Vertical Interior Distance Ratio to Minimum Bounding Rectangle of A Shape

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Zekun Li[1], Baolong Guo[1*], Xia Ren[1], and N N Liao[1]

[1] Xidian University, Xi'an 710071, P. R. China
blguo@xidian.edu.cn

Abstract. This paper proposed a simple shape descriptor, based on the vertical interior distance ratio of the minimum bounding rectangle (VIDR). Shape descriptor is widely used to describe shape, especially in leaves matching and trademark retrieval. VIDR is the proportional distribution of the vertical interior distance between the shape contour points and its four sides of the minimum bounding rectangle. The minimum bounding rectangle can change according to the change of shape scale and direction, which is extremely suitable for describing the changing shape, and it has global characteristics. Compared with the descriptor of centroid contour distance (CCD) and the shape context descriptor (SC), which are all use contour points to describe shape, our descriptor has a vertical direction and is able to distinguish the same centroid shapes or similar contour shapes, it also has simpler feature extracting description process. More importantly, the experimental results show that our descriptor has a higher precision and faster speed.

Keywords: Minimum bounding rectangle, vertical, interior distance, contour.

1 Introduction

Many shape descriptors have been proposed [1-5]. It can be roughly divided into four categories: global descriptors, local descriptors, multi-scale descriptors and multi-faceted descriptors. Shape descriptors are used to extract shape features of objects. FD (Fourier descriptor) [6], CCD (centroid contour distance), FD-CCD (CCD based FD) [6], FPD (farthest point distance) [7], WD (wavelet descriptor) [8], SC (shape context) are some classic descriptors. There are some improved descriptions of FMSCCD (Fourier descriptor based on multi-scale centroid distance) [9], IDSC (shape context based on inner distance) and ASD&CCD (angular scale descriptor based on distance from centroid) [10].

For example, ASD is a descriptor that contains directional characteristics, which can calculate the eigenvectors of Angle sequences of different proportions, including local and global information. The ASD&CCD adds Angle information according to the CCD.

The ASD&CCD is more accurate than the CCD, but a lot of calculations are inevitable and run slowly. In [10], ASD&CCD has the highest bull's eye test score, but the matching time of mpeg-7 CE1 part B is longer than that of CCD. IDSC is improved on the basis of SC. Although the experimental results are better than SC, the matching stage still needs a lot of time, and the shape feature is not directional, and there is a direction defect.

The ability to evaluate a shape descriptor is mainly through translation, rotation and scaling of the shape to see whether it will be unaffected and still be able to correctly identify the shape. The minimum bounding rectangle of an image is one-to-one related to the image. If the image has different positions, angles and sizes, the minimum bounding rectangle will change accordingly. Therefore, the position, Angle and size of the image can be reflected in the parameters of its minimum bounding rectangle. Using the minimum bounding rectangle to describe the image has strong descriptive ability and robustness.

Shape histogram has a relatively intuitive representation of quantity, and it has a strong ability to describe the distribution of quantity, so it is used by most scholars to describe the features of shape. For example, in the classical shape context method, shape histogram is used to describe the region where the contour point belongs to relative to the current point. Since shape histogram is the regional distribution of all quantities, it has a natural advantage for describing shape features, that is, in the process of describing shape, the uncertainty of initial description position can be ignored, and the computational cost of describing process can be greatly reduced, with strong robustness.

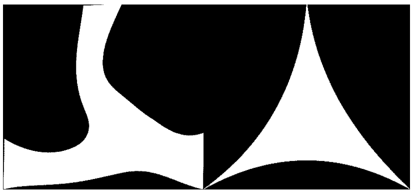
The general principle of simple shape descriptor is simple, simple calculation, but there is no direction, can only on behalf of the general characteristics of shape, and the lack of detailed description such as directional characteristics, such as CCD and SC, only for contour point, is to distinguish the similar centroid contour shape context of distance and similar problems, as shown in figure 1. The method proposed in this paper uses a simple feature - the vertical interior distance ratio of the minimum bounding rectangle to give shape descriptors a vertical orientation feature. Therefore, this descriptor complements the directivity defect of the simple descriptor and has higher resolution capability without increasing the time complexity of the general descriptor algorithm.

2 Related Work

2.1 CCD（centroid contour distance）

Centroid contour distance (CCD) [11] is a simple and effective shape descriptor. The descriptor consists of the shapes of each contour point of the shape to the center of mass. The sequence $P = \{p_1, p_2, p_3, ...p_n\}$ is the contour sample points after uniform sampling of the shape contour.

