



Color Histogram based Image Retrieval – A Survey

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Abstract: Content Based Image Retrieval (CBIR) is an active research area in the field of digital image processing. In Content Based Image Retrieval, images would be described by their visual content comprising of low level feature extraction such as color, texture, shape, edge and size. Representation of visual features and similarity match are important issues in CBIR. Color feature is one of the most widely used low level features. Compared with shape feature and texture feature, color feature shows better stability and is more insensitive to the rotation and zoom of image. Color not only adds beauty to objects but also records more information in particular color histogram for retrieve. Hence it can be used as powerful tool in content-based image retrieval. This paper provides a brief survey of CBIR using color feature in particular as it is the effective feature to express visual information, which is invariant on complexity. The different methods adopted to compare similarity of images have been briefed in addition to the discussion of commonly used color models and performance measures for CBIR.

Keywords: CBIR, Color Models, Color Features, Similarity Measures, Performance Measure.

I. INTRODUCTION

Advances in computer and network technologies are increasing exponentially and the collection of image database is huge in number. Many disciplines and segments in industry including telecommunications, entertainment, medicine and surveillance, need high performance image retrieval systems to function efficiently. Generally different categories of methods for image retrieval are used: Text-based [1], Content-based [2][3][4][5][6][7], Semantic-based, region-based, Object-oriented based and Sketch based image retrieval.

Information Retrieval [53] was proposed by Calvin Moores in 1951. It is a process that organizes and stores information in a specific way, in accordance with the needs of users to find the interrelated information. Retrieval at this stage is based on text of the document. Text-Based Image Retrieval is to establish a relation between a annotated keyword, text description, file names, category-wise descriptors, manual descriptions and other related captions. Text-Based Image Retrieval has limitations. Visual search by text are ineffective on images. Textual Information is linear while image is bi-directional and three dimensional. Brahmi et al. mentioned manual image annotation is time-consuming and costly. Human annotation is subjective. In addition, Scar off et al. indicates that some images could not be annotated because it is difficult to describe their content with words.

In order to overcome these problems, Content-Based Image Retrieval was proposed in the 90's. Fast retrieval of images from large databases is an important problem that needs to be addressed. High retrieval efficiency and less

computational complexity are the desired characteristics of CBIR systems [8][14][36][54]. Classical CBIR Techniques are based on two types of visual features: Global and Local features. Image indexed by their visual content such as Color, Texture, Shape, Edge, Size, Spatial Layout etc [55] are retrieved by these low-level features are also termed as Global features, where as local features are based on key points or salient patches which involve domain knowledge on complex inference procedures. To reduce the 'Semantic Gap' between the low level image features and High level semantics, several technique namely supervised and unsupervised, Machine Learning Technique, Support Vector Machine, Principal Component Analysis, Markov-models, Self-organizing Maps, Binary Decision Tree, Semantic Cluster Matrix, Object Ontology, Relevance Feedback Mechanism, Affinity Matrix have been used. These conventional approaches for image retrieval are based on the computation of the similarity between the feature extracted and compared to the features of users query and image database. Retrieval has two processes: feature extraction and feature matching [9][14][15][32]. Compared with texture and shape information, the color feature is widely used visual feature in image retrieval since it is easier to extract. A typical Content Based Retrieval System is shown in Fig 1.

Name of Data Set	Number of Images	Types of Images	Donor and Year
COREL	68,040	Animals, Outdoor Sports, People, Flowers, Natural Scenery Image.	Kriengkrai Porkaew and Sharad Mehrotra ,1999. http://archive.ics.uci.edu
Caltech	101 Different Object categories	CUB-200, Pedestrian Database, Natural Scenery Image, Home Objects, Giuseppe toys, Web Faces, 3D Objects on Turntable, Cars, Motorcycles, Airplanes etc.	Fei-Fei Li, Marco Andreetto, and Marc 'Aurelio Ranzato. 2003 http://www.vision.caltech.edu
Oliva	2600	Natural Scenery Image	Aude Oliva, Antonio Torralba ,2001 http://cvcl.mit.edu/
SIVAL	25 different image category	Objects and Natural Scenery	Hui Zhang, Saint Louis,2007 http://www.cs.wustl.edu
Vistex data set A	384 Texture Image	Texture Database	Media Lab,2002 ,Ref http://vismod.media.mit.edu
Vistex data set B	832 Small Image	Texture Database	Media Lab,2002 ,Ref http://vismod.media.mit.edu
Outex	320 surface textures, both macro textures and micro textures.	Texture Database	Ojala T, Mäenpää T, Pietikäinen M, Viertola J, Kyllönen J & Huovinen S,2002 http://www.outex.oulu.fi
Brodatz	154	Texture Database	USC-SIPI image database research Group ,1981 http://sipi.usc.edu/database
Meastex	19139	Texture Database	Guy Smith's ,Ian Burns ,1997 http://www.cssip.elec.uq.edu.au/~guy/meastex/meastex.html
ImageCLEFmed	300,000	Medical Database	medGIFT group,2004 http://imageclef.org http://medgift.hevs.ch
MNIST,Pendigit,O ptdigit,Statlog	60,000	Handwritten Characters ,Digits	Yann LeCun, Corinna Cortes, Christopher J.C. Burges, 1998

