

Content Based Image Retrieval Using Color and Shape Features

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Abstract: Content-Based Image Retrieval (CBIR) uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image. Active research in CBIR is geared towards the development of methodologies for analyzing, interpreting cataloging and indexing image databases. In addition to their development, efforts are also being made to evaluate the performance of image retrieval systems. The quality of response is heavily dependent on the choice of the method used to generate feature vectors and similarity measure for comparison of features. In this paper we proposed an algorithm which incorporates the advantages of various other algorithms to improve the accuracy and performance of retrieval. The accuracy of color histogram based matching can be increased by using Color Coherence Vector (CCV) for successive refinement. The speed of shape based retrieval can be enhanced by considering approximate shape rather than the exact shape. In addition to this a combination of color and shape based retrieval is also included to improve the accuracy of the result.

Keywords: - Content Based Image Retrieval, Shape, Color Coherence Vector, Centroid, Segmentation

I. INTRODUCTION

CBIR is the process of retrieving images from a database or library of digital images according to the visual content of the images. In other words, it is the retrieving of images that have similar content of colors, textures or shapes. Images have always been an inevitable part of human communication and its roots millennia ago. Images make the communication process more interesting, illustrative, elaborate, understandable and transparent

In CBIR system, it is usual to group the image features in three main classes: color, texture and shape [1, 2]. Ideally, these features should be integrated to provide better discrimination in the comparison process. Color is by far the most common visual feature used in CBIR, primarily because of the simplicity of extracting color information from images [3, 4]. To extract information about shape and texture [5] feature are much more complex and costly tasks, usually performed after the initial filtering provided by color features.

Many applications require simple methods for comparing pairs of images based on their overall appearance. For example, a user may wish to retrieve all images similar to a given image from a large database of images. Color histograms [6, 7] are a popular solution to this problem, the histogram describes the gray-level or color distribution for a given image, they are computationally efficient, but generally insensitive to small changes in camera position. Color histograms also have some limitations. A color histogram provides no spatial information; it merely describes which colors are present in the image, and in what quantities. In addition, color histograms are sensitive to both compression artifacts and changes in overall image brightness. For the design of histogram based method the main things we require are appropriate color space, a color quantization scheme, a histogram representation, and a similarity metric [8]. A digital image in this context is a set of pixels. Each pixel represents a color. Colors can be represented using different color spaces depending on the standards used by the researcher or depending on the application such as Red-Green-Blue (RGB), Hue-Saturation-Value (HSV), YIQ or YUV etc. [9]

In this paper we describe a color-based method for comparing images which are similar to color histograms, but which also takes spatial information into account. We begin with a review of color histograms. Then describe CCV's and how to compare them. Examples of CCV-based image queries demonstrate that they can give superior results. Finally, we present some possible extensions to CCV's.

This paper also presents an approach to retrieve images through an automatic segmentation technique. This allows us to get approximate information about the shape of the regions in the images. Shape description or representation is an important issue both in object recognition and classification. Many techniques, including chain code, polygonal approximations, curvature, Fourier descriptors and moment descriptors have been proposed and used in various applications. The segmentation is performed through a stochastic algorithm using the brightness of the regions under analysis. We found that the image features generated from the image regions allow higher discrimination among images than the existing approaches. The main idea is to search for the regions in the image [10] looking for typical groups of statistically equally bright elements. First image is

segmented based on a specific brightness represents a class of the image. Then, the features are extracted from the segmented classes [11].

The rest of the paper is organized as follows. In section 2, discuss the color and shape features representation techniques. Then in section 3 describe proposed schemes of color and shape retrieval. Experimental results with accuracy tables are explained in section 4. Finally conclusion is made in section 5 followed by the references.

II. COLOR AND SHAPE FEATURE REPRESENTATIONS

The initial step of CBIR system is to represent color component and shape regions into features vector. There are various ways to represent feature of digital images. In this paper following color and shape feature extraction techniques are proposed.

