

IMAGE RETRIEVAL USING SUM OF HISTOGRAM BINS AS A COLOR FEATURE

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Abstract— The large amount of image collections available from a variety of sources have posed increasing technical challenges to computer systems to store/transmit and index/manage the image data to make such collections easily accessible. Here to search and retrieve the expected images from the database we need Content Based Image Retrieval (CBIR) system. CBIR extracts the features of query image and try to match them with the extracted features of images in the database. Then based on the similarity measures and threshold the best possible candidate matches are given as result. This paper describe a novel & effective approach to content based image retrieval that represent each image in database by a vector of feature values called “Image Retrieval using Histogram Bins Color Feature”. Proposed method is a simple and new which can be easily implemented in a programming language. In this technique sum of value of histogram bins used as a feature vector of image. This classifier is well suitable for features extracted and fast in computation for CBIR systems. Three color planes and two distance measures are used to compare the result. Simple Euclidean Distance and Bray Curtis Distance are used to compute the similarity measures of images for Content Based Image Retrieval application. This technique gives acceptable results in a simple and fast way.

Keywords- Content Based Image Retrieval(CBIR), Histogram, Euclidean Distance(ED), Bray Curtis Distance(BCD), Histogram bins, Precision, Recall, Overall Average Precision, Overall Average Recall.

I. INTRODUCTION

Content Based Image Retrieval (CBIR) attracted many researchers of various fields in effort to automate data analysis and indexing. CBIR is like filter information process and it is used to provide a high percentage of relevant images in response to the query image. The goal of an image retrieval system is to retrieve a set of images from a collection of images such that this set meets the user's requirements. The user's requirements can be specified in terms of similarity to some other image or a sketch, or in terms of keywords. An image retrieval system provides the user with a way to access, browse and retrieve efficiently and possibly in real time form these databases [7,5,9]. Well-developed and popular international standards, on image coding have also long been available and widely used in many applications. The challenge to image indexing/management is studied in the context of image database, which has also been actively researched by researchers from a wide range of disciplines including those from computer vision, image processing, and traditional database areas for over a decade. Image retrieval systems can be divided into two main types: Text Based Image Retrieval and Content Based Image Retrieval. In the early years Text Based Image Retrieval was popular, but nowadays Content Based Image Retrieval has been a topic of intensive research in the recent years [10]. Text Based Image Retrieval is the traditional image retrieval system. In traditional retrieval systems features are added by adding text strings describing the content of an image. In contrast to text, images just consist of pure pixel data with no inherent meaning. Commercial image catalogues therefore use manual annotation and rely on text retrieval techniques for searching particular images. However, such an annotation has three major drawbacks. First, the annotation

depends on the person who adds it. User's perceptions of images vary to a large extent and different users may perceive different meanings from the same image. Even if the two users do have the same perception of an image, they may use different keywords to annotate the image, depending on the individual vocabularies. Naturally the result may vary from person to person and furthermore may depend on the context. The second drawback with manual annotation is that it is very time consuming. While it may be worthwhile for commercial image collections, it is prohibitive for indexing of images within the World Wide Web. One could not even keep up with the growth of available image data. Third drawback is that the user of a Text Based Image Retrieval must describe an image using nearly the same keywords that were used by the annotator in order to retrieve that image. Due to all these drawbacks, Content Based Image Retrieval is introduced [16].

A Content Based Image Retrieval (CBIR) is an interface between a high level system (the human brain) and a low level system (a computer). The human brain is capable of performing complex visual perception, but is limited in speed while a computer is capable of limited visual capabilities at much higher speeds. In a CBIR, features are used to represent the image content. The features are extracted automatically and there is no manual intervention, thus eliminating the dependency on humans in the feature extraction stage. These automated approaches to object recognition are computationally expensive, difficult and tend to be domain specific.

Recent Content Based Image Retrieval research tries to combine both of these above mentioned approaches (Text Based Image Retrieval and Content Based Image Retrieval) and has developed efficient image representations and data models, query-processing algorithms, intelligent query interfaces and domain-independent system architecture. The typical CBIR system performs two major tasks as shown in Fig. 1. The first one is feature extraction (FE), where a set of features called image signature or feature vector is generated to accurately represent the content of each image in the database.

A feature vector is much smaller in size than the original image, typically of the order of hundreds of elements (rather than millions). The second task is similarity measurement (SM), where a distance between the query image and each image in the database using their signatures is computed so that the top "closest" images can be retrieved [3], [9], [10], [8]. Finding good similarity measures between images based on some feature set is a difficult.

