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Color image retrieval technique based on color features and image bitmap

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Abstract

The field of color image retrieval has been an important research area for several decades. For the purpose of effectively retrieving more similar images from the digital image databases, this paper uses the color distributions, the mean value and the standard deviation, to represent the global characteristics of the image. Moreover, the image bitmap is used to represent the local characteristics of the image for increasing the accuracy of the retrieval system. As the experimental results indicated, the proposed technique indeed outperforms other schemes in terms of retrieval accuracy and category retrieval ability. Furthermore, the total memory space for saving the image features of the proposed method is less than Chan and Liu's method.

Keywords: Image bitmap; Color distribution; Content-based image retrieval; Standard deviation

1. Introduction

Image retrieval has been a very active research topic since the 1970s. Most convenient image retrieval schemes are annotated-based that annotate each image in an image database by using keywords for similar image retrieval. However, the annotated-based retrieval method has two major problems that make it impractical. The first problem is that the size of the image database has become larger and larger such that to create keywords for each image is time-consuming. The second problem is that different people may give the same image different keywords. Afterwards, the content-based image retrieval (CBIR) techniques were proposed to solve the problems of the annotated-based image retrieval methods. In a CBIR system, images are automatically indexed by summarizing their visual contents through automatically extracted primitive features, such as shape, texture, color, size, and so on.

Many researchers used color feature to depict image contents for region matching, semantic categorization, and similarity searches (Flickner et al., 1995; Schettini, Ciocca, & Zuffi, 2001). However, the

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performance is poor for a CBIR system, which only uses a color feature to search for similar images from a huge database. Thus, some researchers analyzed the color distribution of the image to increase the retrieval accuracy (Brunelli & Mich, 2001; Du & Wang, 2001; Fuh, Cho, & Essig, 2000; Hsieh, Grimson, Chiang, & Huang, 2000; Kankanhalli, Mehtre, & Huang, 2001; Schettini et al., 2001; Stehling, Nascimento, & Falcao, 2001; Wang & Du, 2001). For example, in 1996, Gong et al. proposed an image indexing and retrieval scheme. In their scheme, an image is split into nine equal sub-areas. They presented each sub-area by using a color histogram to model the color spatial information (Gong, Chuan, & Xiaoyi, 1996). In 1997, Stricker and Dimai split an image into an oval central region and four corner sub-regions for image indexing (Stricker & Dimai, 1997). Gagliardi and Schettini described the image in the CIELAB color space with two palettes and integrated different color information descriptions and similarity measurements to enhance the effectiveness of a CBIR system in Gagliardi and Schettini (1997). Kou used the mean value, the standard deviation, and the skewness of pixels from each bin in a color histogram as the image features to search similar images (Kou, 2001).

In 2003, Chan and Liu proposed a CBIR system based on color differences on edges in spiral scan order (Chan & Liu, 2003). With a view to increasing the retrieval accuracy, Chan and Liu combined the color feature with color differences among adjacent pixels for image retrieval. The color differences can be viewed as the local features of an image.

In this paper, we adopt another local feature, image bitmap, to investigate similar image from the huge database. The image bitmap is obtained from an image compressed with the block truncation coding method. The block truncation coding method uses the properties, the mean value, the standard deviation and the image bitmap, of an image for image compression. In this paper, the retrieval technique is based on these properties instead of numerous image features.

2. Related works

Swain and Ballard (1991) proposed an image indexing scheme based on color histogram in 1991. In their scheme, a color image is transformed into the gray-scale image. Then, they generated a histogram with 256 bins to record the total number of pixel values in the gray-scale image as image feature to search the similar images from the database. In order to reduce the memory space for storing the histogram, they reduce the number of bins in the histogram from 256 to 64. In addition, the color distributions of each bin were used to enhance the retrieve accuracy of the histogram-based retrieval scheme. After that, Stricker and Orengo (1995) used three statistic moments, the average, the variance, and the skewness to represent the image. In their scheme, a color image is transformed to three spectrums, H, S and V. The scheme, then, calculated the three statistic moments for each spectrum. The nine moments obtained from the three spectrums are the features of the image.

