An Effective Image Retrieval Method Based on Multi-features

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***Abstract*— To improve the accuracy of image retrieval methods, an effective image retrieval method based on multi-features is proposed. The color feature of the image is extracted by constructing a (16:4:4) quantization scheme of image color. Perform the marked-watershed to achieve the segmentation of the image, and then extract Jan Flusser invariant moments. Gaussian model is applied to normalize the different subcharacters distance. The final multi-features similarity consists of the color similarity and the shape similarity. Experiments demonstrate the efficiency of the proposed method.**

***Index Terms*— image retrieval, color feature, shape feature, marked-watershed segmentation**

I. Introduction

WITH the development of Internet and multimedia technologies, web servers provide a large number of images. It is more and more difficult to find out useful images from plenty of images. Compare the description text of image with keywords entered by the user, traditional technology of Text-based Image Retrieval not only have poor retrieval results, but also cannot retrieve images of which the text information are unlabeled. Content-Based Image Retrieval (CBIR) have been presented, aiming at solving these problems. The images are retrieved by extracting the features, which can obtain the retrieval results objectively and comprehensively, and can increase the accuracy.

Recently, researchers have had the further study of image retrieval based on color and shape features, and gotten notable accomplishment. Color feature is the most widely used in CBIR. There are many common color features, including color histogram, color distance, color coherence vector and covariance matrix [1]. The most common method for extracting color feature is firstly proposed by Swain and Ballad [2]. It is simple, effective and insensitive to image rotation and stretching transformation. The dimension of the color feature and the size of the feature databases directly affect the performance of retrieval. In order to compress the dimension of the features, decrease the size of the feature databases and increase the speed of on-line query, we can non-uniformly quantize images with the experiential data of color sensation produced by the human visual system [3], [4]. Shape feature depicts one of the most essential attributes of a physical object, and the extraction of the shape feature is mainly to look for some geometric invariants. As the shape feature is usually closely linked with the target objects, and the results of image segmentation directly impact the extraction of the shape feature, we usually have to segment image. The common image segmentation algorithms include threshold, edge segmentation and region segmentation [5].Meanwhile, the different perspectives of the acquired target shape may vary greatly. In order to match the shape accurately, we need to solve the problems of translation, scaling and rotation invariant. According to the theory of invariant moments, Jan Flusser raised the construction method of invariant moments in arbitrary order [6].Jan Flusser affine invariant moments not only can provide good translation, scaling and rotation invariant, but also have a certain robustness of affine transformation. Combine with the theory of invariant moments, [7] results in good.

Academia and industry are committed to the development of CBIR, and have achieved great successes, but there are still many problems. In actual retrieval, features of different types of images are not the same image content, and different image features correspond different retrieval features, so the retrieval method based on a single image feature is often with low universality and unsatisfactory results. Therefore, the technologies of image retrieval based on multi-features have become a hot. [8] takes advantage of color histogram as color feature, with the threshold segmentation of image, utilizes Fourier descriptors as shape feature, eventually combines color feature with shape feature for image retrieval. [9] takes advantage of color auto-correlogram as color fea-

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ture, utilizes edge orientation histogram as shape feature, eventually combines color feature with shape feature for image retrieval. [10] takes advantage of color moments as color feature, extracts Hu invariant moments as shape feature basing on image edge extracted by sobel operator, eventually designs a retrieval system based on color feature and shape feature. The color feature of [10] is too small, and the extraction of shape feature is affected by the edge detection, leading to unsatisfactory retrieval results.

Consider the problems of the inaccuracy and the related images are drop behind in image retrieval, an effective multi-features image retrieval method based on quantization and marked-watershed segmentation is proposed. The color feature is extracted by constructing a (16:4:4) quantization scheme of image color to fully consider the features of the color information while reduce the number of feature dimension. In order to reduce the effects of the results of image segmentation for the extraction of image shape feature and retrieval results, perform the marked-watershed algorithm to achieve the segmentation, and extract Jan Flusser invariant moments. The Gaussian model is used to normalize the different subcharacters distance. The final multi-features similarity consists of the color similarity and the shape similarity. The experiment results show that the proposed method has obvious retrieval results.

