# BINS APPROACH FOR CBIR BY SHIFTING THE HISTOGRAM TO LOWER INTENSITIES USING PROPOSED POLYNOMIALS

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*ABSTRACT*

*This paper describes the novel approach of feature extraction for CBIR systems. It also suggests the use of newly designed polynomial function to modify the image histogram so that the result of the CBIR system can be improved. To support this suggestion multiple polynomial functions have been tried. Out of which the best polynomial can be selected to modify the histogram for feature extraction. This gives better performance for the image retrieval based on contents. The separate histograms are obtained for each of the three color planes of the image so that the color information can be handled separately. These histograms are then divided into two equal parts by calculating the centre of gravity. This division of the R, G and B histograms into two parts lead towards the generation of eight bins. Eight bins are designed to hold different types of information like 'Count of pixels', 'Total of intensities' and 'Average of intensities'. The work done includes the set of three polynomial functions used modify the histograms. Based on each polynomial function and the variation of the information used to represent the eight bin feature vector we could generate the multiple feature vector databases. Two types of bin sets based on type of the bin contents Total and Average of intensities with respect to each of the three polynomial functions for three colors we have 2x3x3 = 18 plus for count of pixels for each polynomial function giving 3 feature vector databases; like this total 18 + 3= 21 feature vector databases are prepared for the system testing. To demonstrate the performance of the system we have used database of 2000 BMP images from 20 different classes where each class has 100 images. 200 images are selected randomly as 10 images from each of the 20 classes to be given as query to the system. To compare the database and query image feature vectors and facilitate the retrieval three similarity measures are used namely Euclidean distance (ED), Absolute distance (AD) and Cosine correlation distance (CD). Performance of the system for all approaches discussed is evaluated using three parameters PRCP (Precision Recall Crossover Point), 'Longest String', and LSRR (Length of String to Retrieve all Relevant).*

*KEYWORDS*

*Polynomial Transform, Histogram Shifting, Bins, Euclidean distance, Absolute Distance, Cosine correlation Distance, PRCP, LSRR, Longest String.*

## 1. INTRODUCTION

This paper proposes feature extraction methods which are giving variable performance based on different polynomial transforms used to modify the original histogram. The image contents are

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extracted from the set of eight bins formed by dividing the R, G and B histograms (modified using polynomial transform) using centre of gravity into two parts. These eight bins are representing the feature vector of an image. Feature extraction is the core part of any CBIR system because it has got direct impact on the performance of the system which can be evaluated using many parameters [1][2][3]. Feature vectors will decide the time required to execute the system for the given query and also the space to store these feature vectors. Image contents are classified in three main types as color, shape, texture. These contents or say image properties can be used effectively to compare the database and query image if are extracted and represented effectively. Various ways to extract the image features are invented in the field of CBIR from frequency and spatial domain [4][5][6][7][8]. Different transforms, wavelets are used and applied over images in various ways to modify and represent the image contents in compact form [9][10][11][12]. Many spatial domain techniques are used to extract the color texture and shape information of the image [13][14][15]. Color is the invariant image feature for rotation and translation and it is widely used in CBIR systems. [16][17]. we have concentrated on the color information of the image and also the color histogram which is the distribution of pixel intensities [18] [19]. We are actually working with the image histograms and their modification towards lower intensities using different polynomial transforms proposed. Because on the basis of previous work, we found that change in histograms has brought positive effect on retrieval as compared to original histogram results.[20][21]. In brief the feature extraction starts with separating the image into R, G and B planes. For each plane calculate the histogram. Modify the histogram using selected polynomial function then use CG i.e. centre of gravity to divide the modified histogram into two parts. This gives the formation of 8 bins. Three histograms (256 bins size each) of three color planes partitioned using CG in two parts are giving $2^3 = 8$ bin addresses. This generates the feature vector size of just 8 components. This greatly reduces the size of the feature vector which makes the comparison process easy and in turn reduces the computational time required by the system to calculate the distance between query and database image, which is not done in the other histogram based CBIR systems discussed in the literature[22][23][24]. These 8 bins are designed to hold the count of pixels falling in specific range of intensities. These eight bins are representing the feature vector of 8 components. Further we have taken the total and average of intensities of these pixels counted in each of the eight bins. This total and average is taken separately for R, G and B intensities and we have obtained different feature vector databases for each color. Same process is followed for each polynomial function applied to modify the histogram and total 21 types of feature vectors obtained and stored in separate 21 feature vector databases. Once the feature vector databases are prepared system is ready to accept the query image to extract its feature and generate the retrieval result. To facilitate retrieval comparison between query and database feature vector is carried out using three similarity measures namely Euclidean distance (ED), Absolute distance (AD) and Cosine correlation distance (CD) [25]. Once the distances are calculated images at minimum distance from the query are selected for the final retrieval. Determining the threshold to decide the minimum distance on trial n error basis is very time consuming process. Instead of this we have used the other method according to which we have to sort the distances in ascending order and we are taking only first 100 images into account. We have to find out the count of images similar to query out of first 100. Each image class has 100 images in our database. Thus this generates the cross over point of precision and recall if we calculate them separately and this is termed as PRCP (Precision Recall Cross over Point) which is used to evaluate the performance of our system. Along with PRCP two more parameters used to evaluate the system performance are 'Longest String' and LSRR i.e Length of String to Retrieve all Relevant images [25]. [26], [27]. This overall work for all polynomial functions used to modify the histogram are demonstrated with database of 2000 BMP images. It includes 100 images of each of the following 20 classes : Flower, Sunset, Mountain, Building, Bus, Dinosaur, Elephant, Barbie, Mickey, Horse, Kingfisher, Dove, Crow, Rainbow rose, Pyramid, Plate, Car, Trees, Ship and Waterfall. Ten query images are selected randomly from each of the 20 classes and all approaches are tested using this same set of 200 query images so that their performance can be compared and evaluated. Work presented in this paper is organized as follows. Section 2 Describes the polynomial functions used to modify the histogram. Section 3 Discusses about the Partitioning of histogram and Bins formation process. Section 4 explains the role of the similarity measures and Evaluation parameters in the system. Section 5 describes the Experimental results and analysis which is followed by the conclusions in Section 6.

