Journal of Computer Science 10 (6): 985-994, 2014 ISSN: 1549-3636 © 2014 Science Publications doi:10.3844/jcssp.2014.985.994 Published Online 10 (6) 2014 (http://www.thescipub.com/jcs.toc)

COLOR PERCEPTION HISTOGRAM FOR IMAGE RETRIEVAL USING MULTIPLE SIMILARITY MEASURES

Malini, R. and C. Vasanthanayaki

Department of Electronics and Communication Engineering, Government College of Technology, Coimbatore, Tamilnadu, India

Received 2013-07-22; Revised 2014-01-30; Accepted 2014-01-30

ABSTRACT

This study aims to increase the retrieval efficiency of proposed image retrieval system on the basis of color content. A new idea of feature extraction based on color perception histogram is proposed. First, the color histogram is constructed for HSV image. Secondly, the true color and grey color components are identified based on hue and intensity. The weight for true and grey color components is calculated using NBS distance. An updated histogram is constructed using weighted true and grey color values. The color features extracted from the updated histogram of query image and for all the images in image database are compared with existing color histogram based technique by using multiple similarity measures. Experimental results show that proposed image retrieval based on the color perception histogram gives higher retrieval performance in terms of high average precision and average recall with less computational complexity.

Keywords: Color Histogram, NBS Distance, Histogram Updation, Distance Measures

1. INTRODUCTION

In recent days, the world is witnessing a rapid growth in the number of images, its importance and accessibility in all applications. However, the real engine of imaging revolution is the field of image processing which deals with image storage, processing, indexing, retrieval and transmission. Due to the advancement and with the growing interest, image processing is finding its application in a variety of new fields like photography, art galleries and remote sensing in addition to traditional image dependent fields of engineering, architecture and medicine. Also the electronic access of images has now enabled the users to access data from anywhere on the planet thus providing a further massive growth in the field of image retrieval. Image retrieval deals with searching and retrieving images from a huge database based on the given search query.

Currently more sophisticated tools are available for interacting with huge collections of images. Traditional mode of search is through keyword matching wherein images are manually annotated before storing in Corresponding Author: Malini, R., Department of Electronics and Communication Engineering, Government College of Technology,

Coimbatore, Tamilnadu, India

database. Image retrieval is based on its corresponding query text. Though the technique is simple, the difficulty lies in organizing and searching image collections in a satisfactory fashion as the images are not stored in an organized manner. This difficulty is due to manual annotation and semantic gap associated with it. Thus searching the relevant images with respect to its content is been formulated by CBIR.

Content Based Image Retrieval (CBIR) is a technique of searching and retrieving images using automatically derived image featues such as color, texture and shape. Reasons for its growth is that in huge image repositories, traditional methods of image annotation have proven to be inefficient, costly and extremely time consuming. In CBIR, image search is based on derived image features extracted using feature extraction and retrieval is based on similarity measures.

2. LITERATURE SURVEY

Van et al. (2012) proposed a new and efficient retrieval technique Bin of Color Histogram (BCH)



based on color features and compared it with the existing Cell/Color Histogram (CCH). In Cell/Color histograms (CCH) technique, image is initially partitioned into a sequence of blocks, later the image is quantized based on the colors and the histogram is calculated for each color. The color histogram of query image and the database image is compared. The distance between two images is calculated by summing the distance of images depending on all colors in query image and database image. CCH is very effective as it increases retrieval effectiveness and reduces the space overhead, but the technique is sensitive to rotation and translation. To overcome the above limitation of CCH, an efficient technique called Bin of Color Histogram (BCH) is propose.

In BCH method, image colors are initially quantized. Each image is divided into a series of sectors and for each color the histogram is calculated. The number of pixels in a sector is represented by a bin in the histogram. A weighted undirected histogram is formed for each database image color and query image color. Euclidean distance is calculated between weighted histogram of query image and target image and its value lies in the range [0 1]. The minimum cost in matching each bin of histogram is calculated and it is considered as the smallest distance between two images. The advantage of bin of color histogram technique is that it is insensitive to variations in rotation and translation.