II. Relevant Theories

A. HSV Color Space

With the high correlation between the three components of RGB color space, we would better not process these components directly. As a color model for the human eyes to distinguish compatibly, the model of HSV color space is with good perception characteristic and the ability to easily convert to the model of RGB color space [11], [12]. Using the following formulas to conversion RGB color space to HSV color space,

$$H = \begin{cases} \theta, & G \geq B \\ 2\pi - \theta, & G < B \end{cases} \tag{1}$$

$$S = 1 - \frac{3}{(R+G+B)} min(R, G, B) \tag{2}$$

$$V = \frac{1}{\sqrt{3}}(R+G+B) \tag{3}$$

Where $R, G, B \in [0, 1]$ and $\theta = \cos^{-1}(\frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}})$.

B. Image Color Quantization Theory

The computation and storage space of the color feature which is based on the true color are nonlinear expansion in the process of the feature extraction and matching. As the ability of human eyes is limited to distinguish color difference, it is not necessary to completely extract the color feature of true color images. We regard certain colors with little difference as the same color, divide the color space into a plurality of color range, and then select a few representative color ranges from the higher color resolution image, namely image color quantization [13].Color components of the quantized image are known as color channels. For each channel, the desired number of colors are predefined, and the quantized colors are assigned and grouped into a per-set class which are no longer consider the range of the original color values. The colors of each channel are linearly mapped to the nearest quantized color value, namely consistent quantitative. The experiments of researchers show that the expression of non-related channel can make use of consistent quantitative. As the three channels of HSV color space model are independent, the method of consistent quantitative is suitable for image color quantization.

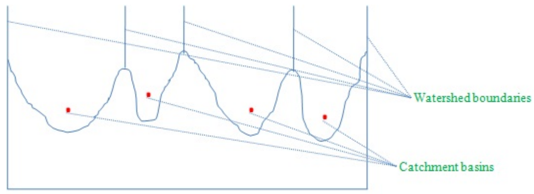

Figure 1. Watershed segmentation.

C. Algorithm of Watershed Segmentation

As a mathematical morphology method [14], [15], the algorithm of watershed segmentation has many advantages, including high implementation speed, a closed object contour and high accuracy. Algorithm of watershed segmentation takes the images as a topographical map, where strong luminance areas are with larger pixel values, and dark areas are with smaller pixel values. As shown in Fig.1, the algorithm is to look for catchment basin and watershed boundaries. As direct application of watershed segmentation algorithm is often ineffective, we can get better segmentation results by marking the foreground and background of the image, and then apply the algorithm of watershed segmentation.

D. Jan Flusser Invariant Moments

The description of the affine invariant region of the image is very important, and the selected description operator should remain basically unchanged under affine transformations, namely being with strong robustness. Regional features can be described effectively by Jan Flusser invariant moments which can be the feature vectors of shape retrieval features [6], [7]. The calculation of Jan Flusser invariant moments is as follows: The origin moments and central moments of discrete digital image $f(x, y)$ are defined as,

$$m_{pq} = \sum_x \sum_y x^p y^q \tag{4}$$

$$\mu_{pq} = \sum_x \sum_y (x - \overline{x})^p (y - \overline{y})^q f(x, y) \tag{5}$$

Where $\overline{x} = m_{10}/m_{00}$ and $\overline{y} = m_{01}/m_{00}$.