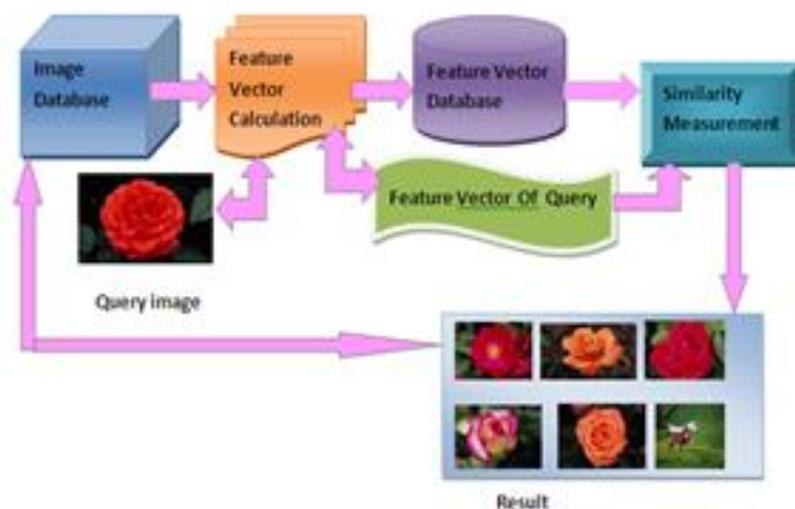


Figure 1. Content Based Image Retrieval System.

Also these similarity functions should be designed to match with human perception, but how humans judge the similarity between images is a topic of ongoing research. Many current retrieval systems take a simple approach by using typically norm-based distances (e.g. Euclidean distance) on the extracted feature set as a similarity function.

Features that can be extracted from an image are color, shape & texture.

A. Color

Color is a very important feature in aerial RS image and other single band image. Histogram is the major tool to express color feature .RGB (Red, Green and Blue) color system is usually used to express colorful image.

B. Shape

Shape is also important image content used in retrieval. The primary mechanisms used for shape retrieval include identification of features such as lines, boundaries, aspect ratio, and circularity and by identifying areas of change or stability via region growing and edge detection.

C. Texture

Texture is a difficult concept to represent. The identification of specific textures in an image is achieved primarily by modeling texture as two-dimensional grey level 4 variations. The relative brightness of pairs of pixels is computed such that degree of contrast, regularity, coarseness and directionality may be estimated.

II. CBIR APPLICATION

A wide range of possible applications for CBIR technology has been identified like geographic information systems, weather forecast , medical imaging , criminal investigations, picture archiving and retrieval , general database maintenance such as removal of duplicates, video archiving and access , image search on the internet , fashion design and advertising, trademark databases , art galleries, museums, archaeology, architecture/engineering design (technical drawings), colorization of grayscale images, panoramic view generation .

Many of these application areas force several restrictions on the type of image data, for priori knowledge based image retrieval. For the retrieval of general image data, no priori knowledge can be identified. Hence, a visual appearance based similarity criterion is decisive. As stated before, image retrieval covers many different fields of research.

This paper organized in the following sections: Section III, review of histogram based image retrieval. Section IV proposed algorithm feature extraction. Experimental results are given in Section V. Finally Section VI is devoted to concluding the remarks.

III. REVIEW OF HISTOGRAM BASED IMAGE RETRIEVAL

Color is independent of image size and orientation, because, it is robust to background complication. Color histogram is the most common technique for extracting the color features of colored images [27, 35]. Color histogram tells the global distribution of colors in the images. It involves low computation cost and it is insensitive to small variations in the image structure. However, color histogram hold two major shortcomings. They are unable to fully accommodate the spatial information, and they are not unique and robust. Two dissimilar images with similar color distribution produce very similar histograms. Moreover, similar images of same point of view carrying different lighting conditions create dissimilar histograms. The proposed methods strive for a light weight computation with effective feature extraction. Digital images undergo the following process in order to produce an effective feature vector describing an eminent feature set targeted to avoid the lack of robustness of a common histogram. The given image histogram split into sixteen fixed bins in order to extract more distinct information from it [29, 30, 32, 33]. The key issue of histogram-based techniques is the selection of an appropriate color space and the quantization of the selected color space. The frequencies of 256 values of each color planes are split into sixteen bins carrying 16 values each (0-15, 16-31, 32-47, 48-63, and so on). Thus 16 bins are obtained for each color plane. This is done by turning off the color values of image which do not lie between all other 15 bins. This gives 16 images, carrying objects which lie in the specific frequency ranges, and all different from each other. This provides a better illustration of image segments and simplifies the computation of features for the distinct portion of image. An example of the mechanism is shown in

Fig. 1.2 and 1.3, in which image is selected randomly. It shows the distribution of frequencies only for four bins.