## 2. Polynomial Functions to modify the histogram

### 2.1. Polynomial Functions

We have introduced and used total three different polynomial functions to modify the histogram to try variations of extracting and representing the image feature vectors by pushing pixels towards lower range of intensities. The polynomial functions and their effect is shown in following Figure3. Polynomial functions which are shifting the pixels from higher to lower side are shown in Figure 1. Equations for the same are given in equation 1, 2 and 3.
The function curves y=x2, y=x3, y=x4 shown are used to modify the image histogram such that intensities are being pushed or shifted to lower side.

$$y = x^2 \quad (1)$$

*Where* $y = 0$; *IF* $x = 0$
$y = 1$; *IF* $x = 1$
$y < x$ *for* $0 < x < 1$

$$y = x^3 \quad (2)$$

$$y = x^4 \quad (3)$$

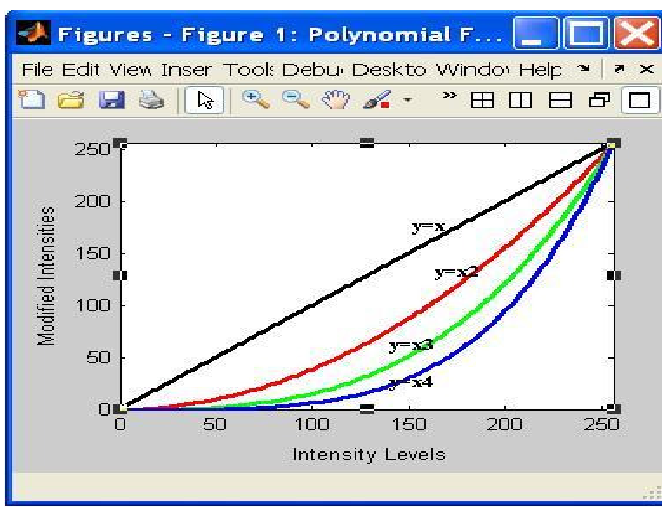



Figure1. Polynomials y=x, y=x2, y=x3, y=x4 Shifting the Intensities to Lower Side.

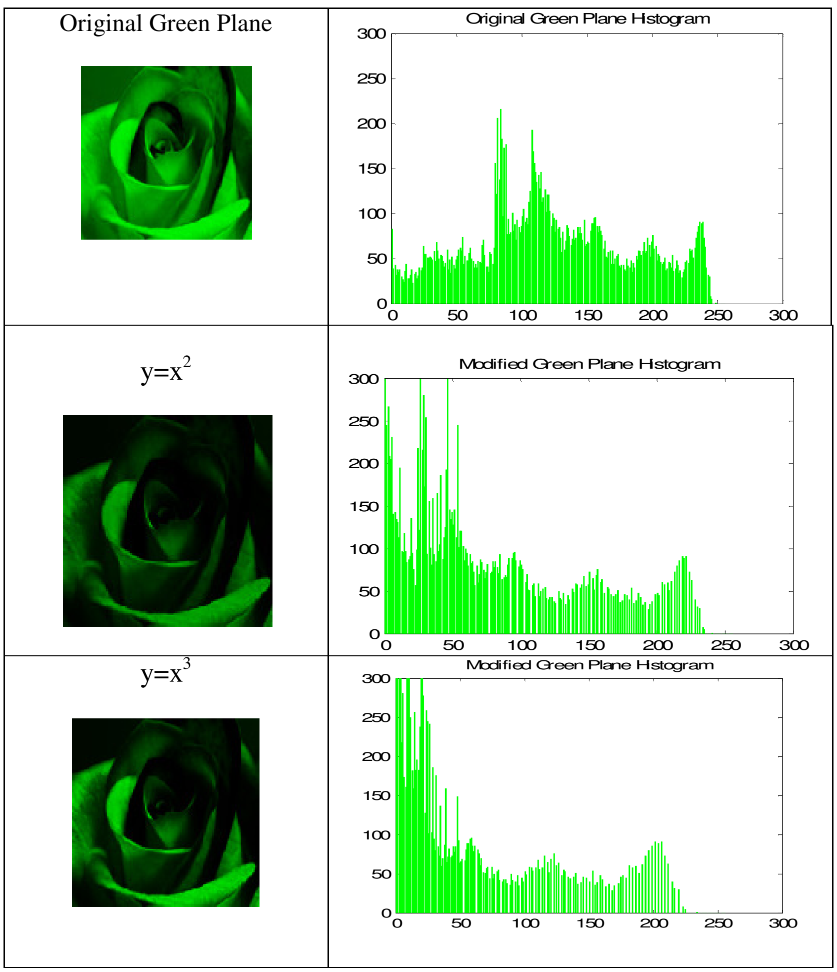
This shifting of histogram helps in feature extraction process and improves the result as compared to already existing histogram modifying or histogram equalization techniques. These three functions are compared with each other by analysing their effect on the histogram shifting. The polynomial functions designed and proposed are actually used as specifications for the histogram to modify. We can observe the three different specifications used to modify are shifting the intensities from higher to lower side as we go on increasing the power of x. The original histogram is mapped into the new histogram specified by each of the three polynomials.

## 2.2 Application of Polynomial Function

Feature extraction process explained in this paper is mainly dependent on the partitioning of the modified histogram which leads towards the formation of eight bins. In this section we are presenting the very first step of feature extraction process which starts from the image separation into R, G and B planes as shown in Figure 2

Figure 2. Separation of Image into R, G and B plane

Effects of shifting the histogram using three different polynomial functions are shown in following Figure 3.