Combine (4) with (5), Jan Flusser affine invariant moments can be exported as follows:

$$\{I_1, I_2, I_3, I_4, I_6, I_7, I_8, I_9\}$$

Because I_5 is not independent, it cannot be the element of the feature vector. The formulas of the invariant moments are defined as:

$I_1 = (\mu_{20}\mu_{02} - \mu_{11})/\mu_{00}^4$

$I_2 = (-\mu_{30}^2\mu_{03}^2 + 6\mu_{30}\mu_{21}\mu_{12}\mu_{03} - 4\mu_{30}\mu_{12}^3 - 4\mu_{21}^3\mu_{03} + 3\mu_{21}^2\mu_{12}^2)/\mu_{00}^{10}$

$I_3 = (\mu_{20}\mu_{21}\mu_{03} - \mu_{20}\mu_{12}^2 - \mu_{11}\mu_{30}\mu_{03} + \mu_{11}\mu_{21}\mu_{12} + \mu_{02}\mu_{30}\mu_{12} - \mu_{02}\mu_{21}^2)/\mu_{00}^7$

$I_4 = (-\mu_{20}^3\mu_{03}^2 + 6\mu_{20}^2\mu_{11}\mu_{12}\mu_{03} - 3\mu_{20}^2\mu_{02}\mu_{12}^2 - 6\mu_{20}\mu_{11}^2\mu_{21}\mu_{03} - 6\mu_{20}\mu_{11}^2\mu_{12}^2 + 12\mu_{20}\mu_{11}\mu_{02}\mu_{21}\mu_{12} - 3\mu_{20}\mu_{02}^2\mu_{21}^2 + 2\mu_{11}^3\mu_{30}\mu_{03} + 6\mu_{11}^3\mu_{21}\mu_{12} - 6\mu_{11}^2\mu_{02}\mu_{30}\mu_{12} - 6\mu_{11}^2\mu_{02}\mu_{21}^2 + 6\mu_{11}\mu_{02}^2\mu_{30}\mu_{21} - \mu_{02}^3\mu_{30}^2)/\mu_{00}^{11}$

$I_6 = (\mu_{40}\mu_{04} - 4\mu_{31}\mu_{13} + 3\mu_{22}^2)/\mu_{00}^6$

$I_7 = (\mu_{40}\mu_{22}\mu_{04} - \mu_{40}\mu_{13}^2 - \mu_{31}^2\mu_{04} + 2\mu_{31}\mu_{22}\mu_{13} - \mu_{22}^3)/\mu_{00}^9$

$I_8 = (\mu_{20}^2\mu_{04} - 4\mu_{20}\mu_{11}\mu_{13} + 2\mu_{20}\mu_{02}\mu_{22} + 4\mu_{11}^2\mu_{22} - 4\mu_{11}\mu_{02}\mu_{31} + \mu_{02}^2\mu_{40})/\mu_{00}^7$

$I_9 = (\mu_{20}^2\mu_{22}\mu_{04} - \mu_{20}^2\mu_{13}^2 - 2\mu_{20}\mu_{11}\mu_{31}\mu_{04} + 2\mu_{20}\mu_{11}\mu_{22}\mu_{13} + \mu_{20}\mu_{02}\mu_{40}\mu_{04} - 2\mu_{20}\mu_{02}\mu_{31}\mu_{13} + \mu_{20}\mu_{02}\mu_{22}^2 + 4\mu_{11}^2\mu_{31}\mu_{13} - 4\mu_{11}^2\mu_{22}^2 - 2\mu_{11}\mu_{02}\mu_{40}\mu_{13} + 2\mu_{11}\mu_{02}\mu_{31}\mu_{22} + \mu_{02}^2\mu_{40}\mu_{22} - \mu_{02}^2\mu_{31}^2)/\mu_{00}^{10}$

III. MULTI-FEATURES IMAGE RETRIEVAL METHOD BASED ON QUANTIZATION AND MARKED-WATERSHED SEGMENTATION

Consider the problems of the inaccuracy and the related images are drop behind in image retrieval, an effective multi-features image retrieval method based on quantization and marked-watershed segmentation is proposed. The color feature is extracted by constructing a (16:4:4) quantization scheme of image color in HSV color space. Perform the marked-watershed to achieve the segmentation of the image, and extract Jan Flusser invariant moments as shape feature. The Gaussian model is used to normalize the different sub-characters distance. The final multi-features similarity consists of the color similarity and the shape similarity. The retrieval framework of the proposed method is shown in Fig.2.

