Bins Approach for CBIR

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***Abstract* — Feature vector dimensionality is an important issue in any CBIR system. It has great impact on the execution time required by the system to process the given query and generate the retrieval results. We have introduced a novel idea in this paper to extract the feature vectors of the image along with dimensionality reduction. It gives the improved performance as compared to already existing methods. The approach used is called bins approach; designed and implemented using image histogram partitioning. Three image histograms are obtained for each image plane R, G and B separately. Each of them is partitioned using two different techniques namely LP-Linear partitioning and CG –Centre of Gravity partitioning. Performance of these two partitioning techniques is compared by taking 4 different cases into consideration. Four different cases implemented in this paper are based on the variations used in the techniques to extract the image features. Multiple feature vector databases are prepared as pre-processing part of this work. Feature extraction techniques used are based on the original-ORG as well as equalized histogram-EQH and their partitioning based on LP and CG. This partitioning generates 8 bins holding the count of the pixels based on the color contents of the image. Further these 8 bins data is processed by computing the first four statistical moments (Mean, Standard deviation-STD, Skewness-SKEW, and Kurtosis- KURTO) representing the feature vectors of dimension 8. Retrieval results obtained by comparing the query image with database feature vectors by means of three similarity measures Euclidean distance (ED), Absolute distance (AD) and Cosine correlation distance (CD).**

***Keywords* — CBIR, Bins, Linear Partitioning, CG Partitioning, Mean, Standard Deviation, Skewness, Kurtosis.**

I. Introduction

This Paper explores the new idea for extracting the feature vectors giving improved performance along with the dimensionality reduction. Development of efficient feature extraction methods and selection of proper similarity metric are important aspects for the successful CBIR system [1][2][3]. Various images feature are classified into local and global image features. It includes low level image features like color, shape, texture and also the various image content descriptors color histograms, fuzzy histograms can be computed using basic image contents. Several methods for retrieving images on the basis of colour have been described in the literature, but most are variations on the same basic idea [4][5][6]. Color features are widely used in CBIR systems. Color features can be defined in various color spaces as per the use for different application [7]. Developing the efficient feature extraction method considers the time required to extract the feature, size and space required to store the feature vectors etc. Its efficiency can be determined on the basis of the accuracy of the retrieval results obtained for the given query [8][9]. There are various techniques implemented by CBIR researchers in frequency and spatial domain of image processing field to extract the image features. Spatial domain techniques includes the use of histograms [10][11]. We are focusing on the use of image histograms to extract the image features and also trying to reduce the size of the feature vector. Image histogram shows the total tonal distribution in the image. It is a bar chart of the count of pixels of every tone of gray that occurs in the image. The histogram is used and altered by many image enhancement operators. Histogram equalization is one of them; based on the assumption that image has to use full intensity range to display maximum contrast [12][13]. We have used histogram equalization in our work before partitioning the histogram to generate the bins and check its effect; which is reflected in the results and discussion. In this work we are mainly focusing on dimensionality reduction of the feature vector using bins approach. As we are using histogram, by default it gives 256 bins for intensity range 0-255. Use of 256 bins as a feature vector increases the time and space complexity [14][15]. To overcome this drawback we are working on reducing the feature vector size along with the improvement in the similarity retrieval [16][17][18].

Feature extraction explained in this paper includes bins formation by partitioning of original and equalized histogram of R, G and B image planes into two parts using two techniques; linear and CG partitioning. Two partitions for three planes leads to generation of 8 bins. Once the bins are ready, data contained in the bins is processed by computing the statistical first four moments for them. The first four moments; Mean, standard Deviation (STD), Skewness (SKEW) and Kurtosis (KURTO) extracted from 8 bins pixel data forms the 4 types of feature vector of dimension 8. These features are extracted separately for R, G and B color contents of the image. Based on the types of feature vectors we have prepared total 12 feature vector databases for 2000 database images. This process is followed with both partitioning techniques for both type of histograms i.e for original and equalized histogram. This leads to the generation of multiple feature vector databases i.e. 192 feature databases with all possibilities tried.

After feature extraction, second important aspect to be considered for CBIR is the similarity measure to be selected to compare the query image feature vector with the database feature vectors to promote the image retrieval. We have used three similarity measures Euclidean distance (ED), Absolute distance (AD) and Cosine correlation distance (CD) [19][20].

Performance of the proposed system is evaluated using three parameters namely PRCP (Precision Recall Cross over Point), LS (Longest String), LSRR (Length of String to Retrieve all Relevant). Experimentation work is carried

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out using database of 2000 BMP images includes 20 classes, in which few of them are taken from Wang database[21].

