An Image Retrieval Method Based on Hu Invariant Moment and Improved Annular Histogram

F. Xiang[1], H. Yong[1], S. Dandan[1], Z. Jiexian[1]
[1] *School of Software, Nanchang Hangkong University, Jiangxi Nanchang, 330063, China*
fxfb163@163.com

***Abstract*—Image retrieval methods based on annular histogram of feature points are calculation efficient, invariant to image rotation and translation transform. However, these methods have two main disadvantages. One is that the annular histogram can't describe the spatial distribution of feature points accurately, thus different images may have similar annular histogram. Another one is the methods based on feature points can not describe the shape information of object. These disadvantages affect the retrieval accuracy to a certain extent. In this paper, an image retrieval method based on Hu invariant moments and improved annular histogram is proposed. Firstly, edge of image is detected and feature points are calculated based on the edge curvature. Then, image features are described based on both the edge and points. Annular histogram combined with standard deviation ellipse method is used to describe the spatial distribution of feature points. Hu invariant moment of the edge is used to represent the object's shape information. Finally, the similarity is measured based on both the point feature and the shape feature. Experiment results show that the proposed method can improve the image retrieval precision effectively.**

***Index Terms*—Image retrieval, Hu invariant moment, annular histogram, shape information.**

I. INTRODUCTION

With the development of computer technique and image processing technique, content-based image retrieval (CBIR) has become an active and fast-advancing research area in image retrieval. Point feature is widely used to CBIR because the feature points of image contain abundant information, can describe many details of image, what's more, retrieval method base on feature points is calculation efficient. An image retrieval method based on feature points' average moments is proposed in [1]. However, for information represented by single feature is limited, many researchers combined different features to improve the retrieval performance. In [2], two kinds of histogram are used to describe image feature. One is that the histogram of circumscribed circle radius from adjacent edge to the centroid of feature points, another is the histogram of distances between feature points and the top left corner of the image. In [3] and [4], the authors use the convex hull of interest points to describe the image feature, combine SVM learning method and Zernike moments respectively to improve the efficiency of image retrieval, moreover, both methods use annular histogram to improve the performance of retrieval. Since the method based on annular histogram is calculation efficient, invariant to image rotation and translation, and it can indicate the spatial distribution of feature points to a certain extent.

However, the methods based on annular histogram cannot describe the spatial distribution of feature points accurately, thus different images may have similar annular histogram, and the methods based on feature points cannot describe the shape information of object. In [5], an image shape characteristics extracting algorithm based on regional pseudo Zernike moment is proposed, then used to image retrieval. In [6], contour points are used to image retrieval. The contour points possess the shape characteristics and point features at the same time.

In this paper, considering the fact that limited information represented by single feature is insufficient to describe the image features, an image retrieval method based on Hu invariant moments and improved annular histogram is proposed. Firstly, the edge feature of image is detected by edge operator, and then the feature points are extracted based on the edge curvature. Secondly, image features are described based on the edge and points. In order to overcome the disadvantage of method based on annular histogram, standard deviation ellipse [7] method is used to describe the spatial distribution of feature points accurately. At the same time, Hu invariant moments [8] of feature edge are used to describe the shape characteristic. Finally, similarity between images are measured based on these two features. The improved annular histogram method takes more consideration of feature points' geometry space distribution, combined with shape feature, the retrieval accuracy is expected to be improved. Experiment results show that this algorithm has good retrieval results.

II. THE PROPOSED ALGORITHM

The block diagram of the proposed method is shown in Fig. 1. First of all, the feature edge and points of query image and current image in image database are detected. Then the space distribution of feature points is described based on improved annular histogram method and shape feature is

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represented based on Hu invariant moment of edge feature. Finally, similarity of images is measured based on these two features and the image retrieval results are obtained.

