Research of Image Retrieval Algorithms Based on Color

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Abstract. With the explosion of multimedia data, the traditional image retrieval method by text couldn't meet people's demand of more accurate retrieval results any longer. Therefore, the content-based image retrieval (CBIR) has been researched to achieve more accurate results. CBIR uses image visual features to represent image and perform retrieval. Color feature is applied most widely in image retrieval systems. In this paper, we choose several common CBIR algorithms based on color to analyze their robustness to the characteristics of images. We test 9 kinds of images for the algorithms. From the experiment performance, we evaluate the adaptability of the algorithms under different kinds of images.

Keywords: Content-based image retrieval, Color histogram, Similarity matching, Evaluation.

1 Introduction

Recent years have witnessed an explosive growth of multimedia data due to higher processor speeds, faster networks, and wider availability of high-capacity mass-storage devices. The most popular traditional method is text-based image retrieval [1]. However, the content of images couldn't be represented by text-based image retrieval adequately. In this case, content-based image retrieval [2] is proposed to meet the demand of more accurate retrieval results. CBIR retrieves images by their visual features, such as color, texture, shape, etc.

A lot of CBIR algorithms have been proposed by researchers [1-4]. Choosing adaptive algorithm is an ultra important step for implementing CBIR system. Color feature is the most widely applied feature in CBIR, because color is generally related to objects in image and insensitive to noise, image degradation, changes in size, resolution or orientation [1, 4]. In this paper, we'll introduce 4 common algorithms used for image retrieval based on color. With different categories of retrieved images, the algorithms might correspond to different retrieval results. Therefore, we test nine categories of images and analyze the final retrieval results to evaluate the adaptability of the algorithms under different kinds of images.

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2 Color Space

2.1 RGB Color Space

RGB color space [5] is defined by the three chromaticities of the red, green, and blue additive primaries. The value ranges of those colors are from 0 to 255. If all the color values are equal to 0, the complex chromaticity is black, and the complex chromaticity would be white while all the color values are 255. RGB is utilized in various applications because of its convenient for computer graphics.

2.2 HSV Color Space

HSV [5] actually is one of the most common cylindrical-coordinate representations of points in an RGB color model. HSV stands for hue, saturation, and value. In each cylinder, the angle around the central vertical axis corresponds to "hue", the distance from the axis corresponds to "saturation", and the distance along the axis corresponds to "value".

Comparing with the RGB Color Space, HSV is more closely to human perspective feeling, therefore we choose HSV to test the retrieval algorithms in this paper.

3 Feature Extraction

3.1 Color Histogram

Color histogram [6-7] represents the color feature properly. For digital images, a color histogram gives the number of pixels that have colors within the same value range, which span the image's color space and the set of all possible colors. In a color histogram, abscissa denotes the color range and ordinate means the number of pixels. The formula is defined as follows:

$$H(i) = \frac{n_i}{N} \quad i = 1, 2, \ldots, k \tag{1}$$

Where N is the total number of pixels, n_i is the number of pixels with color i, and k is the number of color values in the histogram. The color histogram of image M is a vector as $H(M)=(h_1, h_2, \ldots, h_k)$.

3.2 Cumulative Color Histogram

Cumulative color histogram [6] improves the traditional color histogram. While we use the traditional one, the color histogram will appear in several regions of zero value if the pixels of the image cannot take all possible color values. And it will affect the accuracy of histogram calculation negatively. The concept of cumulative color histogram is proposed to solve this problem. Cumulative histogram is defined as follows:

$$CH(i) = \sum_{j=1}^{i} h_i \quad \text{i = 1, 2, …, k} \tag{2}$$

Where h_i is the color histogram above, k is the number of color values of the histogram. The cumulative color histogram of image M is a vector as CH(M)=(ch_1, ch_2, …, ch_k).

3.3 Color Histogram Based on Partitioning

However the retrieval result of color histogram cannot satisfy us as it does not give the distribution of the color. The segmentation-based color histogram [4, 8] can solve the problem. Divide image into several sub-parts, then calculate each sub-parts' local color histogram. After that, calculate the corresponding similarity between the sub-parts at the same position in two images. At last we can get the overall color similarity by cumulating the local similarity of sub-parts with the specified weights.

3.4 Color Histogram Based on Representative Color and Partitioning

Representative color in an image means the color which value number is the most. In most cases, representative color of these images is also similar when two images are similar. Color histogram based on primary color is in view of this thought.