In Chan and Liu (2003) and Chang and Chan (2000) used color differences on edges in spiral scan order feature to depict the color, color complexity, and color differences among neighboring pixels in a color image. In their schemes, all pixels of the images in the database were divided into 64 clusters by using K-mean algorithm. Then, they classified each pixel of the image into the most similar cluster. After classification, the image was scanned in the spiral order to compute the difference between any two neighboring pixels. The scan order is shown in Fig. 1.

In their scheme, each pixel in the classified image was represented by a vector in three primary color spaces, red (R), green (G), and blue (B). Let $P_i = \begin{bmatrix} R_i \\ G_i \\ B_i \end{bmatrix}$ be the ith pixel of the classified image. The scanning process begins from the central pixel of the image in a spiral direction pixel by pixel. If the pixel P_i is different from the next pixel P_{i+1}, then the scheme computes the color difference between two pixels by using $d(P_i, P_{i+1}) = [(R_i - R_{i+1})^2 + (G_i - G_{i+1})^2 + (B_i - B_{i+1})^2]^{1/2}$.

Each cluster has its own bin to record the difference. The difference $d(P_i, P_{i+1})$ is added to the bin of the cluster of P_i. The final values of the bins are the features of the image. For example, assuming that the first

26	27	28	29	30	31	32
49	10	11	12	13	14	33
48	25	2	3	4	15	34
47	24	9	1	5	16	35
46	23	8	7	6	17	36
45	22	21	20	19	18	37
44	43	42	41	40	39	38

Fig. 1. The scan order to extract the features.

pixel of an image is $P_1 = \begin{bmatrix} R_1 \\ G_1 \\ B_1 \end{bmatrix} = \begin{bmatrix} 6 \\ 7 \\ 7 \end{bmatrix}$ and the second pixel is $P_2 = \begin{bmatrix} 43 \\ 78 \\ 67 \end{bmatrix}$. Because P_1 is different from P_2, they compute the difference between P_1 and P_2 by using $d(P_1, P_2) = [(6-43)^2 + (7-78)^2 + (7-67)^2]^{1/2}$. The difference is added to the corresponding bin of the cluster of P_1. After the scanning process, the final values of the 64 bins are the features of the image.

Chan and Liu used the color difference features as the local information to enhance the limited descriptive capacity of the color distributions. In this paper, we adopt image bitmap as the local information to enhance effectiveness of the CBIR scheme.

3. The block truncation coding method

Many image compression methods have been proposed to reduce the size of the image. The block truncation coding method is one of the efficient image compression methods. The block truncation coding method has been adopted to acquire the statistical properties of the block in image retrieval. In the method, an image is firstly divided into several blocks. Then, the method computes the mean value and the standard deviation for each block. Next, they generate a two-level bitmap to record whether the pixel is larger than the mean value of the block or not. If the pixel is smaller than the mean value of the block, the scheme used "0" to represent the pixel. Otherwise, the scheme used "1" to represent the pixel.

For example, assuming that a gray-scale image is divided into several blocks each with 4×4 pixels. Fig. 2 shows one of the blocks. In the first step, they compute the mean value and the standard deviation for this block. The mean value of the block is approximately equal to 79.125, and the standard deviation is about

41	3	122	1
75	233	39	54
5	169	23	86
144	47	208	16

Fig. 2. An example block.

0	0	1	0
0	1	0	0
0	1	0	1
1	0	1	0

Fig. 3. The bitmap of the block.

74.71. In the second step, they compare each pixel value with the mean value to generate the bitmap. The bitmap of the block is shown in Fig. 3.

The block truncation coding method uses the bitmap, the mean value and the standard deviation to represent and recover the image. It is evident that the mean value and the standard deviation properties can be used to state the primary color and the condition of pixel color variation in an image, respectively. Moreover, the bitmap describes the local variation of pixels. These properties depict the characteristics of an image that can be treated as image features. Therefore, this paper adopts these features to construct a similar image retrieval method.