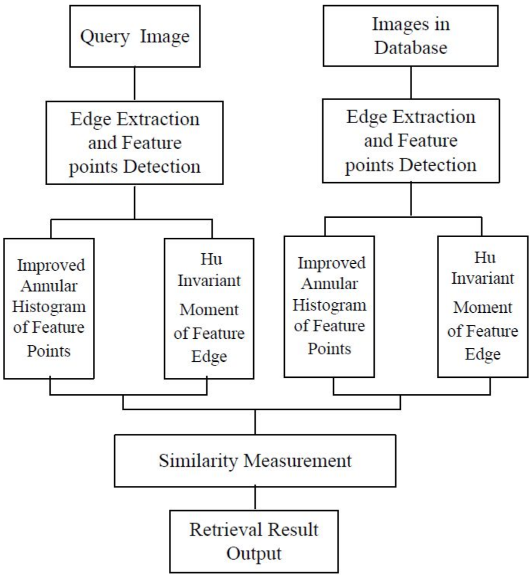


Fig. 1. Block diagram of the proposed method.

A. Feature Extraction

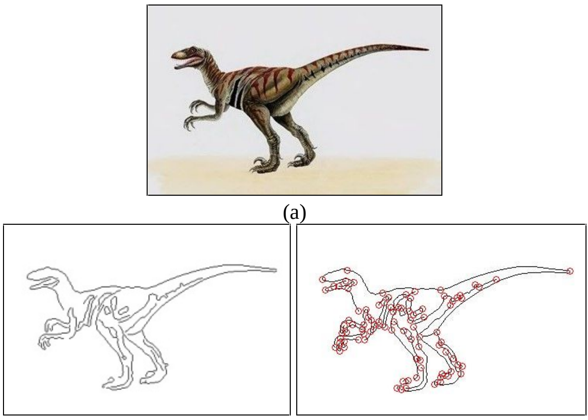
There exist many classical edge detectors such as Canny operator, Roberts operator, Prewitt operator, Sobel operator, Kirsch operator, Compass operator, and so on. Canny operator [9] is adopted in this paper because it has the abilities of preserving important edge information in image, producing little false edge, having good anti-noise and edge location performance. For the original image shown in Fig. 2(a), the edge detected by Canny operator is given in Fig. 2(b).

There are two common ways to feature point extraction. One is that based on gray of image, select points where the gray information changes obviously. Harris is the common used point of interest detection algorithm based on gray information of image. Another way is based on the edge image, the points where the edge curvature changes greatly are selected as feature points. The main drawback of methods base on gray information is susceptible to noise. Moreover, large amount of feature points located in the regions of background may be contained. These points may affect the performance of image retrieval because most of them are disturbing information or information that people not concern. The feature points extracting method based on edge curvature has good anti-noise performance, can reduce the useless points located in background or noise points to a great extent by selecting points on the edge where the curvature changes greatly. Figure 2(c) shows the points detected by the point of interest detection algorithm [10] based on the edge image of Fig. 2(b).

The comparison results are given in Fig. 3. Where the testing results obtained by Harris based on gray image are shown in Fig. 3(a), and feature points extracted based on edge image are shown in Fig. 3(b). It can be seen that compared with Fig. 3(b), there are more points located in the background region are contained in Fig. 3(a). In order to improve the accuracy of image retrieval, the interest point detection algorithm [9] based on local curvature of edge is adopted in this paper.

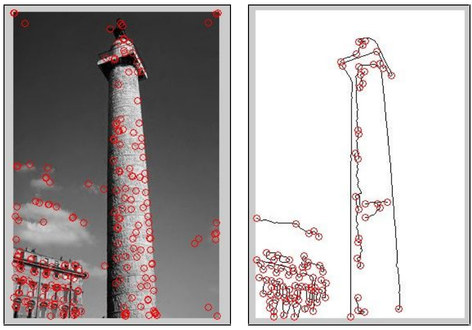
In order to retrieve image accurately and quickly, effective feature description method is necessary. After feature point detection, annular histogram method is adopted to describe the point feature. The points are divided into a series of concentric ring regions with equal interval. The color feature of points in every concentric ring region is described by histogram statistics. Then, standard deviation ellipse method is used to describe the geometric distribution information of points include distribution center, distribution range and distribution direction.