A. Color Feature

For the initial process of histogram matching, we use the HSV color space. The HSV color space is preferred for manipulation of hue and saturation (to shift colors or adjust the amount of color) since it yields a greater dynamic range of saturation [12]. Figure 1 illustrates the single hex cone HSV color model. The top of the hex cone corresponds to $V = 1$, or the maximum intensity of colors. The point at the base of the hex cone is black and here $V = 0$. Complementary colors are 180° opposite one another as measured by H , the angle around the vertical axis V , with red at 0° . The value of S is a ratio, ranging from 0 on the center line vertical axis V to 1 on the sides of the hex cone. Any value of S between 0 and 1 may be associated with the point $V = 0$. The point $S = 0, V = 1$ is white. Intermediate values of V for $S = 0$ are the grays. Note that when $S = 0$, the value of H is irrelevant. From an artist's viewpoint, any color with $V = 1, S = 1$ is a pure pigment whose color is defined by H . Adding white and black corresponds to decreasing S without changing V and corresponds to decreasing V without changing S respectively. Tones are created by decreasing both S and V .

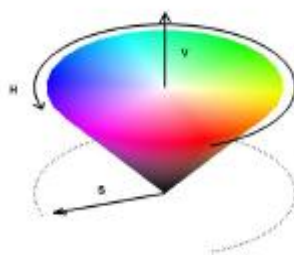


Fig. 1. HSV cone

Unlike general techniques of forming bins we divide the color space into parts depending on perception. Figure 2 shows the variation of Hue against Saturation plot with constant values of Value at its maximum. Note that as shown by the vertical partitions the segmentation of Hue is done. We can observe that the color in each partition is almost correlated and seems similar to the eyes. Thus we have 6 bins in the Hue plane.

Color coherence vector is double color histograms which consist of coherent vector and incoherent vector. We define a color's coherence as the degree to which pixels of that color are members of large similarly-colored regions. We refer to these significant regions as coherent regions, and observe that they are of significant importance in characterizing images. Our coherence classifies pixels as either coherent or incoherent. Coherent pixels are a part of some sizable contiguous region, while incoherent pixels are not. A color coherence vector represents this classification for each color in the image. This notion of coherence allows us to make fine distinctions that cannot be made with simple color histograms.

The initial stage in computing a CCV [13] is similar to the computation of a color histogram. First blur the image slightly by replacing pixel values with the average value in a small local neighborhood including the 8 adjacent pixels. Define the color space with only n distinct colors in the image. The next step is to classify the pixels within a given color bucket as either coherent or incoherent. A coherent pixel is part of a large group of pixels of the same color, while an incoherent pixel is not. After words determine the pixel groups by computing connected components

When this is complete, each pixel will belong to exactly one connected component. Classify pixels as either coherent or incoherent depending on the size of its connected component. A pixel is coherent if the size of its connected component exceeds a fixed value τ ; otherwise, the pixel is incoherent.

For a given discredited color [14], some of the pixels with that color will be coherent and some will be incoherent. Let us call the number of coherent pixels of the j^{th} discrete color α_j and the number of incoherent pixels β_j . Clearly, the total number of pixels with that color is $\alpha_j + \beta_j$, and so a color histogram would summarize an image as

$$\langle \alpha_1 + \beta_1, \dots, \alpha_n + \beta_n \rangle \quad (1)$$

Instead, for each color we compute the pair (α_j, β_j) which we will call the coherence pair for the j^{th} color. The color coherence pair's vector for the image consists of

$$\langle (\alpha_1, \beta_1), \dots, (\alpha_n, \beta_n) \rangle \quad (2)$$

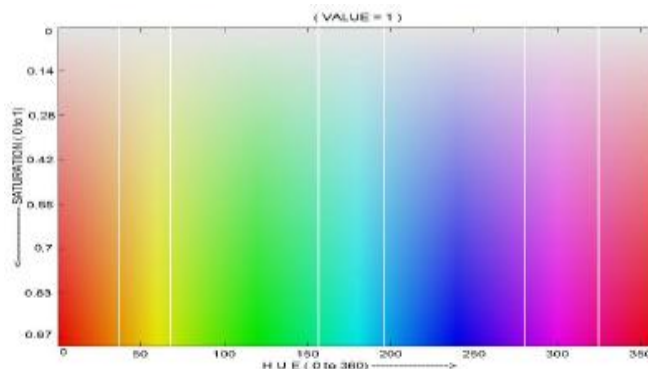


Fig.2. Hue v/s Saturation plot

Classification of coherence is determined by a fixed value τ . Each pixel is checked whether coherent or not. A pixel is coherent if its surrounding pixels have the same values to form a large contiguous region. Two images I and I_1 can be compared using their CCV's, by using the L distance. Let the coherence pairs for the j^{th} color bucket is (a_j, b_j) in I and $(a1_j, b1_j)$ in I_1 . Using the L distance to compare CCV's, the j^{th} bucket's contribution to the distance between I_1 and I is