Vilvanathan and Rangaswamy (2013) proposed an image retrieval technique based on color indexed image histograms. In this work, the input 24 bit RGB image is converted to an indexed image with 256 colors and the color map of a single image is used to decompose the entire dataset images. After decomposing, the images are indexed so that each bin in a histogram correspond to a specific color based on the index value. The similarity between each bin of query image and its target image is calculated using euclidean distance.

Alaoui *et al.* (2009) examined the use of tansformation geometry using color spatial entropy and color hybrid entropy. The two spatial color indexing methods are used to describe the spatial information of colors on multiresolution images.

Though the above mentioned color histogram techniques produce efficient results there still exist few limitations like more query execution time and more computational complexity. To overcome these drawbacks, a new technique based on color perception histogram for image retrieval is proposed.

3. CONTENT BASED IMAGE RETRIEVAL

CBIR is an important alternative to conventional keywod based image retieval and it greatly increases the retrieval efficiency. "Content" in CBIR refers to the actual contents of an image which includes color, texture and shape. CBIR involves two major steps in its implementation: Feature extraction and similarity measures.

In Text Based Image Retrieval (TBIR), search is done based on the metadata such as keywords, tags and descriptions in contrast to CBIR where search analyses the actual contents of an image. CBIR is more useful compared to existing TBIR (Patrick *et al.*, 2004), because in TBIR humans manually enter keywords to label images before storing in image database, thus making the system inefficient as the technique does not capture every text used to describe an image during storage. Thus a system which sort out images automatically, based on the image content is required to provide better indexing with minimal query execution time.

Figure 1 shows the block diagram of proposed CBIR system. The color feature of database images are extracted and stored in a feature database. The retrieval system calculates the similarity between the feature vectors of the query image and its target image using distance measures.

Some existing CBIR systems are MIFile (Amato *et al.*, 2012), FIRE (Alexe *et al.*, 2012) and QBIC (Shanmugapriya and Nallusamy, 2014).

3.1. Necessity of Color in CBIR

Color is the most visually striking feature of any image and it has a significant bearing on the scene beauty of an image. Vision and hearing are the two most important means by which human perceive the outside world. It is estimated that 75% of the information received by a human is visual. One of the main application of using color as a feature vector is in Agriculture (Lian *et al.*, 2012), Trademark (Phan and Androutsos, 2009) and Robotic vision (Trong *et al.*, 2012).

Colors can be represented using different color models (Moustafa and Alqadi, 2009) such as Red-Green-Blue (RGB) or Hue-Saturation-Value (HSV) or HSB (Hue, Saturation and Brightness). The RGB color model is extensively used to represent digital images on majority of computer systems.



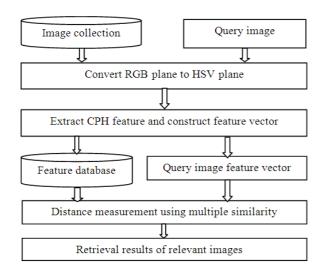


Fig. 1. Block diagram of proposed CBIR system

RGB color model is the simplest model of color data storage and by far the most widespread in computational applications. RGB color model is useful because, in human visual system, the sensitivity curves of the rho (red), gamma (green) and beta (blue) sensors in the human eye determine the intensity of the colors that one perceives for each of the wavelengths. However, RGB color model is not very efficient in dealing with real world as any modification to an image requires modifying the pixel values of all three planes.

In the HSV color model, the color are separated into three parts: Hue, saturation and value. The color sense of hue depends on the wavelength of light and it ranges from 0° to 360° . Saturation explains the purity of a color. It is obtained by adding white to pure color. Value correspond to the brightness of a color. Value determines lightness or darkness of a color. The benefit of HSV color space is that it is similar to human perception of colors.

The proposed Color perception histogram is based on HSV color model in which the hue and intensity are considered as the dominant factor.

3.2. Color Perception Histogram

Color Perception Histogram (CPH) technique is mainly used for retrieving high dense background images. Color histogram (Xiaoling, 2009) technique is well suited for image retrieval applications because it produces a strong perception to our human eye. The saturation and intensity values are used to find the color perception of a pixel. If the saturation value is higher than the intensity value, the pixel is considered as a grey color pixel otherwise it is considered as a true color pixel.