Figure 1.2 Image selected at random as a sample.

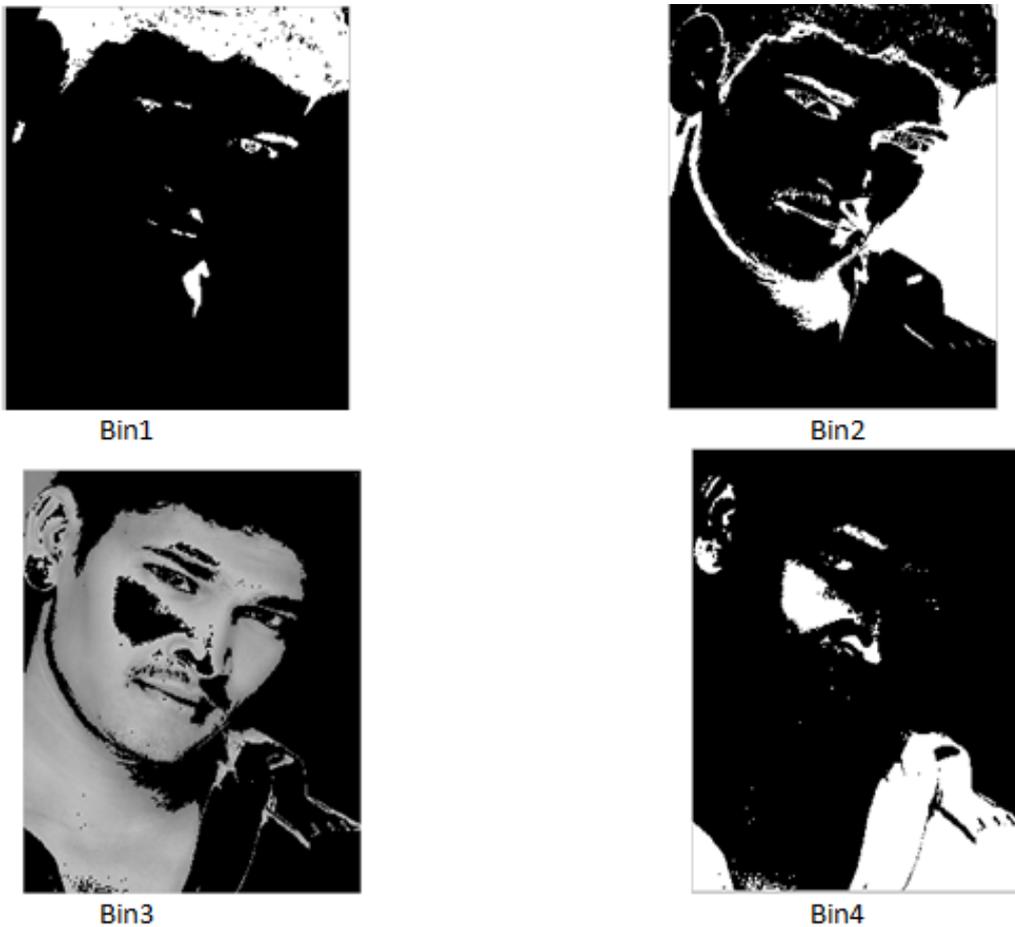


Figure 1.3 Bins generation from the image.

IV. PROPOSED ALGORITHM FEATURE EXTRACTION

Here feature extraction steps are explained for the RGB color space, the same steps are followed for YCbCr color space also and on single gray scale image.

1. To compute feature vector from each color plane red, green and blue planes are separated as shown in Fig.1.4.
2. Plot histogram of each plane, which is having 256 bin values for red, green and blue plane.
3. The histogram of given image are split into 16 fixed bins in order to extract more distinct information from it. The frequencies of 256 values of red, green and blue color are split into sixteen (16) bins carrying 16 values each color space as shown in table 3.1

Table 1.1 Sum of the values listed against bins.

Bin#	1	2	3	4	5	6	16
Sum	121	177	19	5	67	77	123

5. Thus 16 bin sum values for red plane, 16 bin sums values for green plane and 16 bin sum values for blue plane are obtained. So feature vector has size of 48. The feature vector database for gray scale, RGB color space and YCbCr color space is prepared as mentioned above.



Figure 1.4 Red, green and blue color plane.

V. EXPERIMENTAL RESULTS

When a query image is submitted by a user, we need to compute the feature vector as before and match it to the precomputed feature vector in the database. This is shown in Figure 1.5. block diagram of retrieval process consists of feature extraction process, feature vector storage process and similarity measure process . The feature extraction process is based upon the following .Which the batch feature extraction and storage process as described in the following steps.

