A Novel Shape Representation and Retrieval Algorithm: Distance Autocorrelogram

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***Abstract*—This paper introduces a new shape representation and retrieval method called distance autocorrelogram. Firstly, distance autocorrelogram is obtained under the premise of getting the contour' centroidal distances. Then, we apply this shape descriptor to content-based image retrieval (CBIR). This feature depends on the centroidal distances and correlation between neighboring edges, so it can express the edge' spatial distributing information. This scheme is effective and robust to translation, scaling and rotation. Experimental results and algorithm analysis demonstrate the efficiency and feasibility of this shape-based image retrieval approach. Beside, it has better performance compared to traditional distance histograms.**

***Index Terms*—image retrieval; distance histograms; distance autocorrelogram; shape representation**

I. INTRODUCTION

Researchers generally consider the color, texture, shape and spatial relationship of image as retrieval features in CBIR. Many CBIR systems employ color as retrieval feature vector, such as color histograms [1,2,3,4]. Color histograms are computationally efficient, and generally insensitive to small changes in viewing position. However, they ignore spatial information. Color-spatial methods incorporate spatial information with color [5,6,7,8,9]. These methods offer more effectiveness in comparison with the primary method with little efficiency reduction. Despite the achieved advantage, they suffer from sensitivity to color and illumination changes. For example, Figure 1 shows a landscape with two different illumination conditions, but the color-spatial based feature vectors of these images are very different.

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Thanks to the shape feature is often linked to the target and does not change with the change of surrounding environment, so shape can be seen as steady feature compared to color and texture. In shape-based image retrieval, one of the most important problems is the shape feature's representation and extraction, shape representation is to deal with or calculate the objective shape by some way and then form feature vector which stands for the shape. Shape representation methods can be mainly divided into edge-based methods and region-based methods [10]. Edge-based methods utilize the edge' information and region-based methods make use of the pixel' distributing information in the target region.

Edge-based feature extraction uses perimeter, curvature, edge direction [11,12], chain code [13], Fourier descriptors [14,15,16], polygonal approximation[17], autoregressive model [18] and interest points to denote shape on the basis of edge detection. This kind of method has a better effect for images which have clear edges and the edges are easy to get. Region-based feature extraction extract image region of interest and use the pixels feature in the region to express shape on the basis of image segmentation. Some of the region-based methods is moment invariants [19] and grid-based method [20]. This method is suitable for images can be segmented easily.

Edge gradient orientation is a popular shape representation method. Edge gradient orientation has the advantage of less calculation and easily realization. Jain A K and Vailaya [11,12] introduced edge direction histogram (EDH) as the shape descriptor. Since this method use edges individually and ignores the spatial distribution of edges, its effectiveness is limited. Fariborz Mahmoudi et al [26] introduced a new shape descriptor called edge orientation autocorrelogram (EOAC) which can reflect the correlation between neighboring edges. However, due to the discrete nature of digital images, EDH and EOAC is sensitive to rotation.

Centroidal distances histogram [21] is an effective edge-based shape representation method which is invariable to translation and rotation. Normalization

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makes distances histogram invariable to scaling. However, distances histogram does not reflect the spatial information and two different shapes of graphics may have the same histogram. To solve this problem, based on the distances histogram method, a shape vector called distance coherence is proposed in [22]. The basic idea of distance coherence is that put the pixels in each interval divide into coherent pixels and incoherent pixels. This approach makes use of the spatial information of contours effectively. On the basis of extracting contour' corners, Boaz and Sun et al [23,24] used corners as the contour' index. Although these methods considered the spatial information of contours, the correlation of adjacent pixels is ignored.

Autocorrelationgram can reflect the spatial relationship between adjacent pixels. Huang [25] proposed color correlationgram and applied it to color-based image retrieval. Fariborz et al [26] proposed edge orientation autocorrelogram (EOAC) and get better results. We proposed distance autocorrelogram (DAC) based on the distance histograms. The advantages of our method is that not only remain the advantages of the distance histogram, namely, translation, rotation and scaling invariance, but also introduced spatial information and the correlation between adjacent pixels. In addition, the realization of our algorithm is simple, and it can be applicable to all types of image libraries and so on. A large number of experiments verified the effectiveness of the algorithm and better precision and recall compared to traditional methods.

