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Histogram Specification with Higher Order Polynomial Functions over R, G and B Planes for CBIR Using Bins

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Abstract: This work Proposes a histogram specification to modify the original histogram such that the intensities form lower level will get shifted to higher side which gives improvement in the results obtained for retrieval of images based on contents. Three polynomial functions proposed in this paper are designed and implemented for modifying the histogram of R, G and B planes of each image. These modified histograms are then partitioned into two parts using the center of gravity. Each partition has got id as '0' and '1'. The three planes partitioned into two parts generating the eight combinations from 000 to111, which are used as eight bin addresses. These eight bins are holding the count of pixels having particular range of intensities based on the R, G, and B values falling in specific partition of respective plane's modified histogram. Bins further are directed to have 'Total of intensities' and Average of intensities' information of the image to be represented as feature vector. Total 21 feature vector databases are prepared by applying the feature extraction process to all 2000 BMP images in the database. Each feature vector in all databases is of dimension 8. This system is tested by comparing 200 query image feature vectors with all feature vector databases by means of the three similarity measures namely Euclidean distance (ED), Absolute distance(AD) and Cosine correlation distance (CD). Performance of the system is evaluated using three parameters PRCP (Precision Recall Cross over Point) Longest String and LSRR (Length of string to retrieve all Relevant images).

Keywords: Histogram Specification, Polynomial function, Bins, Count of Pixels, Total of Intensities, Average of Intensities, ED, AD, CD, PRCP, Longest String, LSRR

I. INTRODUCTION

The core part of any Content Based Image Retrieval system is the approach used to extract the contents of the image and represent them in compact form termed as feature of the image. Image is the high dimensional object consists of thousands of pixels. Feature extraction process reduces the dimension and represents that image and makes the comparison process simple and easy. Important reason behind searching these new techniques for feature extraction is to reduce the feature vector dimension and have good discriminating ability [1][2]. This is one of the important issues we have handled in this work by extracting the entire image content to just eight bins and representing the feature vector of dimension eight. Image contents are broadly classified into two types global and local feature vectors. Global texture features and local features provide different information about the image. It happens because of the variation in the extraction, calculation and representation of the contents. Global features include the descriptors computed on the whole image e.g. contour representations, shape descriptors, and texture descriptors. Local feature includes color shape and texture low level features of the image [3-7].Color represents one of the most commonly used visual features in CBIR systems. Color spaces RGB, Kekre's LUV, HSV, YCrCb and the hue-min-max-difference are closer to human perception and used widely in CBIR systems.[8-11] Color histogram (CCH) of an image indicates the frequency of occurrence of every color in the image. From a probabilistic point of view, it refers to the probability mass function of the image intensities. It captures the joint probabilities of the intensities of the color channels. In quantized color space it is constructed by counting the no of pixels. In Matlab maximum 256 bins can be obtained for the histogram [12-15]. In this work we are using the separate histogram for each (R, G and B) plane of image. In previous papers we have worked with original histogram. Original histogram of each plane was partitioned into parts to form the set of different bin sizes to represent the feature vector of that image [16-18]. In this work, we have proposed and implemented three polynomial functions to modify the original histogram. These functions are actually used as histogram specification functions. Histogram specification is a method where contrast enhancement is obtained by suitably changing the image histogram into a desired one. In histogram equalization, gray levels are spread over the entire scale and an equal number of pixels are allocated to each gray level [16-17]. In our work we are specifying the function to modify the histogram such that pixels from lower side will be shifted to higher grey level side. Each image is separated into R, G and B planes. Pixels from original grey levels are mapped to new grey level specified by the histogram specification. Histogram of each plane obtained and modified separately. The modified histogram is divided into two parts by means of Center of Gravity (CG). This partitioning leads to 8 bins formation [18-19]. Contents of these bins are the count of pixels falling in particular partition of the histogram. Further these bins are used to carry total and average of intensities of R, G and B colors separately for the pixels counted into each of them. 'Count of Pixels', 'Total of intensities' and 'Average of Intensities' are the types of feature vectors extracted in this system for each database image and multiple feature vector databases are prepared. When a query image is fired to the system, same set of feature vectors are computed for it. Query and database feature vectors are compared by means of three similarity measures namely Absolute distance (AD), Euclidean distance(ED) and Cosine correlation distance (CD)[18][21-23]. This CBIR system is experimented with database of 2000 BMP images having 20 different classes. Performance of the system for all the approaches used is evaluated using parameters Precision Recall Cross over Point (PRCP), Longest String and LSRR (Length of the String to Retrieve all Relevant)[18], [21].The presentation of the work is organized as follows. Section 2 describes the phases involved in the feature extraction process with implementation details. Section 3

II. HISTOGRAM SPECIFICATION

This technique helps in modifying the image into desired image by transforming the original histogram into new histogram specified by the desired specification function. This is remapping of the original intensities to new scale.