Figure 2 shows the flow diagram of CBIR system using proposed color perception histogram. True color pixels are represented in '1' and Grey color pixels are represented with '0'. The color model do not completely represent human color perception. This is because vision under well-lit conditions is primarily due to cone cells and monochromatic vision in low light is due to rods cells in eye. Thus, there is a gradual shift from monochromatic vision to photopic vision of human eye. The characteristics of human perception of color is determined based on the dominant property of a pixel which is hue in case of true color and intensity in case of grey color. This characteristic property of pixel is used to generate histogram in image retrieval application and is called Color Perception Histogram (CPH).

Step 1: Color Histogram

A color histogram is generated by quantizing the colors within an image and achieved by summing up the pixels of similar color in the image. A major concern regarding the usage of image color histogram for indexing lies in selecting a suitable color model. Retrieval using image color histogram is considered as simple and efficient technique for processing image content. The main advantage of color histogram is that it is easy to compute, compare and store.

Step 2: Identification of Image Pixels

Hue is the dominant factor in true color pixels. If intensity is high and saturation is low, a pixel color is very much close to the "true color". The grey color pixel is approximated by its intensity. The intensity and saturation values are the dominant factor in grey color pixels. If the intensity is low and saturation is high, a pixel color is very much close to the "grey color".

Step 3: Determine the Weight

The weight can be calculated for true and grey color components by using the following formula.

For true color, the weight is given by Equation (1):

$$SW_{H(S,1)} = 100 - \lfloor (NBS - 1.5) * 10 \rfloor$$
 (1)

For grey color, the weight is given by Equation (2):

$$SW_{I(S,D)} = 1 - SW_{H(S,D)}$$
⁽²⁾



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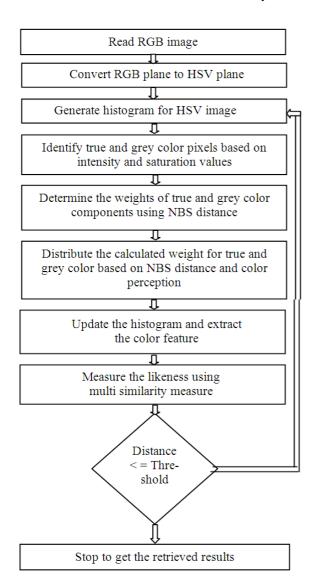


Fig. 2. Flowchart of proposed CBIR system using color perception histogram

National Bureau of Standards (NBS) (Rahman *et al.*, 2006), is a measurement standards laboratory. NBS distance is calculated only for true color and it is not calculated for grey color as the color difference is minimum for grey color. NBS distance formula for true color in HSV color space is given by Equation (3):

$$d(\vec{x}, \vec{y}) = 1.2*$$

$$\sqrt{\left[2x_2y_2(1 - \cos((2\pi\Delta H) / 100)) + \Delta S^2 + (4\Delta I)^2\right]}$$
(3)

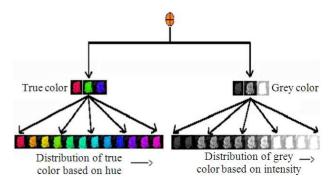


Fig. 3. Distribution of true color and grey color components

Table 1. Weight distribution based on NBS

| NBS distance | Color perception | Weight distribution (%) |
|--------------|-------------------------|-------------------------|
| 0 -1.5 | Negligible color change | 100 |
| 1.6 - 3.0 | Minor color change | 75 |
| 3.1 - 6.0 | Gradual color change | 50 |
| 6.1 - 12 | Major color change | 25 |
| > 12.1 | Different color | 0 |

For true color, ΔS and ΔI remains zero since the saturation and intensity distributed difference is minimum with respect to a single pixel. For grey color, ΔS and ΔH remains zero as the saturation and hue difference appears to be very low.

Step 4: Weight Distribution

After calculating the NBS distance value for true color, the weight for true and grey color components are calculated.

