Study on Image Retrieval Method of Integrating Color and Texture

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Abstract

The retrieval using single feature has a certain limitation, which fails to comprehensively describe an image. Aiming at such retrieval defect, this paper proposes an image retrieval method integrating color and texture. Firstly, carry out image segmentation with uniformly-spaced method, and then extract color feature of each segmentation with weighting processing done; and then, extract textural feature vector of the image by using gray-level co-occurrence matrix; lastly, accumulate color similarity distance and texture similarity distance of the image with total similarity distance gained. The experience result indicates that image retrieval method based on combination feature is superior to simple image retrieval algorithm.

Keywords

Image retrieval; Color feature; Texture feature; Co-occurrence matrix.

1. Introduction

With rapid development of multimedia technology and communication technology and rapid rise of multimedia data scale, in order to assist users in fast and accurately finding image which they are interested in, image retrieval based on content is proposed. The main idea of image retrieval based on content is to retrieve image by using low-level features of the image, such as color, shape, texture, space relation with image meeting users' needs retrieved by extracting image features.

Color is the image feature which is on the lowest level and the most visualized because in image retrieval, color is always closely relevant to object or scene included in the image. In addition, as for image size, translation, rotation and other features, color feature has higher robustness. Since Swain and Ballard proposed to describe colorful image by color histogram [1], the color histogram as common feature vector has been used in image retrieval in many research approaches. But two images with totally different contents may share the same color histogram, for example, blue sky and ocean, which states that just color histogram cannot reflect image features causing considerable error The texture feature doesn't depend on color or luminance to reflect homogeneity phenomenon of the image, and it contains important information about organization arrangement of object surface structure and relationship with ambient environment. It is the essential feature shared by different materials, such as desert and trees, which have their own texture features.

Therefore, this paper proposes a method by combining color and texture feature to gain similarity for image retrieval. In terms of color feature, the method can segment image by uniformly-spaced segmentation, and then extracts segmentation color feature to carry out weighting processing for each segmentation; in terms of texture feature, the method can extract texture feature by gray-level co-occurrence matrix [2]. Lastly, the method can combine color feature and texture feature to form final image retrieval similarity distance.

2. Color feature extraction

2.1 Color space quantization

As the distinguishing ability of human beings' visual system is limited, pure eyes cannot differentiate too many changes in color. Besides, if there are too many colors in an image, the quantization of histogram will be quite a lot. And the increase of quantization will occupy more storage space and also the calculation will be larger. Therefore, it is necessary to quantize color space to reduce color dimensions. There are mainly two ways of quantizing color space: equal interval quantization and non-equal interval quantization. The former may centralize the information on a small number of colors. In addition, it also makes it possible that the same color can contain different information. So this article employs the non-equal interval quantization[3]. According to the distinguishing ability of naked eyes, this article divides hue (h) into eight parts, saturation into 3 parts and brightness (v) into 3 parts, and the values after quantizing are H, S, and V correspondingly. Based on different color ranges, the quantization is as follows:

$$S=\begin{cases}0 & s\in[0,0.2]\\ 1 & s\in[0.2,0.7]\\ 2 & s\in[0,7,1]\end{cases} \tag{1}$$

$$V=\begin{cases}0 & v\in[0,0.2]\\ 1 & v\in[0.2,0.7]\\ 2 & v\in[0,7,1]\end{cases} \tag{2}$$

$$H=\begin{cases}0 & h\in[316,20]\\ 1 & h\in[21,40]\\ 2 & h\in[41,75]\\ 3 & h\in[76,155]\\ 4 & h\in[156,190]\\ 5 & h\in[191,270]\\ 6 & h\in[271,295]\\ 7 & h\in[296,315]\end{cases} \tag{3}$$

According to this quantization level, compose the 3 color components into the feature vector of one dimension:

$$L = HQ_sQ_v + SQ_v + V \tag{4}$$

Among which, Q_s and Q_v are quantization series of S and V respectively. In this article, given that $Q_s = 3$, $Q_v = 3$, then the formula above can be transformed into:

$$L = 9H + 3S + V \tag{5}$$

Thus, H, S and V are distributed on the one-dimension vector. According to Formula (5), the value range of L is [0, 1, 2,…,71]. The HSV color space after quantization is divided into 72 colors, which can effectively compress color features and are quite favorable for the visual perception of the eyes.