A. *Higher order polynomial functions*

We have used three higher order polynomial functions as specifications to modify the original histogram before feature extraction. Three polynomial functions proposed and used in this work are given as follows:

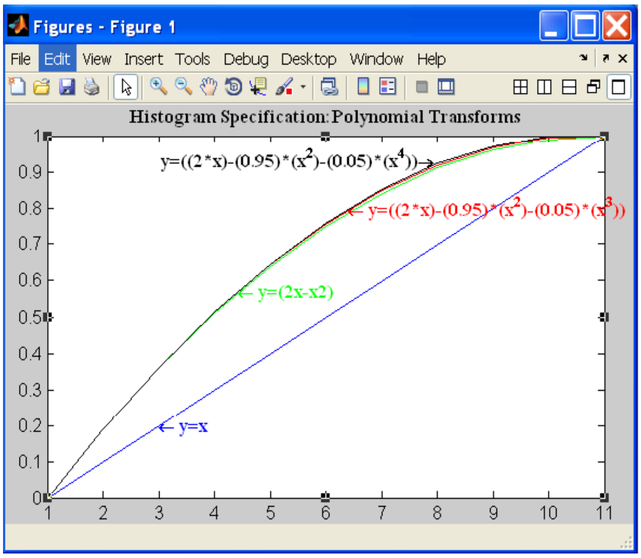


Figure 1. Histogram Specification: Higher Order Polynomial Functions

$$y = \left(2x - x^2\right) \quad (1)$$

$$y = \left(\left(2 * x\right) - \left(0.95\right) * \left(x^2\right) - \left(0.05\right) * \left(x^3\right)\right) \quad (2)$$

$$y = \left(\left(2 * x\right) - \left(0.95\right) * \left(x^2\right) - \left(0.05\right) * \left(x^4\right)\right) \quad (3)$$

where y = 0; IF x = 0
y = 1; IF x = 1
y > x for 0 < x < 1

Equations 1, 2 and 3 are showing the higher order polynomial functions used to modify the histogram. The curves for these three functions are shown in Figure1. We can observe in the Figure1.that when y=x we got straight line and for all other three functions we can see that ‘y > x’, i.e. intensities are being shifted from lower side to higher side. These functions are used to push the histogram more towards the higher intensities so that it will benefit in the feature extraction and to improve the retrieval.

B. *Modification of Histogram using Specification*

Original histogram intensities can be mapped to new intensities by means of polynomial functions discussed in section 2.1. This mapping and its effect on the image can be seen in the following Figure 2. It shows the image is first separated into three planes R, G and B. Then for each plane histogram is obtained and modified using above three polynomial functions given in eq. 1, 2 and 3.

As shown in Figure 2. Top row shows the Image from Horse class. In second row it is separated into R, G and B planes. In third row original histograms of the three planes are shown below respective plane. Next three rows are showing the polynomial functions $y = \left(2x - x^2\right)$, $y = \left(\left(2 * x\right) - \left(0.95\right) * \left(x^2\right) - \left(0.05\right) * \left(x^3\right)\right)$ and $y = \left(\left(2 * x\right) - \left(0.95\right) * \left(x^2\right) - \left(0.05\right) * \left(x^4\right)\right)$ with their effect on the original histogram shown for blue plane which is reflected in modified histogram images. In these three modified histogram images we found that the intensities are getting shifted towards higher side by means of three polynomials. Green plane images obtained for new histograms are shown beside each modified histogram for each of three polynomials. Same process is applied to other two planes (Red and Blue) histograms.

III. FEATURE EXTRACTION

Efficiency of all the CBIR systems depends on the approach used to extract the image contents and represent them in proper format called feature vector. There are various approaches designed by the researchers from two domains of image processing that are spatial and frequency domain [20][21]. We have used the approach based on histogram specification from spatial domain to extract the feature vectors. The complete feature extraction process is divided in three steps we followed is explained below.

A. *CG partitioning*

Feature extraction process starts with the separation of image into R, G and B planes. Histogram of each plane is modified using the histogram specification given by equations 1, 2 and 3. After modification the new histograms are partitioned into two parts based on the uniform distribution of the mass of intensities in two parts. This uniform distribution of mass of intensities is obtained by computing the Center of Gravity. Center of Gravity gives the exact balancing point where two parts of the data will have equal mass. Equation 4 is identifying the formula used to compute the CG. and Figure 3 is highlighting the partitioning of modified blue plane histogram in parts with id ‘0’ and ‘1’. This assignment of id’s to the two parts is applied to each plane.

$$CG = \left[\frac{\left(L_1 W_1 + L_2 W_2 + \ldots + L_n W_n\right)}{\sum_{i=1}^{n} W_i} \right] \quad (4)$$