- Images taken one by one from the database.
- Feature is computed using the feature extraction process.
- Make feature vector database for given database images.

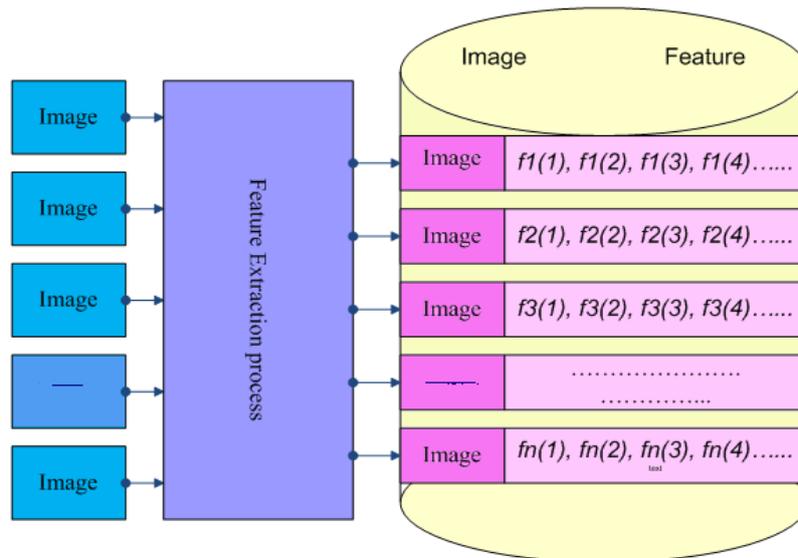


Figure.1.5 Feature extraction and storage process for an image collection

After that query image and database image matching is done using similarity measures. In this paper two similarity measures are used Euclidean Distance(ED) and Bray Curtis Distance (BCD) for the comparison. Minkowski (Euclidean distance when $r=2$) distance is computed between each database image & query image on feature vector to find set of images falling in the class of query image.

$$Ed(Q, I) = \left(\sum_{M=0}^{M-1} |H_Q - H_I|^r \right)^{1/r} \quad (1)$$

- Where
- Q-Query image
 - I- Database image.
 - H_Q -Feature vector query image.
 - H_I -Feature vector for database image.
 - M-Total no of component in feature vector.

Bray Curtis Distance is computed between query image and database image using equation.2

$$Bd(Q, I) = \frac{\sum_{k=1}^n |H_{Qk} - H_{Ik}|}{\sum_{k=1}^n (H_{Qk} + H_{Ik})} \quad (2)$$

- Where
- n-Total no of component in feature vector.
 - Q-Query image
 - I- Database image.
 - H_{Qk} -Feature vector query image.
 - H_{Ik} -Feature vector for database image.

A. Performance of CBIR

Performance of image retrieval system can be analyzed by using two parameters precision and recall. As shown in Figure 1.6. Testing the effectiveness of the image search engine is about testing how well can the search engine retrieve similar images to the query image and how well the system prevents the return results that are not relevant to the source at all in the user point of view. A sample query image must be selected from one of the image category in the database. When the search engine is run and the result images are returned, the user needs to count how many images are returned and how many of the returned images are similar to the query image. The first measure is called Recall. All the relevant images from the database is recall. The equation for calculating recall is given below:

$$\text{Recall} = \frac{\text{Number_of_relevant_images_retrived}(A)}{\text{Total_number_of_relevant_images_in_database}(A+D)} \quad (3)$$

The second measure is called Precision. It is accuracy of a retrieval system to present relevant as well as non relevant images from the database which is mathematically given as:

$$\text{Precision} = \frac{\text{Number_of_relevant_images_retrived}(A)}{\text{Total_number_of_images_retrived}(A+B)} \quad (4)$$