A. Extract Color Feature

Construct a (16:4:4) quantization scheme to quantify the color of an image [3], [16]. Specific quantization scheme is as follows:

$$H = \begin{cases} 0, & h \in (345,360) or (0,15) \\ 1, & h \in (16,25) \\ 2, & h \in (26,45) \\ 3, & h \in (46,55) \\ 4, & h \in (56,80) \\ 5, & h \in (81,108) \\ 6, & h \in (109,140) \\ 7, & h \in (141,165) \\ 8, & h \in (166,190) \\ 9, & h \in (191,220) \\ 10, & h \in (221,255) \\ 11, & h \in (256,275) \\ 12, & h \in (376,290) \\ 13, & h \in (291,315) \\ 14, & h \in (316,330) \\ 15, & h \in (331,345) \end{cases}$$

$$S = \begin{cases} 0, & s \in [0,0.15) \\ 1, & s \in [0.15,0.4) \\ 2, & s \in [0.4,0.75) \\ 3, & s \in [0.75,1] \end{cases} \quad V = \begin{cases} 0, & v \in [0,0.15) \\ 1, & v \in [0.15,0.4) \\ 2, & v \in [0.4,0.75) \\ 3, & v \in [0.75,1] \end{cases}$$

We get 16 * 4 * 4 = 256 colors by the quantization of image color, and combine them into one-dimensional vector $L = 16 * H + 4 * S + V (L \in (0,255))$.Color histogram can be obtained by calculating L to get 256 handles color components. Obtain 256 dimensions vector Vr by the order statistics of color histogram, and take Vr as the color feature of an image.

B. Extract Shape Feature

Perform the marked-watershed to achieve the segmentation of an image. The basic steps of the proposed algorithm are as follows:

1) Read image and seek its boundary. Filter the horizontal and vertical directions of an image with sobel operator and then obtain the value of gradient magnitude image.
2) Label the prospect and background respectively. Use the technology of morphological reconstruction to label the prospect and background of the image. Based on 3 * 3 disc structure element, we firstly apply the opening operation which is a combination of dilation and erosion to the image. Then we apply the closing operation to remove some small goals of the image.
3) Modify the gradient magnitude image based on the label of the prospect and background, and apply watershed transform.

Extract Jan Flusser invariant moments $I = (I_1, I_2, I_3, I_4, I_6, I_7, I_8, I_9)$ by binding the theory of invariant moments on the segmented image, and take I as the shape feature of an image.

C. Gaussian Normalization

The range of the similarity value and the importance degree of the feature vectors which extracted based on the

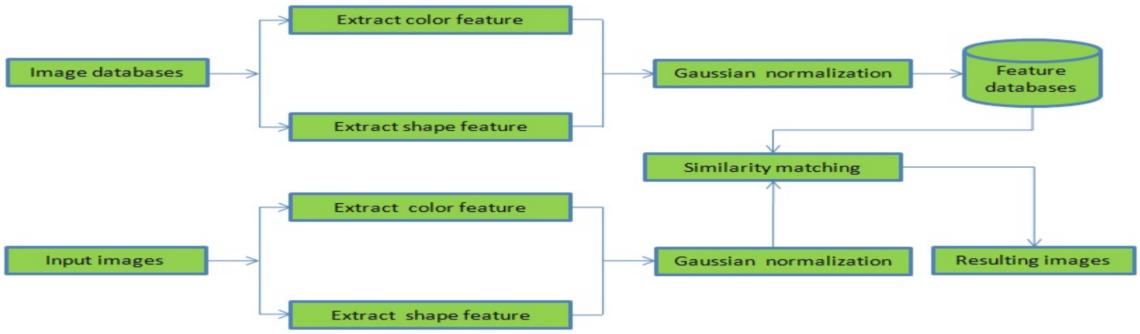

Figure 2. The retrieval framework of the proposed method.

color and shape of an image are not the same. We need to normalize features to avoid the similarity which has large value range weakening the importance of the other similarity in the global similarity. The normalization of features is described as follows:

1) Calculate the feature similarity between image I_m and image I_n in image databases:
$$S_{m,n}(r_{ij}) = F(r_{ij}, W_{ijk}) \quad m,n = 1,2,\ldots,M \quad and \quad m \neq n \tag{6}$$
Where F is the similarity algorithm(Euclidean distance), r_{ij} is the expression of features, W_{ijk} is the component of the expression of features.
2) Calculate the similarity value of any pair of images in image databases which includes M images. we can obtain $C_M^2 = \frac{M(M-1)}{2}$ similarity values, and calculate the mean μ_{ij} and standard deviation σ_{ij} of those similarity values.
3) Calculate the feature similarity $S_{m,q}(r_{ij})$ between the image m in image databases and the sample image q(without being normalized):
$$S_{m,q}(r_{ij}) = F(r_{ij}, W_{ijk}) \tag{7}$$
4) Gaussian normalization of the feature similarity which without being normalized:
$$S'_{m,q}(r_{ij}) = \frac{S_{m,q}(r_{ij}) - \mu_{ij}}{3\sigma_{ij}} \tag{8}$$

99% of $S'_{m,q}(r_{ij})$ fall in the closed interval [-1,1], and ultimately those values will fall in the closed interval [0,1] by the following translation operation:
$$S''_{m,q}(r_{ij}) = \frac{S'_{m,q}(r_{ij}) + 1}{2} \tag{9}$$

D. Similarity Matching

Combine (9), we can obtain multi-features similarity $S''_{m,q}(r_{ij})$ by calculating the similarity of color feature $S1''_{m,q}(r_{ij})$ and shape feature $S2''_{m,q}(r_{ij})$:
$$S''_{m,q}(r_{ij}) = sS1''_{m,q}(r_{ij}) + (1-s)S2''_{m,q}(r_{ij}) \tag{10}$$

$S''_{m,q}(r_{ij})$ is the basis for similarity matching. Where s is the weight of color feature, (1-s) is the weight of shape feature, $s \in [0,1]$, and s is a statistical quantity and we set its step-size to be 0.1 in our experiments.

IV. EXPERIMENTS

A. Experimental Platform and Data

All the programs are operated by Windows 7, AMD Athlon(tm) X2 Dual-Core QL-64 2.1GHz and MATLAB R2011b.

Select 8 classes from the Corel image database, including butterflies, figures, flowers, horses, etc. Each class includes 50 images.

B. Evaluation Standards

Evaluate the image retrieval performance based on precision and average sorting.

Precision: The retrieved images which are relevant to the query image take the percentage of the total retrieved images. The precision is to reflect the accuracy of image retrieval and the ability to reject irrelevant images. The higher the precision is, the better the retrieval method is. The formula of the precision is as follow:
$$P = p(AB) = \frac{p(A \cup B)}{p(B)} = \frac{a}{a+b} \tag{11}$$

Where A is the set of the retrieved relevant images in the first retrieval, a is the elements in set A, B is the set of the retrieved images in the first retrieval, b is the number of the retrieved irrelevant images in the first retrieval.

Average sorting: The position of the retrieved relevant images in the returned images. The more anterior position of the retrieved relevant images is, the higher degree of intensity is, the better the retrieval results are.

Let the number of the returned images is N, N_R is the number of the relevant images in the returned images, N_A is the number of the actual relevant images in the returned images, ρ_r is the serial number of the relevant images. Specific formula is as follows:
$$K1 = \frac{1}{N_R}\sum_{r=1}^{N_R} \rho_r \tag{12}$$
$$K2 = \frac{N_A}{2} \tag{13}$$

Where $K1$ is the average sorting of the relevant images, $K2$ is the average sorting of the ideal relevant images, the more closely the ratio of $K1/K2$ approached 1, the better the retrieval results are.

Figure 3. Sample image.

Figure 4. Color histogram.

Figure 6. Reference [10].

Figure 7. Proposed method.