If we combine representative color-based color histogram with the histogram based on partitioning, we can get a new algorithm: color histogram based on representative color and partitioning [3]. Instead of calculate every sub-block's local color histogram, we calculate their representative colors.

4 Similarity Matching

4.1 Histogram Intersection

Histogram intersection [6] is proposed by Swain in 1991, and it suppresses the background effect well. The calculation process of histogram intersection is simple and fast. It is defined as follows:

$$d(A,B) = \sum_{i=1}^{n} \min(a_i, b_i) \tag{3}$$

Where A and B represent feature vectors of image A and image B, and n is the dimension of the vector.

4.2 Euclidean Distance

Euclidean distance [7] calculates the distance between two points which would measure with a ruler. While we can calculate two pixels' distance by using it. The formula is given below:

$$d(A,B)=[\sum_{i=1}^{n}|a_i-b_i|^2]^{\frac{1}{2}} \tag{4}$$

Where A and B are feature vectors, n is the dimension of the vector. Many image retrieval systems choose the Euclidean distance to measure the image similarity. For example, MARS system calculates the similarity of texture feature by using it; Netra uses it to calculate similarity of color and shape.

4.3 Quadratic Distance

Quadratic distance [7] has proven to be more effective than the Euclidean distance and histogram intersection in similarity measurement, because the similarity between different colors is taken into account in this method. Quadratic distance can be expressed as that:

$$d(A,B)=\sqrt{(A-B)^T M(A-B)} \tag{5}$$

In this formulation, $M=[m_{ij}]$, m_{ij} means the similarity between two colors which values are i and j in color histogram. This approach consider of the color that are similar but not the same. But the calculation of Quadratic distance is complex.

As Euclidean distance is being widely used and effective, in this paper, we choose Euclidean distance in feature matching.

5 Experiment and Evaluation

5.1 Approach of Evaluation

The evaluation methods have the representative features: precision and recall. They are two popular metrics for evaluating the correctness of a pattern recognition algorithm, and also used in evaluate images' retrieval results recently.

Precision [4] in image retrieval is the fraction of retrieved images that are relevant to the search:

$$P=\frac{\{relevant\_images\}\bigcap\{retrieved\_images\}}{retrieved\_images} \tag{6}$$

Recall [4] in image retrieval is the fraction of the images that are relevant to the query which are successfully retrieved.

$$R=\frac{\{relevant\_images\}\bigcap\{retrieved\_images\}}{relevant\_images} \tag{7}$$

5.2 Experiment

Image database used in our experiments is Corel Image Gallery. There are over 60,000 images in Corel image database, covering people, natural scenery, animals, plants, buildings and so on. In this experiment, we picked up 9 categories of images from the Corel: bus, elephant, scenery, flower, coastline, beach, horse, waterfall and mountain. The number of image of every image category is around 100, which the number of similar images is 25 or so. We choose 4 algorithms to test (Table 1).

Table 1. Retrieval algorithms

Color Space	*Feature extraction*	*Match*	*Symbol*
HSV	Color Histogram	Euclidean distance	H-CH-E
	Cumulative Color Histogram		H-CCH-E
	Color Histogram based on partitioning		H-PCH-E
	Color Histogram based on representative color and partitioning		H-RPCH-E

During the experiment, we set threshold N, which indicates the maximum number of retrieved images in once retrieval.

Set N = 10,20, ..., 60, calculate each relevant image's precision and recall rate, then use the total number of images to calculate the average precision and the average recall.

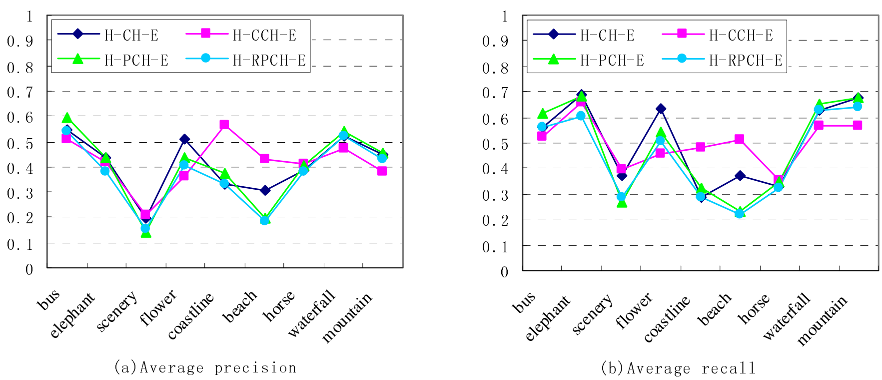

Fig. 1. Average precision and average recall on the 9 categories of images

Since the similar images' total number of our selected image category are around 25, close to 30, so firstly we take N = 30, calculate the average precision and average recall on the 9 categories of images, then compare algorithms' efficiency with different types of images. The retrieval result is as Fig. 1.

