Stone Images Retrieval Based on Color Histogram
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Abstract — Stone images’ color features are chosen for its retrieval and indexing in this paper. Cross color histogram, annular color histogram, and angular color histogram are respectively combined with HSV color space to accord with human’s visual uniformity. In HSV color space, H, S, V three components carry on unequal interval quantization to improve retrieval precision and efficiency, and then different weight values are given and adjusted to different color channel. Stone images are sorted according to their similarity in retrieval results. Experiments showed that cross color histogram in HSV color space has excellent performance on stone images retrieval.

I. INTRODUCTION
Along with the development of multimedia technology and the arrival of information age, image information resources have increased rapidly. Traditional image database retrieval based on keywords or descriptive text is no longer enough. Therefore, content-based image retrieval is proposed to extract images’ visual feature by computers, including color, texture, shape, position of the objects and their interrelationship, etc. Among them color is perhaps the most direct and distinguishing visual feature; it is also invariant to translation and rotation. So far, color histogram is the most widely used color descriptor in content based retrieval research.

Several methods based on color histogram have been proposed in image retrieval. They are mainly divided into two types: global feature index and local feature index. The technology of global feature index [4] was first proposed by Swain and Ballard, the main idea of which is to analyze each color’s statistical frequency in an image. However, with this way, the special information of colors is not preserved. Pass and Zabih define the concept of color coherent vector (CCV) and use it to segment a color histogram into two parts. A pixel is called coherent if its connected component is over a certain value while the opposite is called non-coherent. A CCV of an image is the statistical ratio of each color’s coherent and non-coherent pixels; this way, the special information is preserved to a certain degree. Typical local feature index includes color histogram based on representative colors, which splits an image into several parts and selects a representative color for each part. Stricker and Dami consider that the center of an image as the most significant part. They partition an image into 5 fuzzy regions, and then extract the first three moments of the color distribution for each region. With the method of local feature index, the special distribution of an image is considered coupled with color.

Taken together, there are already several techniques researched for the retrieval of color images. For stone images, color is also considered as a typical feature for retrieval and indexing. Colors distribute evenly in a stone image, furthermore, the image has no definite objects and can’t be distinguished as background and foreground. In this paper, the color space is firstly transformed from RGB into HSV color space, quantized with proper quantization parameters, and then three algorithms are used for the stones image retrieval: cross color histogram, annular color histogram, and angular color histogram. According to the results of experiments, analyses and comparisons are made to their retrieval effect.

II. COLOR-SPACE CONVERSION
HSV color space is color space model designed for human vision consideration. Hue, saturation and value are used to describe colors in this color space. They can preferably reflect human perception and identification of color images. In HSV color space, hue is distinguished by different color, such as red, green, which is measured by angle ranged in 0~360; saturation refers to the concentration of color which is measured by percentage; value refers to an image’s luminance which is measured by percentage as well [3]. This is illustrated in Figure 1.

For a true color image, color histogram after color-space conversion will still have high dimension. Therefore, in order to reduce calculation time and enhance retrieval efficiency, proper quantization is necessary. In this paper, the three components $H$, $S$, $V$ are quantized in unequal interval respectively according to human’s visual resolving power and subjective perception.

For photographs, because the photographer plans the composition. Not true for "scene shots" like our scene collect.
The color space is partitioned into 8×3×3=72 color eigenvalues. Following the above quantization levels, the three components of color can be weighted respectively and transformed into a one-dimension vector

\[ s = + + \]

Here \( Q \) and \( V \) refer to the quantization levels of \( S \) and \( V \). Take \( Q_s=3, Q_v = 3 \), the formula can be expressed as

\[ L = 9H + 3S + V \]

This way, the weight value can fully capture the images’ color information. Moreover, it reduces the influence of an image’s luminance. For the one-dimension vector \( L \), it ranges from 0 to 71. Color histogram is created by statistics of the 72 color eigenvalues.

III. THREE ALGORITHMS BASED ON HISTOGRAM

Cross color histogram [4] is first proposed by Swain and Ballard. It is a one-dimension discrete function expressed as

\[ H(k) = \frac{n_k}{N}, \quad k = 0, 1, \ldots, l - 1 \]

In the formula, \( n_k \) represents the number of pixels while the eigenvalue is \( k \), while \( N \) is the total number of pixels in an image. \( l \) refers to the number of eigenvalues after quantization, and also it is the element number of vector \( L \).

Let \( H_Q \) and \( H_D \) be the color histograms of queried image \( Q \) and target image \( D \), the similarity matching between the two images is:

\[ P(Q, D) = \sum_{k=0}^{l-1} \min \left[ H_Q(k), H_D(k) \right] \]

Formula 7 describes the proportion of the histogram of the cross part in that of the queried image. It is illustrated in Figure 2.

The calculation procedure is simple when using the method of cross color histogram. It is also insensitive to scale, translation and rotation. However, global histogram can’t capture the special distribution of colors. Retrieval effect is limited when two images have similar colors but totally different distribution. So, color histogram including the special information is also adapted into the stone image retrieval.

According to Aibing Rao’s annular and angular histograms [5], the distribution of colors in an image can be well described.

Let \( (p_{ij}) C\times R \) be an image of size \( C\times R \) where \( p_{ij} \) is the color of pixel \((i,j)\). Set \( U = \{(x, y) \mid 1 \leq x \leq R; 1 \leq y \leq C\} \), \( B_1, B_2, \ldots, B_w \) are the eigenvalues after quantization with \( M \) color bins. Let \( S_q = \{(x, y) \mid (x, y) \in U, p_{ij} \in B_q \} \) for \( 1 \leq q \leq M \), then

\[ U = \bigcup_{q=1}^{M} S_q \]

is a partition of \( U \). Each \( S_q \), called histogram subset of bin \( B_q \), is the set of pixels whose color is in the \( q^{th} \) bin.