(a) (b)

Figure 1. An example of two images with different illumination.

II. DISTANCE AUTOCORRELOGRAM

The concept of correlogram is derived from color correlogram. Color correlogram is an expression method of describing image color's spatial distribution by making use of the color relation among pixels of image [25]. Color correlogram not only depicts proportion that a color's pixel accounts for the whole image, but also reflects the spatial relativity among various sets of color. Color autocorrelogram which just takes account of the spatial relation of the pixels that have identical color in image space is an easier method in comparison with the huge calculation of color correlogram.

Correlogram is an important method of showing the correlation among image elements. Fariborz Mahmoudi et al [26] expanded the concept of autocorrelogram to edge gradient orientation. This paper will advance the concept of distance autocorrelogram on the basis of distance histograms. Firstly, we will introduce the concept of centroidal distance and centroidal distance histogram in the following.

A. Distance histogram

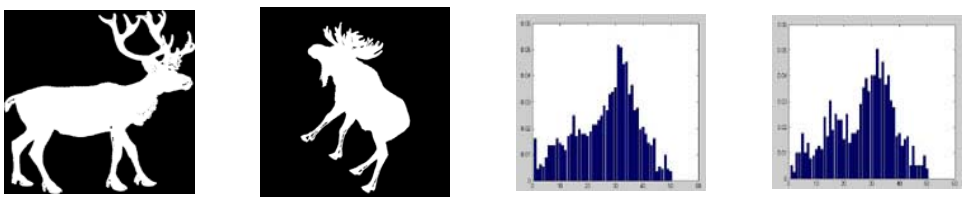
Centroidal distances are the distances between points on the shape and the centroid of shape. Centroidal distances contain the shape information that can be used to describe the shape of the target. Fan [27] used the target's distance histograms (DH) to describe the shape and defined the distance histograms as follows:

To calculate centroidal distances and quantify them to certain intervals, the distance histograms are expressed as:

$$D:(d_0, d_1, \cdots d_{N-1}) \tag{1}$$

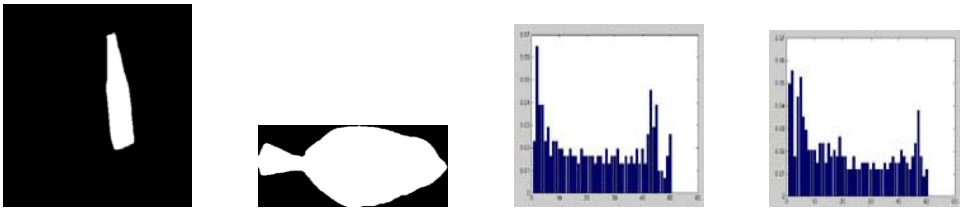
where N is the number of buckets in the histograms and $d_i (i = 0,1,\cdots,N-1)$ is the number of centroidal distances, which were discretised into bucket i.

From the statistical point of view, distance histograms describe the shape, different histograms correspond to different shapes and similar distance histograms have similar shapes. Figure 2(a) and (b) are two similar images and their distance histograms (c) and (d) are similar too. Obviously, distance histograms are invariable to translation and rotation. Normalization makes distances histogram invariable to scaling. However, the histogram only reflects the contour' statistical characteristics but not the spatial distribution characteristics. Therefore, different contours may have the same distance histograms. Figure 3 shows examples of different shapes have similar histograms. Figure 3 (a) and (b) are dissimilar images in the visual but their histograms shown as (c) and (d) are very approximate.



(a) (b) (c) (d)

Figure 2. Similar shapes have similar distance histograms



(a) (b) (c) (d)

Figure 3. Examples of different shapes have similar histograms

B. The definition of distance autocorrelogram

Distance autocorrelogram expresses the attribution of their shape by making use of the correlation between centroidal distances and neighboring edges. Based on distance histograms, we define the distance set as

$$K = \{1,3,5,7\} \tag{2}$$

The elements of K express pixel's distance between the current edge's pixels and other pixels when compute the edge's correlation.