From Fig. 1, we can see that, the retrieval results are significantly different when retrieving different images with same algorithm. For further analysis, we calculate different algorithms' precision and recall with 9 categories of images when N = 10, 20, …, 60. Based on Fig. 1, we choose two categories of images which retrieval results are typical: Bus and Scenery.

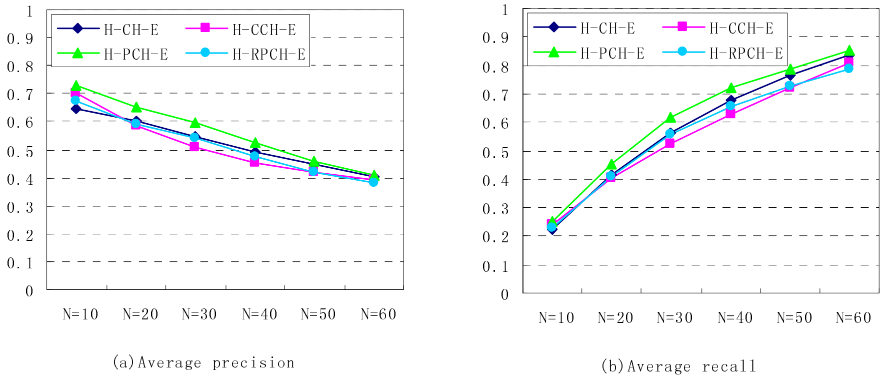

Fig. 2. Average precision and average recall on Bus image database

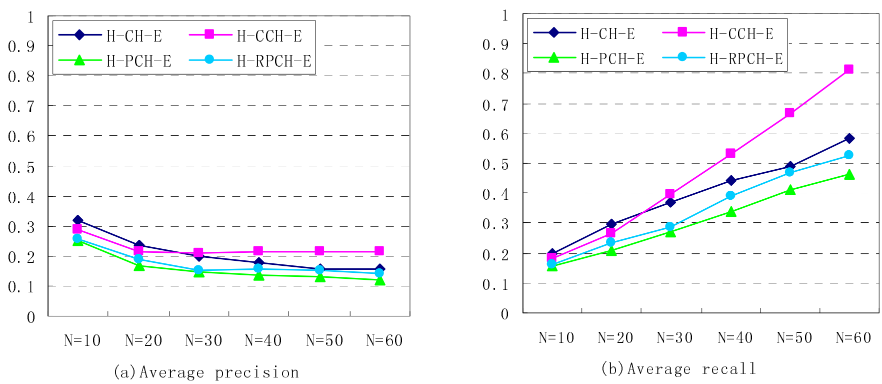

Fig. 3. Average precision and average recall on Scenery image database

From Fig. 2 and Fig. 3, we can conclude that, H-PCH-E(color histogram based on partitioning) and H-RPCH-E(color histogram based on representative color and partitioning) can get better retrieval results when we retrieve Bus image database. For Bus image, the main part is prominent and there is a big difference between foreground color and background color. When we use the partitioning-based algorithm, the main parts of images will be given relatively large weights to distinguish the main parts and the backgrounds to make the retrieval more accurate.

However, with Scenery image database, the retrieval accuracy of H-CH-E(color histogram) and H-CCH-E(cumulative color histogram) is higher. Images like scenery do not have specific substance, so we cannot distinguish foreground and background well. In that case, raising the main part's weight makes no sense, and global algorithm can get better retrieval results.

6 Conclusion

We introduce 4 algorithms in this paper and have experiment on them with 9 categories of images. When we retrieve images, algorithm's accuracy depends on image's characteristic. Algorithms based on partitioning apply to images having specific main parts while global algorithms are more accurate when retrieve image without clear substance. We can also improve these algorithms with cumulative or representative color histogram.

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