IMAGE RETRIEVAL USING BOTH COLOR AND TEXTURE FEATURES

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Abstract:

This paper has a further exploration and study of visual feature extraction. According to the HSV (Hue, Saturation, Value) color space, the work of color feature extraction is finished, the process is as follows: quantifying the color space in non-equal intervals, constructing one dimension feature vector and representing the color feature by cumulative histogram. Similarly, the work of texture feature extraction is obtained by using gray-level co-occurrence matrix (GLCM) or color co-occurrence matrix (CCM). Through the quantification of HSV color space, we combine color features and GLCM as well as CCM separately. Depending on the former, image retrieval based on multi-feature fusion is achieved by using normalized Euclidean distance classifier. Through the image retrieval experiment, indicate that the use of color features and texture based on CCM has obvious advantage.

Keywords:

Image retrieval; GLCM; CCM

1. Introduction

The need for efficient content-based image retrieval has increased tremendously in many application areas such as biomedicine, military, commerce, education, and web image classification and searching. Currently, rapid and effective searching for desired images from large-scale image database becomes an important and challenging research topic [1,2]. Content-based Image Retrieval (CBIR) technology overcomes the defects of traditional text-based image retrieval technology, such as heavy workload and strong subjectivity. It makes full use of image content features (color, texture, shape, etc.), which are analyzed and extracted automatically by computer to achieve the effective retrieval [3,4].

Using a single feature for image retrieval can not be a good solution for the accuracy and efficiency. High-dimensional feature will reduce the query efficiency; low-dimensional feature will reduce query accuracy, so it may be a better way using multi features for image retrieval. Color and texture are the most important visual features. Firstly, we discuss the color and texture features separately. On this basis, a new method using integrated features is provided, and experiment is done on the real images, satisfactory result is achieved, verify the superiority of integrated feature than the single feature.

2. Feature extraction of HSV color

HSV color space is widely used in computer graphics, visualization in scientific computing and other fields [5]. In this space, hue is used to distinguish colors, saturation is the percentage of white light added to a pure color and value refers to the perceived light intensity [6]. The advantage of HSV color space is that it is closer to human conceptual understanding of colors and has the ability to separate chromatic and achromatic components.

2.1. Non-interval quantization

Because of a large range of each component, if directly calculate the characteristics for retrieval, then computation will be very difficult to ensure rapid retrieval. It is essential to quantify HSV space component to reduce computation and improve efficiency. At the same time, because the human eye to distinguish colors is limited, do not need to calculate all segments. Unequal interval quantization according the human color perception has been applied on H , S , V components.

Based on the color model of substantial analysis, we divide color into eight parts. Saturation and intensity is divided into three parts separately in accordance with the human eyes to distinguish. In accordance with the different colors and subjective color perception quantification, quantified hue(H), saturation(S) and value(V) are showed as equation (3).

In accordance with the quantization level above, the H, S, V three-dimensional feature vector for different values of

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with different weight to form one-dimensional feature vector named G [7]:

$$G = Q_S Q_V H + Q_V S + V \quad (1)$$

Where Q_S is quantified series of S, Q_V is quantified series of V.

Here we set $Q_S = Q_V = 3$, then

$$G = 9H + 3S + V \quad (2)$$

$$H = \begin{cases} 0 & if \quad h \in [316,20] \\ 1 & if \quad h \in [21,40] \\ 2 & if \quad h \in [41,75] \\ 3 & if \quad h \in [76,155] \\ 4 & if \quad h \in [156,190] \\ 5 & if \quad h \in [191,270] \\ 6 & if \quad h \in [271,295] \\ 7 & if \quad h \in [296,315] \end{cases} \quad S = \begin{cases} 0 & if \quad s \in [0,0.2) \\ 1 & if \quad s \in [0.2,0.7) \\ 2 & if \quad s \in [0.7,1) \end{cases} \quad V = \begin{cases} 0 & if \quad v \in [0,0.2) \\ 1 & if \quad v \in [0.2,0.7) \\ 2 & if \quad v \in [0.7,1) \end{cases} \quad (3)$$

In this way, three-component vector of HSV form one-dimensional vector, which quantize the whole color space for the 72 kinds of main colors. So we can handle 72 bins of one-dimensional histogram. This quantification can be effective in reducing the images by the effects of light intensity, but also reducing the computational time and complexity.