Let D expresses contour image's distance matrix, and D_{d_i} is all the pixels have distances d_i, we define the distance autocorrelogram as

$$\Gamma_{d_i}^{(k)} = N_d[\{p_1 \in D_{d_i}, p_2 \in D_{d_i}, | p_1 - p_2 |= k\}] \tag{3}$$

N_d is the number of pixels meet the conditions.

It can be seen that distance autocorrelogram is a $N \times D$ matrix. $E < i,k > (1 < i < N, k \in K)$ express the total number of pixels, including the pixels which centroidal distance are d_i in contour pixels , and which are k pixels unit apart from the former ones and centroidal distance are d_i, too. We adopt 4-neighboring method when measure the neighboring pixels' distance. Figure 4 shows the locations when the neighboring pixels' distance are 1, 2 and 3. That is, the distances between b and a are 1, the ones between c and a are 2, and the ones between d and a are 3.

			d			
			c			
			b			
d	c	b	a	b	c	d
			b			
			c			
			d			

Figure 4. Shows 4-neighboring's distance when *k*=1,2,3

C. The computation of distance autocorrelogram

The algorithm of generating DAC consists of five steps as follows:

(1) Edge detection: The Sobel operator is more accurate about locating edges than other edge detectors. Therefore it was used for edge detection in this paper.

(2) Computing centroidal distance matrix $D(x, y)$: A gray image $f(x, y)$ become binary image $B(x, y)$ after edge detection. First, the centroid $c(x_c, y_c)$ is computed from the sample points as shown below.

$$x_c = \frac{1}{N}\sum_{i=0}^{N-1} x_i \,,\, y_c = \frac{1}{N}\sum_{i=0}^{N-1} y_i \tag{4}$$

Then, the distance between a sample point $b_i(x_i, y_i)$ and the centroid $c(x_c, y_c)$ is computed as follows.

$$d(b_i, c) = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \tag{5}$$

Centroidal distance matrix $D(x, y)$ is formed by (4) and (5).

(3) Centroidal distance standardization: Centroidal distance matrix is a discrete, irregular number set, so it is sensitive to scaling. In order to make calculation simple and eliminate the impact of scaling, we plan all centroidal distances to the intervals between 0 to $W/2$ by (6) as follows.

$$norm\_dis = \frac{dis - dis_{\min}}{dis_{\max} - dis_{\min}} \times \frac{\mathrm{W}}{2} \tag{6}$$

where, dis are values in distance matrix, $dis_{\max}$ is the maximum centroidal distance and $dis_{\min}$ is the minimum centroidal distance. norm_dist is the normalized

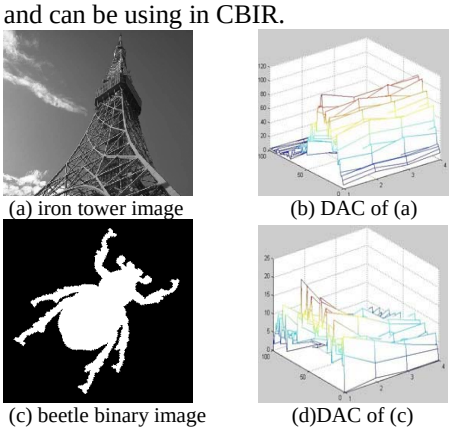
centroidal distance for dist . W is the maximum size of contour image $B(x, y)$' rectangular bounding box. If the size of $B(x, y)$' rectangular bounding box is $a \times b$, then, $\mathrm{W} = \max(a, b)$.

(4) Quantizating centroidal distance to n bins: Centroidal distances are quantized to n bins by unit $\frac{\mathrm{W}}{n}$.

(5) Computing elements of DAC: In the final stage, the DAC is constructed by counting the numbers of distances belong to n and apart to itself 1,3,5,7 pixel unit. Generally, the calculation of distance between pixels is adopting 8-neighboring method. In order to reduce the computational complexity, we use 4- neighboring method to measure the distance, namely, only the horizontal and vertical distances are computed.

Figure 5 illustrates the DAC matrixes for two sample images as 3D graph. Figure 5 (a) and (c) are iron tower image and beetle binary image. Figure 5 (b) and (d) are 3-

D graph of Figure 5 (a) and (c)'DAC respectively. Where, horizontal axis denotes the size of distance sets and the number of interval. Vertical axis denotes the number of related pixels. As can be seen from Figure 5, DAC is a matrix which contains the target audience' shape information, DAC can describe the shape of target audience and can be using in CBIR.



