A CBIR METHOD BASED ON COLOR-SPATIAL FEATURE

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Abstract

Along with the analysis of color features in HSV space, a new dividing method to quantize the color space into 36 non-uniform bins is first introduced in this paper. Based on this quantization method, we propose a color-spatial method to include several spatial features of colors in an image for retrieval. These features are area and position, which mean the zero-order and the first-order moments, respectively. Experiments on an image database of 838 images show that the algorithm performs well in precision and adaptability.

Keywords: *Image retrieval, HSV color space, color histogram, moments, color-spatial feature*

I. INTRODUCTION

In recent years, more and more attention is focused on Content-Based Image Retrieval (CBIR), which is a sub-problem of Content Based Retrieval (CBR). The tremendous growth of the numbers and sizes of digital image and video collections on Web is making it necessary to develop power tools for retrieving this unconstrained imagery. In addition, CBIR is also the key technology for improving the interface between user and computer.

Among various low-level features, the color information has been extensively studied because of its invariance with respect to image scaling and orientation. In 1990, a simple and effective color-indexing scheme based on color histograms was proposed by Swain and Ballard. Further, attempts have been made to develop general purpose image retrieval systems based on color feature, such as QBIC system in IBM [2], Visual Seek system in Columbia University [1]. These systems contribute lots for the research of CBIR.

Except for the color histogram information, the position information of each color plays an important role too. In this paper, we propose a fast algorithm, which could include several spatial features of color in an image for retrieval. These features are area and position, which mean the zero-order and the first-order moments, respectively. By computing the moments of each color region, we can evaluate the similarity of two images according to the weight of each factor. In fact, these features are a kind of representation for image in the scale of low resolution, and the sample image given by a user is usually a draft drawn by hand. Moreover, when a user judges the similarity between two pictures, he will firstly judge them in coarse scale. In this sense, this method is close to the vision model of our eyes. Because the features are simple and can be calculated in fast speed, better result can be made easily through training.

This paper is organized as follows. In section 2, along with the analysis of color features, the quantization scheme for HSV color space is presented. Section 3 presents the algorithm based on the color-spatial feature in detail. Section 3 presents the experimental results of the proposed algorithm and comparison with other algorithms. Thereafter, we give concluding remarks in Section 5.

II. COLOR QUANTIZATION SCHEME

Among several models for representing for color, the HSV (Hue, Saturation and Value) color space is a suitable one for perception [1]. Since it is nearly perceptually uniform, the similarity of two HSV colors is determined by their proximity in the HSV color space. The similarity between two colors given by indices can be measured by the Euclidean distance between the color points in the cylindrical HSV color space.

To use the HSV space in CBIR application, we must quantize it into several bins. J.R.Smith [1] designed a quantization scheme to produce 166 colors. Li Guohui [4] designed a non-uniform quantization method to produce 72 colors. Along with the advanced analysis of color features in HSV space, we propose a new dividing method to quantize the color space into 36 non-uniform colors.

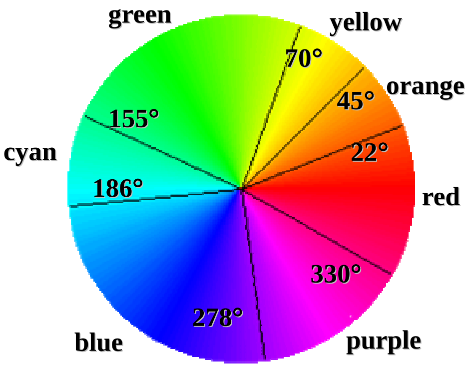

Figure.1. Hue panel quantization

First, we find that the hue shows the colors of red, orange, yellow, green, cyan, blue and purple from 0° to 360°. Each color is not uniform according to the range of hue. For instance, three primaries of red, green and blue occupy more space than other colors. Similar to the vision model, the colors we can easily tell their name are these seven colors in Chinese. Enlightened by this thought, we quantize the hue dimension into seven non-uniform colors, as shown in figure 1.

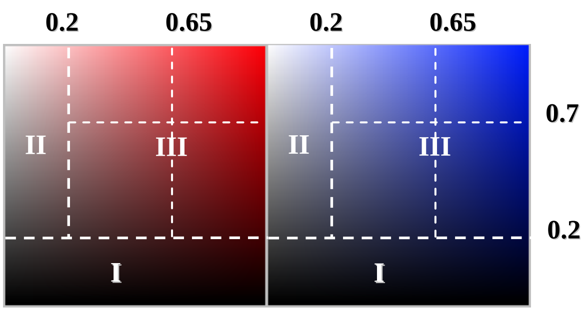

Figure.2. SV panel quantization

Second, we find that the SV panel can be quantized non-uniformly too. Figure 2 shows the SV panels of two primary colors. Notice that in each panel, when V is small enough, for instance V <= 0.2, region-I can be perceived as a black area despite of H and S. So it can be quantized with only one index. When S is small enough, for instance S <= 0.2, region-II can be perceived as a gray area despite of H. So it can be quantized to seven indices. Only region-III (S, V >= 0.2) can be perceived as a color area of four sub-region with boundaries of S=0.65 and V=0.7, as shown in figure-2. Considering to different H, we give region-III 4x7 indices in our quantization scheme.