The weight is distributed to the neighborhood bins. The amount of weight to be distributed to the adjacent bins is calculated based on NBS Distance. Figure 3 shows the distribution of true color and grey color components. Depending on the color difference and distance, the true color and its weight are distributed to the adjacent pixels.

Table 1 shows the weight distribution based on NBS distance and color perception. Weight distribution is done 100% when the color change between the reference bin and its immediate neighboring bin is negligible.

Step 5: Histogram Updation

After distributing the weight for true color and grey color, the histogram is updated for both true and grey color by using the formula.

For true color, it Equation (4):

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True color hist [round (distributed hue * Mult_{factor})] = True color hist [round (distributed hue * Mult_{factor})] (4) $SW_{H(S,I)}$

For grey color Equation (5):

 $Grey color hist [round(2\pi^* Mult_{factor})] + 1$ +round(distributed intensity / div_{factor}) = Grey color hist [round(2\pi^* Mult_{factor})] + 1 +round(distributed intensity / div_{factor}) + SW_{I(S,I)}
(5)

Where:

 $\begin{array}{ll} Mult_{factor} = Number \ of \ quantization \ levels \ for \ true \ color \\ Div_{factor} & = Number \ of \ quantization \ levels \ for \ grey \ color \\ SW_{H(S, I)} & = True \ color \ weight \\ SW_{I \ (S, I)} & = Grey \ color \ weight \end{array}$

A typical value for $Mult_{factor}$ is 8 and for Div_{factor} is 16. The updated histogram is the feature for query image. Similarly, the updated histogram is obtained for each image in database and it is stored in the feature database of size 1xn where n is the total number of images in database. The extracted features of query image is compared against the extracted features of database images using multiple similarity measures and the query relevant images are retrieved.

Step 6: Similarity Measure

The similarity between the features of query image and the features of database images is calculated using three distance measures namely, Euclidean Distance (ED), Manhattan Distance (MD) and Bray-Curtis Distance (B-CD).

Euclidean distance is the difference between the set of pixels in each bin of a histogram of one image versus each bin in a histogram of another image. A major advantage of using euclidean distance is that addition of a new image to the database does not affect the distance between query image and the existing database images.

For a 2D image, the distance between two image pixel x and y where, $x = (x_1, x_2)$ and $y = (y_1, y_2)$ is given by Equation (6):

$$D(x,y) = \sqrt{\left(\left(x_{1} - y_{1}\right)^{2} + \left(x_{2} - y_{2}\right)^{2}\right)}$$
(6)

Manhattan distance calculates the similarity from one pixel to the other in a grid-like path. Similarity between two image pixels using manhattan distance is



the summation of the difference of their corresponding pixels Equation (7):

Manhattan distance =
$$\sum |V_{pi} - V_{qi}|$$
 (7)

where, i = 1 to n.

Bray-Curtis Distance is a distance measure to calculate the compositional distinction between the two image pixels. The distance metric for Bray-Curtis is given as Equation (8):

Bray - Curtis =
$$\Sigma((\mathbf{x}_i - \mathbf{y}_i) / (\mathbf{x}_i + \mathbf{y}_i))$$
 (8)

where, i = 1 to n, x_i is the query image and y_i is the image in the database.

4. PERFORMANCE MEASURES

The performace metrics used to calculate the retrieval efficiency of image retrieval system is based on metrics used in information retrieval. The performace measures include precision and recall.

Precision is defined as the ratio of the number of the relevant images retrieved to the total number of images retrieved. Precision is given by Equation (9):

$$Precision = R_r / T_r$$
(9)

Where:

 R_r = Number of relevant images retrieved T_r = Total images retrieved

Recall is defined as the ratio of the number of relevant images retrieved to the total number of the relevant images in the database Equation (10):

$$\operatorname{Recall} = \operatorname{R}_{r} / \operatorname{T}$$
(10)

Where:

 R_r = Number of relevant images retrieved

T = Total number of relevant images in the database

Precision signifies exactness, whereas recall represents completeness. An ideal precision is that every retrieved image is relevant but it does not give any information stating whether all relevant images are retrieved. An ideal recall is that all relevant images are retrieved but it does not provide any details about the number of irrelevant images that might also have been retrieved.