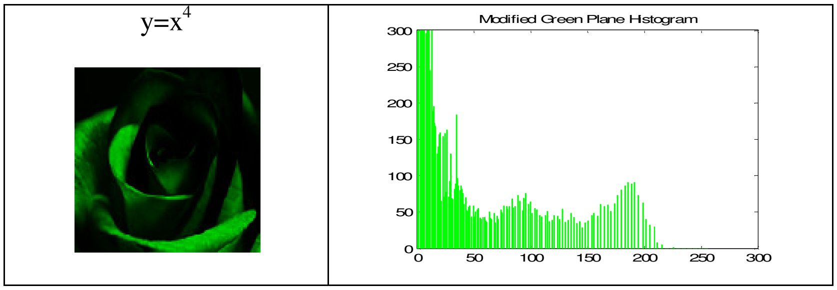



Figure3. Green Plane original Histogram modified using polynomial functions $y=x^2$, $y=x^3$ and $y=x^4$

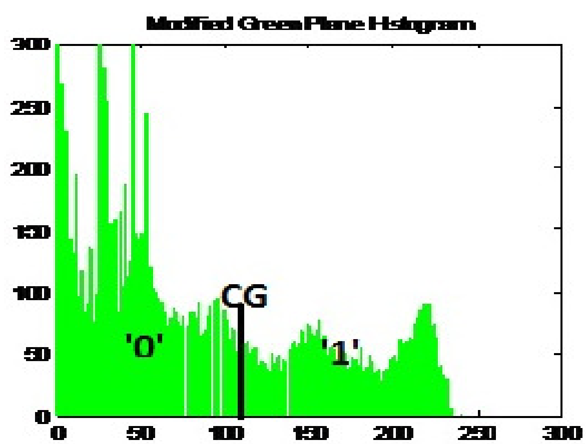
We can observe in above Figure 3 the influence of applying the polynomial functions shifting the intensities to lower side. The more is the power of x in the polynomial more will be the shift to the lower side. This change of intensities is reflected in the green plane images shown in left column after modifying its histogram.

## 3. CG Based Partitioning: Bins Formation

The modified histogram is then partitioned into two parts by calculating the centre of gravity given in following equation 4.

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

After dividing the histogram intensities into two ranges we have named them by assigning id '0' and id '1' to part 1 and 2 respectively. This process is applied to modified histogram of R, G and B planes of image. Same process is applied with all polynomial functions used to modify the histogram. The CG based partitioning of histogram is shown in Figure 4




Figiure4. CG Based Partitioning of green plane Histogram modified using function $y=x^2$.

Once each image plane is partitioned into two parts with id'0' and '1' bins formation comes in process. Here we pick up the pixel from the original image for which the feature vector is being extracted. We check its R, G and B value and we have to identify its id based on which partition of the histogram it falls with its respective color. If for R value it falls in part 1 of R plane's modified histogram, for G in part 2 and for B in part 2 , then that pixel will get id '011' this is the actual bin address of that pixel to reside or to be counted in. This way we can have eight possible combinations of the addresses for the pixels to be counted based on their R, G and B value falling in the specific range of intensities. This is what we call the set of eight bins. Count of all pixels of the image under process is distributed into the 8 bins according to the addresses they acquire. These 8 bins are representing the entire image information and it is called the feature vector of that image. If the image size is 128x128 means total 16384 pixel information is represented in terms of just 8 components. If we take the complete histogram we have total 256 bins showing the distribution of pixels which is used by many researchers as it is for comparison process in CBIR systems [22][23][24]. It is time consuming and tedious process of comparing the feature vectors of 256 components. Here we could greatly reduce the size of the feature vector to just dimension 8. This reduces the computational complexity and saves the execution time required by the system to compare two images.

# 4. Similarity Measures and Evaluation Parameters

To facilitate the image retrieval process in all the CBIR systems the major task to be carried out is to compare the query image and database image feature vectors. This comparison can be done by means of the various similarity measures. Evaluation parameters are equally important in any CBIR system. These are useful to interpret, determine the behaviour and response of the system.

## 4.1 Similarity Measures: ED, AD and CD

In all the CBIR systems retrieval of similar images from large image databases is mainly depends on the distance between the query image and database image feature vectors. Where ever the distance is minimum that image will be considered as image closer to query image and will be selected for the retrieval. This distance calculation between feature vectors plays very important role in the system. It decides the time and complexity of the comparison process. In our system we have made use of three similarity measures namely Euclidean distance (ED), Absolute distance (AD) and Cosine correlation distance (CD) which are given in equation 5, 6 and 7 respectively. Each has its own way of calculating the distance between two vectors. Based on their features we have thought of analysing their performance for this system designed with 8 bins feature vector.

**Euclidean Distance :**

$$D_{QI} = \sqrt{\sum_{i=1}^{n} \left|\left(FQ_i - FI_i\right)\right|^2} \tag{5}$$

**Absolute Distance:**

$$D_{QI} = \sum_{1}^{n} \left|\left(FQ_I - FI_I\right)\right| \tag{6}$$

**Cosine Correlation Distance**

$$\frac{\left(D(n)\right) \bullet \left(Q(n)\right)}{\sqrt{\left[\left|D(n)\right|^2 \left|Q(n)\right|^2\right]}} \tag{7}$$

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

## 4.2 Performance Evaluation: PRCP, Longest String, LSRR

When CBIR user enters the query image into the system to retrieve the images similar to it from large size databases; the retrieval result generated by the system may contain relevant (similar to query) and irrelevant images too. Ideally the system should retrieve only those images which are of query class. But practically it is difficult to get such result for any image retrieval system. Here the need arises to decide the efficiency and strength of the system to retrieve images similar to query. For this we have used following three parameters [25][26][27].

### 4.2.1 PRCP

Many CBIR systems in past years are using two traditional parameters to evaluate the performance of the system namely Precision and Recall which are defined in equation 8 and 9 respectively.