2.2. Characteristics of color cumulative histogram

Color histogram is derived by first quantize colors in the image into a number of bins in a specific color space, and counting the number of image pixels in each bin. One of the weaknesses of color histogram is that when the characteristics of images should not take over all the values, the statistical histogram will appear in a number of zero values. The emergence of these zero values would make similarity measure does not accurately reflect the color difference between images and statistical histogram method to quantify more sensitive parameters. Therefore, this paper represents the one-dimensional vector G by constructing a cumulative histogram of the color characteristics of image after using non-interval HSV quantization for G.

3. Texture feature extraction

3.1. Texture feature extraction based on GLCM

GLCM creates a matrix with the directions and distances between pixels, and then extracts meaningful statistics from the matrix as texture features. GLCM texture features commonly used are shown in the following:

GLCM is composed of the probability value, it is defined by $P(i, j|d, \theta)$ which expresses the probability of the couple pixels at θ direction and d interval. When θ and d is determined, $P(i, j|d, \theta)$ is showed by $P_{i,j}$. Distinctly GLCM is a symmetry matrix; its level is determined by the image gray-level. Elements in the matrix are computed by the equation showed as follow:

$$P(i, j|d, \theta) = \frac{P(i, j|d, \theta)}{\sum_i \sum_j P(i, j|d, \theta)} \quad (4)$$

GLCM expresses the texture feature according the correlation of the couple pixels gray-level at different positions. It quantificationally describes the texture feature. In this paper, four features is selected, include energy, contrast, entropy, inverse difference.

Energy $$E = \sum_x \sum_y p(x, y)^2 \quad (5)$$

It is a gray-scale image texture measure of homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture.

Contrast $$I = \sum \sum (x - y)^2 p(x, y) \quad (6)$$

Contrast is the main diagonal near the moment of inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth. Contrast is large means texture is deeper.

Entropy $$S = -\sum_x \sum_y p(x, y) \log p(x, y) \quad (7)$$

Entropy measures image texture randomness, when the space co-occurrence matrix for all values are equal, it achieved the minimum value; on the other hand, if the value of co-occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image gray distribution is random.

Inverse difference $$H = \sum_x \sum_y \frac{1}{1 + (x - y)^2} p(x, y) \quad (8)$$

It measures local changes in image texture number. Its value in large is illustrated that image texture between the different regions of the lack of change and partial very evenly.

Here $p(x, y)$ is the gray-level value at the coordinate (x, y).

3.2. Feature extraction based on CCM

Assuming color image is divided into $N \times N$ image sub-block, for anyone image sub-block

$T_{(i,j)}(1 \le i \le N, 1 \le j \le N)$, using the main color image extraction algorithm to calculate the main color $C_{(i,j)}$. For any two 4-connected image sub-block $T_{(i,j)}$ and $T_{(k,l)}(|i-k|=1$ and $j=l$; or $|j-l|=1$ and $i=k)$, if its corresponds to the main color and in the HSV space to meet the following condition[8,9]:

(1) C_j And C_i belong to the same color of magnitude, that is, its HSV components $h_i = h_j, s_i = s_j, v_i = v_j$;

(2) C_j And C_i don't belong to the same color of magnitude, but satisfy $s_i * 3 + v_i = s_j * 3 + v_j$, and $|h_i - h_j| = 1$; or satisfy $h_i = h_j, s_i = s_j$ and $v_i, v_j \in \{0,1\}$.

We can say image sub-block $T_{(i,j)}$ and $T_{(k,l)}$ are color connected. According to the concept of color-connected regions, we can make each sub-block of the entire image into a unique color of connected set $S = \{R_i\}(1 \le i \le M)$ in accordance with guidelines 4-connected.