For the reason that the methods based on feature points cannot describe the shape information of object. Hu invariant moments of edge are used to describe the shape feature in the next step. Edge feature can represent the shape characteristics of objects, and Hu invariant moments are robust to rotation, scale and translation transformation.



(a) (b) (c)

Fig. 2. Feature detection results. (a) The original image; (b) Edge detected by Canny operator; (c) Feature points extracted based on edge curvature in (b).



(a) (b)

Fig. 3. Feature points detection results comparison. (a) Feature points detected by Harris based on grey image; (b) Feature points extracted based on edge image.

B. Shape Feature Description based on Hu Moments

Hu invariant moments, also called geometric invariant moments are widely used in image processing because of the robustness to image translation, scale and rotation transformation. In this paper, the 7 order Hu invariant moments are calculated to describe the shape feature based on the normalized central moments of the edge image.

Firstly, for image $f(x, y)$ with size $M \times N$, the $p+q$ order moments are defined as

$$m_{pq} = \sum_{m=1}^{M} \sum_{n=1}^{N} x^p y^q f(x, y). \quad (1)$$

Then the central moments are defined as

$$\mu_{pq} = \sum_{m=1}^{M}\sum_{n=1}^{N}(x-\bar{x})^p (y-\bar{y})^q f(x,y), \quad (2)$$

where $\bar{x} = m_{10}/m_{00}$, $\bar{y} = m_{01}/m_{00}$.

In order to normalize the central moment η_{pq}, each η_{pq} is divided by μ_{00}^{γ}. The normalized central moment is shown as (3)

$$\eta_{pq} = \mu_{pq} / (\mu_{00}^{\gamma}), \quad (3)$$

where $\gamma = (p+q)/2+1$.

Finally, the 7 order Hu invariant moments are defined as follows:

$$\begin{cases} M_1 = \eta_{20}+\eta_{02}, \\ M_2 = (\eta_{20}-\eta_{02})^2 + 4\eta_{11}^2, \\ M_3 = (\eta_{30}-3\eta_{12})^2 + (3\eta_{21}-\eta_{03})^2, \\ M_4 = (\eta_{30}-\eta_{12})^2 + (\eta_{21}-\eta_{03})^2, \\ M_5 = (\eta_{30}-3\eta_{12})(\eta_{30}+\eta_{12})((\eta_{30}+\eta_{12})^2 - 3(\eta_{21}+\eta_{03})^2) + \\ +(3\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03})(3(\eta_{30}+\eta_{12})^2 - (\eta_{21}+\eta_{03})^2), \\ M_6 = (\eta_{20}-\eta_{02})((\eta_{30}+\eta_{12})^2 - (\eta_{21}+\eta_{03})^2) + \\ +4\eta_{11}(\eta_{30}+\eta_{12})(\eta_{21}+\eta_{03}), \\ M_7 = (3\eta_{21}-\eta_{03})(\eta_{30}+\eta_{12})((\eta_{30}+\eta_{12})^2 - 3(\eta_{21}+\eta_{03})^2) + \\ -(\eta_{30}-3\eta_{12})(\eta_{21}+\eta_{03})(3(\eta_{30}+\eta_{12})^2 - (\eta_{21}+\eta_{03})^2). \end{cases} \quad (4)$$

C. Spatial Distribution of Points Feature Description based on Improved Annular Histogram

At the beginning, the image is divided into k concentric ring regions based on the distribution of feature points. The concentric ring method used in this paper is similar to that of in [11], which has good translation, scale and rotation invariance. Firstly, the maximum distance between the features points in the current image is calculated and makes it as the maximum diameter. Then divide the feature points into k concentric ring regions with equal intervals. This kind of image partition method has translation, scale and rotation invariance, and can be used to improve the robustness of image retrieval to image transformation. Obviously, the larger the k is, the more clear the image detail information representation. Fig. 4 shows the image divided into concentric ring regions based on the distribution of feature points in Fig. 2(c).