2.2 2.2 Image segmentation

The traditional way of using color histogram for image retrieval only considers the color statistics of the whole image but neglects the spatial distribution of color in images, which inevitably causes very large retrieval errors. To improve this situation, it is necessary to segment images before conducting the statistics of color histogram. Usually this method divides images into certain blocks, makes statistics of the histogram of each block and then compares the similarity between the blocks corresponding to the two images. The commonly used blocking method is to divide the images into equal m*n blocks, as shown in Figure 1. This blocking method has certain defects: 1) this blocking strategy is not qualified with the invariability of rotation and scale, 2) the main content of the images is principally located in the middle part of the images and this blocking neglects the attention of human eyes on the central area. To highlight the importance of different areas of the images and overcome the defects such as the sensitiveness of traditional blocking algorithm to the transformation of rotation and scale, this article puts forward to segment images based on the rectangular frames with equal interval.

The dividing way based on the rectangular frames with equal interval: take the diagonal intersection M as the center, and then divide the rectangular frames with this center. Assume to divide images into S rectangular frames and given that the distance between frames are equal, as shown in Figure 2. Then the side length of the rectangular frame is:

$$\begin{cases} a' = ka/S \\ b' = kb/S \end{cases} \quad (k = 1, 2, 3, \ldots, S) \tag{6}$$

In the formula, a and b are the size of the whole image.

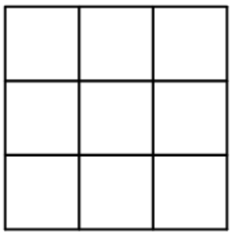

Figure. 1 Illustration of Image Blocking

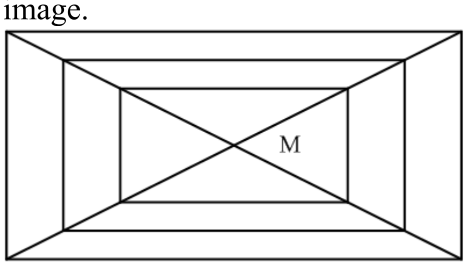

Figure.2Block Division with Equal Interval

In general, when checking an image, we often focus on the middle area of the image but neglect the fringe. Besides, when dealing with an image, usually we put important information in the middle of the image. Then the information of the central area appears relatively more important. Therefore, to highlight the center of images, this article gives each rectangular frame a different weight wk and each weight reduces successively from the inside of the rectangular frame to the outside[8]. The feature of the weight of each block is as follows:

$$\sum_{k=1}^{N} w_k = 1 \tag{7}$$

2.3 Feature extraction and matching

When extracting the color features of images, if traditional histogram cannot extract all the values, then the situation of zero value may arise after working out the color histogram. These zeros have a great influence on similarity measurement and also on the retrieval results. Accumulation color histogram generates a new histogram by accumulating every component of the histogram. This method makes a great improvement of the zero situation in statistical histogram. And this method is shown as follows:

$$I(k) = \sum_{i=0}^{k} \frac{n_i}{N} \quad k = 0, 1, 2, \ldots, L \tag{8}$$

In the formula, k is the value of the color features of images, L is the number of feature values, n_i is the number of feature values as k and N is the total number of the image picture element.

The similarity matching of color features adopts the method of Euclidean Distance. First calculate the similarity distance of each corresponding block; second multiply weight to the similarity distance of each block; and then work out the total distance. Suppose that Q and P are two images and that the color histograms of each sub-block are h_i and s_i, then the distance between each sub-block is:

$$D(j) = \sum_{i=1}^{L} \left| h_i - s_i \right|^{1/2} \tag{9}$$

In the formula, L is the dimension of color quantization. Finally work out the actual similarity distance of the two images according to the weight w_j of each rectangular frame. The statistical formula is as follows:

$$D(P,Q)=\sum_{j=1}^{n} w_j D(j) \tag{10}$$

n is the number of blocks.

3. Texture feature extraction

Gray-level co-occurrence matrix[4] is the basic approach to describe texture feature. Element of gray-level co-occurrence matrix ((i, j|d, θ) is described on the direction of θ(0°, 45°, 90°, 135°), a pair of pixels separated in distance by d (set d=1) pixel distance respectively have probability of gray value i and j occurrence, and matrix order is equal to gray layer number (L). This matrix is function of distance and direction, and count quantity of pixel pair meeting conditions in the stated calculation window or image area Co-occurrence matrix reflects comprehensive information of image gray level distribution with respect to direction, local area and range. On the basis of gray-level co-occurrence matrix P, extract texture characteristic quantity called as quadratic statistic. Following 4 common features are included:

(1) Moment of inertia for leading diagonal

$$f_1=\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}(i-j)^2 P(i,j) \tag{11}$$

f_1 can be explained as clear degree of image texture which reflects gray change of the whole image. In case of f_1 being big, gray-level difference between image pixels is large.