4. The proposed method

This paper uses two features, the color distribution and image bitmap, to represent an image.

4.1. The color distribution feature

Each image in an image database may be different from all the others, but at the same time all images may share certain common characteristics. Hence, we need the statistical description of images to capture these common characteristics and use them to represent an image with fewer bits. The statistical descriptions used in this paper are the mean values and the standard deviations of images.

In the proposed scheme, each pixel of a color image is represented by a vector

$$P_i = \begin{bmatrix} R_i \\ G_i \\ B_i \end{bmatrix}, \tag{1}$$

where P_i is the ith pixel of the image, $1 \leqslant i \leqslant M$, the size of the image is M and the components of P_i are the RGB components of the color image.

The mean value (μ) and the standard deviation (σ) of the color image are determined as follows:

$$\mu = \frac{1}{M}\sum_{i=1}^{M} P_i \quad \text{and} \tag{2}$$

$$\sigma = \left[\frac{1}{M-1}\sum_{i=1}^{M}(P_i - \mu)^2\right]^{1/2}, \tag{3}$$

respectively, where $\mu = \begin{bmatrix} \mu R \\ \mu G \\ \mu B \end{bmatrix}$ and $\sigma = \begin{bmatrix} \sigma R \\ \sigma G \\ \sigma B \end{bmatrix}$, the components of μ and σ are the RGB components. The mean value and the stand deviation are the global feature of the image that depicts the global characteristics of images. For the purpose of enhancing the retrieval accuracy, this paper adopts image bitmap as the local feature to describe the local characteristics of the image.

4.2. The image bitmap feature

In the first step to generate the image bitmap, the scheme divides the image into several non-overlapping blocks. Let $B_j = \{b_1, b_2, \ldots, b_k\}$ be the jth block of the image, where $1 \leqslant j \leqslant m$. The symbol k is the total number of pixels in the block, and m is the total number of blocks in the image. In the second step, the scheme computes the mean value for each block. Let μ_{B_j} be the mean value of the block B_j that is computed using the expression

$$\mu_{B_j} = \frac{1}{k}\sum_{x=1}^{k} b_x, \tag{4}$$

where $\mu_{B_j} = \begin{bmatrix} \mu R_{B_j} \\ \mu G_{B_j} \\ \mu B_{B_j} \end{bmatrix}$ and the components of μ_{B_j} are the RGB components.

In the third step, the scheme compares the mean values of the block μ_{B_j} with the mean value of the image μ to determine the characterization of the block B_j for generating the image bitmap. Let $T = \begin{bmatrix} TR \\ TG \\ TB \end{bmatrix}$ be the image bitmap of the image. Each component in T is expressed as $TR = (TR_1, TR_2, \ldots, TR_m)$, $TG = (TG_1, TG_2, \ldots, TG_m)$, and $TB = (TB_1, TB_2, \ldots, TB_m)$, respectively. In which, TR_j, TG_j, and TB_j are respectively given by

$$TR_j = \begin{cases} 1, & \text{if } \mu R_{B_j} \geqslant \mu R, \\ 0, & \text{otherwise}, \end{cases} \tag{5}$$

$$TG_j = \begin{cases} 1, & \text{if } \mu G_{B_j} \geqslant \mu G, \\ 0, & \text{otherwise}, \end{cases} \quad \text{and} \tag{6}$$

$$TB_j = \begin{cases} 1, & \text{if } \mu B_{B_j} \geqslant \mu B, \\ 0, & \text{otherwise}. \end{cases} \tag{7}$$

Finally, the scheme uses the global features, μ and σ, and the local feature T to represent the image. The overall feature of the image is (μ, σ, T).