After partition the image into k annular blocks, the color feature of points in every concentric ring region is described by histogram. Suppose $h[m]$ means histogram statistical value of the *m*-th concentric ring. It has

$$h[m] = \frac{N_m}{N}, \quad (5)$$

where N_m is the sum of the color value for points in the *m*-th concentric ring and N is the sum of the color value for points in the whole image.

Annular histogram method can describe the distribution density of feature points, but it is incompetent to the description of spatial distribution and different images may have similar histogram. It is found that standard deviation ellipse can describe the spatial information of feature points in 2-dimensional space. The spatial distribution information described by standard deviation ellipse includes the distribution direction and the distribution shape of feature points. The description method based on standard deviation ellipse is robust to translation and rotation transformation of images. Therefore, as a supplement, the standard deviation ellipse method is adopted to describe the spatial distribution of feature points.

The description and definition of the standard deviation ellipse include mainly three parameters, the major axis L_l, the minor axis L_s and the main direction θ, i.e. the direction of major axis:

$$L_l = 2\sigma_l = \sqrt{\frac{\sum_{i=1}^{n}\left[(x_i-\bar{x})\cos\theta - (y_i-\bar{y})\sin\theta\right]^2}{N}}, \quad (6)$$

$$L_s = 2\sigma_s = \sqrt{\frac{\sum_{i=1}^{n}\left[(x_i-\bar{x})\sin\theta - (y_i-\bar{y})\cos\theta\right]^2}{N}}, \quad (7)$$

where σ_l, σ_s are the standard deviation of the major axis and the minor axis of the ellipse, they equal to half length of major axis and minor axis respectively; $\{(x_i, y_i) \mid i = 1, 2, \cdots, n\}$ is the coordinate values of n feature points: $\bar{x} = \sum_{i=1}^{n} x_i / n$, $\bar{y} = \sum_{i=1}^{n} y_i / n$ are the mean center coordinates in x direction and y direction for all n points; the value range of θ is from 0 to π. A standard deviation ellipse computed based on the distribution of feature points in Fig. 2(c) is shown in Fig. 5

$$\theta = \arctan\frac{\left[\sum_{i=1}^{n}(x_i-\bar{x})^2 - \sum_{i=1}^{n}(y_i-\bar{y})^2\right] \pm}{2\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}$$

$$\pm\sqrt{\left[\sum_{i=1}^{n}(x_i-\bar{x})^2 - \sum_{i=1}^{N}(y_i-\bar{y})^2\right]^2 + 4\left(\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})\right)^2}. \quad (8)$$

A one dimensional feature vector is constructed based on the annular histogram and the standard deviation ellipse as (9), where in order to reduce the computational complexity, the annular histogram is normalized.

$$H = \left[\frac{h[1]}{\sum_{i=1}^{k} h(m)}, \frac{h[2]}{\sum_{i=1}^{k} h(m)}, \cdots, \frac{h[k]}{\sum_{i=1}^{k} h(m)}, \frac{L_s}{L_l}\right]. \quad (9)$$

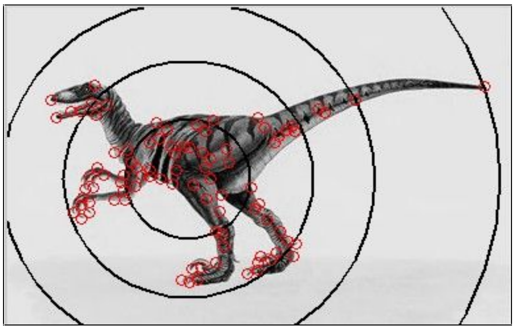


Fig. 4. The image is divided into concentric ring regions.