Precision: Precision is the fraction of the relevant images which has been retrieved (from all retrieved)

Recall: Recall is the fraction of the relevant images which has been retrieved (from all relevant)

$$\text{Precision} = \frac{\text{Relevant Retreived Images}}{\text{All Retrieved Images}} \tag{8}$$

$$Recall = \frac{Relevant\ \ Retreived\ \ Images}{All\ \ Relevant\ \ In\ \ Database} \tag{9}$$

Precision is the measure of ‘Accuracy’ and Recall measures the ‘Completeness’ of the CBIR system. We have taken the cross over point of these two parameters which is termed as Precision Recall Cross over Point. Ideal value for PRCP is 1 which states that retrieval set for the given query contains all relevant images from database and it does not contain any irrelevant image. PRCP values obtained for various queries show us that how far we are from the ideal system. Here we are taking first 100 images into consideration after sorting the distances obtained on comparison of query with 2000 database images. As we have 100 images of each class in database we got this as the cross over point for precision and recall.

### 4.2.2 Longest String

This parameter identifies longest string of relevant images from the sorted distances. When we sort the distance between the query and 2000 database images in ascending order we may get few relevant images in the beginning but there is possibility that we may get long continuous string of relevant images anywhere in between 1 to 2000. This continuous string of images should be considered although it may be at little far distance than the initial relevant string of images. This is what we have considered and designed and implemented to be considered as performance evaluation parameter.

### 4.2.3 LSRR

It is ‘Length of String to Retrieve all Relevant images’ from database. This parameter calculates the length required to traverse the sorted distances while collecting all the images relevant to query (or make recall ‘1’). The shortest length indicates the better performance of the system

# 5. Experimental Results and Discussion

The proposed system designed with newly introduced polynomial functions to modify the histogram to extract the feature vector to eight bins formed by partitioning the histogram using CG is experimented with following details.

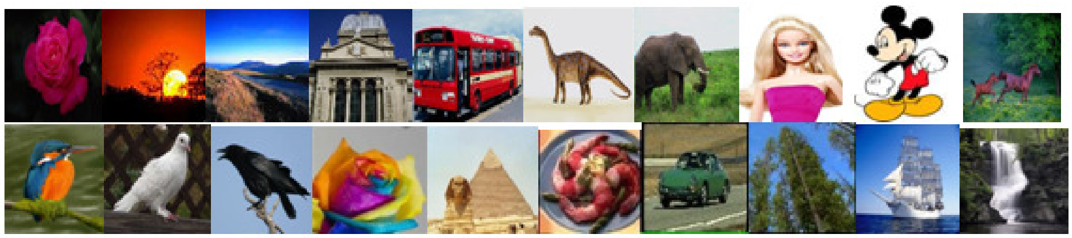


Figure. 5. 20 Sample Images from database of 2000 BMP Images having 20 classes

## 5.1 Database and Query Image

The proposed system is experimented with database of 2000 BMP images. It includes 100 images from each of the 20 different categories. Sample database images are shown in following Figure 5.

The CBIR system discussed in this paper makes use of 'query by example' approach to give input to the system [28]. We have randomly selected set of 200 query images from the database to be given as input to the system to test its performance. This set includes 10 images from each of the 20 classes shown above.

All the results discussed in the following section are with respect to same set of query images and same set of performance evaluation parameters

## 5.2 Results and Discussion

All proposed approaches used to create multiple feature vector databases discussed in this paper are based on the three different polynomial functions and also on the variation used to extract the image contents into 8 bins formed by partitioning the modified histograms of R, G and B color separately. We have obtained total 21 feature vector databases and all are tested using the same set of 200 query images so that we can compare their performance and give some conclusive recommendations. The 21 feature vector databases are given as follows:

| **Feature Vector Databases:21** | | | |
|---|---|---|---|
| ***Type of Contents*** | ***Polynomial function*** | | |
| | $y=x^2$ | $y=x^3$ | $y=x^4$ |
| Count of pixels | **1**.Count of Pixels | **2**. Count of Pixels | **3**. Count of Pixels |
| Total of Intensities | **4.** $R_{Total}$<br>**5**. $G_{Total}$<br>**6**. $B_{Total}$ | **7**. $R_{Total}$<br>**8**. $G_{Total}$<br>**9**. $B_{Total}$ | **10**. $R_{Total}$<br>**11**. $G_{Total}$<br>**12**. $B_{Total}$ |
| Average of Intensities | **13.** $R_{Avg}$<br>**14**. $G_{Avg}$<br>**15**. $B_{Avg}$ | **16.** $R_{Avg}$<br>**17**. $G_{Avg}$<br>**18**. $B_{Avg}$ | **19.** $R_{Avg}$<br>**20**. $G_{Avg}$<br>**21**. $B_{Avg}$ |

The above 21 feature vector databases, all are containing the feature vectors of same size i.e of dimension 8 based on contents extracted to 8 bins. Performance of all feature vector databases is evaluated using PRCP, Longest string and LSRR parameters.

Table 1, 2 and 3 are showing the results obtained for PRCP for three types of feature vector databases Count of pixels, Total of intensities and Average of intensities respectively. Each entry in the table is showing the total PRCP obtained out of 20,000 for 200 queries from 20 classes. Each table contains result obtained for R, G and B color contents for each of three polynomial functions $y=x^2$, $y=x^3$ and $y=x^4$. PRCP obtained with respect three different similarity measures are shown separately row wise (ED, AD and CD) in each table.

We can observe in the table that few columns are highlighted with yellow color. It is actually showing the best results obtained among ED, AD and CD while comparing them on the basis of polynomial functions. We can see that for each color result analysed separately we found best result is obtained for polynomial 'y=x2'. In Table 2 and 3 we found that 'y=x2' is performing better in all cases as compared to other two polynomial functions for total and average of intensities and in Table 1 it is doing best in two out of three cases.

The maximum value obtained for PRCP is 5926 for Green color for function '$y=x^2$' it indicates that precision and recall is '0.3' as average of 200 queries. As we have obtained separate result sets for each of the three colors R, G and B ; further we have combined these results by applying OR criterion where we have taken the image in final retrieval set even if it is being appearing all three, any two or any one of three color results set. Because of this 'OR' criterion we could combine and improve the results obtained for parameter PRCP. Now this PRCP is reached to 0.45 which is representing the average of 200 query images. This is very good achievement for any CBIR system. The results obtained after applying criterion 'OR' to the results shown in table 2 and 3 ( PRCP: Total, and PRCP: Average) are shown in charts 1, 2 along with data.