(2) Entropy

$$f_2=-\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}p(i,j)\log_2 p(i,j) \tag{12}$$

f_2 represents gray change complexity within image region. In case of the image having no any texture, gray-level co-occurrence matrix is almost the null matrix with f_2 being approximately zero. In case of the image being full of textures, when all p (i, j) values have small difference and are relatively decentralized, f_2 is big. Whereas, in case of p (i, j) values are co centralized, f_2 is small.

(3) Energy

$$f_4=\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}p^2(i,j) \tag{13}$$

f_3 refers to metric with spray deposition uniformity to image gray-level. When element p (i, j) values in co-occurrence matrix are centrally distributed near the leading diagonal, f_3 is big; whereas, f_3 value is small.

(4) Relevance

$$f_4=\frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}(i-\mu_x)(j-\mu_y)P(i,j)}{\sigma_x\sigma_y} \tag{14}$$

Among them， $\mu_x=\sum_{i=0}^{L-1} i\sum_{j=0}^{L-1}P(i,j)$ $\mu_y=\sum_{i=0}^{L-1} j\sum_{j=0}^{L-1}P(i,j)$

$$\sigma_x=\sum_{i=0}^{L-1}(i-\mu_x)^2\sum_{j=0}^{L-1}P(i,j) \quad \sigma_y=\sum_{j=0}^{L-1}(j-\mu_y)^2\sum_{i=0}^{L-1}P(i,j)$$

f_4 describes level of similarity between row or column elements in the matrix which is metric of gray-level linear relation.

Based on statistics of image texture feature at four directions, texture feature vector is:

$$f=[f_1, f_2, f_3, f_4]$$

Gray-level co-occurrence matrix texture feature similarity calculation. Set P, Q as two images, separately extract their texture feature vector $f_{mn}(P)$, $f_{mn}(Q)$, the similarity distance is calculated as follows:

$$D(P,Q)=\sum_{m}^{4}\sum_{n}^{4}\left|f_{mn}(P)-f_{mn}(Q)\right| \tag{15}$$

4. Comprehensive retrieval steps

The algorithm adopts search method based on examples, users submit query image P and image database Q, and feature of the image in Q shall be extracted according to following steps, the procedure is as follows:

1) Divide the image into 1 rectangle and 6 rectangular rings, 7 parts in total.

2) As for 7 divided parts of the image, extract accumulated color histogram for each segmentation based on multiple color space.

3) Weight allocation, weight of each segmentation outward from image center decreases in proper order which are respectively set to 7/28, 6/28, …, 1/28.

4) Calculate color feature similarity distance D1 of these two images according to the above method.

5) Extract texture feature vector of the image by gray-level co-occurrence matrix and calculate texture similarity distance D2.

6) Color similarity distance D1 added by texture similarity distance D2, which is final total similarity distance.

5. Experimental analysis

The retrieval method takes MATLAB as experience platform for simulation, selects 500 images as feature image library of simulation experience from Corel image library in the experiment, including food, flower, sandy beach, horse and car with each type including 100 images. In order to verify effectiveness of this algorithm, retrieval method based on overall situation color histogram and retrieval method based on texture are respectively carried out for comparison, Figure 3 is output example for above three methods.

(a) Input image

(b) Color feature (c) Texture feature (d) Method in this paper

Figure 3 Example of Output Result

Image retrieval based on content uses precision ratio and recall ratio as evaluation criterion of retrieval[5]. In the experiment, select top 15 images that have largest similarity as image results retrieved, set quantity of correlation image in retrieved image as n, precision ratio as n/15 and recall ratio as n/100 with above two being proportionate, and select precision ratio as performance index of this paper. In order to decline experiment error, conduct random drawing of different 10 images from each type of images in the image library as input image to calculate average precision ratio and recall ratio, and the result is as shown in Table 1.

Table 1 Performance Comparison for Image Retrieval Method

Images	Average Precision Ratio		
	Color feature	Texture feature	Method in this paper
cars	47.7	55.3	71.6
flowers	53.4	64.5	81.7
horse	43.6	55.1	73.4
beach	46.8	59.4	68.3
food	41.7	48.6	58.3

It can be known from the experiment result analysis that distinct improvement happens to the method in this paper compared to overall situation color histogram.

6. Conclusion

This paper proposed an image retrieval method based on color and texture, extract color feature by uniformly-spaced segmentation, and then extract texture feature by gray-level co-occurrence matrix with this method. The experiment verifies that its retrieval effect is better than that of only using color feature or texture feature. However, this method also has some disadvantages. For example, it can only roughly describe image texture with not accurate enough description for complex image leading to low retrieval accuracy for complex image. Further work of this study is to enhance feature vector accuracy for describing image content aiming at these shortcomings, and take user's subjective factors into account by introducing related feedback technology for the purpose of further improving retrieval accuracy.

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