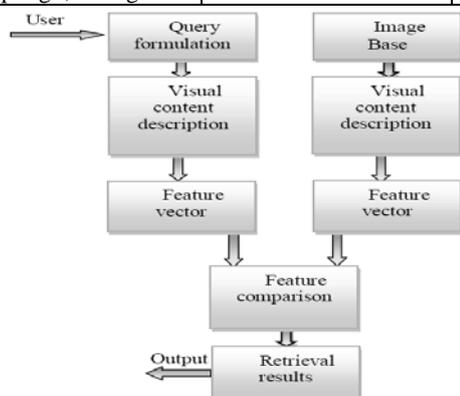


Fig 1: A Frame work of a CBIR System [10]

Region-based Image Retrieval Systems (RBIR) have proven to be more efficient in terms of comparing images based on individual region-to-region similarity. Object Oriented Based Image Retrieval (OOBIR) provides a qualitative definition of the high level query concepts where images are categorized with keywords consisting of total description of an Image based on Knowledge [56]. Semantic-based Image Retrieval (SBIR) is a technique evolved for reducing the semantic gap between low level image feature and high level semantics. Sketch based Image Retrieval (SKBIR) was introduced in QBIC [57] and Visual SEEK systems. In Sketch-based image retrieval the user draws color sketches and blobs on the drawing area. Sketch based image retrieval systems are typically driven by queries comprising blobs of color or predefined texture [60][61], which are augmented with shape descriptors [9] and spectral descriptors such as wavelets [62]. An important design feature for any descriptor based retrieval system is that the distance metric in feature space correlates with perceptual similarity.

The CBIR has been used in various fields including art galleries, museum management, architectural, engineering design, interior design, remote sensing and management of earth resources, geographic information systems, scientific database management, weather forecasting, retail, fabric and fashion design, trademark and copyright database management, law enforcement and criminal investigation, picture archiving and communication systems, press agencies, medical analysis, training and education, industrial quality control [6][25][26][35][41][42][46][47].

Commonly available datasets for CBIR are summarized in below Table 1.

This paper is organized as follows: Various color models are represented in Section 2. Color features are outlined in Section 3. The various popular distance measures are discussed in Section 4. Performance Measures is briefed in

Table 1: Commonly used datasets in CBIR research area Section 5. Finally the conclusions of literature survey is presented in Section 6.

II. COLOR MODELS

Color model describes colors in a formal way according to a certain specification. Usually color models represent a color in the form of tuples (generally of three). For example, according to RGB (Red, Green, Blue), white color is represented by the tuple (0, 0, 0) and the black color is represented by (255,255,255). The purpose of a color model is to facilitate the specification of colors in a certain way and common standard [17]. Color models lend themselves to (in principle) reproducible representations of color, particularly in digital representations, such as digital printing or digital electronic display [18]. The commonly used color model namely RGB, HSV, CIE XYZ, YCbCr, $L^*a^*b^*$ models.

A. RGB Model

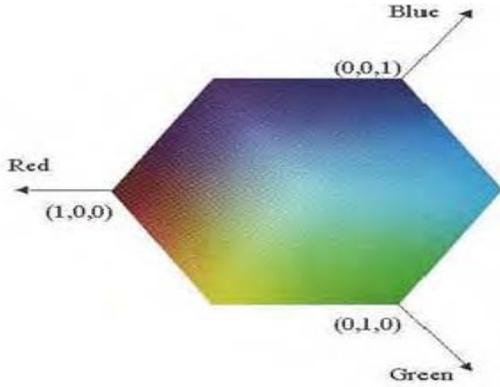


Fig 2. RGB coordinate system where the “x” axis represents red colors, “y” axis represents green colors and “z” represents blue colors [21]. As this figure shows changing the values of RGB component can form a new color.

RGB is the acronym for Red, Blue and Green. This model is the most used color model in computer graphics and it uses its red, green and blue components to create a new color [19]. To form a new color it is necessary to increase the values of one or more of the components of the RGB components [20]. The RGB model provides a useful starting point for representing color features of images. However, the RGB color model is not perceptually uniform [21]. RGB Model illustrated in Figure 2.

B. HSV Model

HSV color model is the acronym of Hue, Saturation and Value; this color model is the closest perception of the human eye. The human eye perceives colors by the excitation of two cells of the eye, which are rods and cones [22]. The HSV color model separates the luminance component (Intensity) of a pixel color from its chrominance components (Hue and saturation). This representation works as the human eye because it works like the separation of the rods and cones.

On the representation of the components for this model Hue represents the chromatic component, saturation represents the predominance value of a hue a color and Value represents the intensity of the color. According to [23], Hue defines the color by changing its angle hue is defined as an angle in the range $[0, 2\pi]$. Saturation is the depth or purity of the color and is measured as a radial distance from the central axis with value between 0 at the center to 1 at the outer space. Finally, value is represented by the vertical central axis. The HSV color model is approximately perceptually uniform. The HSV values is widely used in the field of color vision. Figure 3 is illustrating HSV color model.