(a) iron tower image (b) DAC of (a)

(c) beetle binary image (d)DAC of (c)

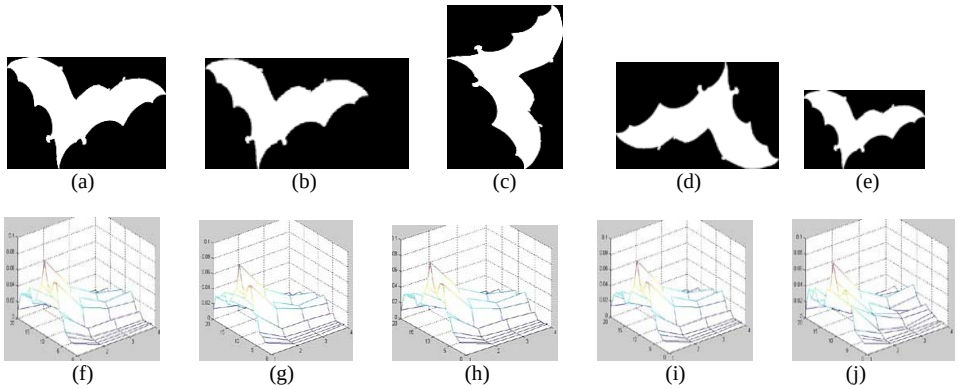
Figure 5. DAC graphs for two-image samples

III. FEATURE VECTOR NORMALIZATION

In shape-based image retrieval, the feature vectors which depict the shape must size up human similarity judgment, such as the feature vectors should keep the quality of invariability to translation, rotation and scaling for the identical objects. Obviously, translation has no influence on shape's centroidal distances and interrelation of edge pixels. Besides, rotation has also no influence on the distribution of centroidal distances' general states. Therefore, centroidal distance autocorrelogram possesses the invariability of translation and rotation. Centroidal distance can possess scaling invariability as well, if we standardize centroidal distance by Eqn 6. Each element of distance autocorrelogram's matrix is the pixels' number, therefore the image's scales are different, so are the pixels' numbers. In order to prevent the scale from changing, we should normalize distance autocorrelogram. Namely, DAC is divided by pixels' number sum of the whole intervals. Thus, feature matrix's elements are normalized to the interval between 0 and 1.

Figure 6 shows the bat binary image and its DAC's performance after translation, rotation and scaling. Figure 6 (a) is a bat binary image. Figure 6 (b), (c), (d) are new images by translating, revolving 90 degrees along the clockwise, and revolving 180 degrees along the clockwise basing on figure 6 (a) respectively. Figure 6 (e)'s size is 0.5 time as figure 6 (a)'s. Figure 6 (f), (g), (h), (i), (j) are DAC of Figure 6 (a), (b), (c), (d), (e) respectively.

We can know from Figure 6 that distance autocorrelogram which is normalized can be used as the image retrieval's feature, because it possesses invariability to rotation, translation and scaling.



(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

Figure 6. Shows as bat' distance autocorrelogram after translation, rotation and scaling.

IV. SIMILARITY MEASURE

Similarity measure [28] is to judge the similarity of two images. The color, the texture and the shape were considered as the 1st level features which have the relatively direct-viewing characteristics. The semantic content is the 2nd level feature which has the relatively subjective abstract characteristics. At present, the image similarity researches mainly concentrate on the first level. Generally, people use the distance between images features to measure their similarity. The smaller of the distance value, the smaller difference between images, and the more similar of images, otherwise, they are more dissimilar. One of the space distance measurement methods is the Minkowsky distance.

The Minkowsky distance is defined based on the L_p norm, its expression is

$$L_p(X,Y) = [\sum_{i=1}^{n} | x_i - y_i |^p]^{\frac{1}{p}} \tag{7}$$

If $p = 1$, has

$$L_1(X,Y) = \sum_{i=1}^{n} | x_i - y_i | \tag{8}$$

Equation (8) is called city-block distance.