4.3. The similarity measure of the features

This paper uses two different measurements for the global features and the local feature to evaluate the similarity between the two images. For the global features, μ and σ, the scheme uses Euclidean distance to calculate the similarity. On the other hand, for the local feature, the scheme uses hamming distance to evaluate the distance between the two bitmaps. Afterwards, the overall similarity is obtained by linearly combining of these two similarity values. However, the linear combination will become meaningless because the magnitude similarity value may dominate the others. We need to range the two similarity values on the same scale. This paper uses the Gaussian normalization to normalize the features into the same criterion. The mean value μ of the image is normalized by using

$$\mu' = \frac{\mu - \alpha}{\gamma}, \tag{8}$$

where α the average value of whole μ in the database that is given by $\alpha = \frac{1}{N}\sum_{y=1}^{N}\mu^y$. The symbol N is the total number of images in the database, μ^y is the mean value of the yth image, and γ is the standard deviation of whole μ that is given by $\gamma = \left[\frac{1}{N}\sum_{y=1}^{N}(\mu^y - \alpha)^2\right]^{1/2}$. While the standard deviation σ of the image is normalized by using

$$\sigma' = \frac{\sigma - \beta}{\tau}, \tag{9}$$

where β is the average value of whole σ in the database that is given by $\beta = \frac{1}{N}\sum_{y=1}^{N}\sigma^y$, where σ^y is the standard deviation of the yth image, and τ is the standard deviation of whole σ that is given by $\tau = \left[\frac{1}{N}\sum_{y=1}^{N}(\sigma^y - \beta)^2\right]^{1/2}$.

For two given images A and B, the hamming distance used to evaluate the similarity is defined by

$$H(T^A, T^B) = \sum_{x=1}^{m}\left(TR_x^A - TR_x^B\right) + \sum_{x=1}^{m}\left(TG_x^A - TG_x^B\right) + \sum_{x=1}^{m}\left(TB_x^A - TB_x^B\right), \tag{10}$$

where TR_x^A is the xth component of the bitmap TR of image A. The final similarity measure is formed as follows:

$$d(A,B) = \frac{H(T^A, T^B)}{3 \times m} + \sqrt{\sum_{z \in \{R,G,B\}}\left(\mu_z'^A - \mu_z'^B\right)^2 + \sum_{z \in \{R,G,B\}}\left(\sigma_z'^A - \sigma_z'^B\right)^2}, \tag{11}$$

where $\mu_z'^A$ is the normalized mean value of the image A in z color space, meanwhile, $\sigma_z'^A$ is the normalized standard deviation of the image A in z color space. The scheme computes the distance between a user query image and each image in the database by using Eq. (11). The image with the smallest distance is the image the most similar to the query image.

5. Experiments and results

The proposed scheme was developed on an AMD 1.4 GHz personal computer with 512 RAM. Three existing methods, the color histogram (Swain & Ballard, 1991), the color moment (Stricker & Orengo, 1995), and Chang and Liu's method (Chan & Liu, 2003), were used to benchmark the proposed scheme. This paper used two measurements, the retrieval accuracy and category query ability, to test the performance of the proposed scheme.