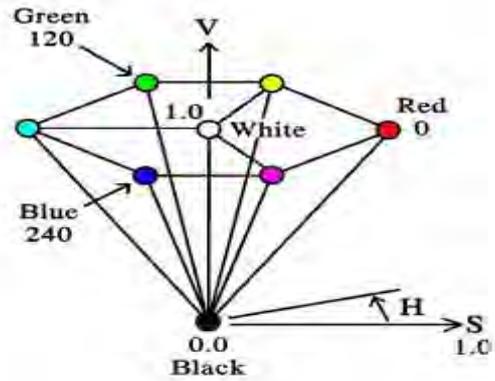


Fig 3. Representation of a HSV color descriptor. The value V is represented by the main axis orthogonal of the plane. The angle represents the Hue value, while radius represents the level of Saturation (purity of color) [24].

HSV can be computed using RGB using Equations 1 to 3

$$H = \cos^{-1} \left[\frac{\frac{1}{2} [(R - G) + (R - B)]}{\sqrt{(R - G)^2 + |(R - B)(G - B)|}} \right] \quad (1)$$

$$S = 1 - \frac{3}{R + G + B} [\min(R, G, B)] \quad (2)$$

$$V = \frac{1}{3} (R + G + B) \quad (3)$$

C. CIE XYZ color model

The first color model developed by CIE is XYZ color model. The Y component is the luminance component defined by the weighted sums of R (0.212671), G (0.715160), and B (0.072169). X and Z are the chromatic components. The XYZ color model is not perceptually uniform. The transition from RGB to CIE XYZ is a simple linear transformation, which means that XYZ model is proportional to RGB color model. XYZ model is only an RGB model like another. We find the same notation of colors by triplets. The chromaticity plan is materialized by the Maxwell triangle as shown in Figure 4.

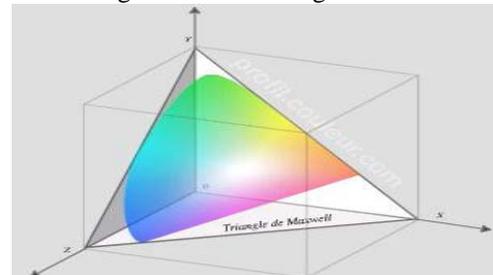


Fig. 4. Representation of CIE XYZ model by Maxwell's triangle.

D. YCbCr Model

This color space represents each color with 3 numbers, similarly as the RGB space. The Y component represents the intensity of the light. The Cb and Cr components indicate the intensities of the blue and red components relative to the green component. This color space exploits the properties of the human eye. The eye is more sensitive to light intensity changes and less sensitive to hue changes. When the amount of information is to be minimized, the intensity component can be stored with higher accuracy than

the Cb and Cr components. Possible RGB colors occupy only part of the YCbCr color space see Figure 5 represents RGB Colors Cube in the YCbCr Space

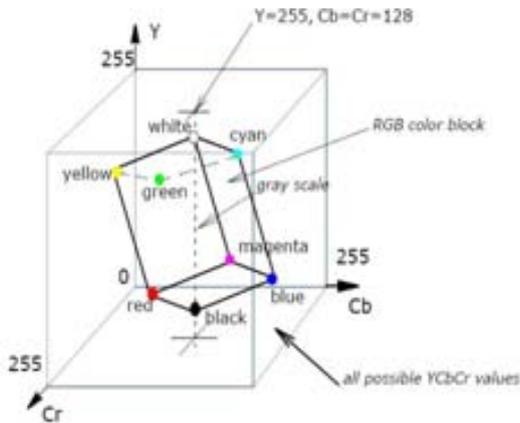


Fig.5 Representation of RGB colors in YCbCr

E. L*a*b* Color Model

These are perceptually uniform color spaces and are totally device independent representations of color. Some of these perceptually uniform color spaces include the Hue-Max-Min-Diff (HMMD), the HSV and the L*a*b* (CIELAB) color space. There is evidence that the CIELAB color space generally performs better than HSV [16]. To define a color in the CIELAB color space three values need to be provided: The L channel, which represents the lightness in a range from 0 to 100 for black to white, and two opponent color channels between -128 and +128, the a channel encoding magenta to green, the b channel representing yellow to blue [58]. The conversion between RGB and CIELAB is a computationally expensive operation, as it includes a non-linear transformation, which is necessary for the conversion into a uniform color model.

III. COLOR FEATURES

Color features are extracted using color moments, color histogram (local and global histogram), fuzzy histogram, Color Correlogram. These methods of extracting color features are briefed below.

A. Color Moments

Color moments [32][37][45] are measures that can be used to differentiate images based on their color feature. Once calculated, these moments provide a measurement for color similarity between images. These values of similarity can then be compared to the values of images indexed in a database for tasks like image retrieval.

The basis of color moments [43][46] lies in the assumption that the distribution of color in an image can be interpreted as a probability distribution. Probability distributions are characterized by a number of unique moments (e.g. Normal distributions are differentiated by their mean and variance). It therefore follows that if the color in an image follows a certain probability distribution, the moments of that distribution can then be used as features to identify that image based on color.