Table1. PRCP obtained for Count of Pixels with ED, AD and CD

| | PRCP : COUNT | | |
|---|---|---|---|
| SM | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ |
| ED | 4990 | 4946 | 4907 |
| AD | 5400 | 5324 | 5253 |
| CD | 4886 | 4884 | 4906 |

Table 2. PRCP obtained for Total of Intensities for R, G and B colors with ED, AD and CD

| PRCP : TOTAL | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | R | | | G | | | B | | |
| SM | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ |
| ED | 4736 | 4509 | 4527 | 4403 | 4263 | 4246 | 4134 | 4030 | 4043 |
| AD | 5066 | 4784 | 4751 | 4766 | 4563 | 4525 | 4436 | 4273 | 4269 |
| CD | 4736 | 4528 | 4261 | 4430 | 4218 | 3977 | 3964 | 3753 | 3563 |

Table 3. PRCP obtained for Average of Intensities for R, G and B colors with ED, AD and CD

| PRCP : AVERAGE | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | R | | | G | | | B | | |
| SM | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ |
| ED | 5258 | 5152 | 5135 | 5419 | 5079 | 4756 | 5238 | 4958 | 4681 |
| AD | 5589 | 5541 | 5538 | 5715 | 5392 | 5225 | 5661 | 5376 | 5137 |
| CD | 4915 | 4635 | 4429 | 5926 | 5445 | 5100 | 5500 | 5134 | 4765 |

Chart 1. Criterion 'OR' over 'Total of Intensities' for R, G and B Colors with ED, AD, CD

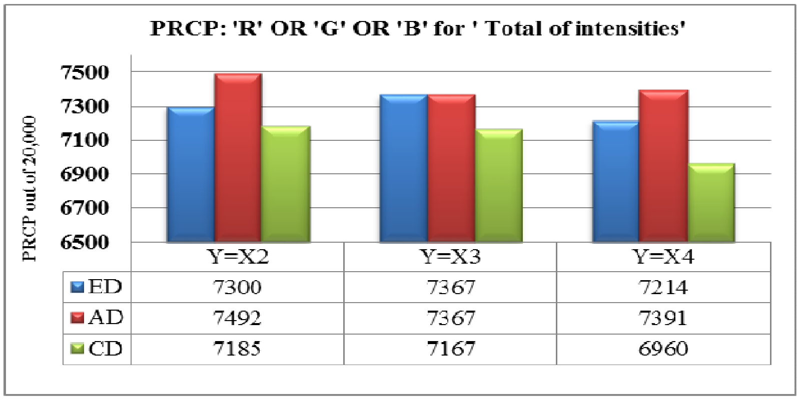
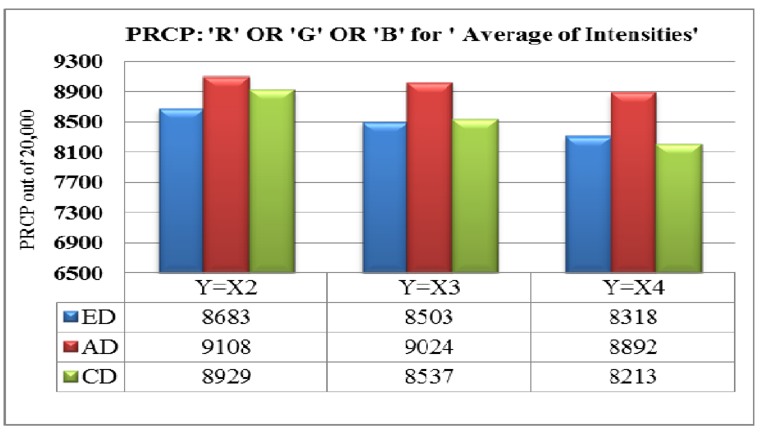



Chart 2. Criterion 'OR' over 'Average of Intensities' for R, G and B Colors with ED, AD, CD




After applying the criterion 'OR' to combine R, G and B colors we could improve the results for both types of feature vector i.e total and average of intensities. The best value or maximum PRCP we obtained is for average of intensities. It has reached to 0.45 means precision and recall for average of 200 query images is reached to good height of 0.45.

Next parameter used to evaluate the system performance is "Longest string' of images. As discussed earlier in section 4 part 4.2.2, it identifies the longest continuous string of images. Here this parameter is also obtained for all 200 query images. The results obtained for 'Longest String' are taken as maximum longest string among three color results. Because of this we could analyse the performance of three colors and we can state that among three colors green is giving its best for longest string as well as for PRCP. Results obtained for Count of pixels, Total and average of intensities are shown in tables 4, 5 and 6 respectively. These tables are coloured to highlight the analysis done for those results. Results of each similarity measure are highlighted with different color. Observations made on the basis of analysis done are given below each table. In brief we can state that for count of pixels for each similarity measure different polynomial function is performing better but for average value we found $y=x^2$ is better in all cases. In total and average of intensities tables (5 and 6) we found $y=x^2$ is better in all the cases.

Results obtained for parameter LSRR which calculates percentage of length required to traverse the sorted string of images (according to the sorted order of distances from min to max) to collect all images relevant to query from database images. Results of LSSR are plotted in charts 3, 4 and 5 for Count of pixels, Total of intensities and Average of intensities respectively. Best values in LSRR are nothing but the minimum % of length required to traverse to make recall 1.

In Chart 3 it is found that average of queries from all 20 classes are giving the minimum LSRR for function $y=x^2$. Chart 3 states that few classes like Barbie, Dinosaur, Sunset, Bus and Dove are giving best performance. The best LSRR we found is for class Barbie where just 11to 14 % traversal gives 100% recall.  On average of queries from all classes LSRR is below 65%.

In Chart 4 we found that classes Dinosaur, Barbie, Sunset, Flower and Horses are giving better performance as compared to other classes. Here also we found that polynomial y=x2 gives better performance as shown in last column bars. For total of intensities the average LSRR obtained is between 60% to 70% traversal of 2000 database images.