5. IMPLEMENTATION STEPS

The proposed Color Perception Histogram based image retrieval technique has been implemented using MALAB R2010a Image Processing toolbox.

Step 1: Input RGB image

Figure 4a shows the input RGB image. The size of the input RGB image is 256×384. HSV image of RGB image is shown in **Fig. 4b**.

Step 2: Generate Histogram for Query Image

Histogram of hue, saturation and intensity are plotted as a single histogram in **Fig. 5**. Hue, saturation and intensity values are taken in the X-axis and pixel count is taken in the y-axis.

Step 3: Identification of True and Grey Color Pixels

A pixel is considered as true color when the intensity is high and saturation is low. A pixel is considered as grey color when the intensity is low and saturation is high. **Figure 6** true color pixels are represented in white color and its value is set as '1' and Grey color pixels are represented in black color and its value is '0'.

Step 4: Calculation of NBS Distance

NBS distance is calculated for true color pixels using the Equation 3. NBS distance is not calculated for grey color since the color difference is minimum. **Figure 7** shows the NBS distance value based on which weight distribution is done.

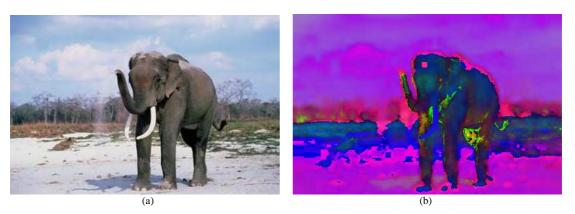


Fig. 4. (a) Query image (b) HSV image

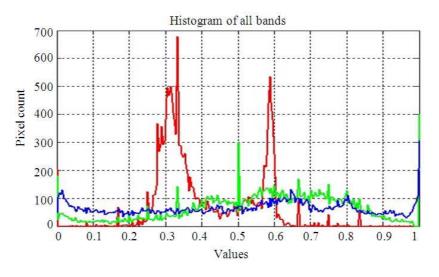


Fig. 5. Histogram of all bands



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Fig. 6. Identification of true and grey color pixel

| | PLOTS | VARIABLE | V | EW | 242.50 | <u>ک</u> | 国人国 | L 2 C | - ? · | • |
|---|--------------|------------|--------|------------|--------|----------|--------|--------|--------|-----|
| S | <128x128 dou | ible> | | | | | | | | _ |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
| 1 | 0 | 0.1149 | 0.0136 | 0.0374 | 0.0478 | 0.0072 | 0.0235 | 0.0235 | 0.0706 | - |
| 2 | 1.7078 | 0.0136 | 0.0103 | 2.2884e-04 | 0.0033 | 0.0101 | 0.0333 | 0.0233 | 0.0466 | |
| 3 | 1.6830 | 0.0103 | 0.0205 | 0.0101 | 0.0271 | 0.0200 | 0.0098 | 0.0462 | 0.0368 | |
| 4 | 1.6545 | 1.1460e-04 | 0.0205 | 0.0376 | 0.0099 | 0.0314 | 0.0098 | 0.0559 | 0.0692 | Ξ., |

Fig. 7. NBS distance value

| F | LOTS | VARIABLE | VIE | w | 242,81 | <u>ک</u> | EL & E | L D C | × 🕄 🖬 | |
|------|--------------|----------|----------|----------|----------|----------|----------|----------|----------|--|
| E SB | H <128x128 d | ouble> | | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
| 1 | 115 | 113.8511 | 114.8635 | 114.6261 | 114.5224 | 114.9281 | 114.7647 | 114.7647 | 114.2941 | |
| 2 | 97.9215 | 114.8637 | 114.8970 | 114.9977 | 114.9666 | 114.8988 | 114.6668 | 114.7670 | 114.5340 | |
| 3 | 98.1703 | 114.8971 | 114.7949 | 114.8991 | 114.7294 | 114.8002 | 114.9017 | 114.5385 | 114.6319 | |
| 4 | 98.4545 | 114.9989 | 114.7949 | 114.6239 | 114.9005 | 114.6856 | 114.9019 | 114,4413 | 114.3077 | |

