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Efficient Image Retrieval Mechanisms using Color Feature

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Abstract*— Many areas of commerce, government, academia, and hospitals create large collections of digital images . Digital image databases open the way to content-based searching. One of the tool that is essential for electronic publishing is a powerful image retrieval system. Most commercial image retrieval systems associate keywords or text with each image and require the user to enter a keyword or textual description of the image. This text based approach is incompetent as some features are nearly impossible to describe with text. In an effort to overcome these problems and to improve image retrieval performance researchers are focusing on content based image retrieval (CBIR). In CBIR retrieval is accomplished by comparing image features directly rather than textual descriptions of image features. Features that are commonly used in CBIR include Color, Texture, Shape and Edges. These features are primitive image descriptors in content based image retrieval systems. Among these features, color feature is the most widely used features for image retrieval because color is the most intuitive feature and can be extracted from images conveniently. In this paper we survey some technical aspects of current content-based image retrieval systems using Color as a feature.

***Index Terms*—CBIR, Color, Image Retrieval, Retrieval efficiency**

I. INTRODUCTION

Now a days, access to information requires to manage multimedia databases effectively, and among challenges offered to scientific community. Since last decades, multimedia retrieval techniques (particularly image retrieval) have became an active research direction. CBIR is currently attracting significant research because of the availability of large image databases in various fields and easy access to large collections of images via the world wide web. CBIR is introduced to overcome the main drawbacks encountered by text-based images retrieval. By the past, text-based image retrieval has encountered two main drawbacks. First, manual images annotation is time consuming, this is particularly true with large collection of data. Second, human annotation is subjective, the same image can be annotated differently by different observers. Content based images retrieval (CBIR) systems are devoted to overcome these difficulties. They index images according to low-level visual features such as color, texture, shape to retrieve similar images. To do so, a set of features need to be extracted from the images and stored in the database prior to accepting users query. The term 'texture' is used to specify the roughness or coarseness of object surface.

Shape feature is usually described after images have been segmented in to regions or objects. Shape does not refer to the shape of an image but to the shape of a particular region that is being sought out. Color is the most intuitive and straight forward for the user while shape and texture are also important visual attributes but there is no standard way to use them compared to color for efficient image retrieval. The rest of the paper is organized as follows. Section II describes various techniques for image retrieval using color feature. Section III describes various content based image retrieval systems based on color.

II. IMAGE RETRIEVAL USING COLOR

Global Color Histogram (GCH) is the most traditional way of describing the color attribute of an image [3]. It is constructed by computing the normalized percentage of the color pixels corresponding to each color element. An example of a true colored (RGB) image and the corresponding histograms of each component is displayed in Fig. 1.

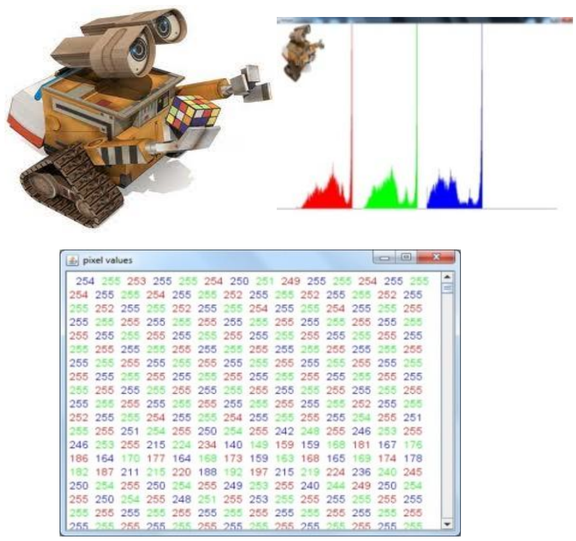

Fig.1 A colored image , corresponding histogram for red green and blue components , and the corresponding pixel values.

To construct the color feature vector for both the query image and all images in the database, the three-color components (R, G, and B) are identified and corresponding histograms of these components is computed. Color histogram is widely used in image retrieval because of its lower complexity as compared to traditional techniques of pattern recognition [7].