C. Experimental Results

Retrieve the image respectively based on color histogram, Jan Flusser invariant moments, Reference [10], and proposed method. Take figure image as an example, Fig.3 is the sample image, Fig.4, Fig.5, Fig.6 and Fig.7 correspond to the retrieval results of color histogram, Jan Flusser invariant moments, Reference [10] and proposed method(s=0.8). It returns 25 images, in which the first image is the sample image, the rest images are arranged by the size of similarity from left to right, top to bottom. From the figures we can see that the proposed method has good retrieval results in precision and average sorting, better than the retrieval methods based on color histogram, Jan Flusser invariant moments and Reference [10].

Take the class of figure images as an example. Select 3 images randomly from the class of figure images as the sample images, retrieve the images, and take the average of $K1/K2$ in three retrievals as the evaluation standard. The statistical results in experiments of the proposed method are shown in table I. The quantity of retrieval results change along with the change of the color weights. From table I we can see that the accuracy of image retrieval reached the maximum when $s \in [0.6, 0.8]$. The average of $K1/K2$ is nearest to 1 when s=0.8, and the ordination of the returned relevant images is the best. The contrast of the four methods is shown in table II, where s=0.8 in the proposed method. We can clearly see that the proposed method has good retrieval results in precision and average sorting, better than the retrieval methods based on color histogram, Jan Flusser invariant moments and Reference [10].

In order to further verify the retrieval results of the proposed method, select 3 images randomly from per class as the sample images. We choose proper s to make the average precision to be the highest and let the average of $K1/K2$ to be the nearest to 1. The ideal retrieval results of each class of image databases are shown in table III. The results bars for four retrieval methods on the Corel image database are shown in Fig.8 and Fig.9. From Fig.8 and Fig.9 we can clearly see that the proposed method has obviously effect in precision and average sorting, better than the retrieval method based on single feature or integrated features. Even though the retrieval method of Reference [10] has a slightly higher accuracy than proposed method for the part of the image classes, the proposed method has a much better average precision and average sorting. As the classes of butterfly and dinosaur, in which have obviously different from color and shape, the precision of the proposed method reached 100%, and the average sorting reached ideal sorting. As the classes of construction and elephant, in which are similar to color and shape and have not obviously different from the target area and the background area, the effectiveness of retrieval results are affected.

Figure 5. Jan Flusser invariant moments.

TABLE I.
THE STATISTICAL OF THE RETRIEVAL RESULTS FOR THE PROPOSED METHOD ON FIGURE IMAGE DATABASE

s	Average precision(%)	Average of K1/K2
0	33.33	2.45
0.1	56	1.4
0.2	70.67	1.33
0.3	77.33	1.13
0.4	78.77	1.15
0.5	81.33	1.13
0.6	84	1.12
0.7	84	1.1
0.8	84	1.09
0.9	81.33	1.07
1	61.33	1.44

TABLE II.
THE STATISTIC OF THE RETRIEVAL RESULTS FOR FOUR RETRIEVAL METHODS ON THE FIGURE IMAGE DATABASE

Retrieval methods	Average precision(%)	Average of K1/K2
Color histogram	49.33	2.48
Jan Flusser invariant moments	33.33	2.43
Reference [10]	58.67	2.07
Proposed method	84	1.09

TABLE III.
THE STATISTICAL OF THE RETRIEVAL RESULTS FOR THE PROPOSED METHOD ON COREL IMAGE DATABASE

Image types	s	Average precision(%)	Average of K1/K2
Butterfly	0.2∼1	100	1
Figure	0.8	84	1.09
Construction	0.7	50.67	1.67
Bus	0.5	89.33	1.06
Dinosaur	0.3∼0.8	100	1
Elephant	0.5	36	1.6
Flower	0.9	70.67	1.29
Horse	0.3	77.33	1.3