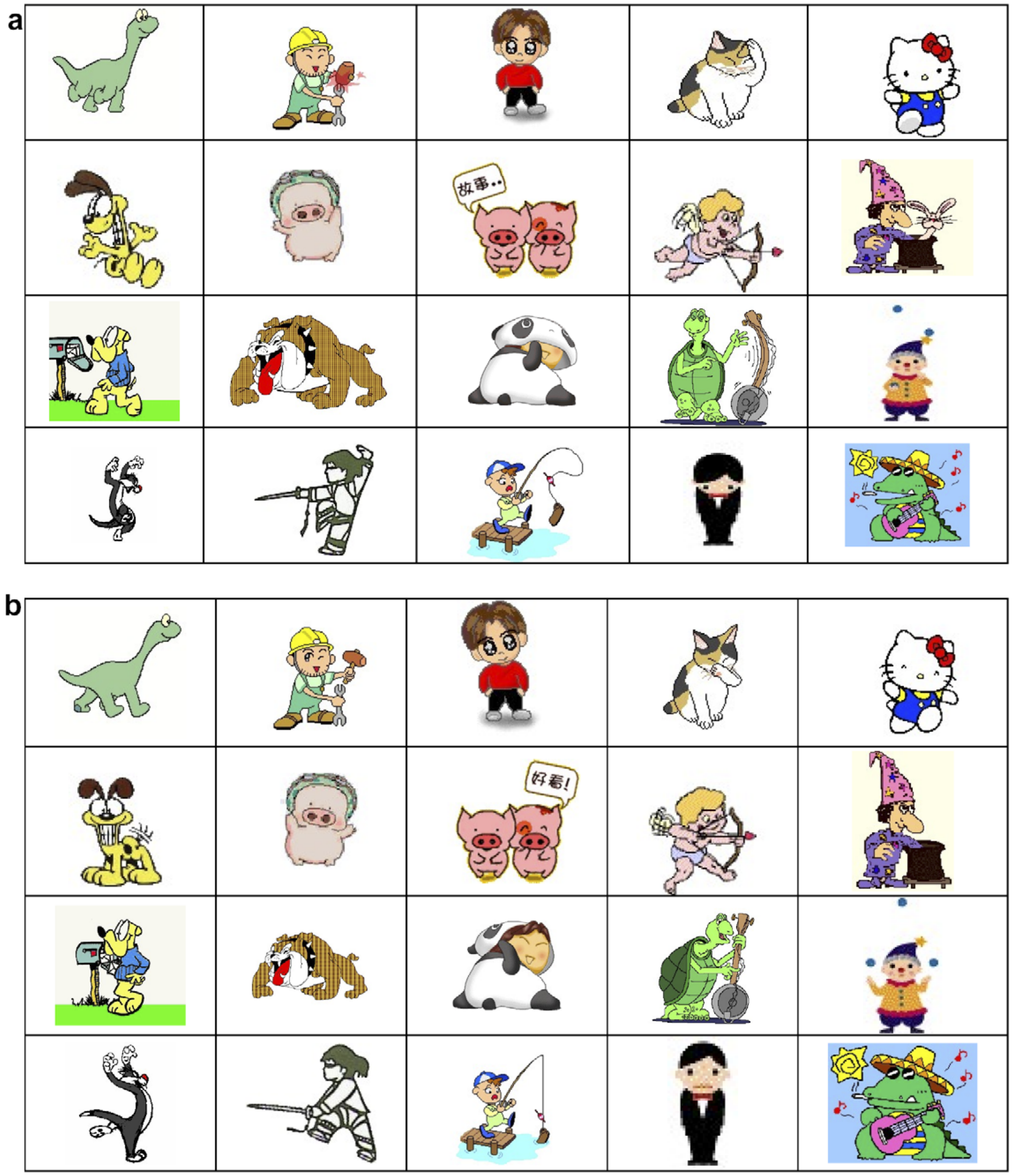

Fig. 4. Example animations in the sets Q_1 and D_1: (a) Example images in Q_1 and (b) corresponding target images of (a) in D_1.

5.1. The retrieval accuracy

Two image databases were used to test the retrieval accuracy. The first database contains 800 full color animations (Chan & Liu, 2003). We divided the database into two sets, the query set Q_1 and the target set D_1, where each set has 400 animations. Each image in Q_1 has a corresponding image in D_1 in pairs. Some images of Q_1 are shown in Fig. 4(a) and its corresponding target images in D_1 are shown in Fig. 4(b). The second

Fig. 5. Example images in the sets Q_2 and D_2: (a) Example images in Q_2 and (b) corresponding target images of (a) in D_2.