$$\Delta CCV = (a_j - a1_j) + (b_j - b1_j) \quad (3)$$

B. Shape Feature

Shape is an important visual feature and it is one of the basic features used to describe image content. However, shape representation and description is a difficult task. This is because when a 3-D real world object is projected onto a 2-D image plane, one dimension of object information is lost. As a result, the shape extracted from the image only partially represents the projected object. To make the problem even more complex, shape is often corrupted with noise, defects, arbitrary distortion and occlusion. Further it is not known what is important in shape. Current approaches have both positive and negative attributes; computer graphics or mathematics use effective shape representation which is unusable in shape recognition and vice versa. In spite of this, it is possible to find features common to most shape description approaches.

Basically, shape-based image retrieval consists of measuring the similarity between shapes represented by their features. Some simple geometric features can be used to describe shapes. Usually, the simple geometric features can only discriminate shapes with large differences; therefore, they are usually used as filters to eliminate false hits or combined with other shape descriptors to discriminate shapes. They are not suitable to stand alone shape descriptors. A shape can be described by different aspects [15]. These shape parameters are Mass, Center of gravity(Centroid) [16], Mean, Variance, Dispersion, Axis of least inertia, Digital bending energy, Eccentricity, Circularity ratio, Elliptic variance, Rectangularity, Convexity, Solidity, Euler number, Profiles, Hole area ratio, etc. Some of these are described as follows.

Mass is the no. of pixels contained in one class. It is given as

$$mass = \sum_{xy} h(x, y) \quad (4)$$

where

$$h = \begin{cases} 1 & \text{if } s(x, y) \in c \\ 0 & \text{if } s(x, y) \notin c \end{cases}$$

Centroid is also called as the center of mass; h is a mask of cluster c over image $S(x, y)$. The co-ordinates (x_c, y_c) of the Centroid are defined as:

$$x_c = \frac{\sum_{xy} x * h(x, y)}{mass} \quad (5)$$

and

$$y_c = \frac{\sum_{xy} y * h(x, y)}{mass} \quad (6)$$

The mean and variance features of the class c are computed over the original image I considering the resulting segmentation S , and they are respectively denoted by μ_c and σ_c^2

$$\mu_c = \frac{\sum_{x,y} I_{x,y} * h_c(x, y)}{mass} \quad (7)$$

and

$$\sigma_c^2 = \frac{\sum_{x,y} (I_{x,y} - \mu_c) * h_c(x, y)}{mass} \quad (8)$$

Dispersion is the sum of the distances of each region of a class from the class Centroid. The distance is calculated by Euclidean distance formula. The dispersion can be given as

$$Disp = \sum_i dist(O_c, O_{i,c}) \quad (9)$$

Where, $dist(O_c, O_{i,c})$ is the Euclidean distance

O_c = centroid of the class c

$O_{i,c}$ = centroid of region I of class c

III. PROPOSED WORK

A. Color Retrieval

Color retrieval system works in two stages.

- 1) In the first stage, Histogram based comparison is done and matching images are short listed.
- 2) In the second stage, the Color Coherence Vectors of the short listed images (stage 1) are used to refine the results.

Numbers of coherent and non-coherent pixels for all color intensities are calculated in the image. Then size of coherency array, coherency array and no. of coherency pixels are stored as a vector. The Euclidean Distance is used for matching two histograms h and h' each of which n bins is given as

$$d = \sqrt{\sum_{i=1}^n (h_i - h'_i)^2} \quad (10)$$

It operates by assuming each vector as a point in an n -dimensional vector space and computes the physical distance between the 2 points.

B. Algorithm for Color Retrieval

- Step1: Read the image
- Step2: Convert from RGB to HSV
- Step3: Find HSV histogram and create vectors $v1$.
- Step4: Read the vectors from database and compare one by one by one with vector $v1$.
- Step5: Shortlist all the images which fall within the threshold.
- Step6: find coherency of the query image for each color and create coherency vector $c1$.
- Step7: Compare coherency vectors of all the short listed images from step5 with $c1$.
- Step8: Store all matching images in results folder and also display them.