If $p = 2$, then

$$L_2(X,Y) = (\sum_{i=1}^{n}(|x_i - y_i|)^2)^{\frac{1}{2}} \quad (9)$$

Equation (9) is called Euclidean distance. This article use (8) to measure two images' similarity.

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Performance evaluation mechanism

Usually, researchers take Precision and Recall as criterions to evaluate the performance of image retrieval algorithm. Where, Precision is the ratio between the related image number in the retrieval Result queue and the returns image number. Recall is the ratio between the retrieved related image number and the related the image quantity in the entire image database. Suppose R is the retrieved result image number, R_+ is the related image number in the retrieval Result queue, D_+ is the related image quantity in the entire image database. Then,

$$\Pr ecision = |R_+| / |R| \quad (10)$$

$$\mathrm{Re}call = |R_+| / |D_+| \quad (11)$$

In the experiment, we use the Precision and Recall of the first N retrieval results returned [29] as our algorithm's evaluation mechanism. In addition, in order to examine the performance of our algorithm, we do the comparative experiment with distance histogram [21], coherence distance [22] , EOAC [26] and EDH [12].

B. Experiments

The MPEG-7 test image database is used to perform experiments and test the proposed method. This database is already widely applied in shape-based image retrieval experiment. We chose 500 images from 25 different classes in that database as our image database. Table I shows each kind of semantic demonstration image and the number.

Regarding our algorithm and the algorithm in literature [26], literature [12], we quantified DAC, EDH and EOAC to 20 bins and adopted city-block distance to measure image similarity. Regarding the literature [21] algorithm, we quantified distance histogram to 20 bins and used Euclidean distance to measure image similarity. Regarding the literature [22] algorithm, we quantified coherence distance to 10 bins and used city-block distance to measure the coherence elements and incoherence elements respectively, and we used the threshold $\Gamma = 10$ to recognize whether the elements is coherence or not.

TABLE I.
SEMANTIC IMAGE CATEGORY AND NUMBER

Image category										
Image number	20	20	20	20	20	20	20	20	20	20

C. Comparing accuracy of DAC with other method

In order to test the performance of our approach, we have measured the averages of precision and recall rates for the demonstration images. In the experiments, we select 5 images from each kind of semantic images at random and get the average Precision and Recall of the first N retrieval results returned respectively.

We have implemented some shape-based retrieval methods. These methods are as follow: the edge direction histogram (EDH) [12], the edge orientation autocorrelogram (EOAC) [26], the distance histogram (DH) [21], the coherence distance (CD) [22]. We have measured the average Precision and the average Recall when $N = 10, 25$, namely, returned number is 10 and 25. The experimental results presented in Table II indicate the superiority of our method. Figure 7 shows 4 algorithm of first N result Precision curve and Figure 8 is its Recall curve.

D. The correlation experiments

In this subsection, we have done the correlation experiments. Since EOAC and DAC has consider the correlation between edges compare with EDH and DH, the accuracy of the former is higher than the latter. Figure 9 describe the effecs of correlation increase on the accuracy of 4 methods. The graphs of Figure 9 (a) and (c) show EDH and EOAC curves, and the Figure 9 (b) and (d) show DH and DAC curves. As shown in Figure 9, methods which consider the spatial feature and correlation between neighboring edges have better accuracy.

E. Image retrieval examples and Discussion

Figure 10, Figure 11, Figure 12, Figure 13 and Figure 14 have shown 5 algorithms, 4 kinds of demonstration images' retrieval effects graph separately. Where, the first image of each chart's left side is query image which is also in the database. The rest of 9 are the most similar images compared to query image. The graphs show our algorithm has made good retrieval results.

We have done some comparative experiments about shape-based retrieval methods. The experiments indicate that our algorithm has clearer advantages than traditional ones. Our algorithm not only possesses the invariability of rotation, translation and scaling, but also contains the spatial information and edge-neighboring pixels' related information. Our algorithm possesses better rotation invariability in comparison with literature [26]; by comparison with coherence distance, our algorithm introduces spatial information and neighboring-pixels' related information. Therefore, our algorithm has better Precision and Recall. Our distance autocorrelogram

which is based on distance histogram own centroidal distance's advantages----the invariability of rotation, translation and scaling. Meanwhile, it introduces pixels' spatial and related information so that more precise shape representation.