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Let I be an image quantized to m colors c_1, c_2, ….c_m. For a pixel p=(x,y) Є I , we denote I(p) as its color and Ic = {p | I(p) = c } . Then color histogram is defined by

h_{ci} (I) = n. Pr [p Є I $_{ci}$] p Є I

where n is the total number of pixels in an image. For any pixel in the image normalized histogram H_{ci} (I) = h_{ci}(I)/n gives the probability that the color of the pixel is ci. A GCH considers neither the color similarity across different bins nor the color dissimilarity in the same bins. Hence it is found to be sensitive to noisy interference such as illumination changes and quantization errors. Moreover, Global Color Histogram's large dimension or histogram bins require large computation on histogram comparison. To address these concerns, K. Satya Sai Prakash and RMD. Sundaram proposed new color histogram representation, called Fuzzy Color Histogram (FCH) [4], by considering the color similarity of each pixel's color associated to all the histogram bins through fuzzy-set membership function in comparison with the (GCH), which assigns each pixel into one of the bins only. FCH spreads each pixel's total membership value to all the histogram bins. Also, to reduce the computational complexity, Fuzzy C–Means (FCM) clustering algorithm can be used. Taking a color space containing n different color bins, the color histogram of image I containing N pixels is represented as H (I) = [h1, h2, …hn], where hi = Ni / N is the probability of a pixel in the image belonging to the ith color bin, and Ni is the total number of pixels in the ith color bin. According to the probability theory, hi can be defined as

$$h_i = \sum P_{i/j} P_j = (1/N) \sum P_{i/j}$$

where Pj is the probability of a pixel chosen from image I being the jth pixel, which is 1/N and P i/j is the conditional probability of the chosen jth pixel belonging to the ith color bin. FCH, on the other hand considers each of the N pixels in image I, related to all the n color bins via Fuzzy set membership function such that the degree of "belongingness" of the jth pixel to the ith color bin is found by distributing the membership value of the jth pixel, μij, to the ith color bin. Thus the Fuzzy color Histogram (FCH) of image I can be expressed as F(I) = [f1, f2… fn], where

$$f_i = \sum \mu_{ij} P_j = (1/N) \sum \mu_{ij}$$

Thus when compared to Global Color Histogram, Fuzzy Color Histogram considers not only the similarity of different colors from different bins but also the dissimilarity of those colors from the same bin. Alternative approach to extract robust color feature is proposed by Dengsheng ZhangLu [5]. He proposed perceptually weighted histogram or PWH.

Basically, the PWH is acquired by using CIEL*u*v* color space. It assigns a perceptual weight to each histogram bin according to the distance between the color of the pixel and the color of the bin. We briefly describe the steps of PWH in the following.

Step 1:The first step to extract color features is to select an appropriate color space. Several color spaces are available, such as RGB, CMYK, HSV and CIEL*u*v*. Most digital images are stored in RGB color space. However, RGB color space is not perceptually uniform, which implies that two colors with larger distance can be perceptually more similar than another two colors with smaller distance, or simply put, the color distance in RGB space does not represent perceptual color distance. In view of this drawback, CIEL*u*v* space is chosen because it is an uniform color space in terms of color distance.

Step 2: In order to use L*u*v* space, color values are first converted from RGB space into CIEXYZ space with a linear transform and then from CIEXYZ space into L*u*v* color space using the following transform:

$$\begin{array}{llll} L^* = 116X\sqrt[3]{Y/Y_n} - 16 & Y/Y \geq 0.008856 & & u' = 4X/(X+15Y+3Z) \\ L^* = 903.3X(Y/Y_n) & Y/Y_n \leq 0.008856 & where & v' = 9Y/(X+15Y+3Z) \\ u^* = 13XL^*(u' - u'_n) & & & u'_n = 4X_n/(X_n+15Y_n+3Z_n) \\ u^* = 13XL^*(v' - v'_n) & & & v'_n = 9Y_n/(X+15Y_n+3Z_n) \end{array}$$

And $(X_n, Y_n, Z_n)$is the reference white in XYZ space.

In the L*u*v* space, representative colors are used instead of quantizing each color channel by a constant step. The number of representative colors is given by the combinations (512) of the three components L,u,v components in L*u*v* space. These representative colors are uniformly distributed in L*u*v* space.