The three central moments of a image’s color distribution are Mean, Standard deviation and Skewness. A color can be defined by 3 or more values. Moments are calculated for each of these channels in an image. An image therefore is characterized by 9 moments-3 moments for each 3 color channels.

Let N represent the total number of images and P_{ij} represents the value of pixel on ith color channel at the jth pixel, then the three color moments can be defined as:

MOMENT 1 – Mean :

$$E_i = \sum_{j=1}^N \frac{1}{N} P_{ij} \tag{4}$$

Mean can be understood as the average color value in the image.

MOMENT 2 Standard Deviation :

$$\sigma_i = \sqrt{\left(\frac{1}{N} \sum_{j=1}^N (P_{ij} - E_i)^2 \right)} \tag{5}$$

The standard deviation is the square root of the variance of the distribution.

MOMENT 3 – Skewness :

$$s_i = \sqrt[3]{\left(\frac{1}{N} \sum_{j=1}^N (P_{ij} - E_i)^3 \right)} \tag{6}$$

Skewness can be understood as a measure of the degree of asymmetry in the distribution [27][44].

B. Color Histogram

Color Histogram serve as an effective representation of the color content of an image. The color histogram is easy to compute. The histogram of an image is a graph which contains the occurrence of each intensity value found in that image, obtained by counting all image pixels having that intensity value. For an 8-bit grayscale image there are 256 different possible intensities. So, the histogram will graphically display 256 grayscale values showing the distribution of pixels amongst those numbers. Histograms can also be taken of color images. A color histogram is the representation of the distribution of colors in an image. It is a standard statistical description of the color distribution in terms of the occurrence frequencies of the different regions in a color space [11][12][13][33][34][45][49].

There are two types of color histograms, Global Color Histograms [GCHs] and Local Color Histograms [LCHs]. GCHs represent one whole image with a single color histogram and an image will be encoded with its color histogram. The distance between two images will be determined by the distance between their color histograms. While the LCHs divide an image into fixed blocks and takes the color histogram of each of those blocks [16]. While comparing two images distance is calculated using their histograms between a region in one image and a region in same location in the other image. The distance between the two images will be determined by the sum of all these distances. Thus when comparing GCHs one may get inconsistent result in terms of similarity of images when compare to LCH.

Color quantization is a process that reduces the number of distinct colors used in an image, usually with the intention that the new image should be as visually similar as possible to the original image. For a true color image, the numbers of kind of colors are up to 2²⁴ = 16777216, so the direct

extraction of color feature from true color will lead to a large computation. In order to reduce the computation, without a significant reduction in image quality, some representative color is extracted to represent the image, there by reduction the storage space and enhancing the processing speed [48].

C. Fuzzy Histogram

The color histogram is viewed as a color distribution from the probability viewpoint. Given a color space containing n color bins, the color histogram of image I containing N pixels is represented as $H(I)=[h_1, h_2, \dots, h_n]$, where $h_i=N_i/N$ is the probability of a pixel in the image belonging to the i^{th} color bin, and N_i is the total number of pixels in the i^{th} color bin. According to the total probability theory, h_i can be defined as

$$h_i = \sum_{j=1}^N p_{ij} p_j = \frac{1}{N} \sum_{j=1}^N p_{ij} \quad (7)$$

where p_j is the probability of a pixel selected from image I being the j^{th} pixel, which is $1/N$ and p_{ij} is the conditional probability of the selected j^{th} pixel belonging to the i^{th} color bin.

Each histogram bin represents a local color range in the given color Space. Color histogram represents the coarse distribution of the colors in an image. Two similar colors will be treated as identical provided that they are allocated into the same histogram bin. On the other hand, two colors will be considered totally different if they fall into two different bins even though they might be very similar to each other. This makes color histograms sensitive to noisy interference such as illumination changes and quantization errors. To efficiently address the issue new color histogram, called fuzzy color histogram (FCH) was introduced [31]. In contrast with conventional color histogram (CCH) which assigns each pixel into one of the bins only, FCH considers the color similarity information by spreading each pixel's total membership value to all the histogram bins.

The fuzzy color histogram (FCH) of image I can be expressed as $F(I)=[f_1, f_2, \dots, f_n]$

$$f_i = \sum_{j=1}^N \mu_{ij} p_j = \frac{1}{N} \sum_{j=1}^N \mu_{ij} \quad (8)$$

D. Color Correlogram

Color Correlogram is one of the most promising spatial color descriptors. The highlights of this feature are: (i) it includes the spatial correlation of colors (ii) it can be used to describe the global distribution of local spatial correlation of colors (iii) it is easy to compute and (iv) the size of the feature is fairly small.