Work done for the proposed system presented in this paper is organized as follows. Section I gives the introduction of the system, Section II Histogram with Equalization. Partitioning techniques are discussed in section III. Preprocessing work for feature databases is elaborated in Section IV. Section V defines the similarity measures and evaluation parameters used in the system. Experimental Results are discussed in section VI which is flowed by conclusion in section VII.

II. Histogram and Histogram Equalization

Histogram gives summary of count of pixels in the number of bins. Histogram bins are representing the no of grey levels in the image. By default Matlab generates 256 bins for the image histogram. It represents 0 to 255 intensity levels of the image. Bin pixel count means count of pixels having same grey level or intensity will appear in the same bin. For bins having count zero can be interpreted that image does not contain the pixels of that particular intensity (bin). Normal or say original image histogram shows the distribution of pixels in 256 bins according to the intensity they carry without manipulating the original intensity values.

We have thought of modifying the image histog ram so that we can have uniform distribution of the pixels across 256 intensities (bins). To promote this modification we have used histogram equalization and we have checked its performance for the CBIR.

These two histograms are partitioned using linear and CG partitioning techniques. Partitioning has variable impact on the feature vectors and in turn on the retrieval results. We have compared the results with respect to partitioning techniques used for the original (ORG) as well as equalized (EQH) histogram.

Fig.1. Shows the image with RGB planes and Fig.2. Shows the original and equalized histograms of R, G and B planes.

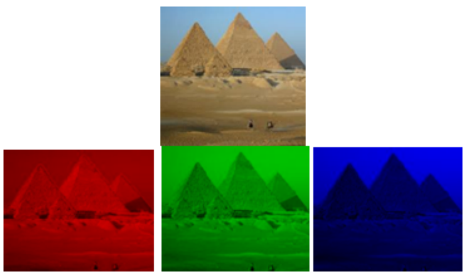

Fig.1. Pyramid Image with R, G and B Planes

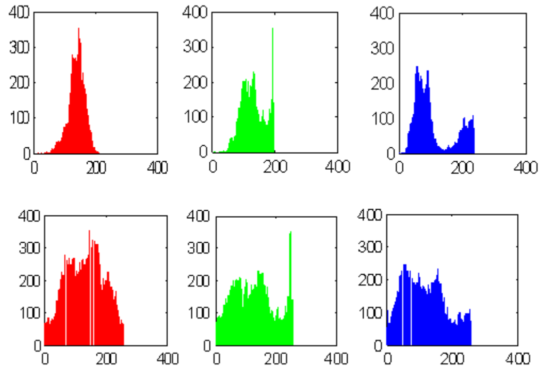

Fig.2. Pyramid Image with R, G and B Original and Equalized Histograms

III. Partitioning Techniques

As discussed in the introduction, we are concentrating on the feature vector dimensionality reduction; we have used two partitioning techniques to divide the histograms into two parts.

We are avoiding the use of 256 bins of histogram to be selected as feature vector because of time and space complexity. Division of histogram in two partitions for the R, G and B planes leads towards generation of just 8 bins. These 8 bins are used as feature vector rather than using the 256 bins of histogram.

A. Linear Partitioning: LP

Linear Partitioning is simple partitioning technique which divides the total number of pixels of image into two equal parts. The grey level at which this partitioning occurs, acts as threshold for the pixels to be counted in two parts identified as part 0 and part1. Fig. 3 a and b. Shows linear partitioning in black color for original and equalized histogram respectively.

B. Centre of Gravity Partitioning: CG

After applying linear partitioning we found that it is actually giving unbalanced partitioning because it takes only the count of pixels into consideration, ignoring the intensity values. But in CG we are giving equal importance to the pixels and their intensities. These intensities are considered as weight of the pixels so that according to their weights we are dividing the pixels into two parts by computing the CG. By computing CG we can obtain two partitions identified as part0 and part1 such that the both partitions will have same weight (intensities). This partitioning gives improvement in the retrieval performance of the system as compared to LP. Fig 3a and b. Shows the CG partitioning of original and equalized histogram respectively in blue color. We use following equation 1 to compute CG.

$$CG = \left[\frac{\left(L_1 W_1 + L_2 W_2 + ... + L_n W_n \right)}{\sum_{i=1}^{n} W_i} \right] \qquad (1)$$

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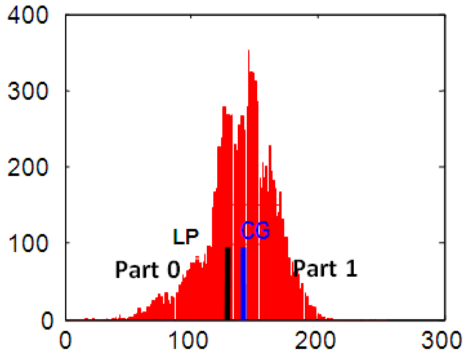