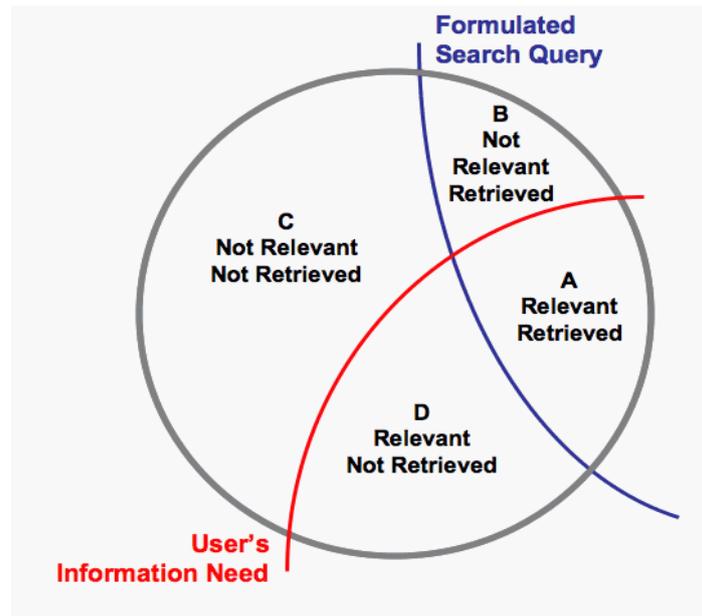


Figure 1.6. Evaluation of CBIR

B. Implementation and Result

The implementation of CBIR technique is done in MATLAB 7.0 using a computer with Intel Core 2 Duo Processor T8100 (2.1GHz) and 2 GB RAM. We have tested performance with a general purpose image database that consist of 1200 with 15 categories some from Corel Image Gallery. Some sample images from of general database by randomly selecting one image from each category is shown in Figure 1.7 Categories and total no of images are given below.

Table 1.2 Image Categories and Number of Images

Name of Category	Motorbikes	Beaches	Historical Mountains	Buses	Dinosaurs
No. of Images	100	100	100	100	100
Name of Category	Elephants	Flowers	Horses	Tribal Peoples	Mountains
No. of Images	100	100	100	68	62
Name of Category	Flying Birds	Flower lawn	sunset	Butterfly Scenery	Guitar
No. of Images	63	48	48	52	59

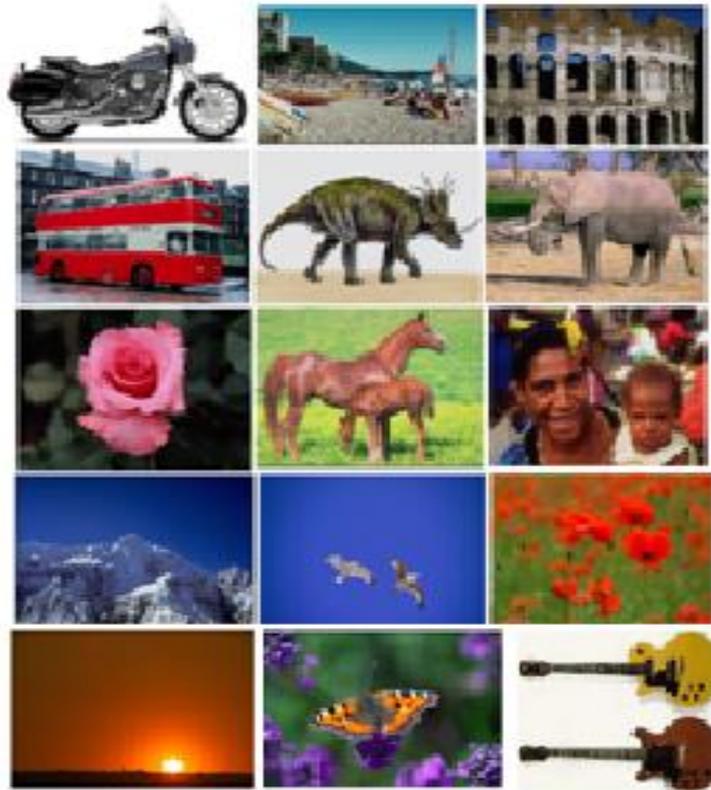


Figure 1.7 Sample images from database.

The average precision is calculating by using following equation 5, 6. The average precision for images belonging to the qth category (A_q) has been computed by:

$$\bar{P}_q = \sum_{k \in A_q} P(I_k) / |A_q|, q=1,2,\dots,5 \quad (5)$$

Where $P(I_k)$ is the precision for query image I_k .

Finally, the average precision is given by:

$$\bar{P} = \sum_{q=1}^5 \bar{P}_q / 5 \quad (6)$$

The average recall is also calculated in the same manner. The average precision and average recall of this CBIR technique act as a important parameter to find out performance. To determine which method and which colour space have better performance.

The proposed approach tested on the augmented Wang database [32] which includes 1200 different size images spread over 15 different category. 75 query images (5 from each class) are fired on the database and similarity matching is done by using ED and BCD measure. The average precision and average recall values are computed by grouping the number of retrieved images sorted according to ascending distances with the query image.

