

# A SHAPE DETECTION METHOD BASED ON THE RADIAL SYMMETRY NATURE AND DIRECTION-DISCRIMINATED VOTING

Gang WU, Weijie LIU\*, Xiaohui XIE, Qiang WEI

Panasonic R&D Center of China, Beijing Laboratory (PBJL)

\*Panasonic AV Core Technology Center (ACC)

[wugang@cmrd.panasonic.com.cn](mailto:wugang@cmrd.panasonic.com.cn)

## ABSTRACT

This paper describes a new method for shape detection based on the radial symmetry nature and direction-discriminated voting. Multiple shapes including circles, regular and non-regular polygons can be detected under a general framework. The novelty of our approach is that different shapes can be simultaneously located and classified. It is implemented by taking account of both voting accumulations and voting directions. We show that the approach can reduce false detection and computation burden compared to some existing methods. Moreover, by modeling a shape based on its partial radial symmetry characteristics and the geometrical relationship among the symmetry centers, our approach is extended to detect non-regular polygons. Experiments on traffic sign detection demonstrate good performance of our method.

**Index Terms**— Shape detection, traffic sign detection, radial symmetry, direction-discriminated voting

## 1. INTRODUCTION

Many objects appear as the shapes of polygons or circles. Detecting such shapes has wide applications in computer vision. One typical example is traffic sign detection. Its purpose is detecting appeared traffic signs in some captured images and then giving alerts to a driver in case that he may miss noticing. Traffic signs are commonly designed as the noticeable shapes, such as triangle, square and circle. Compared with color cues, shape features are more insensitive to weather and lighting conditions.

Several detection methods have appeared in the past years. Piccioli et al [1] retrieved triangular and square contours in an edge image by selecting the edge segments with proper slopes and checking whether their endpoints are close enough and form certain angles. This approach usually suffers difficulties when retrieving broken edges. Escalera et al [2] located triangular signs by seeking the coexistence of three types of corners that form a triangle; and the similar principle was applied to square and circle detection. However, this method strongly relies on corner detection

and classification, which is not robust in clutter scenes. Jimenez et al [3] developed a sign shape classification algorithm based on the FFT imposed on the contour signature of segmented blobs. But this kind of classification requires that the blobs can be filled completely; thus an intractable preprocessing of enclosing blobs' gaps is necessary. Loy and Barnes [4] applied the radial symmetry algorithm [5] to detect regular polygons. They took advantage of the radial symmetry nature of a regular polygon to locate its center. Moreover, they used a rotation-invariant measure, named  $n$ -angle gradient, to distinguish polygons that have different side number  $n$ . This voting-based method is inherently more robust to broken edges and image noises. But it can only deal with regular shapes. Besides, the parameter  $n$  of the  $n$ -angle gradient need be given in advance, so different types of polygons have to be detected separately with different  $n$  given, which results in a high computation burden for multi-shape detection. Barnes et al [6] defined a probability density function for the appearance of regular polygons, and then detected them by using a posteriori probability approach. Yet it cannot detect non-regular shapes.

In this paper, we present first a direction-discriminated voting approach. Based on it multiple shapes including circles and regular polygons can be located and classified simultaneously. Comparing to some existing methods, we show that our approach also reduces false detection rate and computation burden. Secondly, the approach is extended to detect non-regular polygons by locating the partial radial symmetry centers of a target shape and making use of the geometrical relationship among those centers. The rest of this paper describes the approach in detail in section 2, gives the experimental results in section 3, and finally draws conclusions in section 4.

## 2. METHOD DESCRIPTION

### 2.1. Regular shape detection

A regular shape, such as a regular polygon or circle, possesses the characteristic that within the shape there exists a point that has an equal distance to each side or the

boundary of the shape. Such a point is right the center of the inscribed circle of the shape. This radial symmetry nature opens a way to detecting regular shapes.

Our detection method operates on an edge image. Each edge pixel votes for the potential shape center which has a distance  $r$  away along its gradient direction, where  $r$  is the radius (or scale) of the shape being considered. Multi-scale detection is achieved by repeatedly voting with different  $r$ ,  $r \in [R_{\min}, R_{\max}]$ . Rather than voting for a single point as the circular Hough transform does [7], following [4], the voting area is extended to a line segment with its direction perpendicular to the gradient direction of the edge point. The voting scheme is illustrated in Fig. 1, where the real lines represent a potential regular polygon formed by some edge pixels with different gradient directions, and the broken lines are voting areas of three edge pixels. The peak value in the voting accumulation map, which results from the intersection of the voting areas, indicates the presence of a regular shape. And the peak position corresponds to the shape center.