Fig.3.a. Original with CG (in Blue) and LP (in Black) Partitioning

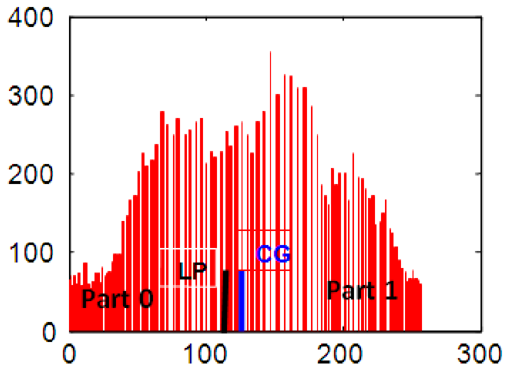

Fig.3.b. Equalized Histogram with CG (in Blue) and LP(in Black) Partitioning

IV. Feature Vector Databases: Pre-processing Work

As discussed earlier feature extraction and selection of similarity metric are important stages of any CBIR system. We have achieved reduction in the feature dimension by two partitioning techniques applied on histograms and dividing them into two parts and forming bins out of them. The process of bins formation and preparing the multiple feature vector databases is explained in following parts A and B.

A. Bins Formation: 8 Bins

This process starts with separation of an image into R, G and B planes. For each plane two histograms are obtained original and equalized histogram. These histograms are then partitioned into two parts namely part0 and part1 by LP and CG techniques.

Now, three histograms R, G and B each with two partitions 0 and 1 leads to generation of 8 bins as follows:

First, Pick up the pixel from an image under feature extraction process, check its R, G and B intensities so that which of the two (Part 0 or 1) partitions of respective R, G and B histogram it falls will be assigned to that pixel as flag.

Let, the pixel under process has R, G and B intensities falling in range of parts 0, 1and 1 of the respective histograms; then that pixel will be counted in bin number 3.('011'). This process is applied to all image pixels and all pixels are segregated into 8 bins addresses from '000' to '111' as count of pixels. This way we could generate the feature vector of just 8 components from the three histograms of sized 256 bins. Example 8 bins for same pyramid image are shown in Fig.4.

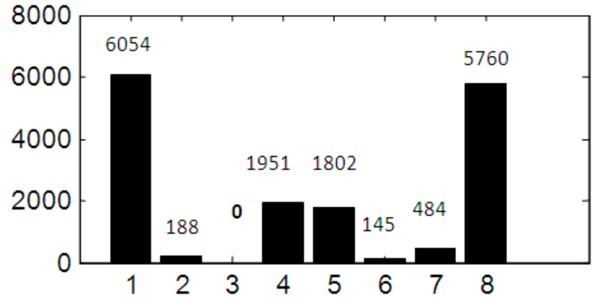

Fig.4. Sample 8 Bins Containing Count of Pixels for Pyramid Image

Each bin in above image is labelled with the count of pixels it has. Bin 3 is showing '0', it means no of pixels with flag '011' falling in partition 0,1 and 1 for R, G and B values respectively are not present in the image. We can interpret that count of pixels in bins3 is zero.

B. Multiple Feature Vector Databases

Once we obtain the count of pixels into 8 bins, this information is used to compute the feature vectors. We have considered RGB intensities of the pixels counted into 8 bins and computed first 4 moments for them. Moments computed and stored separately as feature vector in separate database namely MEAN, STD, SKEW and KURTO for R, G and B separately. This way we get 12 feature databases for 1 partitioning technique with one histogram.

While partitioning the histograms we thought of taking 4 different cases into consideration so that the system proposed in this paper can be evaluated through all the possible cases to recommend precise partitioning leads to reduce the size of the feature vector. Based on the LP and CG partitioning of the ORG and EQH histograms we have worked out the following 4 cases for each partitioning technique as given below

Note: (FV-feature Vector, LP Linear partitioning, CG-Centre of Gravity, ORG – Original, EQH- Equalized)

LP Partitioning

Case1 : LP on ORG and FV Extracted from ORG
Case2 : LP on EQH and FV Extracted from EQH
Case3 : LP on ORG and FV Extracted from EQH
Case4 : LP on EQH and FV Extracted from ORG

CG Partitioning

Case1 : CG on ORG and FV Extracted from ORG
Case2 : CG on EQH and FV Extracted from EQH
Case3 : CG on ORG and FV Extracted from EQH
Case4 : CG on EQH and FV Extracted from ORG

For each of the above cases we have prepared the 12 feature vector databases; thus total 12 x 4(for LP) x 4(for CG) = 192 feature vector databases are prepared before the query fired to the system.