Table 4.  Maximum Longest String for 'Count of Pixels' with polynomials $y=x^2$, $y=x^3$, $y=x^4$

| LONGEST STRING FOR 'Count Of Pixels' | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | ED | | | AD | | | CD | | |
| Classes | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ |
| Flower | 7 | 9 | 9 | 11 | 13 | 11 | 6 | 9 | 7 |
| Sunset | 20 | 26 | 25 | 23 | 27 | 26 | 21 | 26 | 21 |
| Mountain | 3 | 3 | 5 | 3 | 3 | 4 | 3 | 3 | 4 |
| Building | 3 | 4 | 4 | 4 | 4 | 5 | 3 | 3 | 5 |
| Bus | 7 | 5 | 5 | 7 | 6 | 6 | 7 | 4 | 6 |
| Diansour | 35 | 29 | 23 | 40 | 33 | 26 | 39 | 34 | 27 |
| Elephant | 5 | 4 | 5 | 3 | 4 | 6 | 3 | 4 | 4 |
| Barbie | 5 | 9 | 6 | 6 | 7 | 6 | 7 | 6 | 8 |
| Mickey | 11 | 8 | 6 | 11 | 8 | 5 | 11 | 7 | 9 |
| Horses | 43 | 22 | 15 | 40 | 30 | 16 | 38 | 27 | 14 |
| Kingfisher | 4 | 4 | 4 | 4 | 5 | 5 | 4 | 5 | 4 |
| Dove | 16 | 17 | 12 | 21 | 18 | 15 | 16 | 16 | 9 |
| Crow | 5 | 6 | 7 | 8 | 7 | 15 | 8 | 5 | 5 |
| Rainbowrose | 16 | 17 | 22 | 16 | 13 | 10 | 11 | 13 | 9 |
| Pyramids | 11 | 14 | 15 | 10 | 11 | 11 | 12 | 13 | 15 |
| Plates | 4 | 7 | 7 | 5 | 7 | 5 | 4 | 5 | 7 |
| Car | 4 | 3 | 4 | 3 | 4 | 4 | 3 | 4 | 5 |
| Trees | 9 | 8 | 9 | 7 | 9 | 13 | 9 | 11 | 14 |
| Ship | 5 | 6 | 6 | 6 | 7 | 7 | 7 | 6 | 7 |
| Waterfall | 6 | 5 | 4 | 5 | 6 | 5 | 10 | 5 | 5 |
| AVG | **10.95** | 10.3 | 9.65 | **11.65** | 11.1 | 10.05 | **11.1** | 10.3 | 9.25 |

Observation

| Observation for Best results Out of 20 Cases for Table 4 | ED | | | AD | | | CD | | |
|---|---|---|---|---|---|---|---|---|---|
| | $Y=x^2$ | $Y=x^3$ | $Y=x^4$ | $Y=x^2$ | $Y=x^3$ | $Y=x^4$ | $Y=x^2$ | $Y=x^3$ | $Y=x^4$ |
| | 9 | 11 | **12** | 8 | **11** | 9 | **10** | 8 | 7 |
| **Average of 20 queries is showing that '$y=x^2$' is better as compared to other two polynomials** | | | | | | | | | |

Chart3. Minimum % LSRR for 'Count of Pixels' for polynomials $y=x^2$, $y=x^3$, $y=x^4$

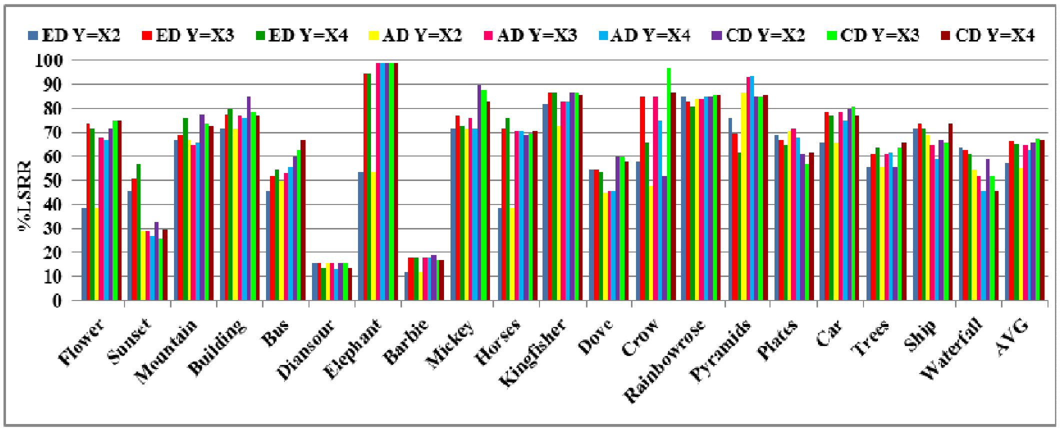



Table 5. Max. Longest String for 'Total of Intensities' for polynomials $y=x^2$, $y=x^3$, $y=x^4$