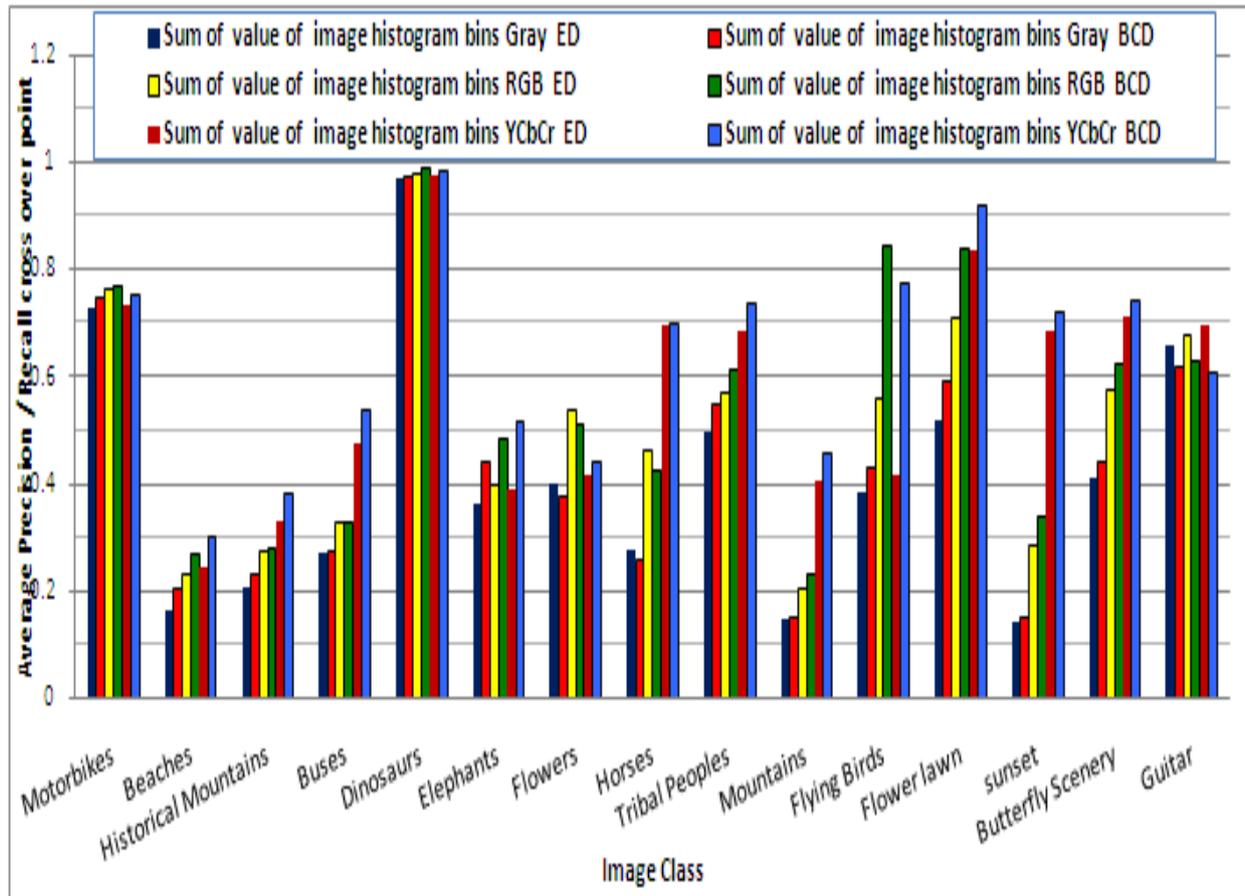


Figure 1.8 Comparisons of average precision and recall crossover points for (a) sum of the value of image histogram bins.

Average precision and recall crossover points performance of proposed methods plotted against the each class of image with the two similarity measures as shown in Fig.1.8. It is observed that in sum of the value of image histogram bins approach motorbikes, dinosaurs, flower lawn and guitar image classes performances are greater than 50% for both the similarities. Dinosaur image class performance is highest performance for these three color spaces. In Fig.1.9. (a) beaches, historical mountains, sunset, mountain image classes performances are below 30% for RGB color space and gray color space. On the other hand, YCbCr color space performances are slightly greater for the same classes. Elephants, flowers, horses, tribal people, flying birds and butterfly scenery image classes performances are average and it is above 40%. Beaches, historical mountain, mountain images have number of random color intensity at different location. In these image classes more number of images background and foreground color intensities are not different. Therefore, these image classes performances are poor.

Table 1.3 Overall average precision and recall crossover points for Sum of the Value of Histogram Bins and Equalized Histogram Image Bins.

Feature vector computation method	Color Image	Overall average precision/recall cross over points	
		ED similarity measure	BCD similarity measure
Sum of the Value of Image Histogram Bins	Gray	0.3949	0.41796
	RGB	0.4776	0.52185
	YCbCr	0.5571	0.6126

Table 1.2 shows the overall average precision and recall crossover points for gray scale, RGB and YCbCr color space using both the similarity measures. It is observed that for these approaches, YCbCr color plane performance is highest and it is above 61% using BCD similarity for sum of the

values of image histogram bins. For gray color space, it is above 41 % , for RGB color space it is above 52%. BCD similarity performing better than the ED similarity.