Where L_i is intensity Level and W_i is no of pixels at L_i

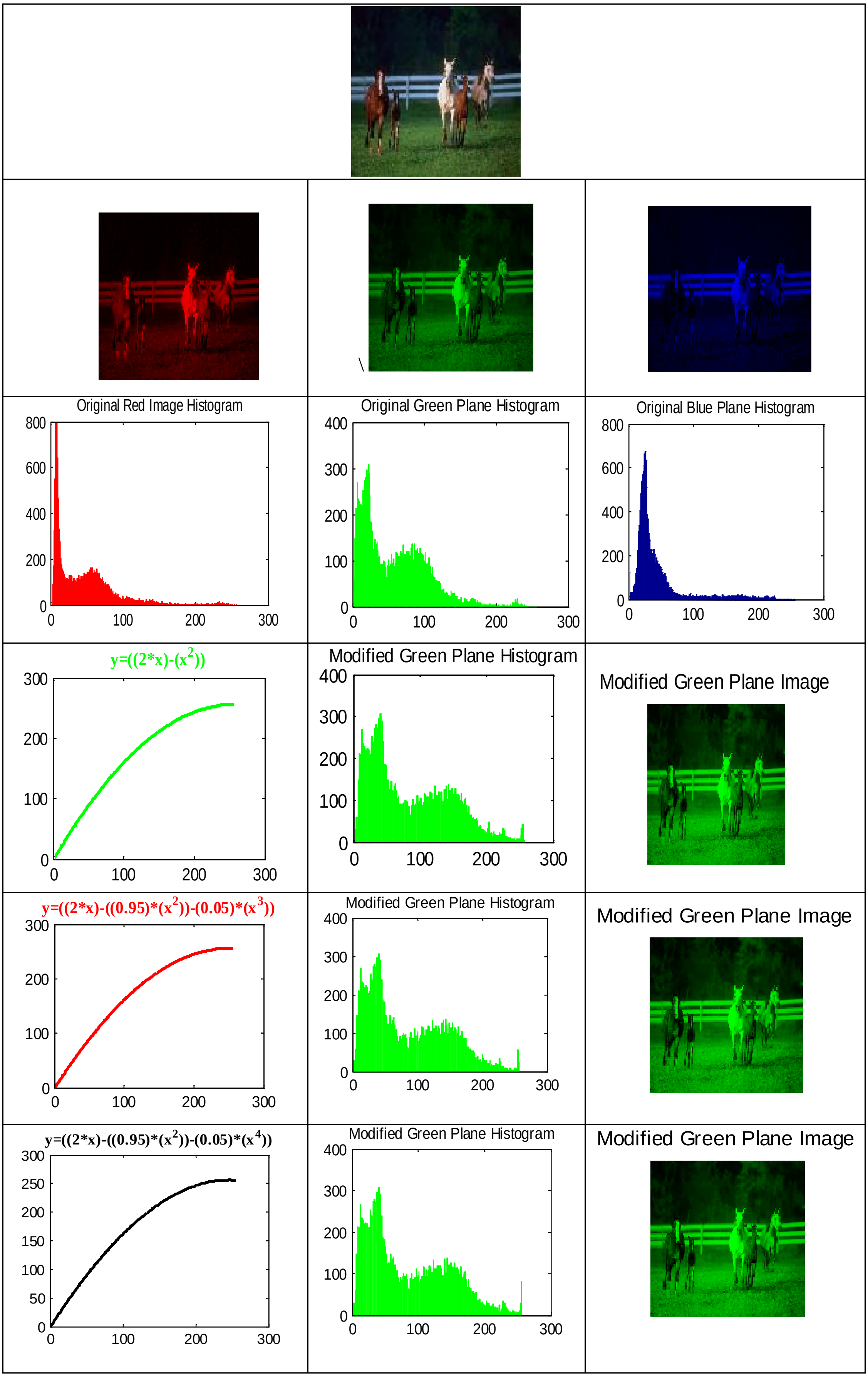


Figure 2. Histogram Modification Using Histogram Specification

B. Bins formation

Once the id is assigned to each partition of all three planes the next process starts i.e formation of bins. Three planes, each with two ids gives us $2^3 = 8$ combinations from ‘000’ to ‘111’. Theses combinations are treated as bin addresses to extract the feature vectors.

When the feature is being extracted the R, G and B intensities of the pixel of images under process will be taken into consideration. Now, suppose the R value falls in the partition 1of red plane, G in part ‘0’ and B in part ‘1’ then that pixel gets flag ‘101’ assigned to it. This flag itself indicates the pixel’s destination bin address. Same process is applied for each pixel of the entire image and their destination bin addresses will be acquired.

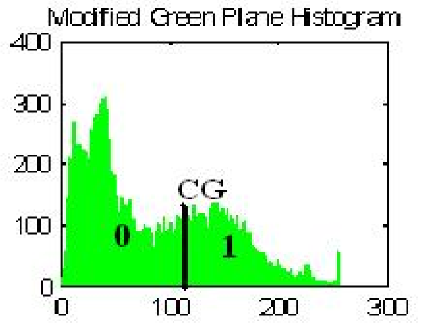


Figure 3. Green Plane Modified histogram with CG Partitioning

C. Feature Vector Generation

Bins formation process lead towards the actual feature extraction. As explained above in section 3.2 the whole process is applied to entire image pixels and their distribution will be shown through these eight bins from 000 to 111. These eight bins are used as feature vector of dimension 8 for comparing the images. Means the size of feature vector based on histogram which is actually of size 256 bins, is reduced to just 8 bins. This greatly reduces the size of feature vector which reduces computational complexity and also the time to compare images. Based on the variation in extraction process we have obtained different types of feature vectors as follows.

- ‘Count of Pixels’:It represents the count of pixels based on R, G and B values falling in the specific partitions of their respective histogram. (from bin 000 to bin 111).

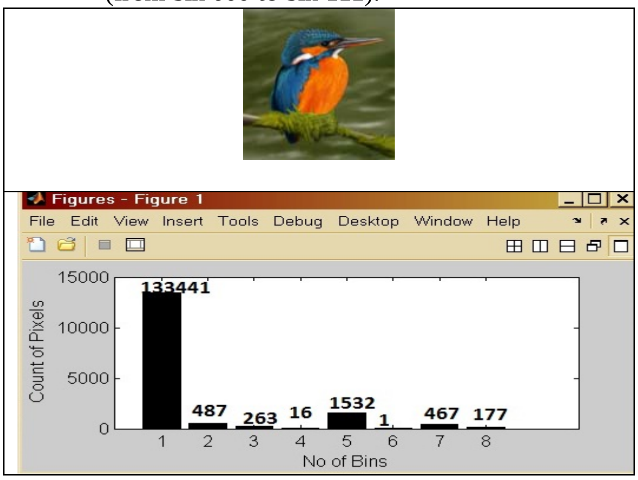


Figure 4. Kingfisher Image with Sample of 8 bins with Count of Pixels

Figure 4 shows the sample kingfisher image with its eight bins from 1 to 8 having the count of pixels. Image size is 128 x128. These 8 bins are showing the distribution of 16384 pixels, we can cross check this by adding the no of pixels counted in all bins, we should get 16384 pixels.