| LONGEST STRING FOR 'Total of Intensities' | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | ED | | | AD | | | CD | | |
| Classes | Y=X2 | Y=X3 | Y=X4 | Y=X2 | Y=X3 | Y=X4 | Y=X2 | Y=X3 | Y=X4 |
| Flower | 18 | 13 | 12 | 20 | 17 | 17 | 14 | 16 | 12 |
| Sunset | 21 | 16 | 19 | 20 | 25 | 24 | 25 | 25 | 17 |
| Mountain | 5 | 4 | 5 | 4 | 4 | 6 | 5 | 4 | 4 |
| Building | 4 | 4 | 5 | 4 | 7 | 5 | 5 | 4 | 5 |
| Bus | 14 | 10 | 9 | 16 | 16 | 12 | 7 | 4 | 8 |
| Diansour | 42 | 26 | 28 | 33 | 25 | 25 | 18 | 21 | 14 |
| Elephant | 5 | 3 | 5 | 4 | 4 | 7 | 3 | 5 | 4 |
| Barbie | 33 | 35 | 39 | 29 | 29 | 31 | 5 | 7 | 10 |
| Mickey | 10 | 18 | 18 | 9 | 14 | 13 | 8 | 9 | 5 |
| Horses | 29 | 27 | 11 | 27 | 21 | 12 | 15 | 14 | 11 |
| Kingfisher | 7 | 5 | 3 | 6 | 7 | 4 | 6 | 5 | 5 |
| Dove | 11 | 8 | 9 | 18 | 14 | 10 | 35 | 17 | 15 |
| Crow | 6 | 5 | 6 | 9 | 4 | 7 | 14 | 5 | 8 |
| Rainbowrose | 10 | 9 | 12 | 12 | 7 | 8 | 13 | 16 | 12 |
| Pyramids | 10 | 7 | 7 | 10 | 7 | 6 | 12 | 8 | 9 |
| Plates | 4 | 6 | 7 | 5 | 6 | 6 | 4 | 6 | 6 |
| Car | 9 | 7 | 6 | 5 | 7 | 7 | 4 | 7 | 6 |
| Trees | 9 | 5 | 7 | 9 | 8 | 5 | 9 | 8 | 10 |
| Ship | 14 | 9 | 8 | 12 | 8 | 7 | 12 | 9 | 7 |
| Waterfall | 6 | 6 | 5 | 5 | 5 | 6 | 8 | 6 | 7 |
| AVG | **13.35** | 11.15 | 11.05 | **12.85** | 11.75 | 10.9 | **11.1** | 9.8 | 8.75 |

Observation

| Observation for Best results Out of 20 Cases Table 5 | ED | | | AD | | | CD | | |
|---|---|---|---|---|---|---|---|---|---|
| | $Y=x^2$ | $Y=x^3$ | $Y=x^4$ | $Y=x^2$ | $Y=x^3$ | $Y=x^4$ | $Y=x^2$ | $Y=x^3$ | $Y=x^4$ |
| | **14** | 3 | **7** | **10** | **8** | 5 | **10** | 8 | 5 |
| **Average of 20 queries is showing that ‘$y=x^2$’ is better as compared to other two polynomials** | | | | | | | | | |

Chart 4. Minimum LSRR for ‘Total of Intensities’ for polynomials $y=x^2$, $y=x^3$, $y=x^4$

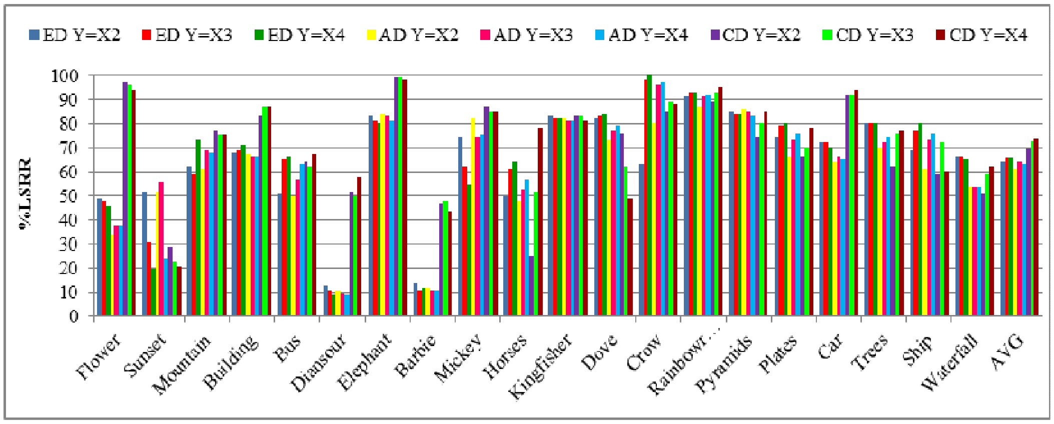


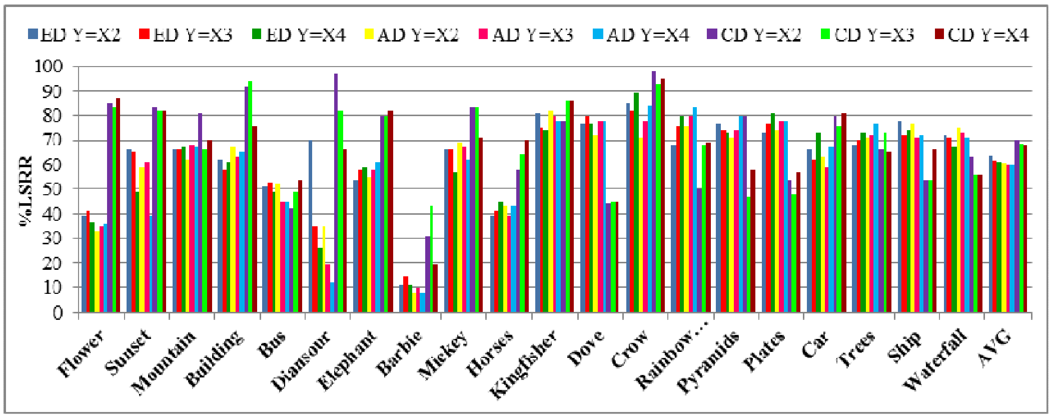

Table 6. Max. Longest String for ‘Average of Intensities’ for polynomials $y=x^2$, $y=x^3$, $y=x^4$