(1)



(2)

Fig. 1. Two shape pairs, upper pair having similar centroid contour distance and the following pair having similar shape context.

The centroid contour point $p_c$of these contour points is first calculated, using Equation：

$$p_c = \frac{1}{n}\sum_{i=1}^{n} p_i = (\frac{1}{n}\sum_{i=1}^{n} x_i , \frac{1}{n}\sum_{i=1}^{n} y_i) \tag{1}$$

where$n$means how many sampling points there are on the contour, (x_i, y_i) is theithcontour point p_i of a shape. Then, the Euclidean distance between each contour point $p_i(x_i, y_i)$ and the centroid contour point $p_c(x_c, y_c)$ is calculated, using Equation：

$$d_{ic} = ((x_i - x_c)^2 + (y_i - y_c)^2)^{\frac{1}{2}} \tag{2}$$

Finally, The Euclidean distance$d_{ic}$is normalized to obtain the centroid contour distance$d^i{}_{ccd}$, calculated with Equation：

$$d^i{}_{ccd} = (\frac{d_{ic}}{(1/n)\sum_{j=1}^{n} d_{jc}})/\sqrt{n} = d_{ic}\sqrt{n}/\sum_{j=1}^{n} d_{jc} , i = 1,2,3,\ldots n \tag{3}$$

The sequence$\{d^1{}_{ccd}, d^2{}_{ccd}, d^3{}_{ccd}, \ldots d^n{}_{ccd}\}$is the CCD feature of a shape.

When the starting point position of the contour changes, the distance sequence will also change accordingly. Therefore, the distance between two shapes, $s1, s2$,is computed with Equation:

$$dis_{ccd}(s1, s2) = \min_{0 \le m \le n} (\sum_{i=1}^{n}(d^i{}_{ccd} - dd^{m+i}{}_{ccd})^2)^{\frac{1}{2}}, m \in Z \tag{4}$$

where， $d^{m+i}_{ccd} = d^{m+i-n}_{ccd}$ .This distance is used for shape matching. When the distance is less than a given threshold, it is regarded as in the same class, when the distance is greater than this threshold, it is regarded as in the different class.

The CCD descriptor has translational invariance because its European distance is normalized. Under the above matching method, it has rotation invariance, but the efficiency of matching method is low, the speed of matching is slow, and the time complexity is high. Although the idea of this descriptor is simple, it is a scalar distance without direction and lacks the description of shape direction information.

2.2 SC（shape context）

The shape context (SC) [12] is a classic descriptor based on shape contour features introduced by Serge Belongie.et .al in 2002，it is a global shape descriptor. The shape contour is generally represented by a uniformly sampled set of points, the shape context of each point in the point set is a histogram of the point distribution, the target shape context is represented by a set of histograms.

The contour of a shape is represented by a sequence of continuous point sets, after sampling uniformly, a contour sample point is obtained $P = \{p_1, p_2, p_3, \ldots p_n\}$. Take any one of these points $p_i$as the reference point, and take $p_i$as the center of the circle, Nconcentric circles are constructed with Ras radius and logarithmic distance intervals. Then, the concentric circle region is divided into M equal parts along the circumference to form the template as shown in the figure. The number of points in each small area of the template is counted to constitute the histogram $h_i(k)$, $h_i(k)$ is the shape context of p_i, calculated with Equation:

$$h_i(k) = \#\{p_j : j \neq i, p_i - p_j \in bin(k)\} \tag{5}$$

Where, $k = \{1,2,3, \ldots M \times N\}$, $h_i(k)$ is a $M \times N$matrix square. When p_i is the reference point, take as the origin of coordinates and construct the polar coordinate system on the template, the abscissa of the histogram is θ, the ordinate is $log\, r$. Each square represents a small area in the template, and the darker the square, the more points fall within this area.

For the whole point set P, take the point $p_1, p_2, p_3, \ldots p_n$ as the reference point respectively, the shape context of each point is calculated in turn, and finally the shape context of the target is obtained.

The SC is invariant to translation, scale and rotation, but in terms of discernibility, the descriptor lacks the orientation feature description of the target.

3 VIDR

An in-depth study of CCD and SC reveals that these two feature-description algorithms based on contour have the same weaknesses. SC has better anti-interference performance in describing shape contour features, so the experimental results are better than CCD. However, in the two pairs of shapes as shown in Figure 1, the naked eye can distinguish well, and since both algorithms only process and calculate contour points, neither algorithm can distinguish well. FIG. 2 show the CCD feature vector curve of the pair (1) in Figure 1.