Fig. 8. True color weight

| | PLOTS | VARIABLE | VIE | EW | | | 國法國 | L D C | 🗢 🕐 🛰 |
|-----|----------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| 🗄 s | BI <128x128 do | uble> | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 1 | -114 | -112.8511 | -113.8635 | -113.6261 | -113.5224 | -113.9281 | -113.7647 | -113.7647 | -113.2941 |
| 2 | -96.9215 | -113.8637 | -113.8970 | -113.9977 | -113.9666 | -113.8988 | -113.6668 | -113.7670 | -113.5340 |
| 3 | -97.1703 | -113.8971 | -113.7949 | -113.8991 | -113.7294 | -113.8002 | -113.9017 | -113.5385 | -113.6319 |
| 4 | -97.4545 | -113.9989 | -113.7949 | -113.6239 | -113,9005 | -113.6856 | -113.9019 | -113,4413 | -113.3077 |

Fig. 9. Grey color weight



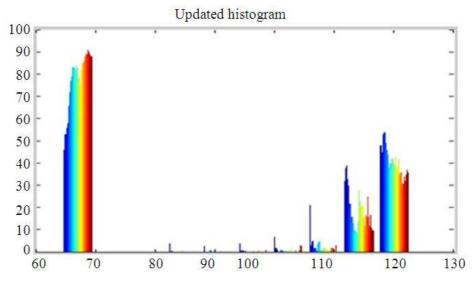


Fig. 10. Updated histogram

Step 5: Weight Calculation

For true color, the weight, WH(S, I) is calculated by using the Equation (1). **Figure 8** shows the true color weight. For grey color, the weight, $W_I(S, I)$ is calculated by using the Equation (2). **Figure 9** shows the Grey color weight. Weights are calculated based on the NBS distance value. The calculated weights are updated in the original histogram to get the updated histogram.

Step 6: Histogram Updation

The histogram is updated for true and grey color components by using the Equation (4 and 5). The updated histogram shown in **Fig. 10** is the extracted feature. The features are extracted for query image and target image. The similarity between the extracted features of query image and extracted features of database image is calculated using Euclidean distance, Manhattan distance and Bray-Curtis distance. Smaller the distance, greater is the likeliness between two images. Larger the distance, greater is the dissimilarity between two images.

6. EXPERIMENTAL RESULTS

Experiments are conducted on Wang databases to calculate the performance of proposed CPH method for image retrieval. Wang's (James *et al.*, 2001)



dataset comprises of 1000 Corel images with ground truth. The image collection in 1000 images is divided to 10 categories with each category comprising of 100 images. Experimental images cover a wealthy of content including people, beach, building, buses, dinosaurs, elephant, flowers, horses, mountains, food. The images are of the size 256×384 . Images in each category are of a similar type with respect to its background and foreground. The proposed technique is implemented using MATLAB R2010a Image Processing Toolbox.

Table 2 shows the top 5 retrieved results for the given query image. It is observed from the results, the retrieved images are relevant to the query image and all the retrieved relevant images fall under the same category as the query image.

The results of Color Perception Histogram (CPH) are compared with normal Color Histogram (CH) for image retrieval using the performance measures, precision and recall.From the result observed in **Table 3-5**, the proposed technique performs better with high precision and higher recall when tested using multiple similarity measures.

Figure 11 shows the precision and recall graph of existing and proposed technique for various distance measures. It is observed from the graph, Euclidean distance based retrieval performs better compared to Manhattan and Bray-Curtis distance.

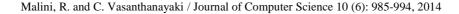


 Table 2. Top 5 retrieved images for a given Query

 Query
 Top 5 retrieved image

 Image: Constraint of the second se

 Table 3. Comparison of precision value

| | Euclidean distance | | Manha distan | | Bray-Curtis distance | |
|---------------|--------------------|------|-----------------|------|----------------------|------|
| Query | | | | | | |
| Image ID | CH | CPH | CH | CPH | CH | CPH |
| 30 | 0.91 | 0.96 | 0.93 | 0.95 | 0.93 | 0.95 |
| 54 | 0.40 | 0.72 | 0.44 | 0.61 | 0.44 | 0.57 |
| 86 | 0.80 | 0.84 | 0.86 | 0.82 | 0.67 | 0.73 |
| 18 | 1.00 | 0.70 | 0.71 | 0.70 | 1.00 | 0.67 |
| 61 | 0.70 | 0.93 | 0.47 | 0.69 | 0.55 | 0.70 |
| Avg. Precisio | n 0.76 | 0.83 | 0.68 | 0.75 | 0.71 | 0.72 |