| **LONGEST STRING FOR ‘ Average of Intensities’** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **ED** | | | **AD** | | | **CD** | | |
| **Classes** | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ | $Y=X^2$ | $Y=X^3$ | $Y=X^4$ |
| **Flower** | 16 | 14 | 12 | 16 | 20 | 12 | 14 | 15 | 12 |
| **Sunset** | 26 | 17 | 18 | 23 | 20 | 16 | 19 | 12 | 13 |
| **Mountain** | 11 | 5 | 5 | 5 | 5 | 5 | 9 | 5 | 4 |
| **Building** | 7 | 8 | 10 | 8 | 8 | 8 | 8 | 9 | 6 |
| **Bus** | 12 | 7 | 7 | 13 | 14 | 8 | 17 | 10 | 7 |
| **Diansour** | 34 | 40 | 55 | 34 | 40 | 49 | 13 | 19 | 14 |
| **Elephant** | 10 | 7 | 9 | 9 | 8 | 10 | 18 | 9 | 7 |
| **Barbie** | 87 | 79 | 68 | 79 | 69 | 64 | 73 | 52 | 34 |
| **Mickey** | 19 | 26 | 38 | 18 | 24 | 26 | 15 | 19 | 17 |
| **Horses** | 13 | 17 | 13 | 9 | 14 | 18 | 15 | 17 | 14 |
| **Kingfisher** | 7 | 6 | 6 | 5 | 5 | 5 | 12 | 9 | 8 |
| **Dove** | 11 | 8 | 8 | 13 | 9 | 8 | 11 | 8 | 7 |
| **Crow** | 5 | 9 | 6 | 7 | 7 | 6 | 7 | 7 | 6 |
| **Rainbowrose** | 28 | 16 | 11 | 23 | 14 | 18 | 33 | 32 | 27 |
| **Pyramids** | 14 | 15 | 7 | 17 | 13 | 10 | 13 | 16 | 11 |
| **Plates** | 8 | 5 | 6 | 6 | 7 | 6 | 12 | 15 | 7 |
| **Car** | 7 | 5 | 5 | 6 | 5 | 5 | 8 | 8 | 9 |
| **Trees** | 8 | 10 | 10 | 8 | 11 | 9 | 14 | 8 | 8 |
| **Ship** | 9 | 13 | 14 | 10 | 10 | 14 | 20 | 13 | 7 |
| **Waterfall** | 5 | 9 | 5 | 4 | 7 | 6 | 7 | 6 | 7 |
| **AVG** | **16.85** | 15.8 | 15.65 | **15.65** | 15.5 | 15.15 | **16.9** | 14.45 | 11.25 |

Observation

| Observation for Best results Out of 20 Cases in Table 6 | ED | | | AD | | | CD | | |
|---|---|---|---|---|---|---|---|---|---|
| | $Y=x^2$ | $Y=x^3$ | $Y=x^4$ | $Y=x^2$ | $Y=x^3$ | $Y=x^4$ | $Y=x^2$ | $Y=x^3$ | $Y=x^4$ |
| | 11 | 4 | 5 | 10 | 9 | 8 | 12 | 8 | 2 |
| Average of 20 queries is showing that '$y=x^2$' is better as compared to other two polynomials | | | | | | | | | |

Chart 5. Minimum LSRR for 'Average of Intensities' for polynomials $y=x^2$, $y=x^3$, $y=x^4$




Observation of Chart 5 states that classes Barbie, Horses, Dinosaur and Flower are performing better. Here when we observed average LSRR results of 20 queries we found $y=x^4$ is better in all cases. The average LSRR values are in between 60 % to 70%.

All the Longest string and LSRR results are taken as maximum and minimum length respectively from the results obtained among three colors R, G and B. This is analysed in detail that whatever values we have selected as max and min are belong to which color actually and here we found that green color results are appearing in most of the cases for both the parameters. Then at second place red color and then blue color according to their performance for longest string and LSRR parameter.

## 6. Conclusion

The CBIR system designed, implemented and presented in this paper is based on the 'Bins approach'. These bins are formed by partitioning the histogram into two parts using the centre of gravity (CG) so that pixels will be distributed equally into two parts based on their (mass of) intensities. Before partitioning the histograms of R, G, and B planes of image are modified using the polynomial function. We have used three polynomial functions to modify the histogram. Effect of these polynomials is shifting the histogram towards lower side of intensities which is shown clearly in Figure 3. Through this experimentation of the approaches, designed with 2000 BMP image database and 200 query images, we have come to following conclusions.

First thing is that this CBIR system is based on Bins approach. Here the eight bins are representing the entire image as its feature vector of 8 components. This greatly reduces the size of the feature vector than other approaches using 256 bins of histogram as it is [22][23][24]. It reduces the computational complexity to a great extent.

Shifting of histogram discussed in this paper is based on the newly introduced polynomial functions $y=x^2$, $y=x^3$ and $y=x^4$ is playing important role in the system by shifting the intensities from higher to lower side. On observation and analysis of the results obtained separately for each polynomial when compared with the results obtained for original histogram we found that there is positive improvement in the retrieval with respect to all the evaluation parameters [21].

Performance comparison of these three polynomials introduced in this work shows that best performance is given by function $y=x^2$.

We have used multiple variations while extracting the contents of image to bins. One is just the count of pixels into each bin, second and third is total and average of intensities of these pixels in each of the eight bins respectively. For the second and third variation, we have collected the image information separately for each color. We found green is dominating among three colors then next best is red and at last blue color. Among three types of representations of information, we found that count and average of intensities are performing better as compared to total of intensities.

Results obtained for three different similarity measures are analyzed and it can be concluded that order of their performance is AD, CD and ED means Absolute and Cosine correlations distances are far better than Euclidean distance.

Now the role of performance evaluation parameters i.e PRCP, Longest String and LSRR is core part of the system to be delineated here.

Best value obtained for PRCP among all the results set is for polynomial $y=x^2$. At first stage best PRCP obtained is 0.3 which is average performance of 200 query images from 20 classes. Further it has reached to 0.45 which is good achievement as average of 200 queries after applying the criterion OR to combine the separate PRCP results of R, G and B colors.

Maximum Longest string obtained is ‘87’ for class Barbie for average of intensities for function $y=x^2$.

Ideal value for parameter LSRR is the minimum value of traversal; here the best LSRR obtained is again for class Barbie where 11% traversal itself is enough to collect all images relevant to query from database or to make recall 1.

Average performance for 20 classes for parameter longest string is 11 to 17. For parameter LSRR the average performance range for all cases is in 60% to 70%.

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