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V. Similarity Measure and Performance Evaluation

As discussed earlier after feature extraction, the second important aspect to be considered for CBIR is selection of similarity measure. It compares the query image feature vector with the database feature vectors and calculates the distance between them. Calculating distance is nothing but finding similarity between the query and database images. Images closer to query will be selected for the final retrieval. Retrieval set may contain images relevant to query and irrelevant to query as well. It becomes an important issue to be handled in CBIR to analyse the results so that performance of the CBIR system can be evaluated and strength of the system in retrieving the similar images will be delineated.

A. Similarity Measure

To facilitate the comparison process we have used three similarity measures namely Euclidean distance (ED), Absolute distance and Cosine Correlation distance (CD) shown in equations 2, 3 and 4 respectively. Each of them has their own features and they are performing better in different factors.

Euclidean Distance

$$D_{QI} = \sqrt{\sum_{i=1}^{n} (FQ_i - FI_i)^2} \qquad (2)$$

Absolute Distance:

$$D_{QI} = \sum_{i=1}^{n} |(FQ_i - FI_i)| \qquad (3)$$

Cosine Correlation Distance

$$\frac{\langle D(n) | Q(n) \rangle}{\sqrt{[\langle D(n) | D(n) \rangle \langle Q(n) | Q(n) \rangle]}} \qquad (4)$$

'Where D(n) and Q(n) are Database and Query feature Vectors resp.

When query image is fired to the system; feature extraction is carried out for it and the comparison process starts and distance between query and database feature vectors is calculated using the equations 2, 3 and 4. These distances are then sorted in ascending order from (min. distance to max.).

Usually retrieval set is prepared by selecting the images closer to query from the sorted distances. To decide this, a threshold is selected on trial and error basis [22][23]. But this is time consuming method of selecting the threshold on trial and error basis which may not give uniform performance for all types of queries. In our case instead of selecting threshold on trial and error basis we are taking first 100 images from the sorted distances (2000 in our database) to be selected as set similar images to be retrieved. This is because we have total 100 images of each in the database.

Performance evaluation parameters used for the proposed system are illustrated in next section.

B. Performance Evaluation Parameters

We have used three parameters to evaluate the system performance that are PRCP, LS and LSRR and are defined as follows.

1. PRCP: Precision Recall Cross over Point.

Many researchers have used two conventional parameters precision and recall for the CBIR evaluation [23][24].

Precision is fraction of relevant images retrieved to all images retrieved for the given query.

Recall is fraction of relevant images retrieved to all relevant images in the database.

In both cases, we can see that, user is always interested in images to be retrieved which are relevant query either from the database or from all retrieved. Precision and recall both should be as high as possible as per user's expectations. Taking this into consideration, we are using parameter PRCP which is actually a cross over point of precision and recall, where both have same value. In our case we are selecting initial string of length equal to the no of relevant images in the database to get the PRCP value.

PRCP = 1; indicates the ideal performance of the system; which means all the relevant images in the database are retrieved as initial string.

PRCP = 0; indicates the worst case system performance ; which means that no relevant image is retrieved and PRCP between 0 to 1 tells us that how far we are from the ideal system.

2. LS : Longest String

Longest string is the parameter which retrieves the continuous string of relevant images from the sorted set of distances (2000 in this experiment). This value is expected to be as high as possible.

3. LSRR : Length of String to Retrieve all Relevant

This parameter measures the length of string traversed by the system to collect all images from database relevant to query from the set of sorted distances. Minimum length indicates that system is performing better, takes less time and traversal to collect all query relevant images from database. Maximum LSRR shows worst case performance of the system.

VI. Experimental Results and Discussion

The work presented in this paper is experimented with database of 2000 BMP images from 20 different classes. As part of pre-processing work we have prepared total 192 feature vector databases for 2000 database images. It covers all the 8 cases discussed in section IV B used in the feature extraction method based on the histograms and two partitioning techniques for bins formation.

A. Database and query Images

We have worked with database of 2000 bmp images; it includes total 20 different classes where few are taken from Wang database. Each class of database contains 100 images. Sample image from each of the 20 classes are shown in the following Fig 5.

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Fig.5. Sample Images from 20 classes in Database

Next phase after feature extraction, the system enters in is, comparing the query and database image features. We have used set of 200 query images to check the system performance and response with proposed methods illustrated through 8 different cases. It includes 10 images selected randomly from 100 images of each of the 20 classes.