The color correlogram [59] was purposed to characterize not only the color distribution of pixels, but also the spatial correlation of pairs of colors. The first and the second dimension of the 3-D histogram are the colors of any pixel pair and the third dimension is their spatial distance. Color correlogram is a table indexed by color pairs, where k -entry for (i, j) specifies probability of finding a pixel of color "j" at distance "k" from pixel "i" in the image. Let I represent the entire set of image pixels. $c(j)$ represent the set of pixels whose colors are $c(i)$. Then, the color correlogram is defined

$$\gamma_{ij} = p_r \quad [| p_2 \in I c(j) | | p_1 - p_2 | = k] \quad (9)$$

$$p_1 \in I c(i), p_2 \in I$$

Where $i, j \in \{1, 2, \dots, N\}$, $k \in \{1, 2, \dots, d\}$, and $|p_1 - p_2|$ is the distance between pixels p_1 and p_2 . Its simplified version called color autocorrelogram, is often used. The color autocorrelogram only captures the spatial correlation between identical colors and thus reduces the dimension.

IV. HISTOGRAM SIMILARITY MEASUREMENTS

Distance measures are used for comparing the similarity of two images. Few of the commonly used histogram similarity measurements are described below.

Let m be the total number of bins, and H_q and H_t be the normalized query histogram and normalized target histogram respectively.

A. Histogram Euclidean distance

The Euclidean distance is given by

$$D_e(q, t) = \sqrt{\sum_{m=0}^{M-1} (H_q[m] - H_t[m])^2} \quad (10)$$

The distances only take account for the correspondence between each histogram bin and do not make use of information across bins. This issue has been recognized in histogram matching. As a result, quadratic distance is proposed to take similarity across dimensions into account. It has been reported to provide more desirable result than only matching between similar bins of the color histograms. However, since the histogram quadratic distance computes the cross similarity between colors, it is computationally expensive[28][32].

B. Quadratic Form (QF) Distance

The quadratic distance, also called cross distance, is used in the QBIC-system. This method considers the cross-correlation between histogram bins based on the perceptual similarity of the colors represented by the bins. The set of correlation values is represented in a similarity matrix.

Quadratic-form distance metric compares not only the same bins but multiple bins between color histograms and is defined as:

$$d(q, t) = (H_q - H_t)^T A (H_q - H_t) \quad (11)$$

Where q and t are two images H_q is the color histogram of image Q , H_t is the color histogram of image t , $|A|=[a_{i,j}]$ is a $N \times N$ matrix, N is the number of bins in the color histograms, and $a_{i,j}$ denotes the similarity between colors i and j . The similarity matrix is obtained through a complex algorithm [38].

C. Histogram Intersection

It is a distance measure for comparing histograms. It calculates the common part of the two histograms and neglects the features occurring in a single histogram. The histogram intersection of two histograms H_q and H_t is calculated using equation [29].

$$d_{\cap}(H_q, H_t) = \sum_{m=1}^M (H_q[m], H_t[m]) \quad (12)$$

D. Bhattacharya Distance

The Bhattacharya Distance measures the similarity between two histograms. Where q and t are two images, N is the number of bins in the color histogram. $H_q[i]$ is the value of bin i in color histogram H_q , which represents the image Q , and $H_t[i]$ is the value of bin i in color histogram H_t , which represents the image t [28][30].

$$d(H_q, H_t) = \sqrt{1 - \frac{1}{\bar{H}_q \bar{H}_t N^2} \sum_i \sqrt{H_q[i] H_t[i]}} \quad (13)$$

E. Chi-Square Distance

The Chi-Square Distance $d(H_q, H_t)$ between two histograms is given by

$$d(H_q, H_t) = \sum_i \min(H_q[i], H_t[i]) \quad (14)$$

F. Correlation Distance

In order to quantify the correlation between distance measures, a correlation coefficient measure is given by

$$d(H_q, H_t) = \frac{\sum_i (H_q[i] - \bar{H}_q)(H_t[i] - \bar{H}_t)}{\sqrt{\sum_i (H_q[i] - \bar{H}_q)^2 \sum_i (H_t[i] - \bar{H}_t)^2}} \quad (15)$$

It indicates the strength and direction of a linear relationship between two distance measures. If the value gets close to 1, it represents a good fit, i.e., two distance measures are semantically similar. As the fit gets worse, the correlation coefficient approaches zero. When either two distance or two similarity measures are compared the correlation coefficient is a positive value.

G. Local Color Histogram similarity

Color histograms are classified into two types, global color histogram (GCH) [64] and local color histogram (LCH) [63]. This approach (referred to as LCH) includes information concerning the color distribution of regions. The first step is to segment the image into blocks and then to obtain a color histogram for each block. An image will then be represented by these histograms. A GCH takes color histogram of whole image and thus represent information regarding whole image, without concerning color distribution of regions in image. In the contrary, an LCH divides an image into fixed blocks or regions and takes the color histogram of each of those blocks. LCH contains more information about an image but when comparing images it is computationally expensive.

The distance metric between two images Q and I in the LCH will be defined as:

$$d_{LCH}(q, t) = \sum_{k=1}^M \sqrt{\sum_{i=1}^N (H_q^k[i] - H_t^k[i])^2} \quad (16)$$

where M is the number of segmented regions in the images, N is the number of bins in the color histograms, $H_q^k[i]$ is the value of bin i in color histogram H_q^k which represents the region k in the image q and $H_t^k[i]$ is the value of bin i in color histogram H_t^k which represents the region k in the image t .