TABLE II.
PERFORMANCE COMPARISON OF DIFFERENT IMAGE RETRIEVAL METHODS

	$N=10$					$N=25$				
	EDH	EOAC	CD	DH	DAC	EDH	EOAC	CD	DH	DAC
Average of Precision	0.72	0.74	0.90	0.84	0.94	0.36	0.44	0.45	0.42	0.47
Average of Recall	0.40	0.49	0.57	0.49	0.58	0.51	0.61	0.71	0.51	0.73

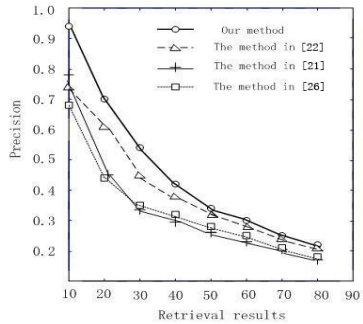


Figure 7. 4 algorithm of first N result Precision curve

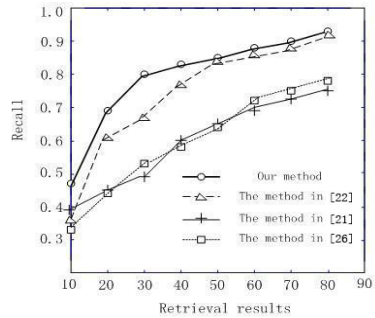
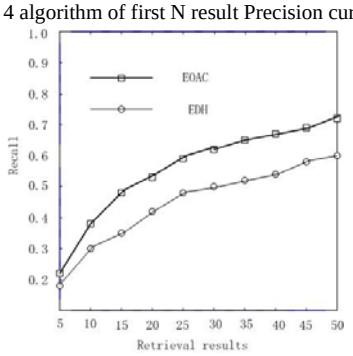
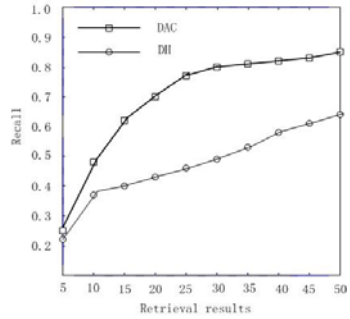


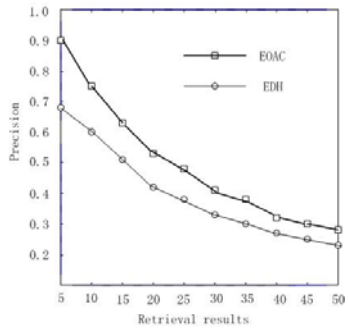
Figure 8. 4 algorithm of first N result Recall curve



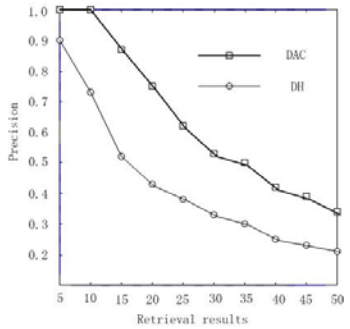
(a)



(b)



(c)



(d)