B. Results and Discussion

We have executed same set of 200 queries for 192 feature vector databases and compared the performance using all the performance evaluation parameters PRCP, LS and LSRR as discussed in section V –B.

Results presented in this section elaborating the system performance for all factors based on the type of the feature vector i.e. MEAN STD, SKEW and KURTO for R, G and B colors separately. It also presents and compares the results on the basis of histogram partitioning techniques used for bins formation. From total 8 cases, cases from both partitioning techniques are compared simultaneously as follows in following tables from I to XXII.

C. PRCP:

Case1 : LP on ORG and FV Extracted from ORG
Case 1 : CG on ORG and FV Extracted from ORG

Table I. Case1: MEAN

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	5567	5607	5848	5644	5651	5728
G	5384	5472	5485	5450	5751	5853
B	5264	5342	5387	5379	5210	5245

Table II. Case 1: STD

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	6046	6234	6292	6526	5604	5736
G	6277	5799	6422	5933	6147	5767
B	5700	5570	5848	5858	5485	5445

Table III Case 1: SKEW

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	4576	5011	4907	5491	4330	5224
G	4984	4711	5264	5190	4806	5111
B	4799	4737	5107	5100	4658	4998

Table IV.Case1 : KURTO

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	6096	6297	6311	6560	5813	5920
G	6704	6081	6868	6300	6344	5846
B	6045	5681	6191	5885	5733	5607

Case2: LP on EQH and FV Extracted from EQH
Case2: CG on EQH and FV Extracted from EQH

Table V. Case2 : MEAN

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	4656	4737	4595	4690	4387	4504
G	5024	5232	5136	5264	4700	5005
B	4619	4641	4596	4548	4298	4283

Table VI.Case 2: STD

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	4794	4586	4877	4594	4785	4708
G	5361	5116	5403	5128	5411	5232
B	5006	4634	5056	4663	5181	4799

Table VII. Case 2: SKEW

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	3863	3702	3965	3755	3441	3460
G	4372	4151	4583	4254	3950	3912
B	4403	4044	4566	4115	3906	3660

Table VIII. Case 2: KURTO

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	4882	4738	4987	4768	4836	4751
G	5625	5305	5682	5366	5536	5359
B	5292	4885	5281	4891	5364	4953

Case3 : LP on ORG and FV Extracted from EQH
Case3 : CG on ORG and FV Extracted from EQH

Table IX Case3: MEAN

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	5064	4777	5230	5142	4789	4786
G	5494	5329	5543	5357	5528	5395
B	5175	4916	5259	5168	5041	4939

Table X. Case3: STD

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP

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R	5269	5328	5434	5603	5138	5346
G	5689	5765	5756	5889	5583	5925
B	5568	5386	5555	5504	5546	5467

Table XI. Case3: SKEW

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	4723	4791	4807	5053	4390	4694
G	4868	5034	5045	5334	4666	4979
B	4482	4693	4618	4974	4211	4598

Table XII. Case3: KURTO

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	5515	5481	5606	5712	5407	5504
G	5857	5882	5817	5962	5744	6015
B	5605	5578	5543	5611	5614	5719

Case4 LP on EQH and FV Extracted from ORG
Case4 CG on EQH and FV Extracted from ORG

Table XIII. Case 4 : MEAN

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	4820	5607	5578	5644	4448	5728
G	4922	5472	5455	5450	4786	5853
B	4535	5342	5037	5379	4308	5245

Table XIV. Case4 : STD

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	7161	6234	7241	6526	6734	5736
G	6651	5799	6856	5933	5965	5767
B	5841	5570	6118	5858	5604	5445

Table XV. Case4: SKEW

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	5167	5011	5426	5491	4885	5224
G	5121	4711	5444	5190	4818	5111
B	5008	4737	5278	5100	4833	4998

Table XVI. Case4: KURTO

	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
R	7215	6297	7336	6560	6625	5920
G	7038	6081	7253	6300	6306	5846
B	6245	5681	6460	5885	6019	5607

PRCP results are obtained by executing all 200 query images with 192 feature vector databases. We are specifying only total PRCP obtained for 200 query images for each factor considered to identify the feature vector separately. Each value shown in the table is out of 20,000. Here we are mainly concern with the importance of the histogram partitioning technique to reduce the feature vector size and improve the retrieval performance.

In above tables we can observe that results are highlighted with pink and yellow color. Yellow color is specifically used for LP when it is better than CG and Pink color is used for CG to show when CG is better than LP.

When we see these highlighted results, we can say that, CG is the best partitioning for histogram to reduce the no of bins and improve the retrieval of similar images. If we analyse these results case wise for 4 cases with two partitioning, we have obtained the following analysis details in brief.