Step 3: In contrast to the conventional histogram building which assigns the color of each pixel to a single color bin, the PWH assigns the color of each pixel to 10 neighboring color bins based on the following weight:

$$w_i = \frac{1/d_i}{1/d_1 + 1/d_2 + ... + 1/d_{10}}$$

Where $d_i = \sqrt{(L_0 - L_1)^2 + (u_0 - u_i)^2 + (v_0 - v_i)^2}$

and (L0, u0, v0) is the color of the pixel to be assigned, (Li, ui,vi) is the color of bin i. In this way use of PWH overcomes the drawback of conventional histogram methods which would in many situations assign a pixel color to a bin of a quite different color and having to assign two quite different colors to a same color bin. As the result, PWH is much more accurate in representing the image than conventional histograms. In an experiment of perception based color and texture measures performed by Sanjoy Kumar Saha and Amit Kumar Das Color is represented using HSV model[6]. A hue histogram is formed using this model. The hue histogram thus obtained can not be used directly for searching similar images. As for example, a red image and an almost red image (with similar contents) are visually similar but their hue histogram may differ. Hence, to compute the color feature the hue histogram is first smoothened with a Gaussian kernel and normalized. Then for each of the six major colors (red, yellow, green, …, magenta), an index of fuzziness is computed as follows.

It is assumed that in the ideal case for an image with one dominant color of hue h, the hue histogram would follow the Gaussian distribution $p_i(x)$ with mean and standard deviation, say σ. The Bhattacharya distance dh between the actual distribution $p_a(x)$ and this ideal one $p_i(x)$ indicates the closeness of the image color to hue h, where

$$dh = \sum i \sqrt{pi(x)\, pa(x)}$$

Therefore, dh gives a measure of similarity between two distributions. Finally, an S-function maps dh to fuzzy membership F(h)where

$F(h) = 1/\ 1+ e^{-ø(dh-0.5)}$

For h=0, 60, 120……membership values corresponding to red, yellow, green etc. are obtained. Image Retrieval can be further improved by combining color feature along with other low level feature such as texture, shape and edges. P. S. Hiremath and Jagadeesh Pujari developed a technique which captures local color and texture descriptors in a coarse segmentation framework of grids, and has a shape descriptor in terms of invariant moments computed on the edge image[9]. The image is partitioned into equal sized non-overlapping tiles. The features computed on these tiles serve as local descriptors of color and texture. This grid framework is extended across resolutions so as to capture different image details within the same sized tiles. An integrated matching procedure based on adjacency matrix of a bipartite graph between the image tiles is provided, yielding image similarity. A two level grid framework is used for color and texture analysis. Gradient Vector Flow (GVF) fields are used to compute the edge image, which will capture the object shape information. GVF fields give excellent results in determining the object boundaries irrespective of the concavities involved. Invariant moments are used to serve as shape features. The combination of these features forms a robust feature set in retrieving applications. Another approach is to index each image using color and texture feature[5]. In the retrieval, images in the database, called target images, are ranked in descending order of similarity to the query image. A number of the top ranked images are presented to the user. The ranking of similarity is determined by the distance between the feature vector of the query image and the feature vector of the target image. For two images with features (*f*11, *f*12, …, *f*1*n*) and (*f*21, *f*22, …, *f*2*n*) respectively, the distance between the two images is given by

$$d = \sqrt{(f_{11} - f_{21})^2 + (f_{12} - f_{22})^2 + \ldots + (f_{1n} - f_{2n})^2}$$

Here, the *fij* can be either the color features or the texture features. Given a query image, the images are first retrieved by using PWH color features. Although PWH is a more accurate color histogram representation of images than conventional histogram, it is still a global representation of images. As the result, the retrieval result given by PWH usually reflects the overall color tone of the images, rather than the actual image content expected by the user. In this situation, texture features of the images can be used to help ranking images with similar content closer. However, the texture features captured are also global features, it may fail to retrieve similar images in some situations. Solution to this problem can be segmenting image into regions and extracting texture features from the regions. In combined retrieval, the images in the database are first ranked using color feature according to the distance between the query and the target images. Then a number of the top ranked images are selected and they are then re-ranked using their texture feature. Considering the color feature K. idrissi, J. Ricard, A. Baskurt proposed a tool for synthetic image data generation. It allows to control the number and location of the dominant colors in the Lab space and also provides spatial coherency. It is then possible to sort exactly the images for the color features. They proposed a new distance as color image similarity measure, in order to match the visual query to the targets. In this case, images are described by their color descriptors (Dominant Percentage and Spread out). Assuming that each dominant color can be modeled by a Gaussian distribution, a new image histogram is generated from the dominant colors. In other words, they modeled the 3D Lab distribution of the quantized images (with 16 dominant color in this study) using a mixture of Gaussian distribution (Fig.2) centered on each dominant color with the standard deviation l_{opt} (the spread out of the associated dominant color).