- **Total of Intensities**: Once the count of pixels is obtained into each bin, R, G and B intensities of these pixels is taken into consideration. We have taken the total of R , G and B intensities falling in each bin separately and it is treated as three new feature vectors in the form of total of intensities ‘Total_R’, ‘Total_G’ and ‘Total_B’ with respective R, G and B color information.

- **Average of Intensities**: Similar to the ‘Total of intensities’ here we compute the average of R, G and B intensities for the count of pixels in each of the eight bins. This feature vectors are termed as ‘Average_R’, ‘Average_G’ and ‘Average_B’ for R, G and B color respectively.

D. Feature Vector Databases

The feature extraction process explained above in sections from 3.1 to 3.3 is applied to all database images. We have used database of 2000 BMP images having 20 different classes. Based on the types of feature vector with respect to color variation and the computations of contents we have prepared total 21 feature vector databases, each containing 2000 feature vectors of dimension eight. The details of 21 feature databases are as follows:

‘Count of Pixels’- 1 database for each of the three polynomials = (3 databases)

‘Total_R’, ‘Total_G’ and ‘Total_B’→ 3 Databases for each of three polynomial s = (9 Databases)

‘Average_R’, ‘Average _G’ and ‘Average_B’→ 3 Databases for each of three polynomials = (9 Databases)

This way in all we have prepared (3+9+9=21) feature vector databases with each feature vector of dimension 8.

IV. SIMILARITY MEASURE : ED, AD AND CD

In CBIR system’s retrieval of the images is facilitated by comparison process where the query image entered by the user will be compared with the database images. The images are compared by their feature vectors used to represent them. To compare and compute the distance we have used three similarity measure, namely Euclidean distance (ED), Absolute distance (AD) and Cosine Correlation distance (CD) and are given in equations 5, 6 and 7 respectively.

Cosine Correlation Distance

$$\frac{(D(n))\bullet(Q(n))}{\sqrt{\left[|D(n)|^2|Q(n)|^2\right]}}$$

Where D(n) and Q(n) are Database and Query feature Vectors resp. (5)

Euclidean Distance	Absolute Distance:

$$D_{QI} = \sqrt{\sum_{i=1}^{n} |(FQ_i - FI_i)|^{2}} \quad (6)$$

$$D_{QI} = \sum_{1}^{n} |(FQ_I - FI_I)| \quad (7)$$

Each of these distance metrics has its own feature and we found all of them are performing better. Euclidean distance varies with variation in the scale of the feature vector but cosine correlation distance is invariant to the scale transformation. Absolute distance also gives better performance for retrieval with less time to compare with reduction in the computational complexity [18].

V. PERFORMANCE EVALUATION OF PROPOSED SYSTEM

Approaches used in this system to extract the features are mainly depending on the histogram specification functions used, bins formation and variations in computing the feature vectors (based on color and statistic). It is essential to determine the role and efficiency of each polynomial and the variation used in feature extraction process. To do this we have used three performance evaluation parameters as Precision Recall Cross over Point (PRCP), Longest String and Length of String to Retrieve all Relevant (LSRR) and are defined as follows[18], [21-25]:

A. *PRCP: Precision recall cross over point*

The conventional parameter 'Precision' gives the measure of accuracy because it concentrates only on the count of relevant images from all retrieved images. Whereas 'Recall' keeps track of the count of relevant image from total images of that class in database, in turn we can say it measures the completeness factor. Hence Cross over point of these two parameters termed as PRCP (which varies between 0 to1), is giving the measure of idealness of the CBIR system. PRCP value 0 indicates worst case performance of the system because it states that system could not retrieve the images similar to query. PRCP value 1 indicates the best case performance of the system. It interprets that retrieval result generated for the given query does not contain a single irrelevant image and it has all the images from the database similar to query.

B. *Longest String*

Whenever query image enters into the system it will be compared with all 2000 images in the database. System calculates the distance between them using the given distance metrics. These 2000 distances will be then sorted in ascending order so that images at minimum distance will appear first in the sequence. But sometimes it happens that very few images will come as initial string of relevant images. If the sorted distances will be travelled further we may found that there is a group of images (more than initial relevant string) which are relevant query are appearing continuously. This possibility cannot be ignored and that is why we have introduced and used this parameter where we can have longest continuous string of images relevant to query.

C. *LSRR : Length of String to Retrieve all Relevant*

As we have discussed that parameter recall measures the completeness of the system. All CBIR users are expecting that recall should be recall as high as possible. Now here is the time to check the strength of the system that how long it takes to retrieve all images relevant to query from database. Here we measure the length of traversal required to collect all images relevant to query (to make recall 1) from set of images arranged according the distances sorted in ascending order.