The quantization scheme can also be summarized as following:

For $v \in [0, 0.2)$, it is a black area:

$l = 0$

For $s \in [0, 0.2]$ and $v \in [0.2, 0.8)$, it is a gray area:

$l = \lfloor (v - 0.2) \times 10 \rfloor + 1$

For $s \in [0, 0.2]$ and $v \in (0.8, 1.0]$, it is a white area:

$l = 7$

For $s \in (0.2, 1.0]$ and $v \in (0.2, 1.0]$, it is a color area:

$$H = \begin{cases} 0 & if \quad h \in (330, 22] \\ 1 & if \quad h \in (22, 45] \\ 2 & if \quad h \in (45, 70] \\ 3 & if \quad h \in (70, 155] \\ 4 & if \quad h \in (155, 186] \\ 5 & if \quad h \in (186, 278] \\ 6 & if \quad h \in (278, 330] \end{cases} \qquad S = \begin{cases} 0 & if \quad s \in (0.2, 0.65] \\ 1 & if \quad s \in (0.65, 1] \end{cases} \qquad V = \begin{cases} 0 & if \quad v \in (0.2, 0.7] \\ 1 & if \quad v \in (0.7, 1] \end{cases}$$

$l = 4H + 2S + V + 8$

As the result, we can calculate the color histogram of 36 bins based on our quantization scheme. The scheme has the following advantages:

- By considering the non-uniform character in both H panel and SV panel, it is more similar to the human vision model.
- By putting similar colors into same bin, it avoids the problem of the color indices redundancy in other quantization schemes.
- Because there are 8 level gray colors, it is suitable for both color images and gray images.
- Because the quantization result has only 36 bins, the computational complexity is decreased tremendously.

III. COLOR-SPATIAL ALGORITHM

3.1 Why to introduce spatial feature?

In the traditional image retrieval using color histogram, the histogram of the query image is compared to that of the image in the database one by one and evaluated by a function. Therefor a result set can be selected and ranked. But the color histogram has one major drawback. That is, it will loss color distribution information in the image, thus leading to some false retrieval. However, if we introduce the spatial information to enlarge the feature space, the precision will be increased notably.

3.2 Spatial features in mathematical form

The simple and effective way to represent a shape in an image is moment [3], which is defined as following:

Define: The set of moments of a bounded function *f(x, y)* of two variables is defined by

$$M_{jk} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^j y^k f(x, y) dxdy$$

where *j* and *k* take on all nonnegative integer values.

For shape-descriptive purposes, suppose *f(x, y)* takes on the value 1 where the pixel is quantized to a constant color *c*, and 0 elsewhere. This silhouette function reflects the shape of pixels with color of quantization value *c*.

The parameter $j+k$ is called the *order* of the moment. There is only one zero-order moment,

$$M_{00} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)dxdy$$

It is clearly the area of the object and the value of the correspond color in the histogram.

The coordinates of the center of gravity of an object can be computed using the first-order moment:

$$\bar{x} = \frac{M_{10}}{M_{00}} \qquad \bar{y} = \frac{M_{01}}{M_{00}}$$

The features can be calculated in fast speed by using moments to describe the shape. In our proposed algorithm, moments are computed according to each quantized color. It is more robust and simple than the traditional segment method. Among several moments, we select the zero-order and the first-order moment as the spatial feature of an image.

3.3 Color-spatial algorithm

As discussed above, we can describe the retrieval algorithm based on color-spatial feature in detail:

First of all, we give the feature representation for a image **I** (N1×N2)：

Step 1: For each pixel in region-I, change it from RGB space to HSV space. As the result, H∈[0,360], S,V∈[0..1].

Step 2: Quantize each pixel in HSV space to 36 bins by using non-uniform quantization scheme described in section 2.

Step 3: Calculate and normalize the histogram of image I [5]:

$$\mathbf{H} = (h[c_1],\ \ h[c_2], \ldots, h[c_k] \ldots h[c_n]),$$
$$\sum_{k=1}^{n} h[c_k] = 1, \quad 0 \le h[c_k] \le 1$$

where $h[c_k]$ represents the frequency of the color with index *k, and*

$$h[c_k] = \frac{\sum_{i=0}^{N_1-1}\sum_{j=0}^{N_2-1} f(i,j,k)}{N_1 \bullet N_2}$$

$$f(i,j,k) = \begin{cases} 1, & if\ Q(T(I[i,j])) = c_k \\ 0, & others \end{cases}$$

Comparing to moment definition discussed above, $h[c_k]$ is equal to the zero moment of the shape composed by pixels with color of quantization value c_k, i.e., M_{00}/A, where $A=N_1 \bullet N_2$.