Table XVII.

Analysis	CG	LP
Case 1	18	18
Case 2	28	8
Case 3	25	11
Case 4	14	22
Overall Score:		
144	85	59

Above details are indicating that total 144 PRCP results compared for the performances against each other; amongst them CG is better than LP for 85 places. Means CG is performing far better than LP and giving very good retrieval results. The best results obtained among these results for each moment with respect to each factor are shown in table XVIII.

Table XVIII: BEST RESULTS

Moment	**CASE 1**	**CASE 2**	**CASE 3**	**CASE 4**
MEAN	5848 AD CG	5264 AD LP	5543 AD CG	5853 CD LP
STD	6526 AD LP	5411 CD CG	5889 AD LP	7241 AD CG
SKEW	5491 AD LP	4583 AD CG	5334 AD LP	5491 AD LP
KURTO	6868 AD CG	5682 AD CG	6015 CD LP	7336 AD CG

Observing these results we can say that the PRCP reached to quite good height. The highest value we obtained is for case 4 for moment KURTO 7336 with CG partitioning and CD measure. Means precision and recall as average of 200 queries has reached to 0.4. These results obtained are actually executed separately by considering the performance of R, G and B colors. To refine and improve these results further we have taken one more step,

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we have combined these results using OR operation applied over R, G and B results obtained separately.

Table XIX. CASE 1 : 'R' OR 'G' OR 'B'

CASE 1	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
Mean	8859	8622	9192	8669	8914	8564
STD	10256	9950	10404	9943	9989	9181
SKEW	9248	8868	9522	9170	8844	8803
KURTO	10678	10076	10826	10084	10218	9320

Table XX. CASE 2 : 'R' OR 'G' OR 'B'

CASE2	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
Mean	7800	7960	7791	7902	7440	7691
STD	8862	8623	8892	8537	8958	8735
SKEW	8153	7688	8210	7676	7726	7333
KURTO	9193	8907	9222	8851	9178	8960

Table XXI. CASE 3 : 'R' OR 'G' OR 'B'

CASE 3	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
Mean	6710	6756	7413	7254	6314	6497
STD	10592	10422	10635	10325	9950	9748
SKEW	9640	9474	9715	9407	9175	8934
KURTO	10774	10576	10803	10477	10064	9981

Table XXII. CASE 4 : 'R' OR 'G' OR 'B'

CASE 4	ED		AD		CD	
	CG	LP	CG	LP	CG	LP
Mean	8125	7693	8039	7583	8182	7953
STD	9307	9008	9177	8942	9367	9074
SKEW	8819	8825	8718	8847	8664	8638
KURTO	9577	9291	9325	9112	9608	9359

Observing above tables we can notice that we could really improve the retrieval by very good amount in all the results. In all four cases. Here also when we are comparing the two partitioning techniques we found that, CG is (marked with pink color) far better than LP in maximum results (43 out of 48 cases) with respect to all other parameters like distance measure and type of moment. All PRCP values have crossed 8000 except few results of Case 3. Among these results, the best results obtained for PRCP are highlighted with green color. The highest value we obtained here is 10826 for CG partitioning case1with AD measure, it tells that PRCP reached to **0.55** as an average PRCP for 200 query images. This is very good achievement for us in the CBIR field.

The next two parameter we have used to evaluate the performance of our system is LS and LSRR. As discussed earlier LS is the continuous longest string of relevant images and should be as high as possible. Whereas LSRR is the length to be travelled to collect all query relevant images from database and should be as low as possible. Taking these factors into consideration as user's point of view; we have executed all 200 queries over 192 feature vector databases but taken only maximum and minimum among those results for LS and LSRR respectively. Parameters, LS and LSRR are also compared with respect to the two partitioning techniques using 4 cases considered so far. Results obtained for LS and LSRR are shown as follows. Chart 1 to 8 is showing LSRR and LS for Case 1 to case 4 respectively.