Now consider the histogram subset \( S_q \) as a geometric distribution on the 2-D plane for each color bin \( B_q \), let \( (x^*, y^*) \) be the centroid of \( S_q \), where \( x^* \) and \( y^* \) are defined as follows

\[ x^* = \frac{1}{|S_q|} \sum_{(x,y) \in S_q} x, \quad y^* = \frac{1}{|S_q|} \sum_{(x,y) \in S_q} y \]

Then the radius of \( S_q \) is defined as

\[ r^* = \max_{x, y \in S_q} \sqrt{(x-x^*)^2 + (y-y^*)^2} \]

Given a number \( N \), divided the radius into \( N \) parts evenly, and then draw \( N \) concentric circles with \( kr/N \) as the radius for each \( 1 \leq k \leq N \) to form \( N \) annular regions. Each region, from inner to outside, is defined as \( R_{r_1}, R_{r_2}, \ldots, R_{r_N} \). Vector \((|R_{r_1}|, |R_{r_2}|, \ldots, |R_{r_N}|)\) is called the annular distribution density. This is illustrated in Figure 3.
Fig. 3. Annular distribution density.

Set $A_i = R_j$ for $i = 1,\ldots,M$ and $j = 1,\ldots,N$. Then a $M \times N$ matrix $A = (A_{ij})_{M \times N}$ is called annular histogram of the image which refers to the number of a certain color in a certain ring. Since the centroid and the annular partition of each histogram subset are translation and rotation invariant, the histogram is tolerant to a small movement before the image is processed, the Euclidean distance is adopted to calculate the similarity distance which is defined as

$$d = \sqrt{\sum_{i=1}^{M} \sum_{j=1}^{N} (A_{ij} - B_{ij})^2}$$

Notice that when $N=1$, the matrix represents the global histogram.

Similar to the annular partition, angular partition introduces another type of special color histogram. In order to keep the advantage of translation and rotation invariant, a starting direction should be chose at first. Let $C^x = (x^x, y^x)$ is the centroid of $S_q$. For each point $(x, y) \in S_q$, the starting direction can be calculated via the following formula

$$\theta(x, y) = \arctan\left(\frac{y - y^x}{x - x^x}\right) \pm \pi$$

Here $+,-$ are to selected depending on which quadrant the point is in. Then the average direction of the subset $S_q$ is denoted as

$$\Theta(S_q) = \frac{1}{|S_q|} \sum_{(x, y) \in S_q} \theta(x, y)$$

This average direction is the starting direction of angular partition. Given a number $N$, for each histogram subset $S_q$, starting from the average direction $\Theta(S_q)$, divided the unit circle centered at $C^x$ evenly into $N$ fan-like domains. From the starting direction, the angular domains are named $R_1, R_2, \ldots, R_N$ in turn. Vector $(|R_1|, |R_2|, \ldots, |R_N|)$ is called angular distribution density of the subset $S_q$, this is illustrated in Figure 4.

Fig. 4. Angular distribution density.

It is obvious that angular partition is also tolerant to the translation and rotation of images.

IV. EXPERIMENTS AND COMPARISONS

Special stone images database is used in this paper. Here granite is chose to extract its color feature. The total number of granite is 26, with 4 couples of similar colors: red, yellow, grey and cyan. The arrangement is made by experts before experiments. These stone images are retrieved and indexed through the above algorithms. The result is ordered according to the similarity from minimum to maximum to compare the retrieval effect of each color histogram.

At present, the evaluation of retrieval effect mainly focuses on the accuracy of the result. The standard of accuracy mostly depends on precision and recall. Precision refers to the ratio of similar images number and the total images number in the retrieval result. Recall refers to the ratio of similar images number in the result and in the database. Let $n_r$ the images number in the retrieval result, $n_s$ is similar images number of it. The total images number in the database is $n$. Precision and recalls [6] are defined as

$$\text{precision} = \frac{n_s}{n_r} ; \quad \text{recall} = \frac{n_s}{n}$$

The retrieval effect will be better when the precision and recall are higher. Generally, precision and recall are usually tradeoffs. If high precision is needed, recall will usually be reduced, and vice versa. Generally a good retrieval system is balance the performance between precision and recall. Partial retrieval results of red granite are in showed in Figure 5, 6, 7. In Figure 5, 6, 7, pictures are named by this way: index-score. Index is the serial number of images after sorting and score means the similarity scoring for each image by experts. Figure 8 is the statistical result of all the images.
Figure 8 lists the results of all the 26 stone images. Three of the algorithms have good effect for stone images retrieval according to the list. Comparatively, the performance of cross color histogram outperforms the other two. With certain recall

<table>
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<th>n</th>
<th>Cross color histogram</th>
<th>Annular color histogram</th>
<th>Angular color histogram</th>
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<td></td>
<td></td>
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<td>rec</td>
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<td>1.000</td>
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</tr>
<tr>
<td>cyan</td>
<td>4</td>
<td>4</td>
<td>0.500</td>
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rate, precision has better effect. Moreover, the sorting of similarity by experiments and experts matches well.

V. CONCLUSIONS

Due to the special color feature of stone images, which have evenly distributed colors and no definite objects, three color histograms respectively combined with HSV color space is adopted for retrieval and indexing in this paper. With the advantage of visual uniformity in HSV color space, global and local feature are both extracted from the stone images. Experiments show that, with a lower dimension and less computing load, the cross color histogram in HSV color space has better effect for stone images. In later work, in order to improve the retrieval precision more, the texture feature of stone images will be considered coupled with its color feature.

REFERENCES