The set S corresponds to the color-connected region. For each color-connected region $\{R_i\}(1 \le i \le M)$, the color components R, G in RGB color space and H in HSV color space are respectively extracted the CCM at the direction $\delta = 1; \theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$. The same operation is done with I (intensity of the image). The statistic features extracted from CCM are as follows:

$$\text{Energy} \quad E = \sum_{i=1}^{D} \sum_{j=1}^{D} [m(i,j)]^2 \qquad (9)$$

$$\text{Contrast} \quad I = \sum_{i}^{D} \sum_{j}^{D} (i-j)^2 \bullet m(i,j) \qquad (10)$$

$$\text{Entropy} \quad S = -\sum_{i}^{D} \sum_{j}^{D} m(i,j) \bullet \log[m(i,j)] \qquad (11)$$

where, if $m(i,j) = 0$, $\log[m(i,j)] = 0$

$$\text{Inverse difference} \quad H = \sum_{i}^{D} \sum_{j}^{D} \frac{m(i,j)}{1+(i-j)^2} \qquad (12)$$

Through this method, we can get a 16 dimensional texture feature for component R, G, H and I, each component correspond to four statistic values E, I, S and H.

$F = [F_R, F_G, F_H, F_I] = [f_{RE}, f_{RI}, f_{RS}, f_{RI}, \ldots, f_{IE}, f_{II}, f_{IS}, f_{IH}]$

4. Experiment and analysis

In this paper, experimental data set contains 1000 images from Corel database of images, divided into 10 categories, each category has 100 images. Experimental images covers a wealthy of content, including landscapes, animals, plants, monuments, transport (cars, planes) and so on. Selection of each type in the 80 images as training samples, 20 samples for testing.

In section 3, we study two kinds of feature extraction techniques: feature extraction techniques based on the HSV color space and texture feature extraction technology. At texture feature extraction techniques, we introduce two different extraction methods the gray co-occurrence matrix and CCM. Color and texture are just in part describing the characteristics of images. Image database varies some images dramatic ups and downs in gray-level, showing a very strong texture characteristic, and some images from a number of smooth but the colors are different regional composition.

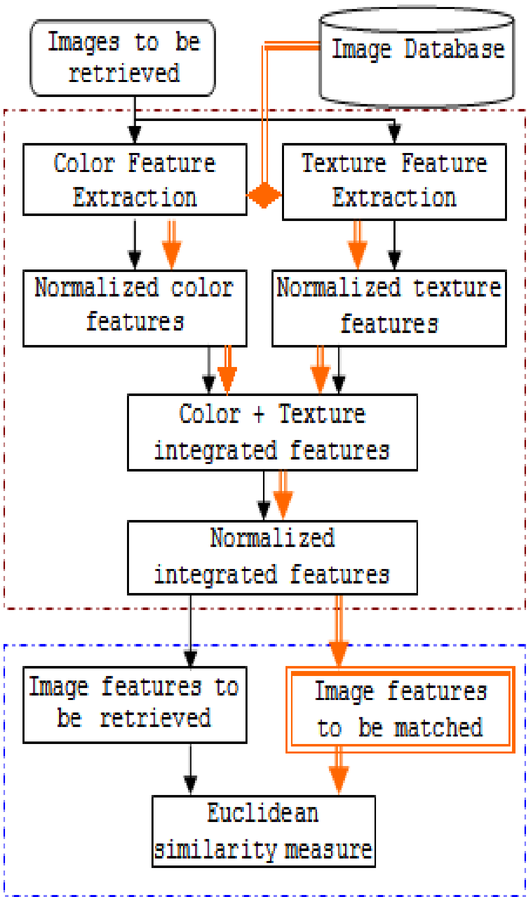

Figure 1. Algorithm scheme

Only simple features of image information can not get comprehensive description of image content. We consider the color and texture features combining not only be able to express more image information, but also to describe image from the different aspects for more detailed information in order to obtain better search results. Retrieval algorithm flow is as follows:

As shown in the figure 1, the similarity measure from two types of characteristic features, including color features and texture features. Two types of characteristics of images represent different aspects of property. So during the Euclidean similarity measure when necessary the appropriate weights to combine them to consider this end.