VI. RESULTS AND DISCUSSION

The proposed system's experimentation is carried in MATLAB with database of 2000 BMP images. We have covered the discussion about the results obtained for each of the 21 feature vector databases. This includes the performance discussion of all small variations in all processes from feature extraction to actual retrieval. It covers the discussion with respect each polynomial, each distance measure, each color and each type of feature vector.

A. *Database and Query Image*

The database used for experimentation is consist of 2000 BMP images having 20 different classes. It includes Flower, Sunset, Mountain, Building, Bus, Dinosaur, Elephant, Barbie, Mickey, Horse, Kingfisher, Dove, Crow, Rainbow rose, Pyramid, Plate, Car, Trees, Ship and waterfall where each class has got 100 images. A sample image from each class is shown in Figure 5.

Ten query images are selected randomly from each class and set of 200 query images is given as query to the system to check its performance with respect to all factors. Results obtained are shown as follows

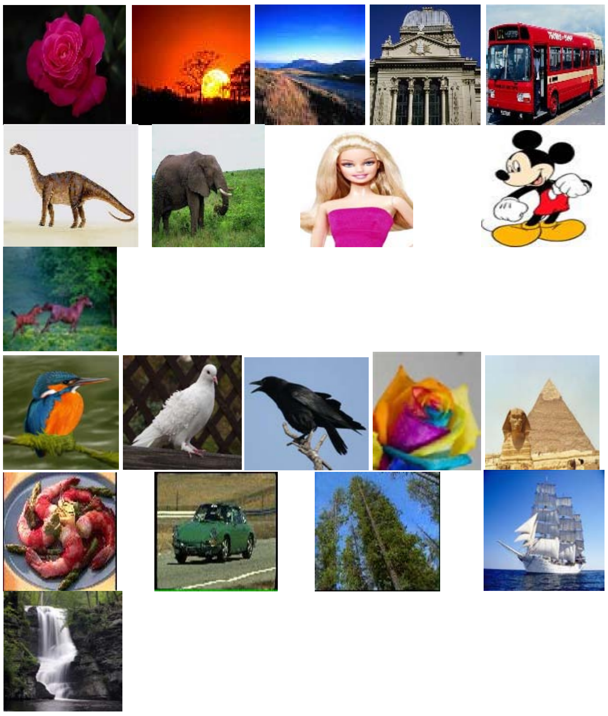


Figure 5. 20 Sample Images from database of 2000 BMP images from 20 classes

B. *Results Obtained for PRCP*

Table 1, 2 and 3 are showing the results obtained for Parameter PRCP for Total of intensities, Average of intensities and Count of pixels respectively. For total of pixels we have got the highest PRCP value as 5694 out of 20,000 means precision and recall obtained is "0.3" for poly 1 with AD measure for red color.

In Table 2 we found best obtained is '6621' out of 20,000 for poly 3 with CD measure for green color means the precision and recall value is "0.33" . Similarly for count of pixel feature vector we found poly 1 is giving highest PRCP value as 5556 means precision and recall are at 0.3 for AD measure. Overall observations written below each table are indicating that poly 1 and poly 3 are performing better.

Note: Poly 1 is $y = \left(2x - x^2\right)$**, Poly 2 is** $y = \left((2*x) - (0.95)*\left(x^2\right) - (0.05)*\left(x^3\right)\right)$ and **Poly 3** is $y = \left((2*x) - (0.95)*\left(x^2\right) - (0.05)*\left(x^4\right)\right)$ in entire result and discussion.

Table I. PRCP : TOTAL

	R			G			B		
SM	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***
ED	5216	5264	5248	4820	4794	4785	4431	4504	4501
AD	5694	5690	5675	5263	5243	5228	4854	4933	4922
CD	4891	4812	4805	4507	4420	4399	4261	4209	4185

Observation: Poly 1 is better at 6 places out of 9

Table II. PRCP : AVERAGE

	R			G			B		
SM	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***
ED	5693	5763	5820	5712	5853	5862	5753	5937	5975
AD	5773	5882	5927	5724	5884	5904	5794	5894	5898
CD	5990	6072	6079	6435	6591	6621	6253	6447	6472

Observation: Poly 3 is better at 9 places out of 9

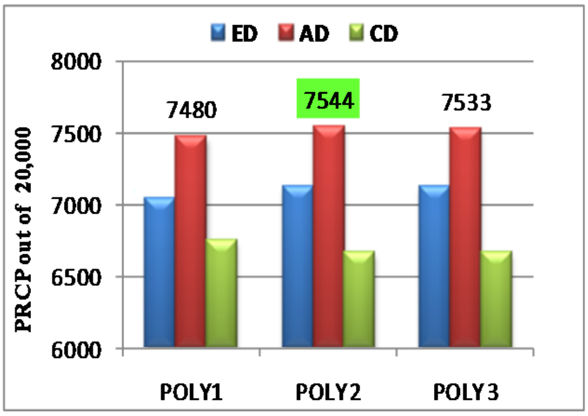
Table III. PRCP : COUNT

SM and Poly	***Poly 1***	***Poly 2***	***Poly 3***
ED	5139	5096	5092
AD	5556	5452	5476
CD	5076	5029	5018