Table 4. Comparison of recall value

| | | Euclidean Distance | | ttan ce | Bray-Curtis Distance | |
|-------------|------|-----------------------|------|------------|-------------------------|------|
| Query | | | | | | |
| Image ID | CH | CPH | CH | CPH | CH | CPH |
| 30 | 0.42 | 0.43 | 0.40 | 0.42 | 0.40 | 0.34 |
| 54 | 0.17 | 0.25 | 0.15 | 0.20 | 0.15 | 0.20 |
| 86 | 0.27 | 0.37 | 0.27 | 0.37 | 0.27 | 0.37 |
| 18 | 0.07 | 0.35 | 0.10 | 0.24 | 0.07 | 0.30 |
| 61 | 0.07 | 0.42 | 0.10 | 0.32 | 0.07 | 0.42 |
| Avg. Recall | 0.2 | 0.37 | 0.20 | 0.31 | 0.19 | 0.32 |

| Table 5. Co | Table 5. Comparison of query execution time | | | | | | | | | |
|-------------|---|------|--------|-------|---------|-------|--|--|--|--|
| | Euclide | ean | Manha | attan | Bray Cu | urtis | | | | |
| | Distanc | e | Distan | ce | Distanc | e | | | | |
| Query | | | | | | | | | | |
| Image ID | CH | CPH | CH | CPH | CH | CPH | | | | |
| 30 | 18.1 | 20.0 | 31.6 | 31.6 | 36.0 | 31.6 | | | | |
| 54 | 16.4 | 15.3 | 28.2 | 28.2 | 40.0 | 43.1 | | | | |
| 86 | 19.6 | 19.1 | 31.6 | 31.6 | 32.1 | 32.0 | | | | |
| 18 | 11.9 | 12.9 | 18.2 | 18.2 | 22.6 | 24.1 | | | | |
| 61 | 13.6 | 15.6 | 24.9 | 24.9 | 28.6 | 27.9 | | | | |
| Avg. Time | 15.9 | 16.6 | 26.9 | 26.9 | 31.9 | 31.7 | | | | |

Figure 12 shows the top 20 retrieved images from a 1000 image database for the given query image using Euclidean distance. It is observed from the existing results the proposed color perception histogram using Euclidean distance gives better results with high precision and recall.



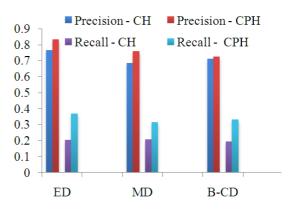


Fig. 11. Precision and Recall crossover

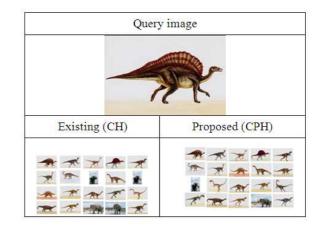


Fig. 12. Top 20 retrieved images from 1000 image database

7. CONCLUSION

Image retrieval is an actively growing research area in the field of image processing, pattern recognition and computer vision. A new and efficient CBIR technique using Color Perception Histogram is proposed. In the proposed technique, the color pixels are extracted and based on the calculated NBS distance, the weights are distributed to get an updated histogram which is used as an image feature. The proposed algorithm is tested using multiple similarity measures and the results are compared. Experimental results indicate the proposed color perception histogram technique using Euclidean distance yields better results with high average precision and recall and with reduced query execution time.

In the proposed work, only the color feature and its distribution information is used for effective retrieval. However, further increase in the iterations, will certainly improve the retrieval results with high precision and recall rate. For future work, it is planned to improve the rate of retrieval by adding more iterations and adding extra features such as texture and shape with the color to improve the relevance. Also the proposed work has to be evaluated for robustness on various databases.

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