VI. CONCLUSION

The paper has presented a new simple and efficient image retrieval approach using Histogram Bins. Two similarity measures and three color planes are used to evaluate the performance of proposed approach. Feature vector is considered as a sum of the value of histogram 16 bins of each color plane. YCbCr outperform RGB color image by 0.903 in overall average precision using BCD similarity. Bray Curtis Distance similarity outperform than Euclidean Distance similarity.

REFERENCES

- [1]M. K. Mandal, T. Aboulnasr, and S. Panchanathan,, "Image Indexing Using Moments and Wavelets", IEEE Transactions on Consumer Electronics, Vol. 42, No. 3, August 1996.
- [2]S. A. Dudani, K. J. Breeding, and R. B. McGhee,,"Aircraft identification by moment invariants.",IEEE Trans. on Computers, C-26(1):pp. 39-46, 1977.
- [3] H.B.Kekare, V.A.Bharadi, "Walsh Coefficients of the Horizontal & Vertical Pixel Distributions of Signature Template", SP-37, National Conference on Communication & signal processing, NCCSP-07, Thadomal Shahani Engg. College, Bandra (E), 51.
- [4]A. Khotanzad and Y. H. Hongs. , "Invariant image recognition by Zernike moments." IEEE Trans. on Pattern Analysis and Machine Intelligence, 12(5):pp. 489-497, 1990.
- [5]C. Teh and R. T. Chin., "On image analysis by the method of moments", IEEE Trans. on Pattern Analysis and Machine Intelligence, 10(4):pp. 496-513, 1988.
- [6]J. J. Li., J. Z. Wang, G. Wiederhold, "SIMPLIcity: semantic sensitive integrated matching for picture libraries," IEEE Trans. Pattern Anal. Machine Intelligence, 23(9):947-963, Sep. 2001.
- [7]T. Hamano, "A similarity retrieval method for image databases using simple graphics," Proc. of IEEE Workshop on Languages for Automation, Symbiotic and Intelligent Robotics, pp. 149-154, University of Maryland, August 29-33, 1988.
- [8]Long Wen Chang, and Ching Yang Wang, 1999, "Image Compression Using Optimal Variable Block Truncation Coding, Multimedia Signal Processing", IEEE 3rd Workshop on, 1999, pp. 413-418, 1999.
- [9]Mohamed Kamel, Sun C. T., and Lian Guan, "Image Compression by Variable Block Truncation Coding with Optimal Threshold", IEEE Transactions on Signal Processing. Vol. 39, No. 1, pp. 208-212, 1991.
- [10]Kai-Krung Ma, and Sarah A. Rajala, 1991, Sub band Coding of Digital Images Using Absolute Moment Block Truncation, IEEE Transactions on Acoustics, Speech, and Signal Processing, 1991. ICASSP-91., International Conference on, 1991 Vol. 4, pp. 2645-2648.
- [11]Guoping Qiu, "Colour Image Indexing Using BTC", IEEE Transition on Image Processing, vol. 12, January 2003.
- [12]H. J Bae & S. H Jung, "Image retrieval using texture based on DCT," IEEE Int. Conf. on Information, Communication and Signal Processing, ICIC'97, Singapore, 9-12 September 1997.
- [13]J. A. Lay and L. Guan, "Image Retrieval Based on Energy Histograms of the Low Frequency DCT Coefficients," IEEE International Conference on Acoustics, Speech and Signal Processing, 1999, vol. 6, pp. 3009-3012.
- [14]M. Shneier & M. Abdel mottaleb, "Exploiting the JPEG compression Scheme for image Retrieval," IEEE Trans. On Pattern analysis and Machine Intelligence, August1996, vol. 8, n° 8.
- [15]B. M. Mehtre, M. S. Kankanhalli, A. D. Nasasunhalu and G. C. Man, "Color marching for image retrieval," Pattern Recognition Letters, March 1995, vol. 16, pp. 325-331. Proceedings of the 2005 5th International Conference on Intelligent Systems Design and Applications (ISDA'05) 0-7695-2286-06/05 \$20.00 © 2005 IEEE.
- [16]Rajashekhara, "Novel Image Retrieval Techniques: domain specific approaches," Ph.D. Thesis Department of Electrical Engineering Indian Institute of Technology – Bombay, Mumbai, 2006.
- [17]C. Liu & M. Mandal, "Image Indexing in the JPEG2000 Framework," In Proc. of the SPIE, Boston - USA, Nov. 5-8 2000, vol. 4210, pp. 272-280.
- [18]E. Albuz & E. Kocalar, "Scalable color image indexing and retrieval using vector wavelets," IEEE Tran. On Knowledge and data engineering, September 2001, vol. 13,n° 5, pp. 851-861.
- [19]Ordóñez J, Cazuguel G, Puentes & J, Solaima, "Medical image indexing and compression based on vector quantization: image retrieval efficiency evaluation," 23rd Conference of the IEEE Engineering in Medicine and Biology Society, 2001.
- [20]J. R. Ordóñez, G. Cazuguel, & J. Puentes, "Spatialtextural medical image indexing based on vector quantization," 25th annual conference of the IEEE EMBS, Cancun Mexico, 17-21 September 2003.
- [21]J. R. Smith and & F. Chang, "Transform features for texture classification and discrimination in large image databases," Proc. of IEEE Inti. Conf on image Processing, 1994, vol. 3, pp. 407-411.
- [22]R. Reeves, K. Kubik and W. Osberger, "Texture characterization of compressed aerial images using DCT coefficients," Proc. Of SPIE: Storage and Retrieval for image and Video Databases V, Feb 1997, vol. 3022, pp. 398-407.