Chart 1: LSRR for Case 1: Partitioning of ORG FV from ORG

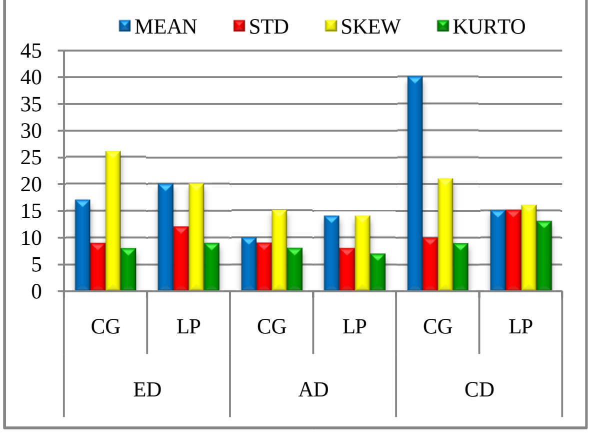
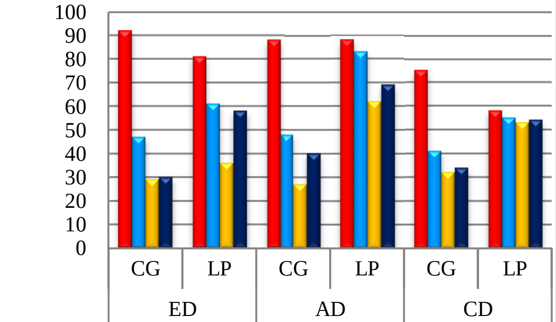


Chart 2: LS for Case 1: Partitioning of ORG FV from ORG



	ED CG	ED LP	AD CG	AD LP	CD CG	CD LP
MEAN	92	81	88	88	75	58
STD	47	61	48	83	41	55
SKEW	29	36	27	62	32	53
KURTO	30	58	40	69	34	54

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Chart 3: LSRR for Case 2: Partitioning of ORG FV from ORG

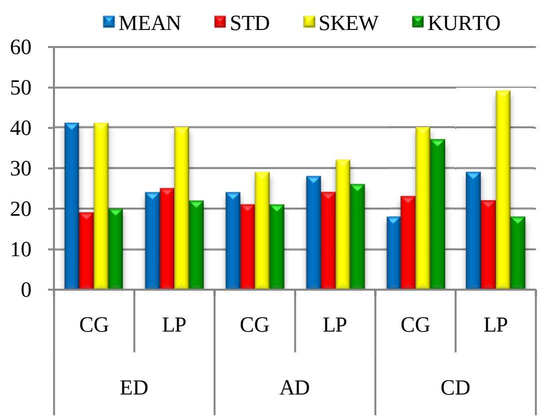
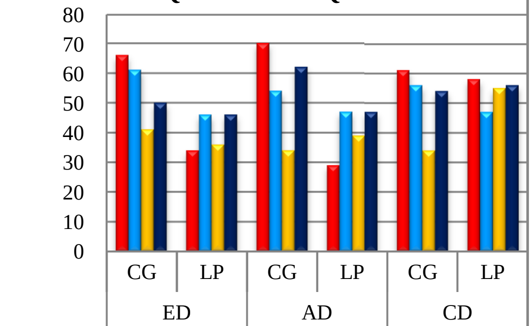


Chart 4: LS for Case 2: Partitioning of EQH FV from EQH



	ED CG	ED LP	AD CG	AD LP	CD CG	CD LP
MEAN	66	34	70	29	61	58
STD	61	46	54	47	56	47
SKEW	41	36	34	39	34	55
KURTO	50	46	62	47	54	56

Chart 5: LSRR for Case 3: Partitioning of EQH FV from ORG

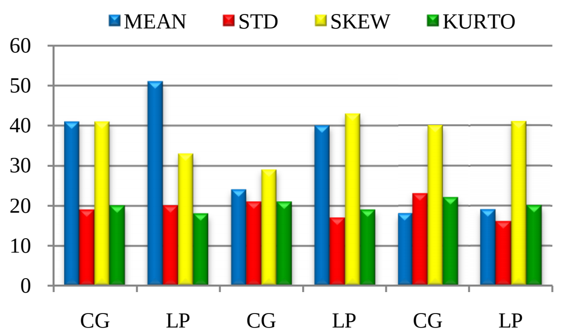
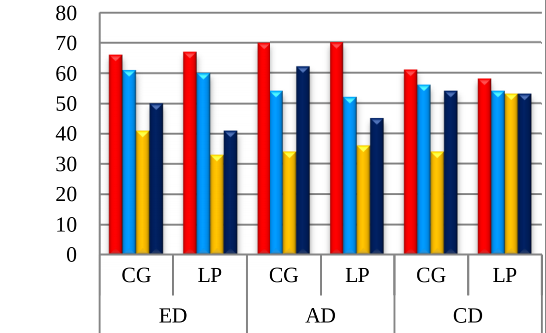


Chart 6: LS for Case 3: Partitioning of EQH FV from ORG



	ED CG	ED LP	AD CG	AD LP	CD CG	CD LP
MEAN	66	67	70	70	61	58
STD	61	60	54	52	56	54
SKEW	41	33	34	36	34	53
KURTO	50	41	62	45	54	53