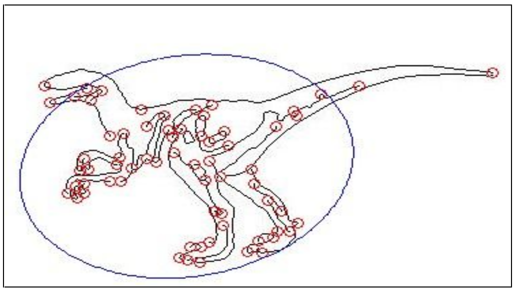


Fig. 5. Standard deviation ellipse for feature points in Fig. 2(c).

III. SIMILARITY MEASUREMENT

The similarities of spatial distribution and shape feature are measured based on Euclidean distance as (10) and (11)

$$S_p = \sqrt{\sum_{i=1}^{k+1} (H_O(i) - H_I(i))^2}, \quad (10)$$

where $H_O(i)$ and $H_I(i)$ are the i-th feature vector defined by (9) for the query image O and the image for matching I respectively

$$S_s = \sqrt{(\sum_{j=1}^{7} (S_O[j] - S_I[j])^2)}, \quad (11)$$

where $S_O[j]$ is the j-th feature vector of Hu invariant moments of the query image O, $S_I[j]$ is the j-th feature vector of Hu invariants moments of image I.

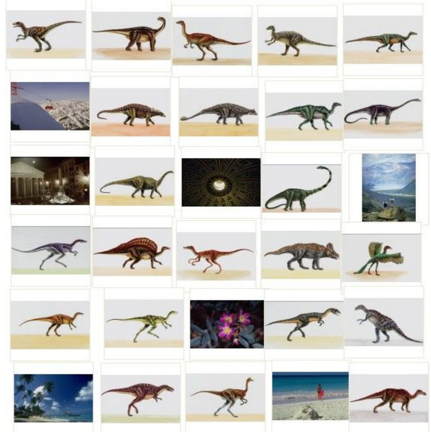
Equation (10) and (11) express the spatial distribution of point feature and shape feature respectively. The final similarity measurement formula is educed by weighting the point and shape features as follows

$$S = \sim S_p + \ S_s, \quad (12)$$

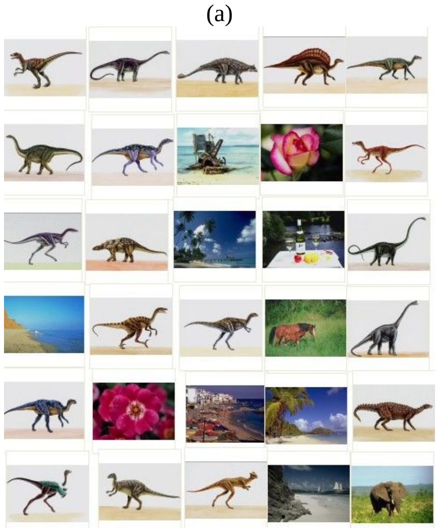
where $\sim$ and are parameters satisfy $\sim + \ = 1$. The smaller the value S is, the more similar the two images are.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

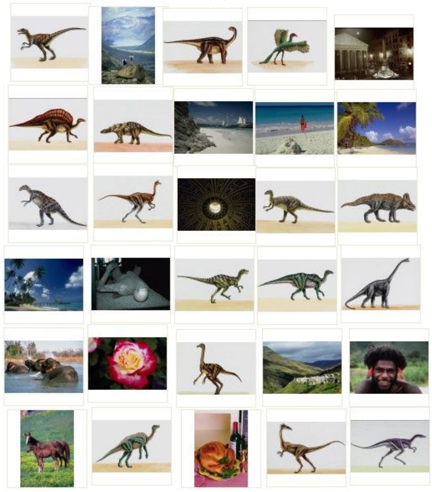
In order to demonstrate the performance of the proposed method, it is compared to the method based on annual histogram and the method based on point of interest presented in [12], where the non interest points located in the background region were eliminated based on local Zernike invariant moments and the similarity is measured based on spatial cohesion of interest points.



(a)



(b)



(c)

Fig. 6. An example of image retrieval results for three methods. (a) The proposed method; (b) The method based on annual histogram; (c) The method in [12].