V. PERFORMANCE MEASURES

Most commonly used evaluation measures for CBIR are precision and recall. In addition Accuracy, Redundancy factor [RF] and Retrieval Score are used as evaluation measures [12][28][44][49][50][51][52].

They are defined as

$$Precision = \frac{A}{B} \quad (17)$$

$$Recall = \frac{A}{C} \quad (18)$$

$$RF = \frac{B - D}{D} \quad (19)$$

$$Accuracy = \frac{C}{B} \times 100 \quad (20)$$

where A is Number of relevant images retrieved

B is Total number of images retrieved

C is Total number of relevant images

D is Total number of images in a class

A retrieval score can be computed according to the following evaluation criterion for each query, the system returns the 'x' closest images to the query, including the query image itself. The number of mismatches can be computed as the number of images returned that belong to a class different than that of the query image, in addition total the number of images that belong to the query image class, but that have not been returned by the system. The retrieval score for one class can be then computed as

$$RetrivalScore = 100 \times \left[1 - \left(\frac{mismatches}{x} \right) \right] \% \quad (21)$$

VI. CONCLUSION

This paper discusses the use of color feature using color moments and histogram (Local histogram, Global histogram, Fuzzy histogram and Color correlogram) for CBIR. It also briefs about the commonly used color models namely RGB, HSV, CIE XYZ, YCbCr, and L*a*b*. From the above survey, it is concluded that euclidean histogram distance is the most commonly used distance measure and Recall and Precision are most frequently used performance measures.

VII. REFERENCES

- [1] Chang, N.S., Fu K.S, "A Relational Database System for Images", in Lecture Notes in Computer Science, Vol.80, pp.288-321, Springer Berlin, Heidelberg 1980.
- [2] Flickner M., Sawhney H., Niblack W., Ashley J., Qian Huang Dom B., Gorkani M., Hafner J., Lee D., Petkovic D., Steele D., Yanker P, "Query by image and video content: the QBIC system", Computer, Vol. 28(9), pp.23-32, Sept 1995.
- [3] Pentland A., Picard R.W., Sclaroff S., "Photobook: Tools for content-based manipulation of image databases", in Proceedings Storage and Retrieval for Image and Video Databases II., Bellingham, WA, SPIE, Vol.2, pp.34-47, 1994.