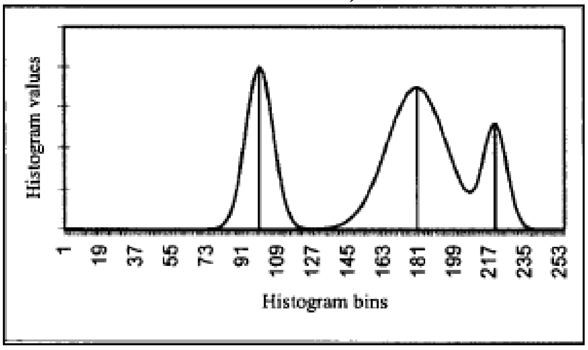

Fig 2. Example of the generation of ID histogram for one of Lab components considering 3 dominant colors.

The histogram contribution of every dominant color *C* is given by:

$$H(x) = \frac{r}{l_{opt}\sqrt{2\pi}} e^{-\frac{(x-c)^2}{2 l_{opt}^2}}$$

Where *r* is the dominant color percentage, l_{opt} is the spread out, while the value *x* of the color corresponds to the bin number in the histogram. The resulting histogram is the sum of the dominant color contributions (Fig. 2).This approach allows us to integrate all the color descriptors in the modeled histogram. A Kullman's distance is then performed in its symmetric form to measure the similarity between 2 generated distributions *R* and *I*:

$$d(R, I) = \sum_{n=1}^{N} \sum_{m=1}^{3} (rn, m - in, m) \log_2 \left(\frac{r_{n,m} + 1}{i_{n,m} + 1} \right)$$

where *N* is the number of histogram bins(256), *M* is the number of color components(*M*=3 Lab spaces),

R is the distribution of the reference image descriptor, $r_{n,m}$ is the percentage o f the mth component of the nth color in *R*, *I* is the distribution for the descriptor of any given image in the database and $i_{n,m}$ is the percentage of the mth component of the nth color in *I*. Thus color plays significant role in content based image retrieval.

III. CBIR SYSTEMS

In this section we are describing some of the content based image retrieval systems based on color[1].

A. AMORE(Advanced Multimedia Oriented Retrieval Engine)

It is developed by C & C Research Laboratories NEC USA, Inc. The image is segmented into at most eight regions of homogeneous color, and downsized to 24 by 24 pixels. The regions in this picture are directly used for matching . The color similarity between two regions is the distance in HLS space between the uniform region colors .

B. BDLP(Berkeley Digital Library Project)

It is developed by University of California, Berkeley. The colors of each image are quantized into 13 colors bins. Six values are associated with each color bin: the percentage of the image with colors in that bin, and the number of ‘very small’, ‘small’, ‘medium’, ‘large’, and ‘very large’ dots of that color found.

C. CHROMA (Colour Hierarchical Representation Oriented Management Architecture

It is developed by School of Computing, Engineering and Technology, University of Sunderland, UK. From each image a color dominance vector is generated, of at most length ten. The vector lists the color classes of decreasing dominance. There are ten classes: {uncertain colors like very dark and very bright}, {white}, {grey}, {black}, {red, pink}, {brown, dark yellow, olive}, {yellow, orange, light yellow}, {green, line}, {blue, cyan, aqua, turquoise}, {purple, violet, magenta}. Each pixel of an image tallies for one class, the first vector component is the class with the highest count, etc. If a class does not occur in the image, the vector does not contain this class, and has less than ten components. A second feature is a 15 by 15matrix of color classes. First the image is represented at 15 by 15 resolution, which color quantization algorithm is used is not mentioned. The matrix contains the color class of each pixel. This provides a rough description of layout in the image.