Observation: Poly 1 is better at 3 places out of 3

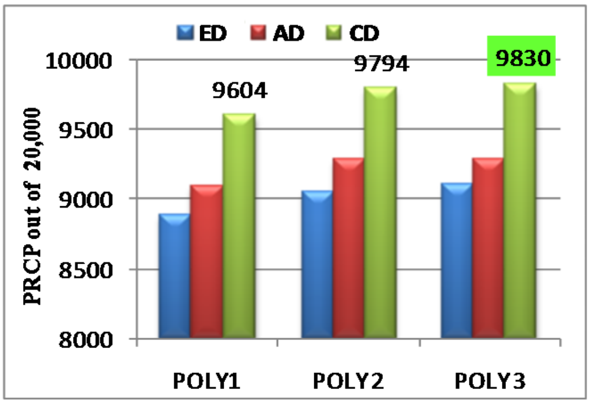
After observing the separate results obtained for three colors R, G and B for feature vector types 'Total' and 'Average' of intensities; we thought of combining them. To do this we have applied OR operation over the results obtained for R, G and B separately. Results obtained after application of OR criterion over PRCP results of Total and Average of intensities are shown below in chart 1 and 2 respectively.

Chart 1. Criterion 'OR' for 'Total of Intensities'



Observation: Chart1 Best result obtained is 7544 for Poly2 with AD measure and

Chart 2. Criterion 'OR' for 'Average of Intensities'



Observation: Chart 2 the best result obtained is for 9830 Poly3 with CD measure.

In above results we observed that the PRCP values are reached to good height after applying the OR criterion. Both charts are highlighting the best results obtained for total and average of intensities. These PRCP values if compared with results obtained before the application of OR criterion, we found very positive difference that precision and recall value for 'Total of intensities' reached to **0.4** from **0.3** and for 'Average of intensities' it has reached to **0.5** from **0.4.**

C. Results for Longest String

Table IV. Maximum Longest String for 'Count of Pixels' with ED, AD and CD for Poly 1, 2 and 3

LONGEST STRING FOR COUNT WITH ED AD and CD									
	ED			***AD***			***CD***		
Classes	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***
Flower	11	10	10	13	13	13	12	10	10
Sunset	11	10	12	11	11	10	11	13	11
Mountain	4	4	3	4	3	4	4	4	3
Building	5	4	4	5	4	5	4	4	4
Bus	7	6	7	7	7	8	7	7	7
Diansour	14	19	25	20	27	25	18	19	21
Elephant	4	4	4	4	4	4	4	7	6
Barbie	22	8	8	25	15	17	35	24	25
Mickey	7	11	8	8	11	11	7	6	6
Horses	15	14	17	11	16	15	16	14	14
Kingfisher	4	3	3	4	3	4	3	5	5
Dove	43	43	43	47	47	46	29	28	28
Crow	7	7	7	11	11	11	6	7	6
Rainbowrose	28	27	28	23	27	27	25	24	25
Pyramids	11	10	10	13	12	12	10	10	11
Plates	8	7	7	11	9	9	11	7	11
Car	3	3	3	4	4	3	4	4	3
Trees	8	8	8	7	9	9	10	7	6
Ship	5	5	5	5	5	4	7	6	4
Waterfall	5	4	5	4	5	6	4	4	4
AVG	11.1	10.35	10.85	11.85	12.15	12.15	11.35	10.5	10.5

Observation for Best results Out of 20 Cases in Table 4	***ED***			***AD***			***CD***		
	Poly 1	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***
	15	9	13	13	12	11	14	9	8
Average of 20 queries is showing that 'poly 2 is better as compared to other two polynomials									

Chart3. Minimum LSRR for 'Count of Pixels with ED, AD and CD for Poly 1, 2 and 3

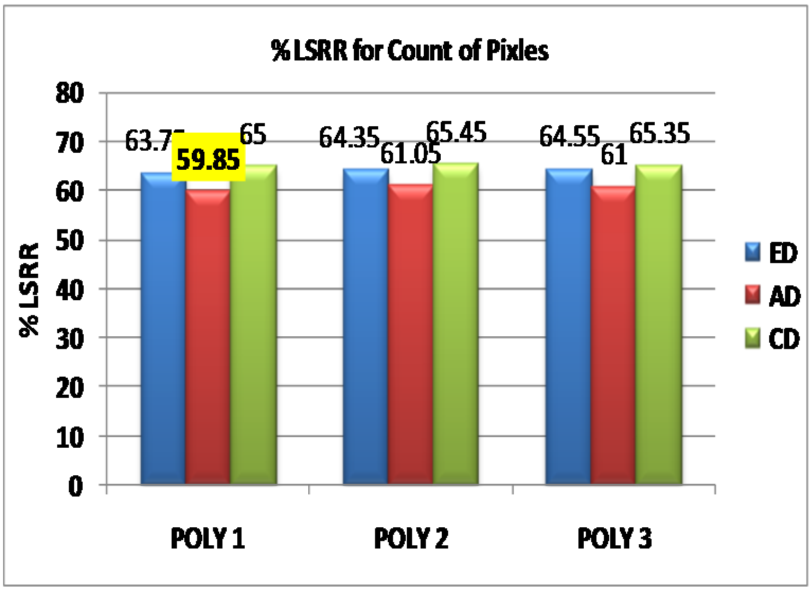


Table V. Maximum Longest String for 'Total of Intensities' with ED, AD and CD for Poly 1, 2 and 3