Step 4: Calculate and normalize each color's center position **P**=($p[c_1]$, $p[c_2]$, .., $p[c_n]$), $p[c_k]$=($\bar{x}[c_k]$, $\bar{y}[c_k]$):

$$\bar{x}[c_k] = \frac{\sum_{i=0}^{N_1-1}\sum_{j=0}^{N_2-1} i \bullet f(i,j,k)}{N_1 \bullet \sum_{i=0}^{N_1-1}\sum_{j=0}^{N_2-1} f(i,j,k)}$$

$$\bar{y}[c_k] = \frac{\sum_{i=0}^{N_1-1}\sum_{j=0}^{N_2-1} j \bullet f(i,j,k)}{N_2 \bullet \sum_{i=0}^{N_1-1}\sum_{j=0}^{N_2-1} f(i,j,k)}$$

Up to now, we can represent the image **I** with two vectors (**H**, **P**).

Step 5: Calculate the similarity metric between query image I_q and target image I_t in the database:

$$D(I_q, I_t) = \alpha \cdot D_h(\mathbf{H_q}, \mathbf{H_t}) + \beta \cdot D_p(\mathbf{P_q}, \mathbf{P_t})$$

For D_h there are several similarity metrics between two histograms. Here we select Euclidean distance. In addition, for D_p, we select the distance between two points in a plane. Therefor we can get the similarity in detail:

$$D_h = \left(\sum_{i=1}^{n} \left(h_q[c_i] - h_t[c_i]\right)^2 \right)^{1/2}$$

$$D_p = \left(\sum_{i=1}^{n} \left[\left(\bar{x}_q[c_i] - \bar{x}_t[c_i]\right)^2 + \left(\bar{y}_q[c_i] - \bar{y}_t[c_i]\right)^2 \right] \right)^{1/2}$$

We can select the weighting coefficients α and β corresponding to the degree of interesting for color or spatial information at run time.

IV. EXPERIMENTAL RESULTS

For evaluating the performance of the algorithm, we used an experimental database which consists of 838 images, including 150 flowers, 534 outdoor natural scenes, 63 cats and 91 other animals. The query image was selected from the database and it would be the first image in the result list. Other images in the result list were retrieved and ranked based on the similarity to the query image.

Retrieval results are evaluated by precision versus recall. Recall is the proportion of relevant images in the database that are retrieved in response to a query. Precision is the proportion of retrieved images that are relevant to the query.

We selected 4 query images represent different scenes, including 2 flowers, 1 countryside scene and 1 sunset scene. We also performed the experiment using 166 color-spatial (uniform) and 36 colors only (non-uniform, without spatial information) in order to provide a comparison. The weighting coefficient α and β are 0.9 and 0.1. Figure 3 gives a retrieval result with query image of little flower and using 36 color-spatial method. The average precision for 4 queries was calculated and summarized in Table 1 and Figure 4.

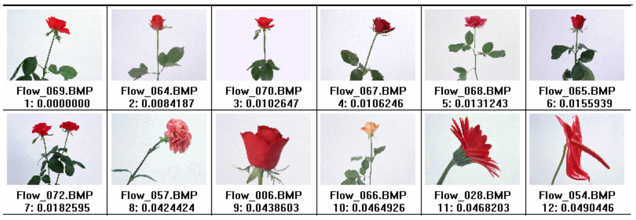

Figure.3. Retrieval result using 36 color-spatial method

Recall / Average Precision	0.2	0.4	0.6	0.8	1.0
36-Color-Spatial	0.896	0.804	0.647	0.451	0.123
36 Colors Only	0.857	0.695	0.500	0.257	0.126
166 Color Spatial	0.781	0.683	0.462	0.375	0.187

Table.1. Average precision vs recall

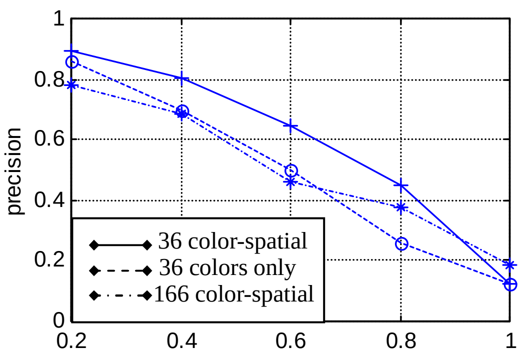

Figure.4. Average precision vs recall

We can seen from both the table and the figure that,

(1) In general, best performance using 36 color-spatial method was obtained at most recall rates.

(2) Comparing between 36 and 166 color-spatial method, we can find that the former works better, because its color quantization scheme is more similar to the vision model. In a sense, 36 color scheme equals to a kind of clustering that the color redundancy is reduced in the histogram.

(3) Comparing between 36 color-spatial method and 36 colors only method, the result of former is better too. The spatial information enlarges the feature vector and increases the precision at the same time.

V. CONCLUSIONS

Along with the analysis of the HSV color space, we presented a new non-uniform quantization method, which is more reasonable to the human vision model. Without decreasing the retrieval performance, the scheme quantizes the color space into 36 bins. Because the quantization result has only 36 bins, the computational complexity is decreased quickly while the performance increases. Based on this quantization method, we propose a color-spatial method to include several spatial features of colors as well. The combination of color and spatial features gives a better result in the experiment with a database of 838 images.

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