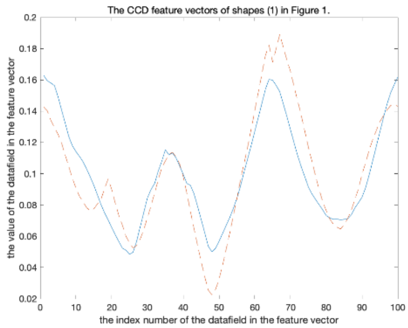


Fig. 2. The dashed line represents the CCD feature of the left shape (1), and the solid line represents the CCD feature of the right shape.

It is clear from Figure 2 that the centroid contour eigenvectors of the two shapes are very similar.

FIG. 3 and FIG.4 show SC shape histogram of the pair (2) in Figure 1, respectively.

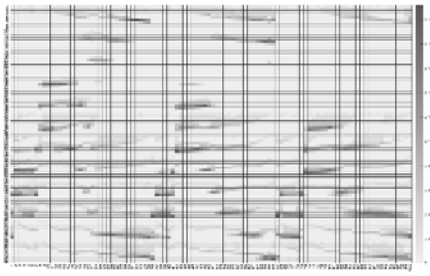


Fig. 3. The shape context histogram for the (2) pair of shapes of the first one in Figure 1

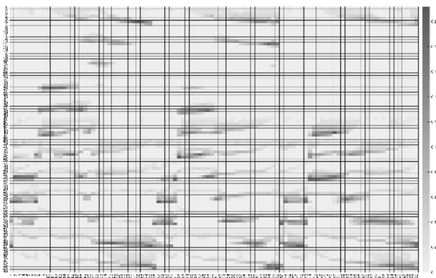


Fig. 4. The shape context histogram for the (2) pair of shapes of the second one in Figure 1

Although SC has stronger robustness and higher recognition accuracy than CCD, it is difficult to distinguish a pair of shapes with very similar shapes because SC and CCD only consider shape contour points, but not the direction of the shapes.

We proposed VIDR method is through from a contour point perpendicular to the shape of the minimum circumscribed rectangle do respectively, so as to calculate the four vertical after shape inside of Euclidean distance and four vertical general Euclidean distance, to calculate the contour points within the vertical distance, finally calculate the shape within all the contour points of vertical distance ratio distribution, to say the shape characteristics of the shape.

Finding the shape of the smallest bounding rectangle is the most critical step in calculating the vertical interior distance. The method of finding the smallest bounding rectangle is introduced first, and then the specific calculation method of vertical interior distance ratio is introduced.

3.1 Minimum bounding rectangle

There are two types of restricted minimum rectangles for general graphics, minimum area limited minimum rectangle and minimum perimeter limited minimum rectangle. In this article, we use the smallest bounding rectangle with the smallest area. The following steps are key to calculating the minimum bounding rectangle.

Step 1: Use the function to find four points with maximum and minimum horizontal and vertical coordinates.

Step 2: Use these four points to construct the four tangents to the shape.

Step 3: If one (or two) lines overlap one side, the rectangular region identified by the four lines is calculated and saved as the current minimum. Otherwise, the current minimum is defined as infinity.

Step 4: Rotate the lines clockwise until one of them coincides with the edge of the polygon.

Step 5: Calculate the area of the new rectangle and compare it to the current minimum. If it is less than the current minimum, update and save the rectangle information that determines the minimum.

Step 6: Repeat steps 4 and 5 until the line is rotated more than 90°.

Step 7: Output the minimum region of the boundary rectangle.

FIG. 5 is a schematic diagram of the smallest bounding rectangle for two pairs of shapes in Figure 1.

3.2 Vertical interior distance proportional distribution

Within the vertical distance calculation is based on external rectangular shape, when calculating the shape of the external rectangular, starting from the shape of a contour point p_i separately to the four of the minimum circumscribed rectangle do vertical edge, $d_{i1}, d_{i2}, d_{i3}, d_{i4}$ are four vertical shape after the internal length of Euclidean distance, respectively, and seeking the sum of the Euclidean distance of four vertical d_0, by formula $R_i = (d_{i1} + d_{i2} + d_{i3} + d_{i4})/d_0$, pray that point within the vertical distance ratio, finally calculate the shape within all the contour points of vertical distance ratio R, forming the shape of the shape of the histogram, The histogram is the shape feature of the shape.