LONGEST STRING FOR TOTAL WITH ED AD and CD									
	ED			***AD***			***CD***		
Classes	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***
Flower	14	12	l	14	15	15	20	21	20
Sunset	16	15	15	22	22	22	22	25	24
Mountain	4	4	3	4	5	4	4	3	3
Building	4	4	5	4	5	5	6	5	5
Bus	16	16	16	17	18	17	10	11	11
Diansour	21	27	25	34	31	30	16	14	15
Elephant	9	6	6	7	6	7	4	4	4
Barbie	13	28	19	7	16	17	8	5	5
Mickey	13	16	15	13	14	14	12	12	12
Horses	17	18	15	20	21	18	19	17	13
Kingfisher	4	4	4	5	6	6	9	7	8
Dove	22	25	25	31	30	32	18	22	22
Crow	18	14	15	21	16	16	8	7	6
Rainbowrose	19	22	20	16	19	20	34	27	28
Pyramids	16	20	20	17	16	14	14	18	18
Plates	5	6	5	5	6	7	7	6	6
Car	4	4	4	4	6	5	4	4	5
Trees	11	11	10	12	11	11	8	8	7
Ship	7	7	5	10	7	7	9	8	8
Waterfall	5	4	6	5	5	5	8	6	6
AVG	11.9	13.15	12.25	13.4	13.75	13.6	12	11.5	11.3

Observation for Best results Out of 20 Cases in Table 5	***ED***			***AD***			***CD***		
	Poly 1	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***
	10	14	7	7	10	12	14	8	6
Average of 20 queries is showing that 'poly 2 is better as compared to other two polynomials									

Chart 4. Minimum LSRR for 'Total of Intensities' with ED, AD and CD for Poly 1, 2 and 3

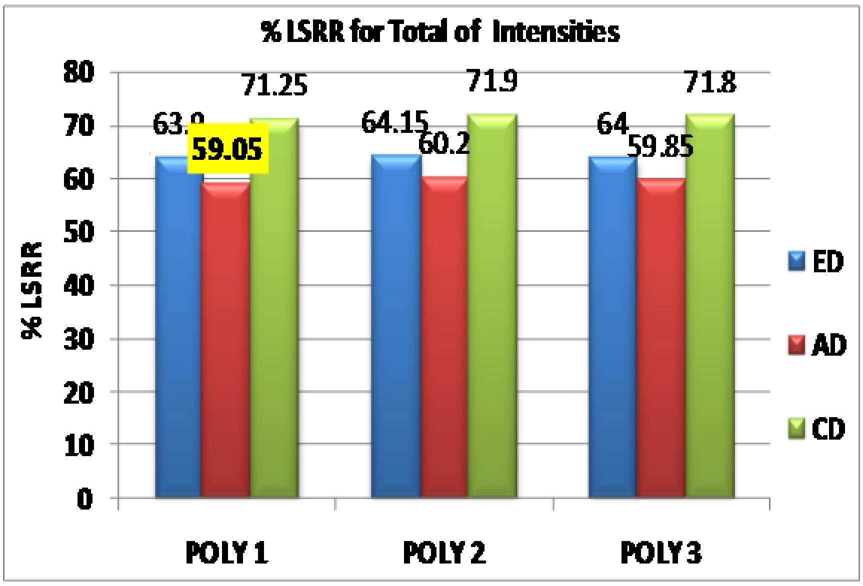
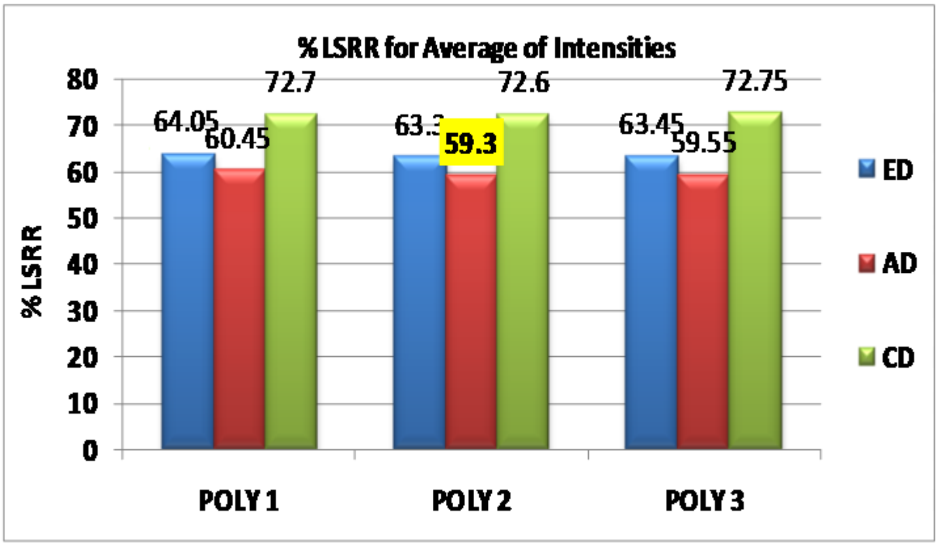


Table VI. Maximum Longest String for ‘Average of Intensities’ with ED, AD and CD for Poly 1, 2 and 3