C. Shape Retrieval

The proposed shape retrieval system based on the automatic segmentations process to get approximate information about the shape of an object. It begins by segmenting the image into 5 classes depending on their brightness. Then three attributes: Mass, Centroid and Dispersion for each class are calculated and stored as the shape vector. For retrieval the vectors of the query image and database images are compared and the most matching images are short listed as results.

D. Algorithm for shape Retrieval

- Step1: read the image
- Step2: convert it from RGB to grayscale

- Step3: determine the range and number of classes.
Step4: calculate the number of pixels i.e. mass belonging to each class.
Step5: calculate the centroid and dispersion for each class.
Step6: compare centroid of each class of query image with the centroids of each class from database image and extract out that class.
Step7: compare that class's mass and dispersion with respective class.
Step8: increase the count if it satisfies certain threshold.
Step9: consider second class and repeat steps 6-8 till all classes get over.
Step10: take another image from the database and repeat the comparison.
Step11: display the images with maximum count.

E. Similarity Measure

In this algorithm we propose that matching is done on color by color basis. By analyzing histograms, first calculate the number of colors in both query image and database image. Then both the images are matched by seeing if the proportions of a particular color in both the images are comparable. The image which satisfies most of the conditions is the best match. Retrieval result is not a single image but a list of images ranked by their similarities with the query image since CBIR is not based on exact matching.

If I is the database image and I' is the query image, then the similarity measure is computed as follows,

1. Calculate histogram vector $v_I = [v_{I1}, v_{I2}, \dots, v_{In}]$ and ccv vector $c_I = [c_{I1}, c_{I2}, \dots, c_{In}]$ of the database images.
2. Calculate the vectors $v_{I'}$ and $c_{I'}$ for the query image also.
3. The Euclidean distance between two feature vectors can then be used as the similarity measurement:
4. If $d \leq \tau$ (threshold) then the images match.
5. From all the matching images we display top 24 images as a result.

Segmenting the query image into 5 classes based on its brightness and calculates the Euclidean distance between the respective classes of query image and database image attributes. Mass, centroid and dispersion parameters are calculated for each class. These features are compared with database images stored features. The features values which are less than defined threshold are sorted based on increasing difference between query and database images then stored separately.

IV. EXPERIMENTAL RESULTS

Both color and shape retrieval algorithms are implemented in MATLAB with the database of 570 images. All the images are stored in JPEG format with size 384×256 or 256×384 . There are six different categories; which includes 100 horse, 100 rose, 100 dinosaur, 100 bus, 100 elephants and 70 bikes. To evaluate the performance of the image retrieval algorithm we use the two most well known parameters; precision and recall.

$$recall = \frac{\text{relevant retrieved}}{\text{all relevant}}$$

$$precision = \frac{\text{relevant retrieved}}{\text{all retrieved}}$$

The system is executed with 10 images from each of the six categories and calculated the average precision and average recall parameters for all of them. The results obtained using shape and color based for different category of images is shown in Table-I. Retrieval result images with query image of shape and color based are shown in Figure 3a-b and 4a-b respectively. The combination of color and shape for different types of images is given in Table-II and corresponding result images are shown in Figure 5a-b. In both tables average accuracy of the proposed method is about more than 70 % which is much greater than the histogram based method.

V. CONCLUSION

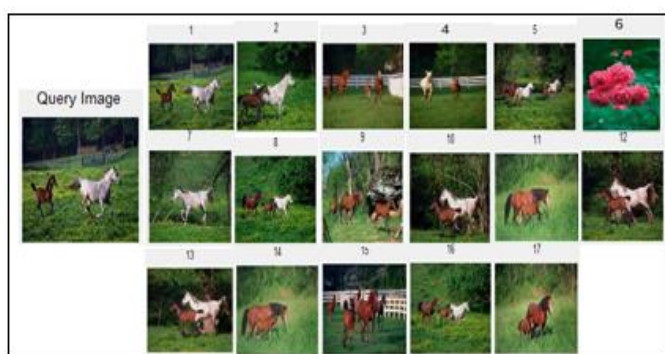
With the advent of various search engines, image searching has become an easier task. But all the search engines use text based retrieval techniques. Though CBIR is a happening topic, we cannot expect the entire upheaval of existing techniques with CBIR. But certainly, CBIR can be used to complement the existing machinery to provide better results. The CBIR methods presented herein use low-level features to generate results. The purpose of this paper was to improve the accuracy (precision) of a CBIR application by allowing the system to retrieve more images similar to the source image. The new algorithms under research and also the recently published ones seem to be extremely invasive on the image. Also each new algorithm is always seen to have certain regions where it works best and poor. The proposed methodology had increased the average precision from an average of 44% to an average of 72%.