Figure 9. Performance evaluation of EDH and EOAC, DH and DAC

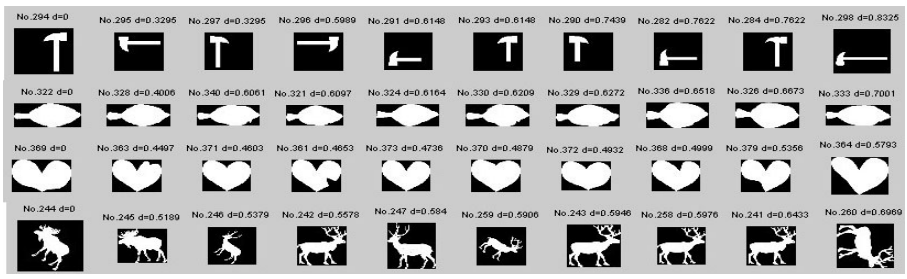


Figure 10. Our algorithm retrieval effect

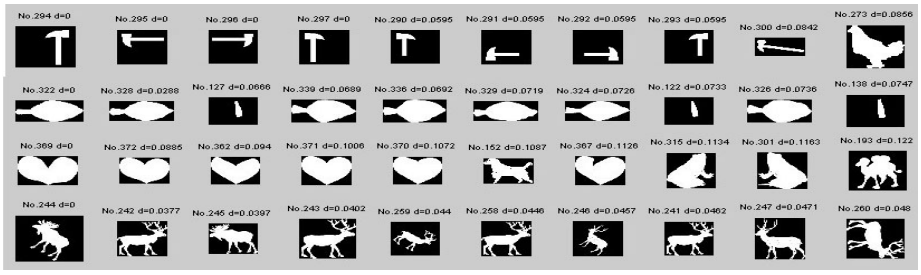


Figure 11. Literature [21] retrieval effect

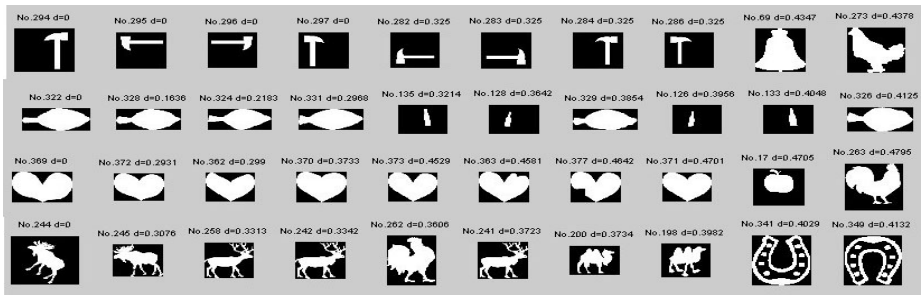


Figure 12. Literature [22] retrieval effect

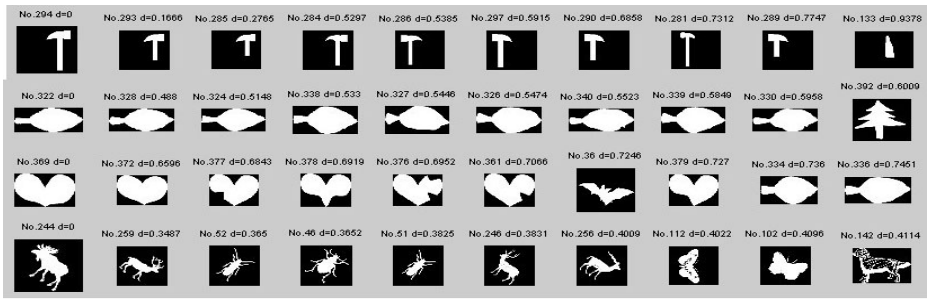


Figure 13. Literature [26] retrieval effect

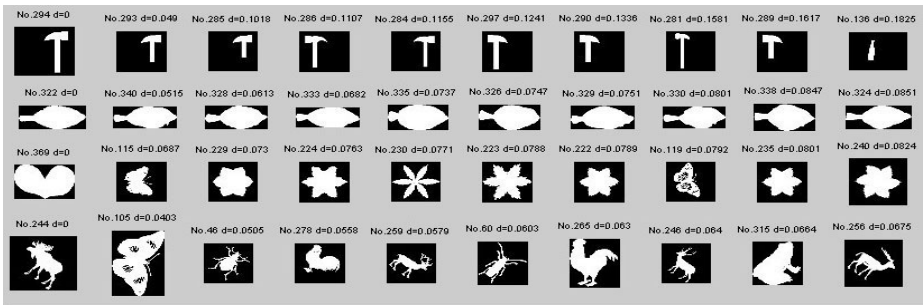


Figure 14. Literature [12] retrieval effect

VI. CONCLUSIONS

Our paper proposed a DAC-based shape retrieval algorithm. Thanks to our method introduced edge pixels spatial information and neighboring pixels' correlation on basis of distance histogram, so, it can avoid that distance histograms' short of spatial information when depict shape. In addition, our algorithm is simple to realize, and invariable to translation, rotation, scaling and illumination. The experiments demonstrate that our algorithm has better Precision, Recall and Robustness.

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