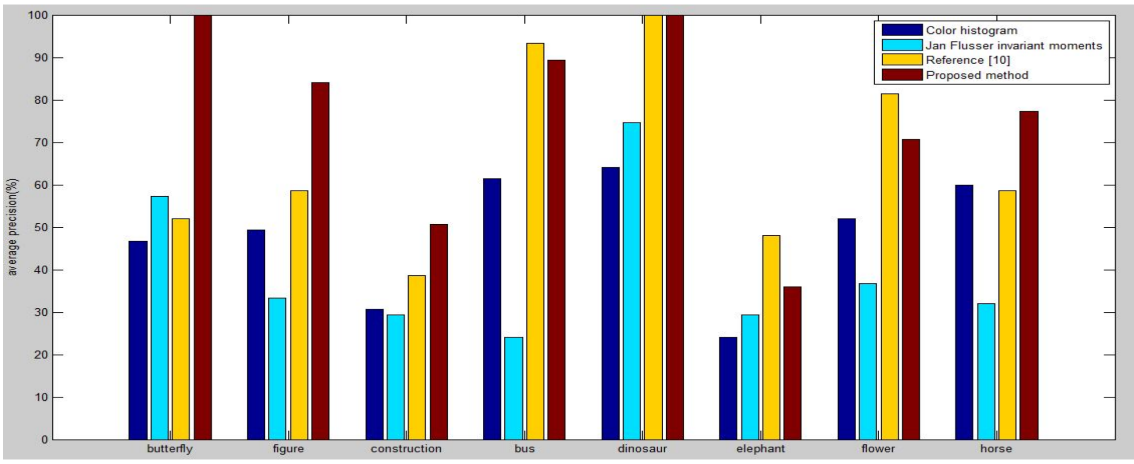

Figure 8. Average precision bars for four retrieval methods on Corel image database.

V. SUMMARY

An effective multi-features image retrieval method based on quantization and marked-watershed segmentation is proposed. The color feature is extracted based on the quantization of image color to fully consider the feature of the color information while reduce the number of feature dimensions. Perform the marked-watershed to achieve the segmentation of the image, reduce the effects of the results of image segmentation for the extraction of image shape feature and retrieval results, and extract Jan Flusser invariant moments, The Gaussian model is used to normalize the different subcharacters distance. The final multi-features similarity consists of the color similarity and the shape similarity. The retrieval accuracy has improved, and the related images are in a more anterior position of retrieval results. Without considering the texture and spatial features, and the high-level semantics of images are not included in the color and shape features. Further work will be combined with the other features and high-level semantics of the image.

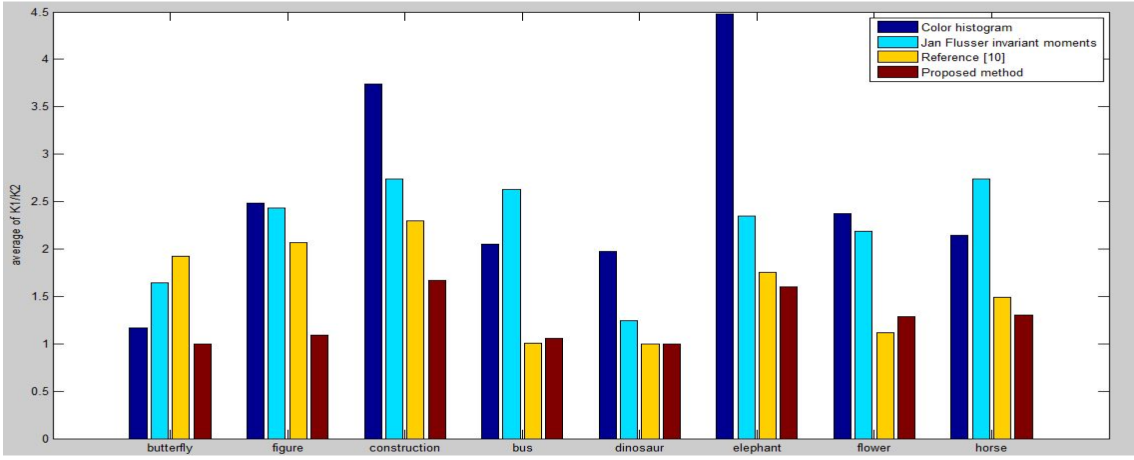

Figure 9. The bars of the average of K1/K2 for four retrieval methods on Corel image database.

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