Table 1
The retrieval accuracy of the proposed scheme with different bitmap sizes on the images in Q_1

Rank	Bitmap size		
	5×5	10×10	15×15
$N_{RT} = 1$	89.02	93.17	93.66
$N_{RT} = 2$	95.85	97.32	97.32
$N_{RT} = 3$	97.07	98.05	98.29
$N_{RT} = 4$	97.02	98.54	98.54
$N_{RT} = 5$	98.51	99.02	98.78
$N_{RT} = 10$	99.51	99.76	99.76
$N_{RT} = 20$	99.51	99.76	99.76

database contains 470 full color images (Chan & Liu, 2003). The database is divided into two sets, the query set Q_2 and the target set D_2. Each image in Q_2 has a corresponding image in D_2. Fig. 5(a) shows some images of Q_2 and its corresponding images in D_2 are shown in Fig. 5(b).

The scheme treated each image in the query sets Q_1 and Q_2 as a query image to retrieve N_{RT} images from D_1 and D_2 with the smallest distances according Eq. (11), and determined their rank values from all those distances arranged in an ascending order. The number of retrieved images is N_{RT}. If the corresponding target image of D_1 and D_2 is one of these retrieved images, it shall be said that the scheme accurately retrieves the target image.

The retrieval accuracy of the method is given by the expression

$$\mathrm{RA} = \frac{C}{|Q|}, \tag{12}$$

where C is the total number of the query images in the query set which can correctly retrieve the target image from the answer set and $|Q|$ is the total number of images in the query set.

With the intention of determining the proper size of block used to divide an image for generating the image bitmap, we performed different bitmap sizes to explore the retrieval accuracies of the proposed method. The retrieval accuracy of the proposed scheme with different block sizes is shown in Table 1. According to the experimental results, the performance of the proposed scheme with bitmap sized 10×10 is similar to that of the proposed scheme with bitmap sized 15×15. In addition, the memory space of the bitmap sized 10×10 is less than that of the bitmap sized 15×15. Hence, in the following experiments, the bitmap sizes were assigned as 5×5 and 10×10.

The retrieval accuracy performance between the proposed scheme and Chan and Liu's scheme is shown in Figs. 6 and 7. According to the experimental results, the proposed scheme with bitmap sized 10×10 has better retrieval accuracy than Chan and Liu's scheme in both Q_1 and Q_2.

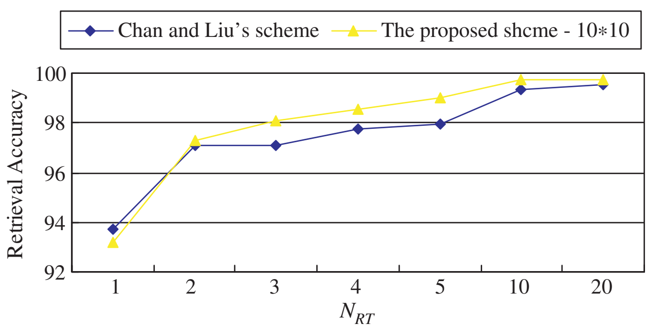

Fig. 6. The experimental results of the proposed scheme and Chan and Liu's scheme on Q_1.

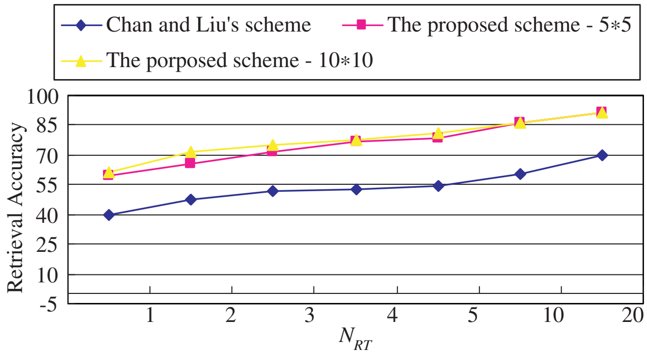

Fig. 7. The experimental results of the proposed scheme and Chan and Liu's scheme on Q_2.