- [4] Gevers T., Smeulders A.W.M., “The PicToSeek WWW image search system”, in IEEE International Conference on Multimedia Computing and Systems, Vol.1, pp.264-269, June 1999.
- [5] Rasheed W., Gwangwon Kang, Jinsuk Kang, Jonghun Chun, Jongan Park, “Sum of Values of Local Histograms for Image Retrieval”, in Proceedings Fourth International Conference on Networked Computing and Advanced Information Management, Vol.2, pp.690-694, doi: 10.1109/NCM.2008.91, Sept 2008.
- [6] Safar M., Shahabi C., Sun X. “Image retrieval by shape: a comparative study”, Proceedings IEEE International Conference on Multimedia and Expo, Vol.1, pp.141-144, July-Aug 2000.
- [7] Jeong-Yo Ha, Gye-Young Kim, Hyung-II Choi, “The Content- Based Image Retrieval Method Using Multiple Features”, Fourth International Conference on Networked Computing and Advanced Information Management, Vol.1, pp.652-657 doi:10.1109/NCM.2008.220, Sept 2008.
- [8] Deb, S., Zhang, Y, “An Overview of Content-based Image Retrieval Techniques”, Proceedings the 18th International Conference on Advanced Information Networking and Application Vol.1, pp.59-64, 2004.
- [9] Remco C., Veltkamp, Mirela Tanase, “Content-Based Image Retrieval Systems: A Survey”, this is a revised and extended version of Technical Report UU-CS-2000-34, Oct 2000.
- [10] Khoulood Meskaldji, Samia Boucherkha, Salim Chikhi, “Color Quantization and its Impact on Color Histogram based Image Retrieval”, Networked Digital Technologies, 28-31 July 2009.
- [11] Imtnan-Ul-Haque Qazi, OlivierAlata, Jean-ChristopheBurie, Ahmed Moussa, ChristineFernandez-Maloigne, “Choice of a pertinent color space for color texture characterization using parametric spectral analysis”, Pattern Recognition Vol. 44, pp.16-31, 2011.
- [12] Neetu Sharma S, Paresh Rawat S, jaikaran Singh S., “Efficient CBIR Using Color Histogram Processing. Signal & Image Processing”, An International Journal(SIPIJ) Vol.2(1), March 2011.
- [13] Deselaers T., Keysers D., Ney H., “Features for image retrieval: an experimental comparison”, Information Retrieval 11(2), pp.77-107, 2007.
- [14] Rao Juan, “Intelligent image retrieval technique based on content” Lanzhou University of Technology, pp.32-64, 2006.
- [15] Ye Yu-guang, “Research of image retrieval based on fusing with multi-character”, Hua Qiao university, pp.14-36, 2007.
- [16] Shengjiu Wang, “ A Robust CBIR Approach using Local Color Histograms”, Department of computer Science, University of Alberta, Edmonton, Alberta, Canada, Oct 2001.
- [17] Virginia Ogle, Michael Stonebraker Chabot, “Retrieval from a relational database of images”, IEEE Computer, 28(9):4048, Sept 1995.
- [18] Egon L., Van den Broek, “Human-Centered Content-Based Image Retrieval”, PhD-thesis Nijmegen Institute for Cognition and Information (NICI), Radboud University Nijmegen, The Netherlands – Nijmegen, 2005.
- [19] Singhai N., Shandilya S., “A survey on: Content based image retrieval systems”, International Journal of Computer Applications IJCA, Vol.4(2), pp.22-26, 2010.
- [20] K. Mekaldji, S., Boucherka C. S., “Color quantization and its impact on color histogram based image retrieval”, in Proceedings of the Second Conference International esur l’Informatique et ses Applications(CIIA’09), Saida, Algeria, May 3-4 2009.
- [21] Miralles.J., Tutorial deGIMP. [Online] <http://sites.google.com/site/tutorialdegimp/>
- [22] Jeong S., “Histogram-based color image retrieval”, Stanford University, Palo Alto,CA, Psych221/EE362 Project Report, 2001.
- [23] A. Vadivel, S. Sural, A. Majumdar, “Human color perception in the HSV space and its application in histogram generation for image retrieval”, in SPIE Proceedings seetings, San José CA, United States of America, 2005.
- [24] S. Sural, G. Quian, S. Pramatik, “Segmentation and histogram generation using the HSV color space for image retrieval”, in Proceedings International conference on Image Processing, 2002.
- [25] W. Burger, M.J. Burge, “Principles of Digital image processing”, Core Algorithms, Springer, 2009.
- [26] R.C. Gonzalez, R.E. Woods, “Digital Image Processing”, 3rd edition, Prentice- Hall, 2007.
- [27] K. Konstantinidis, A.Gasteratos, I.Andreadis, “Image retrieval based on fuzzy color histogram processing”, Optics Communications 248, pp.375-386, 2005.
- [28] Rahman M.M., Bhattacharya M.P., Desai B.C., “A framework for medical image retrieval using machine learning and statistical similarity matching techniques with relevance feedback”, IEEE Trans. Inform. Technol. Biomed., Vol. 11(1), pp.58-69, 2007.
- [29] Deselaers T, Keysers D, Ney H. “Features for image retrieval: an experimental comparison”, Information Retrieval 11(2), pp.77-107, 2007.
- [30] Celia B., Felci Rajam I., “An efficient content based image retrieval framework using machine learning techniques”, Proceedings of the Second international conference on Data Engineering and Management (ICDEM-10), Springer LNCS, pp.162-169, 2010.
- [31] Prabir Bhattacharya, Md. Mahmudur Rahman, Bipin C. Desai, “Image Representation and Retrieval Using Support Vector Machine and Fuzzy C-means Clustering Based Semantical Spaces”, Proceedings of the 18th International Conference on Pattern Recognition (ICPR’06).
- [32] M. J. Swain, D. H. Ballard, “Color indexing”, International Journal of ComputerVision, Vol.7(1), pp.11-32, 1991.
- [33] Markus Koskela, Jorma Laaksonen, Erkki Oja, “Comparison of techniques for content-based image retrieval”, Conference on Image Analysis (SCIA). Bergen, Norway, pp.579-586, 2001.
- [34] P.S.Suhasini, Dr. K.Sri rama Krishna, Dr. I. V. Murali Krishn, “CBIR Color Histogram Processing”, Journal of Theoretical and Applied Information Technology, Vol 6(1), pp.116-122, 2005-2009.