Chart 7: LSRR for Case 4: Partitioning of ORG FV from EQH

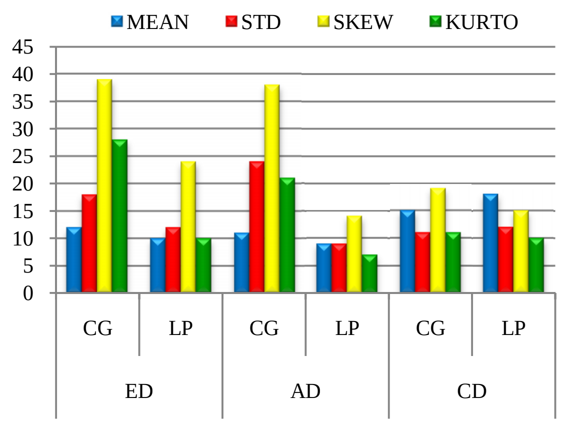
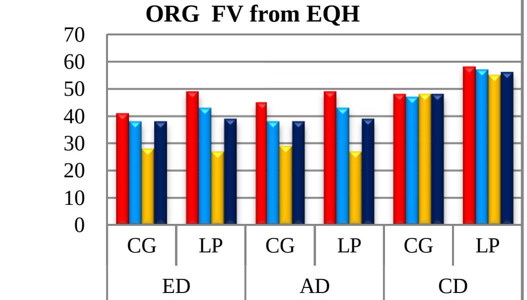


Chart 8: LS for Case 2: Partitioning of ORG FV from EQH



	ED CG	ED LP	AD CG	AD LP	CD CG	CD LP
MEAN	41	49	45	49	48	58
STD	38	43	38	43	47	57
SKEW	28	27	29	27	48	55
KURTO	38	39	38	39	48	56

In above charts we can observe that, here also CG is performing better as compared to LP in most of the cases. The best LSRR value obtained is 8% i.e only 8% traversal of 2000 images sorted according the distances in

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ascending order gives 100% recall. Which means getting all 100 relevant images in first 160 images. Similarly the best value obtain for LS is 92, means we could retrieve 92 images from 100 images of the query class in the database.

Observation based on the results obtained by four moments suggests that even moments (STD and KURTO) are performing far better than odd moments (MEAN and SKEW) in terms of retrieval of similar images.

When we observed the performance given by different similarity measures ED, AD and CD, we found that AD and CD are performing far better than that of ED which used by most of the CBIR researchers as per literature survey [25][26].

We have presented the performances by four different cases with respect to the partitioning applied over and pixels picked up from either ORG or EQH for Feature vector formation histogram. Observing the responses given by these four cases for all other parameters, we found that CG is performing better for the cases where CG partitioning is applied over EQH and feature vectors are also formed using the modified equalized image planes. Means when intensities are distributed uniformly and then we are applying the CG partitioning which gives the two uniformed (having same moments/weights) partitions have positive impact on the retrieval process.

Observing the results obtained for queries from 20 different classes of database we found that few classes are performing very well. Classes Flower, Sunset, Dinosaur, Barbie, Car, Dove, Kingfisher, Rainbow Rose, Ship, Horses, Waterfall are giving better results for the given queries. A close observation of these classes shows that the color intensities are uniformly distributed leading to better performance as we have focused on the color contents of images.

VII. Conclusion

CBIR system presented in this paper is based on the bins approach. The 8 bins are formed by partitioning of histogram and used as feature vector of dimension 8.

Idea behind the design of bins approach is to reduce the feature vector dimension so that space and computational complexity can be reduced. We could greatly reduce the size of the feature vector in this work by avoiding the use of all 256 bins of histogram. To implement this idea two partitioning techniques namely LP and CG are used to form the bins.

We are recommending CG partitioning mainly because the performance given by this technique is far better than that of LP partitioning in almost all other factors used to evaluate the system performance.

Based on the CG and LP partitioning applied over ORG and EQH histograms we worked out 8 different cases so that system can be evaluated for all possibilities with respect to the impact of partitioning over the results of total 192 feature vector databases.

The statistical moments computed for the image contents extracted into 8 bins are performing better, among them even moments are better than odd moments.

Selection of proper similarity measure has great impact on the retrieval. As we used three measures we found that AD and CD are performing better as compared to ED.

Parameters PRCP, LS and LSRR used to evaluate the system are successfully predicting the system's response for the given queries which will surely satisfy the CBIR user. The Highest PRCP value obtained here can be interpreted as precision and recall both **0.55.** This is very good achievement in this field as it is indicating the average value for 200 randomly selected query images.

In this paper we could prove that CG partitioning of histogram performs better as it greatly reduces the feature vector dimension and also improves the retrieval.

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