Table 2
The retrieval accuracy of the proposed scheme, color histogram, and color moment on the database D_3

Scheme	N_{RT}				
	$\leqslant 10$	$\leqslant 100$	$\leqslant 500$	$\leqslant 1000$	>1000
Color histogram	0.00	3.03	8.08	12.12	87.88
Color moment	46.46	70.71	85.86	88.89	11.11
The proposed scheme bitmap size = 5×5	52.34	73.19	89.36	93.19	6.81
The proposed scheme bitmap size = 10×10	55.32	76.60	89.79	94.47	5.53

The second experiment is to explore the retrieval accuracy of the proposed scheme in large database. We tested the proposed scheme on a database D_3, which contains 10,000 full color images (Iqbal et al., 2002; Li & Wang, 2003; Wang, Li, & Wiederhold, 2001). The 235 images in D_2 also were embedded into D_3. We use each image of Q_2 as a query image to retrieve the corresponding target image from D_3. The experimental results are shown in Table 2. For $N_{RT} \leqslant 10$, the retrieval accuracy of the proposed scheme with bitmap is sized 10×10 is 55.32%, while that of the color histogram is 0% and that of the color moment is 46.46%. When $N_{RT} \leqslant 500$, the retrieval accuracy of the proposed method with bitmap sized 10×10 is 89.79%, which is higher than that of the color histogram 8.08% and that of the color moment 85.86%. The average retrieval accuracy of the proposed scheme and the other schemes is shown in Fig. 8. Therefore, the proposed scheme outperforms the other schemes.

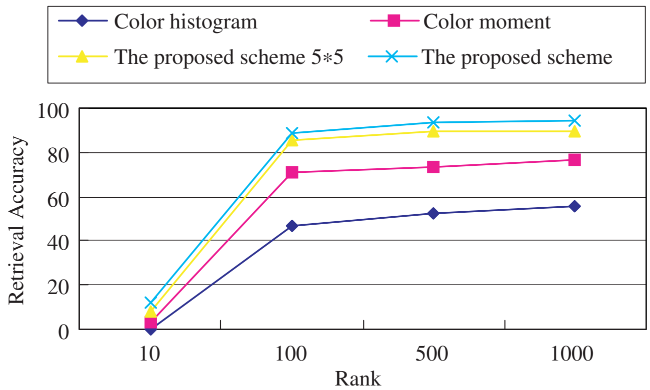

Fig. 8. Average retrieval accuracy of the proposed scheme and the other schemes.

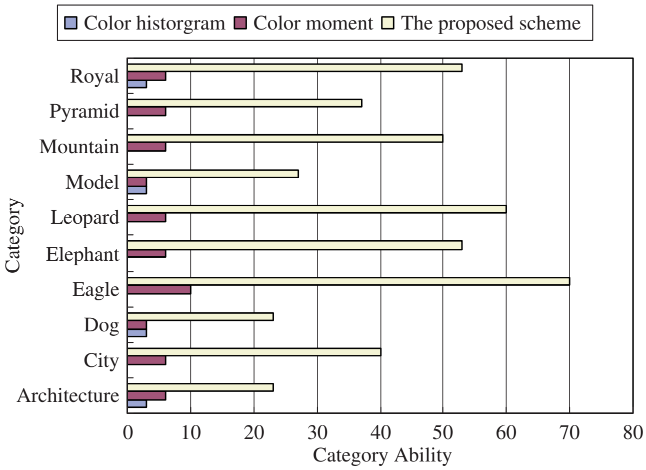

Fig. 9. The experimental results on the ten categories for $N_{RT} = 30$.

5.2. The category retrieval precision

Next experiment is to test the category retrieval ability of the proposed scheme. We categorized the images in the database D_3 into 10 categories, architecture, city, dog, eagle, elephant, leopard, model, mountain, pyramid, and royal. Each category contains 1000 images. Every image in these ten categories as used as query images. For each query, other images belonging to the same category were regarded as the corresponding target images. The performance of the category ability is measured by

$$\mathrm{CA} = \frac{\mathrm{Cr}}{N_{RT}}, \tag{13}$$

where Cr is the total number of the retrieved images whose category is the same as the category of the query image. For example, for $N_{RT} = 30$, if there are 16 retrieved images, which belongs to the same category as the query image, then the category ability is 53%, since $\mathrm{CA} = \frac{16}{30} \approx 0.53$.