Therefore, in carrying out Euclidean similarity measure we should consider necessary appropriate weights to combine them. We construct the Euclidean calculation model as follows:

$$D(A,B) = \omega_1 D(F_{CA}, F_{CB}) + \omega_2 D(F_{TA}, F_{TB}) \quad (13)$$

Normalized form as follows:

$$D(A,B) = \omega_1 \frac{\sqrt{2} - D(F_{CA}, F_{CB})}{\sqrt{2}} + \omega_2 \frac{\sqrt{2} - D(F_{TA}, F_{TB})}{\sqrt{2}} \quad (14)$$

Here ω_1 is the weight of color features, ω_2 is the weight of texture features, F_{CA} and F_{CB} represents the 72-dimensional color features for image A, B. For a method based on GCM, F_{TA} and F_{TB} on behalf of 4-dimensional texture features correspond to image A and B, another based on CCM, F_{TA} and F_{TB} on behalf of 16-dimensional texture features.

Here, we combine color features and two different kinds of texture features separately; the value of ω through experiments shows that at the time $\omega_1 = \omega_2 = 0.5$, with better retrieval performance. The following experiments are part of search results and test statistics. Figure 2, 3 for the same retrieved images were compared, figure 4 for the classic picture plane conducted a search. Table 1 shows the image retrieval result. In this table, recall and precision are computed. Obviously, in three feature extraction mode, integrated feature has effective performance, especially, color combined with CCM is better than others.

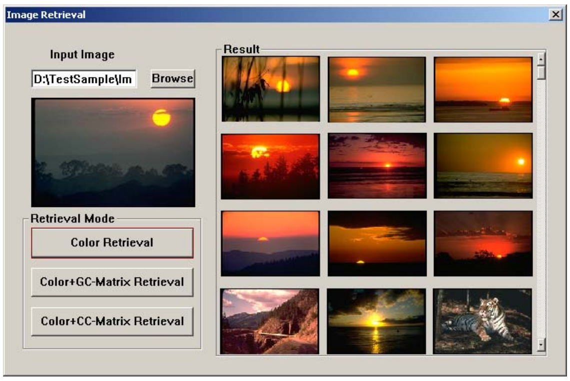

Figure 2. Retrieval Result Based on HSV Color Space

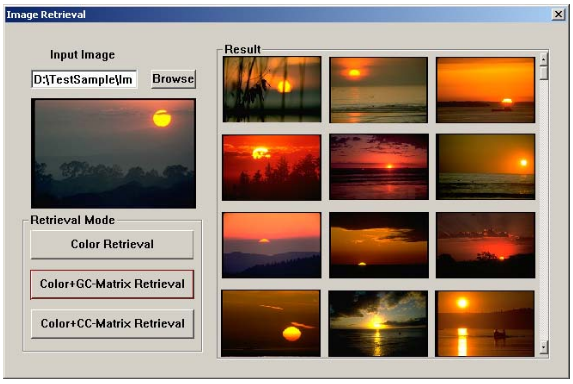

Figure 3. Retrieval Result Based on Color+GLCM

Figure 4. Retrieval Result Based on color+CCM

Table 1. Retrieval result contrast

Retrieval mode	*recall (%)*	*precision (%)*
color	23.1	36.8
color+GLCM	26.5	39.2
color+CCM	29.3	44.1

5. Conclusion

This paper presents an approach based on HSV color space and texture characteristics of the image retrieval. Through the quantification of HSV color space, we combine color features and gray- level co-occurrence matrix as well as CCM separately, using normalized Euclidean distance classifier. Through the image retrieval experiment, indicating that the use of color features and texture characteristics of the image retrieval method is superior to a single color image retrieval method, and color characteristics combining color texture features for the integrated characteristics of color image retrieval has obvious advantages retrieval. Apart from reflecting the CCM texture features, it also reflects the composition of its color, and improve the performance of image retrieval has important research value.

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