In the experiments, 1000 images from Corel image database are selected. These images are divided into 10 categories, and each category contains 100 images. For the dinosaur image in Fig. 2, an example of image retrieval results with three methods are shown in Fig. 6. For each method, the top 30 most similar images are returned automatically. It can be seen that the proposed method is the most effective among three methods, there are 23, 19 and 16 correct images retrieved for the proposed method, the method based on annual histogram and the method in [12] respectively.

TABLE I. COMPARISON OF PRECISION RATE FOR THREE METHODS.

Test image	$\overline{P_{10}}$(%)			$\overline{P_{20}}$(%)			$\overline{P_{30}}$(%)		
	Proposed	**Annual histogram**	**Method in [12]**	**Proposed**	**Annual histogram**	**Method in [12]**	**Proposed**	**Annual histogram**	**Method in [12]**
Africa people	20.2	18.7	20	16.4	15.15	15	11.33	10.67	10
Beach	35.4	33.9	30	28.7	24.6	15	23.17	20.13	13.3
Bulindings	33.1	32.5	20	25.4	22.3	15	33.5	28.0	13.3
Buses	34.7	30.6	30	20.25	18.9	20	14.4	13.67	13.3
Dinosaurs	74.2	73.8	60	66.3	62.5	40	64.7	62.0	40
Elephants	41.3	40.4	40	23.8	20.0	20	22.47	19.67	20
Flowers	75.8	72.3	70	56.35	55.05	55	43.5	42.4	40
Horses	50.2	49.6	50	49.2	48.75	60	46.2	45.67	46.7
Mountains	55.6	54.7	40	50.75	46.3	30	48.33	40.67	23.3
Food	15.3	12.8	10	12.6	12.3	5	9.8	7.5	3.3

The commonly used performance measurement, precision rate, is used for the evaluation of retrieval performance. Precision rate is defined as follows

$$P_R = \frac{C}{R}, \tag{13}$$

where C is the number of images which belong to the same category with query image O; R is the total number of images which output automatically by the retrieval method. Precision P_R measures the accuracy of the retrieval. The experiment strategies are as follows: 10 query images are selected randomly from each category. P_{10}, P_{20} and P_{30} are calculated respectively for each query image based on (13). For 10 query images belong to the same category, the average values $\overline{P}_{10}$, $\overline{P}_{20}$ and $\overline{P}_{30}$ are computed. The comparison of precision rate is shown in Table I.

It can be seen from Table I, there are some easy categories, such as Dinosaurs and Flowers, these images have clear object and simple background, on which all the algorithms perform well. And there are some hard categories, such as Africa people and Food, the object in these images is not clear and the background is complicated, on which all the algorithms perform poorly. For the images of elephants, buses and horses, the results of the proposed method are almost the same as those of the other two methods. That is because the background of the image is very complex, and the object in the image is smaller than the background region, there are large portion of interest points in the background region still preserved when measuring the similarity, and these points will disturb the points in the interest object. For the images of beach, buildings and mountains, the accuracy of the proposed method is better than the other two methods. That is because the whole image is retrieval object for these images, the spatial distribution of points and the shape of object can be well described by the proposed method. By contrast, the method based on annual histogram can neither describe the spatial distribution of feature points accurately, nor describe the shape information of object, the retrieval accuracy is poorAnd for the method based on point of interest presented in [12], [13], where the non interest points located in the background region were eliminated based on local information of points, the algorithm performs poorly because there is no background or obvious object in these images, that algorithm degenerate into measuring the similarity based on spatial cohesion of interest points directly, at the same time, it did not use the shape information of image either.

V. CONCLUSIONS

Point feature contains many detail information of image, has become an important visual feature in image processing field. Edge feature is widely researched because it can describe the shape characteristic of target. A content-based image retrieval method is proposed in this paper, which takes both point feature and edge feature as clue. The annual histogram combined with standard deviation ellipse is used to describe the point feature, and the Hu invariant moments of edge are used to describe the shape feature. Experimental results show that this retrieval method has better performance than the classical methods based on interest points.

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