In the image, we convert the ratio of inner distance to the ratio of the number of pixels

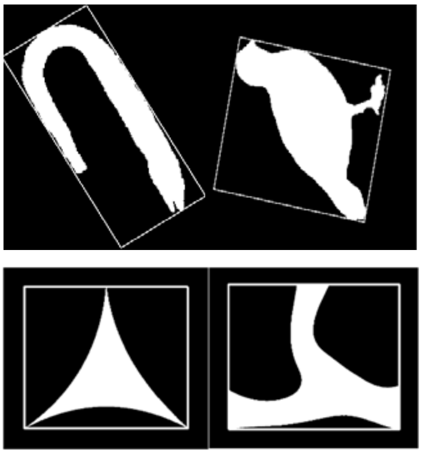


FIG. 5 Two pairs of shape minimum bounding rectangles in FIG. 1

in the image, so that the computation is smaller and the algorithm is faster. The dot product operation of the image was used to calculate the intersection lines of the image interior and four perpendicular lines of a certain contour point p_i. The number of pixel points on the intersection line was first calculated, marked as n_i, and then the number of pixel points on the four perpendicular lines was calculated, marked as n_0. Finally, the formula $R_i = n_i/n_0$ was used to calculate the vertical interior distance ratio of this point. Within the specific range forms as shown in figure 6, respectively from the P point to do vertical rectangular four side, hand in the shape of other contour points P_1, P_2, P_3, P_4, and through the shape internal segment of PP_1, PP_2, PP_3, PP_4 , which is the sum of the contour points of the distance, in the four lines contains the number of pixels to n_i, said again to find the external rectangle contained a long and a wide number of pixels n0, the n_i/n_0 said that point within the vertical distance ratio.

FIG. 6 Inner distance of shape contour point P

The VIDR method is applied to the two pairs of shapes in Figure 1, and the shape histogram is shown in Figure 7 respectively. Obviously, in the shape features obtained by this method, the two pairs of shapes in Figure 1 are significantly different, which can be distinguished by this method. And in the feature matching stage, this method only needs to do the Euclidean distance difference of two shape histograms, which has a faster matching speed.

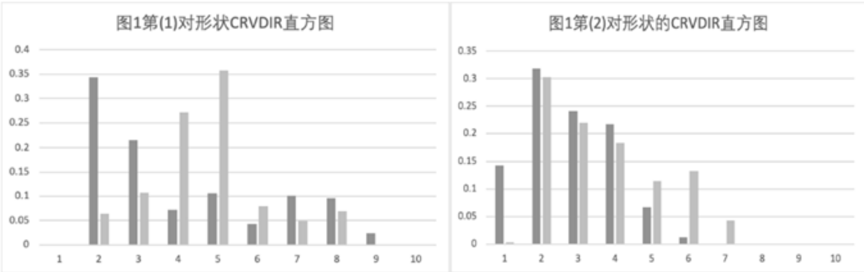


FIG. 7 VIDR feature histogram of two pairs of shapes in Figure 1

3.3 Shape matching

The interior distance scale histogram of each shape can be expressed as sequence {x_j, j=1,2,3... 10}, we use the following formula to calculate the distance between the two shapes, the calculation formula is as follows:

$$dis(s1, s2) = \left(\sum_{i=1}^{10}(x_i - y_i)^2\right)^{\frac{1}{2}} \tag{6}$$

Where, x_i, y_i represents the histogram of the interior distance ratio of the shape $s1, s2$ respectively.

4 Experimental results and analysis

Mpeg-7 CE1B is an image template library used for image shape template by a large number of scholars, and many articles [1-9] use this database for experiments. The library contains 1400 shaped template images (70 categories, each containing 20 shapes), which are ideal for studying the shape characteristics of images. The proposed method is also tested on this data set. The experimental results and the test results of some other shape descriptors are shown in Table 1. Figure 8 shows a part of this datasets.

FIG. 8 some shapes in MPEG-7 Part B

Table 1. Bull's eye test scores and matching time of some descriptors in MPEG-7 CE1 B

Descriptor	Bulls-eye-test score (%)	Matching Time(ms)
VIDR (our)	76.88	80.0
CCD	68.60	112.3
ASD&CCD [10]	76.20	230.5
SC	64.59	85.0
IDSC [13]	68.83	85.2

5 Conclusion

VIDR is a simple, effective shape descriptor with directional features. Because the descriptor uses shape histogram to represent features, it has global features, making it easier to match features. Because it can distinguish the shapes of similar centroid and similar shape context in Mpeg7 Part B database, such as figure 1, it can be seen from the experimental results that compared with other classical descriptors using contour, such as CCD and SC, which supplement the defects of directional features, it has more accurate test accuracy, stronger description ability and robustness. Compared with the improved CCD and SC, such as ASD&CCD and IDSC, it also has more accurate test accuracy and faster feature matching speed.

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