The performance of the proposed method and other methods is shown in Fig. 9. For example, for category Leopard, the proposed method found 18 relevant images, and the category ability was hence 60%, since $\mathrm{CA} = \frac{18}{30} \approx 0.6$. Since the color histogram did not find any relevant images, and color moment scheme only

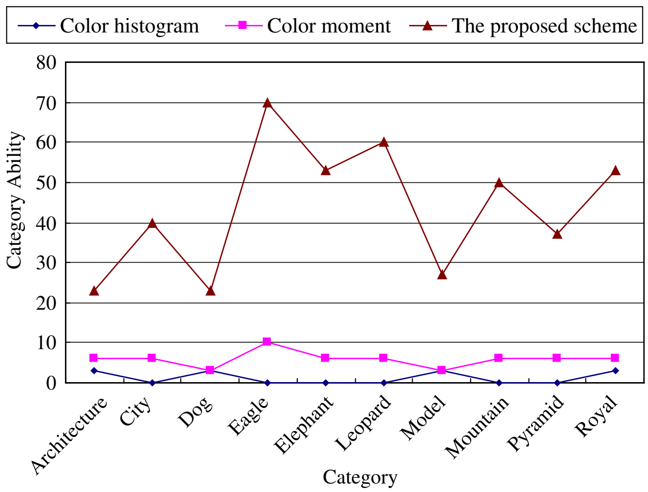

Fig. 10. Aggregated results over all ten categories.

found two relevant images, hence the category abilities of the color histogram and the color moment were 0%, and 6%, respectively. Fig. 10 demonstrates the aggregated results over all the ten categories. According to the results, the proposed scheme indeed outperforms the other schemes in terms of the category ability in most of the cases.

5.3. Memory space analysis

In this section, we shall analyze the total memory space for storing the image feature by using different retrieval schemes. Let N be the total number of images in an image database. Assume that the color histogram scheme uses 64 bins to represent a histogram in one color space. The total memory space taken by the color histogram is $N \times 64 \times 3(\mathrm{RGB}) \times 3(\mu, \sigma, \mathrm{skewness}) \times 4$ bytes (a floating point), while the memory space of Chan and Liu's method is $N \times 64 \times 4$ bytes (a floating point).

The memory space of the proposed scheme is $N \times \left[\frac{3(TR,TG,TB)\times m}{8} + 6\left(\mu = \begin{bmatrix}\mu R\\ \mu G\\ \mu B\end{bmatrix}, \sigma = \begin{bmatrix}\sigma R\\ \sigma G\\ \sigma B\end{bmatrix}\right) \times 4 \text{ bytes (a floating point)}\right]$.

For example, the memory space of the color histogram scheme in D_1 is $400 \times 64 \times 3 \times 3 \times 4 = 921{,}600$ (bytes), while Chan and Liu's scheme is $400 \times 64 \times 4 = 102{,}400$ (bytes). The memory space of the proposed scheme with bitmap sized 10×10 is $400 \times \left[\frac{3\times10\times10}{8} + 6 \times 4\right] = 24,600$ (bytes).

6. Conclusions

This paper proposed a content-based image retrieval scheme based on the color distribution and bitmap. The color distribution features are the global characteristic of an image that associated with the entire image. With the aim to enhancing the retrieval accuracy of the proposed scheme, this paper adopts the image bitmap as the local feature to depict the local characteristics of the image. The image bitmap is associated with pixels.

The proposed method can retrieve images ranging from purely objects, such as an image of a dog, a model, an elephant and so on, to images containing a mixture of structure, such as images of architecture, buildings and a pyramid. According to the experimental results, the performance of the proposed scheme is better than that of the color histogram, the color moment, and Chan and Liu's scheme in the categories of eagle, elephant, leopard, mountain, and royal. Moreover, the total memory space of the proposed method is less than that of the other schemes.

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