- [23]M. Shneie and M. A. Mottaleb, "Exploiting the JPEG compression scheme for image retrieval," IEEE Trans on Pattern Analysis and Machine intelligence, August 1996 vol. 18, n°. 8, pp. 849-853.
- [24]A. A. Abdel-Malek and J. E. Hershey, "Feature cueing in the discrete cosine domain," Journal of Electronic Imaging, Jan. 1994, vol. 3, pp. 71-80.
- [25]B. Shen and I. K. Sethi, "Direct feature extraction from compressed images," Proc. Of SPIE, 1996, vol. 2670, pp. 404– 414.
- [26]NST Sai, Ravindra patil , "Average Row and Column Vector Wavelet Transform for CBIR", Second international conference on Advance in Computer Vision and Information Technology (ACVIT2009),Aurangabad, India.
- [27]NST Sai, Ravindra patil , "New Feature Vector for Image Retrieval Walsh Coefficients", Second international conference on Advance in Computer Vision and Information Technology (ACVIT2009),Aurangabad, India.
- [28]NST Sai, Ravindra patil , "Image Retrieval using DCT Coefficients of Pixel Distribution and Average Value of row and Column Vector "IEEE International Conference on Recent Trends in Information ,Telecommunication and Computing(ITC2009),Kochi, Kerala, India.
- [29]NST Sai, Ravindra patil, " Moments of Pixel Distribution of CBIR" International Conference and Workshops on Emerging Trends in Technology (ICWET2010),Mumbai, India.
- [30]Danqing Zhang, Binh Pham and Yuefeng Li, " Modelling Traditional Chinese Paintings for Content-Based Image Classification and Retrieval", Proceedings of the 10th International Multimedia Modelling Conference (MMM'04), 0-7695-2084-7/04 IEEE -2000.
- [31]Zhang Lei, Lin Fuzong, Zhang Bo, "A CBIR a Method Based on the Color Spatial", Proceeding of the IEEE region 10 conferences 1999 .
- [32][http://wang.ist.psu.edu/docs/related/Image.orig ..](http://wang.ist.psu.edu/docs/related/Image.orig..)
- [33]Juan José de Dios Narciso García , "Face Detection Based on a New Color Space YCgCr"0-7803-7750-8/03/\$17.00 ©2003 IEEE. ICIP 2003.
- [34]NST Sai, Ravindra patil , "Image Retrieval using Bit-plane Pixel Distribution", International Journal of Computer Science and Technology. International Journal of Computer Science & Information Technology (IJCSIT), Vol 3, No 3, June 2011.
- [35]NST Sai, Ravindra patil , "Image Retrieval using Entropy", International Journal of Computer Applications (0975 – 8887) Volume 24– No.8, June 2011 .
- [36]H. C. Andrews and C. L. Patterson, "Singular Value Decomposition (SVD) Image Coding," IEEE Transactions on Communications, 24(4), April 1976, pp. 425-432.
- [37]D. V. S. Chandra, "Digital Image Watermarking Using Singular Value Decomposition," Proceedings of 45th IEEE Midwest Symposium on Circuits and Systems, Tulsa, OK, August 2002, pp. 264-267.
- [38]Ben Arnold, "An Investigation into using Singular Value Decomposition as a method of Image Compression", University of Canterbury Department of Mathematics and Statistics.