- [35] Sharma,N., Rawat,p., singh J., "Efficient CBIR using color Histogram Processing, Signal and image processing", an international Journal (SIPIJ) Vol.2(1), March 2011.
- [36] Deb, Y. Zhang., "An overview of content-based Image retrieval techniques", Proceedings on 18th International conference advanced Information Networking and Applications, Vol.1, pp.59-64, 2004.
- [37] M. Stricker , M. Orenge, "Similarity of color images", in SPIE Conference on Storage and Retrieval for Image and Video Databases III, Vol 2420, pages 381392, Feb. 1995.
- [38] Kondekar V.H., Kolkure V., Kore S.N., "Image Retrieval Techniques based on Image Features: A state of Art approach for CBIR", International Journal of Computer Science and Information Security, Vol.7(1) 2010.
- [39] B. V. Funt, G.D. Finlayson, "Color Constant Color Indexing", Technical Report 9109, School of Computing Science, Simon Fraser University, Vancouver, B.C. Canada, 1991.
- [40] Yu H., Li M., Zhang H., Feng J., "Color texture moment for contentbased image retrieval", Proceedings IEEE International Conference on Image Processing, Sept 2002.
- [41] V.Chitkara, M. A. Nascimento, C. Mastaller, "Contentbased image retrieval using binary signatures", in Technical Report TR0018, Department of Computing Science, University of Alberta,Edmonton, Alberta, Canada, 2000.
- [42] Felci Rajam I., Valli S, "Content-Based Image Retrieval Using a Quick SVM-Binary Decision Tree – QSVMBDT", Springer Communications in Computer and Information Science 205, pp. 11-22, 2011b.
- [43] Felci Rajam I., Valli S. SRBIR, "semantic region based image retrieval by extracting the dominant region and semantic learning", Journal of Computer Science, Vol. 7(3), pp.400-408, 2011a.
- [44] Hatice Cinar Akakin, Metin N., Gurcan, "Content-Based Microscopic Image Retrieval System for Multi-Image queries", IEEE Transactions on Information Technology in Biomedicine, Vol.16(4), pp.758-769, 2012.
- [45] Samuel Rota Bulo, Massimo Rabbi , Marcello Pelillo, "Content-Based Image Retrieval with Relevance Feedback using Random Walks", Pattern Recognition, Vol.44(9), pp. 2109-2122, 2011.
- [46] Yu-Gang Jiang, Qi Dai, Jun Wang, Chong-Wah Ngo, Xiangyang Xue , Shih-Fu Chang, "Fast Semantic Diffusion for Large-Scale Context-Based Image and Video Annotation", IEEE Transactions on Image Processing , Vol.21(6), pp. 3080-3091, 2012.
- [47] Felci Rajam I., Valli S., "Region-based image retrieval using the semantic cluster matrix and adaptive learning", International Journal of Computational Science and Engineering, Vol.7(3), pp.239-252, 2012.
- [48] Hafner, J., Sawhney, H.S., "Efficient color histogram indexing for quadratic form distance functions", IEEE Transactions on Pattern Analysis and Machine Intelligence, 17(7), pp. 729-736, 1995.
- [49] Lining Zhang, Lipo Wang, Weisi Lin, "Generalized Biased Discriminant Analysis for Content-Based Image Retrieval", IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetics, Vol.42 (1), pp.282-290, 2012.
- [50] WangXing-yuan, ChenZhi-feng, YunJiao-jiao. "An effective method for color image retrieval based on texture", Computer Standards & Interfaces 34, pp.31-35, 2012.
- [51] Timothy Tian-Ming Zheng, Wing W. Y. NG, XU-Sheng Huang, Shi-Ting Yang, Patrick P.K. Chan, Weiwei Lai, Daniel S. Yeung, "Shape-Based Image Retrieval of Chinese Paper Cutting Using RBFNN with Invariant Moment", IEEE Ninth International Conference on Machine Learning and Cybernetics, Qingdao, pp.808-814, 2010.
- [52] Mann-Jung Hsiao, Yo-Ping Huang, Tienwei Tsai, Te-Wei Chiang, "A General and Effective Two-Stage Approach for Region-Based Image Retrieval", Life Science Journal, Vol.7(3), pp.73-80, 2010.
- [53] Xinjung,Z, "Research of Image Retrieval based on Color features", Liaoning technical Unviersity,9(2), pp.42-50, 2006.
- [54] S.Mangijao Singh, K.Hemachandran, "Image Retrieval based on the combination of color histogram and color moment", International Journal of Computer Applications, Vol.58(3), 2012.
- [55] Gudivada,V.N., Raghavan.V.V., "Content based Image Retrieval Systems", EEE Computer ,Vol.28(9), pp.18-22, 1995.
- [56] Felci Rajam1, S. Valli2, "A Survey on Content Based Image Retrieval" , Life Science Journal ,10(2),2013.
- [57] J.Kalervo, K.Jaana, N.Timo, "Expansion tool: Concept based Query Expansion and Construction", Information retrieval ,Vol.4(3), pp.231-255, 2001
- [58] Erik Reinhard, Erum Arif Khan, Ahmet Oguz Akyuz, Garrett. M. Johnson, "Color Imaging: Fundamentals and Applications 2008".
- [59] Jing Huang, S. Ravi Kumar, Mandar Mitra, Wei-Jingzhu, Ramin Zabih, "Image Indexing using color correlogram", IEEE international conference on Computer Vision and Pattern Recognition, pp.762-768, Puerto Rico, June 1997.
- [60] J. Ashley, M. Flickner, J. L. Hafner, D. Lee, W. Niblack, D. Petkovic, "The query by image content (QBIC) system", in SIGMOD Conference, pp.475, 1995.
- [61] J.R. Smith, Shih-fu Chang, "Visual seek: a fully automated content-based image query system", in ACM Multimedia, New York, NY, USA, pp.87-98, 1996.
- [62] E. Sciascio, M. Mongiello, M. Mongiello, "Content-based image retrieval over the web using query by sketch and relevance feedback", in Proceeding of 4th International Conference on Visual Information Systems, pp.123-130, 1999.
- [63] Shilpa P. Pant, "Content Based Image Retrieval Using Color Feature", International Journal of Engineering Research & Technology (IJERT) Vol.2 (4), April 2013.
- [64] J. Zhao, Y. K. Zhang, "2-Layer method of Image Retrieval based on Global Color Histogram and Local color spatial features", Proceeding of 6th international conference on cybernetics Aug 2007.