D. Circus (Content-based Image Retrieval and Consultation User-centered System)

The color feature is a global histogram in Lab space. The texture features are the mean, standard deviation, angular second moment, inverse difference moment, sum average, contrast, correlation, and sum variance, all derived from the co occurrence matrix of gray values in the direction of∏/44. These feature vectors are projected onto a lower dimensional space, derived from the ‘feature by image’ occurrence matrix A=(a_{ij}) with a_{ij} = l_{ij}giwhere l_{ij} lij is the local weighting of feature i in image j j, and gi i is the global weighting of feature. iThis is analogous to the ‘term by document’ matrix used in Latent Semantic Indexing for text retrieval. Using singular value decomposition (SVD), an orthogonal base for features and images is computed, in which A is expressed as a linear combination. Matrix A is then approximated by the first few terms of this sum. To speed up the computations, a fast approximation to the decomposition is computed using wavelet packets.

E. FOCUS(Fast Object Color-based Query System)

It is developed by Department of Computer Science, University of Massachusetts, Amherst, MA. Each image is divided in cells of 100_100 pixels and for each cell a color histogram in the HSV space, coarsely quantized along the saturation and value axes (64_10_10), is computed. The peaks of all local histograms are determined and combined in a list of unique peaks for the whole image by merging multiple copies of the same peak. Also, a frequency table is constructed which, for each color in the HSV space, gives the number of images that have a peak of that color. The spatial relationships between color regions are represented by means of a spatial proximity graph (SPG) constructed in two phases. First an intermediate SPG is generated, with one node corresponding to each color peak computed for the image cells. Two nodes in this graph are connected if their corresponding peaks are located in the same cell or are located in neighboring cells and have the same color. This graph is then simplified, by unifying all connected nodes of the same color in a single node, and stored using an adjacency matrix representation. For the query image, a global color histogram is computed and color region relationships are determined at pixel level.

F. QBIC(Query By Image Content)

Fig.3: QBIC

It is developed by IBM Almaden Research Center, San Jose, CA. Color features computed are: the 3D average color vector of an object or the whole image in RGB, YIQ, Lab, and Munsell color space and a 256-dimensional RGB color histogram.

G. Quicklook

It is developed by CNR Institute of Multimedia Information Technologies, Milan, Italy.
Besides text descriptors, Quicklook2 uses two contest-based features. First is the color histogram of 64 bins and other is the color coherence vector in Lab color space, quantized into 64 colors, where pixels are
coherent if they belong to a large similarly colored region.

FIG 4: QUICKLOOK

H. *WebSEEk*

It is developed by Image and Advanced Television Lab, Columbia University, NY. WebSEEk makes text-based and color based queries through a catalogue of images and videos collected from the Web. Color is represented by means of a normalized 166-bin histogram in the HSV color space.

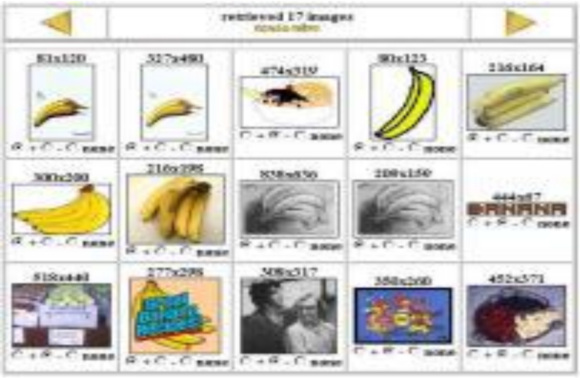

Fig 5. WebSEEk

I. *WISE(Wavelet Image Search Engine)*

FIG. WISE RESULT WITH TOP LEFT QUERY

It is developed by Department of Computer Science, Stanford Univerity. The system, also called WBIIS (Wavelet-Based Image Indexing and Searching), performs queries on color layout information encoded using Daubechies wavelet transforms.

IV. CONCLUSION

In this paper, we have reviewed a CBIR system for images using color and combination of color with other low level feature such as shape and texture. Successful Image Retrieval System requires seamless integration of multiple research community's efforts. We have presented a comprehensive survey highlighting current progress, emerging directions, the spawning of new fields, and methods for evaluation relevant to the young and exciting field of image retrieval . For better Retrieval efficiency color feature can be combined with texture, shape and edges and novel method can be designed. Various CBIR systems are discussed to comprehend the image retrieval using color and combination of other features.

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