Shape Retrieval Algorithm Based on Distance Autocorrelogram

Jiexian Zeng\textsuperscript{1,2}, Yonggang Zhao\textsuperscript{1}, and Xiang Fu\textsuperscript{1,2}
\textsuperscript{1} School of Software, Nanchang HangKong University, Nanchang, China
\textsuperscript{2} Key Laboratory of Nondestructive Test (Ministry of Education), Nanchang Hangkong University, Nanchang, China

Abstract—we introduce a new feature vector for shape-based image retrieval. This feature depends on two factors: the centroidal distances of shape and correlation between neighboring edges, hence this scheme is not only effective and robust to translation, scaling, and rotation, but also has the qualities of expressing the spatial information of edges. Experimental results show the proposed method has clearer superiority and higher average precision and recall rates than several other methods.

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

I. INTRODUCTION

Researchers generally consider the color, texture, shape and spatial relationship of image as retrieval features in content-based image retrieval (CBIR). 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 [1]. Edge-based methods utilize the edge’ information and region-based methods make use of the pixel’ distributing information in the target region.

Centroidal distances histogram [2] is an effective edge-based shape representation method which is invariant to translation and rotation. Normalization makes distances histogram invariant 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 autocorrelogram is proposed in [3]. 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 [4,5] 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 [6] proposed color correlationgram and applied it to color-based image retrieval. Fariborz et al [7] 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 verify the effectiveness of the algorithm and better precision and recall compared to traditional methods.

II. SHAPE REPRESENTATION METHOD: DISTANCE AUTOCORRELOGRAM

A. 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

\[ K = \{1,3,5,7\} \]

(1)

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 \( D_{i,j} \) is all the pixels have distances \( d_{i,j} \), we define the distance autocorrelogram as

\[ \Gamma_{d_{i,j}}^{(k)} = N_{d_{i,j}} \{ p_{i} \in D_{d_{i,j}}, p_{j} \in D_{d_{i,j}} \mid |p_{i} - p_{j}| = k \} \]

(2)

\( N_{d_{i,j}} \) is the number of pixels meet the conditions.

It can be seen that distance autocorrelogram is a \( N \times D \) matrix, \( E < i,j > (1 < i < N,k \in K) \) express the total number of pixels, including the pixels which centroidal distance are \( d_{i,j} \) in contour pixels , and which

This work was supported partially by the National Natural Science Foundation of China (Grant No. 60675022), the Natural Science Foundation of JiangXi, China (Grant No. 2008GZS0034) and Aviation Science Foundation of China (Grant No. 20085556017 ).

Corresponding author: Jie-xian Zeng

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AP-PROC-CS-09CN003
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are \( k \) pixels unit apart from the former ones and centroidal distance are \( d_i \), too.

**B. 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 \( c(x_i, y_i) \) is computed from the sample points as shown below.

   \[
   x_c = \frac{1}{N} \sum_{i=0}^{N-1} x_i, \quad y_c = \frac{1}{N} \sum_{i=0}^{N-1} y_i
   \]

   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.

   \[
   d(b_i, c) = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}
   \]

   Centroidal distance matrix \( D(x, y) \) is formed by (3) and (4).

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 0.5 by (5) as follows.

   \[
   \text{norm\_dist} = \frac{\text{dis} - \text{dis}_{\text{min}}}{\text{dis}_{\text{max}} - \text{dis}_{\text{min}}} \cdot \frac{W}{2}
   \]

   where, \( \text{dis} \) are values in distance matrix, \( \text{dis}_{\text{max}} \) is the maximum centroidal distance and \( \text{dis}_{\text{min}} \) is the minimum centroidal distance. \( \text{norm\_dist} \) 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, \( W = \max(a, b) \).

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

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. 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 1 (a) and (c) are iron tower image and beetle binary image. Figure 1 (b) and (d) are 3-D graph of Figure 1 (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 1, 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.

   ![Figure 1. DAC graphs for two-image samples](image)

### 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 5. Each element of distance autocorrelogram 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 2 shows the bat binary image and its DAC’s performance after translation, rotation and scaling. We can know from Figure 2 that distance autocorrelogram which is normalized can be used as the image retrieval’s feature, because it possesses invariability to rotation, translation and scaling.
IV. SIMILARITY MEASURE

Similarity measure [8] is to judge the similarity of two images. 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

$$L_p(X,Y) = \left[ \sum_{i=1}^{n} |x_i - y_i|^p \right]^\frac{1}{p}$$  \hspace{1cm} (6)

If $p = 1$, has

$$L_1(X,Y) = \sum_{i=1}^{n} |x_i - y_i|$$  \hspace{1cm} (7)

Equation (7) is called city-block distance.

If $p = 2$, then

$$L_2(X,Y) = \left( \sum_{i=1}^{n} (|x_i - y_i|^2) \right)^\frac{1}{2}$$  \hspace{1cm} (8)

Equation (8) is called Euclidean distance. This article use (7) 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, $D_r$ is the related image number in the retrieval Result queue, $D_s$ is the related image quantity in the entire image database. Then,

$$\text{Precision} = \frac{|R|}{|D_r|}$$  \hspace{1cm} (9)

$$\text{Recall} = \frac{|R|}{|D_s|}$$  \hspace{1cm} (10)

In the experiment, we use the Precision and Recall of the first N retrieval results returned [9] as our algorithm’s evaluation mechanism. In addition, we do the comparative experiment with distance histogram [2], coherence distance [3], EOAC [7].

B. Experiments and discussion

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 some semantic demonstration images and their number.

Regarding our algorithm and the algorithm in literature [7], we quantified DAC, and EOAC to 20 bins and adopted city-block distance to measure image similarity. Regarding the literature [2] algorithm, we quantified distance histogram to 20 bins and used Euclidean distance to measure image similarity. Regarding the literature [3] 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.

Figure 3 and Figure 4 shows 4 algorithm of first N result Precision curve and Recall curve. Figure 5 has shown our algorithms, 4 kinds of demonstration images’ retrieval effects graph. Where, the first image of each chart’s left side is query image which is also in the database. The rest of 9 is the most similar images compared to query image.

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 [7]; By comparison with coherence distance, our algorithm introduces spatial information and neighboring-pixels’
related information. Therefore, our algorithm has higher Precision and Recall ratio.

<table>
<thead>
<tr>
<th>TABLE I. SEMANTIC IMAGE CATEGORY AND NUMBER</th>
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<td>Image category</td>
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<td>Image number</td>
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![Figure 3. 4 algorithm of first N result Precision curve](image)

![Figure 4. 4 algorithm of first N result Recall curve](image)

![Figure 5. An image retrieval example of our algorithm](image)

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.

REFERENCES