TABLE I COLOR AND SHAPE BASED PRECISION AND RECALL ANALYSIS

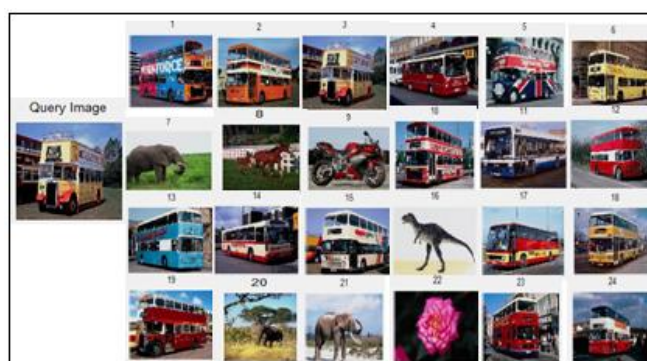
Category	Shape		Color	
	Precision	Recall	Precision	Recall
Rose	0.875	0.18	0.76	0.18
Horse	0.8	0.13	0.91	0.22
Bus	0.75	0.07	0.69	0.16
Elephant	0.51	0.06	0.65	0.15
Bike	0.74	0.09	0.7	0.17
Dinosaur	0.83	0.2	0.75	0.18
AVG	0.75	0.121	0.74	0.17

TABLE II COMBINATION OF COLOR AND SHAPE PRECISION AND RECALL ANALYSIS

Category	Color & Shape (CCV)		Color & Shape (Histogram)	
	Precision	Recall	Precision	Recall
Rose	0.73	0.08	0.45	0.11
Horse	0.81	0.1	0.61	0.14
Bus	0.78	0.06	0.33	0.08
Elephant	0.76	0.04	0.45	0.1
Bike	0.59	0.08	0.38	0.08
Dinosaur	0.69	0.15	0.44	0.1
AVG	0.72	0.08	0.44	0.1



a

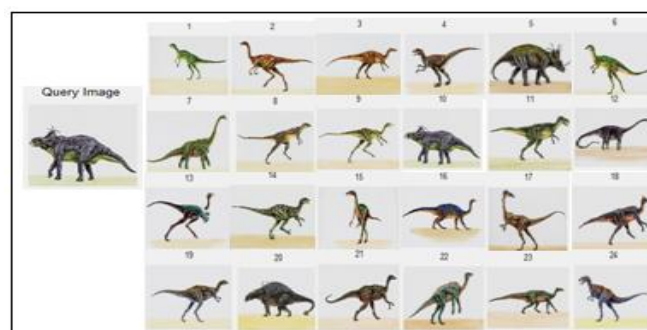


b

Fig. 3a and 3b Results of shape based retrieval for horse and bus image



a

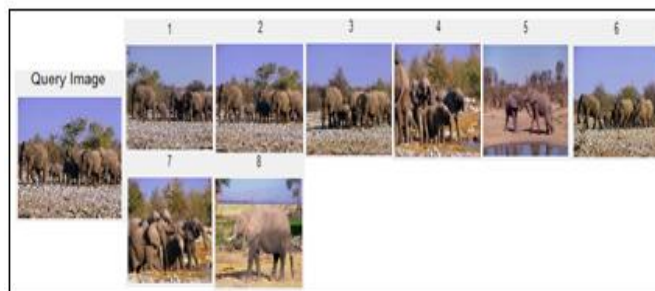


b

Fig. 4a and 4b Results of color based retrieval for flower and dinosaur image



a



b

Fig. 5a and 5b Results of combination of color and shape based retrieval for bike and elephant image

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Biography



Reshma Chaudhari was born in Jalgaon in the Maharashtra, India on September 7, 1978. She graduated from Cummins COE Pune under Pune University, Pune and Pursuing M. E. from J. T. M. COE Faizpur, under North Maharashtra University, Jalgaon. She is mainly interested in Image Processing.



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