LONGEST STRING FOR AVERAGE WITH ED AD and CD									
	ED			***AD***			***CD***		
Classes	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***
Flower	9	9	9	15	13	13	20	23	22
Sunset	26	23	24	34	37	37	32	35	36
Mountain	10	9	9	10	9	9	8	9	9
Building	4	5	7	4	5	6	5	5	8
Bus	22	23	22	24	27	25	26	23	25
Diansour	18	27	29	24	28	32	16	22	21
Elephant	8	9	9	10	10	10	10	11	12
Barbie	74	78	78	78	78	80	67	62	62
Mickey	22	21	26	22	20	20	18	12	15
Horses	17	17	16	21	20	19	27	27	26
Kingfisher	11	12	11	10	10	10	13	13	14
Dove	46	45	47	46	42	44	48	46	47
Crow	11	10	11	10	8	9	13	10	9
Rainbowrose	46	44	40	35	34	34	30	30	31
Pyramids	34	26	26	25	22	22	30	29	27
Plates	7	6	6	7	6	9	8	9	8
Car	14	14	14	15	15	15	20	19	17
Trees	11	11	11	9	10	9	12	9	8
Ship	9	10	10	9	9	10	17	18	18
Waterfall	4	5	8	6	5	5	8	9	8
AVG	20.15	20.2	20.65	20.7	20.4	20.9	21.4	21.05	21.15

Observation for Best results Out of 20 Cases in Table 6	***ED***			***AD***			***CD***		
	Poly 1	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***	***Poly 1***	***Poly 2***	***Poly 3***
	10	9	12	12	6	9	9	7	7
Average of 20 queries is showing that ‘Poly 1’ is better as compared to other two polynomials									

Chart 5. Minimum LSRR for ‘Average of Intensities’ with ED, AD and CD for Poly 1, 2 and 3



Longest string results obtained for ‘Count of Pixels’ are shown in Table IV. Three different colors are showing the discrimination in the results on the basis of three distance measures. Maximum longest strings obtained among results of three polynomials are highlighted for each of the 20 classes in the Table IV. Last row highlights the important or noticeable results obtained as average of 20 queries form 20 classes for each polynomial with all three distance measures.

Table V is showing the maximum longest string of relevant images obtained for feature vector 'Total of intensities' each of the three polynomials irrespective of the three colors using all three distance metrics. The best value among all three polynomials obtained for each class and each distance measure is highlighted with the respective colors selected for identifying the distance measure separately. Last row gives the average of 20 queries obtained for the 20 results obtained for each polynomial. Important observations made on Table IV are given separately below the Table V.

Table VI shows the results obtained for 'Average of Intensities' for three polynomials with three different distance measures. This table highlights the best results obtained for each distance measure separately. ED with green, AD with pink and CD with yellow color. The maximum longest string obtained among results obtained for three polynomials are highlighted with respective color of the distance measure. Last row of the table has average longest string value obtained for 20 queries from 20 classes. When these values are compared we found Poly1 is better as compared to other two polynomials.

D. *LSRR*

Chart 3, 4 and 5 are showing the results obtained for the parameter LSRR for 'Count of Pixels', 'Total of Intensities' and 'Average of Intensities' respectively. We have computed this parameter for all 200 queries with respect to all the other factors. For 'Total' and 'Average' feature vector types three results obtained for R, G and B colors separately. We have taken minimum LSRR among the three results of 10 queries from one class and selected as final LSRR for that query class. Charts are showing the average LSRR values of 20 queries (i.e one minimum LSRR from each class) for each polynomial with respect to each similarity measure ED, AD and CD. Charts are highlighting the best results obtained for LSRR with yellow color. According to LSRR definition LSRR should be as low as possible. In above results we can see that minimum percentage of traversal required to collect all relevant images has not crossed 73%. All the resultant LSRR are in range from 59% to 73% in the above results which shows quite good achievement in the results. When we have observed individual results, we found that few queries have got recall value 1 by just traversing the string at 19 to 20% (LSRR).

VII. CONCLUSION

The work explained in this paper is exploring the idea of histogram specification and its use for CBIR. Histogram specification is specified through three new polynomial functions which are shifting the histogram towards higher intensities. The CBIR system explained in this paper is actually based on the bins approach. Bins formation is achieved effectively by partitioning of the histogram using CG i,e center of gravity where CG divides the mass of pixel intensities. After partitioning of the histogram having 256 bins we reduced the size of the feature vector to just 8 bins. This reduces the computational complexity and saves the time for comparing the feature vectors.

Three polynomial functions Poly1 $y=\left(2x-x^2\right)$, Poly2 $y=\left((2*x)-(0.95)*\left(x^2\right)-(0.05)*\left(x^3\right)\right)$ and Poly 3 $y=\left((2*x)-(0.95)*\left(x^2\right)-(0.05)*\left(x^4\right)\right)$ are shifting the histogram from lower to higher side each with small shift to right side. All three have given good performance in terms of retrieval. Comparing these results with results obtained for original histogram [12, 13, 16, 17,24], we found that the specification i.e. polynomials used for modifying the histogram are giving better results.

Comparing the results on the basis of type of feature vector we found 'Average of Intensities' performing better as compared to total of intensities and count of pixels.

Comparing the results based on the use of similarity measures ED, AD and CD; we found AD and CD are giving better results as compared to ED.

Performance of the proposed system is evaluated using three parameters PRCP, Longest string and LSRR. PRCP value obtained is 0.5 for 'average of intensities' and 0.4 for 'total of intensities' shows good achievement in the results as average result of 200 query images.

Maximum longest string obtained among 200 query images is '80' for class Barbie for feature vector average of intensities, 34 for dove class for feature vector 'Total of intensities' and 47 for dove class for feature vector count of pixels.

Minimum LSRR obtained among results of 200 queries is just 9% traversal gives 100% recall, this the best results we found for 3-4 queries from class Barbie with feature vector type ' average of intensities'.

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