In our method shape detection is performed not only according to the voting accumulations, but also to the voting directions. Here, the voting direction represents the source where a vote comes, i.e., the gradient direction of an edge pixel which has cast the vote. Although it will cost extra memories to record the voting directions, this direction-discriminated voting method has the following benefits:

(1) *Shape classification.* The side number and the orientation of a polygon can be determined by the voting directions. As illustrated in Fig. 2, the votes coming from three gradient directions  $\{30^\circ, 150^\circ, 270^\circ\}$  correspond to a down-triangle, the directions  $\{90^\circ, 210^\circ, 330^\circ\}$  and  $\{0^\circ, 90^\circ, 180^\circ, 270^\circ\}$  correspond to an up-triangle and a square respectively, and the directions distributed uniformly correspond to a circle.

(2) *Reducing false detection.* In some cases (e.g. square detection illustrated in Fig. 3), a non-target shape formed by strong edges (Fig. 3-left) may result in a comparative or even higher accumulation in the voting map than a target shape formed by weak or broken edges (Fig. 3-right). This confusion usually leads to false detection. Considering both the voting accumulations and directions can solve such a problem.

(3) *Reducing computation burden.* Our method locates and classifies the target shapes simultaneously. Therefore it does not have to run the algorithm separately for multiple  $n$  in order to implement multi-shape detection, and thus reduces the computation burden. Quantitatively its time cost is  $O(MR(L+B+N))$ , where  $M$  is the number of image pixels,  $R$  is the number of shape radii (scales) being considered,  $L$  is the maximum length of voting areas,  $B$  is the discrete number of angular bins for voting directions, and  $N$  is the number of shape types to be detected. Compared with the algorithm reported in [4] whose cost is  $O(MRLN)$ , our

method increases the speed by 2-5 times theoretically in usual cases (e.g. about 3 times when  $B=12, L=56, N=4$ ).

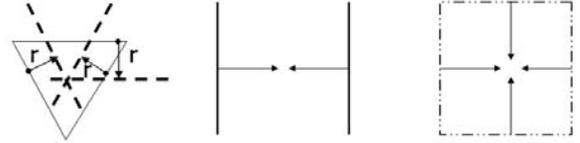


Figure1. Voting scheme

Figure3. False detection

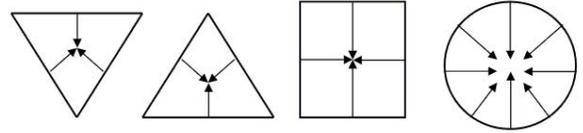


Figure2. Shape classification

The summary of our algorithm is described as follows.

(1) *Edge detection.* Edge points are extracted from an input image and their gradient directions are calculated. The gradient directions are quantized into discrete angular bins. For instance, twelve bins ( $B=12$ ) with an interval of 30 degrees  $\Omega = \{\theta_i = 30i, i = 0, 1, \dots, 11\}$  are sufficient for the detection of triangular, square and circular signs in our implementation.

(2) *Direction-discriminated voting.* For each edge pixel, the voting accumulation is increased for each point in its voting area (Fig. 1). The length of the voting area  $l_r$  is proportional to the considered voting radius  $r$ . The resulted voting map is  $S_r^\theta(x)$ , with  $\theta \in \Omega$  and  $r \in [R_{\min}, R_{\max}]$ . It denotes the voting accumulation at pixel  $x$  where the voting direction is  $\theta$  and the voting radius is  $r$ .

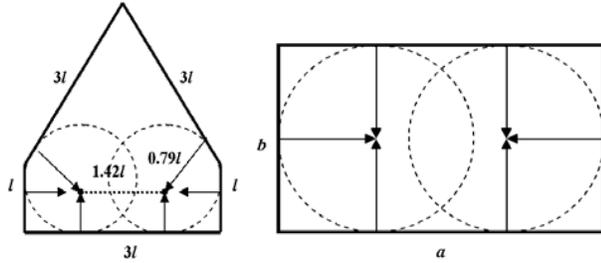
(3) *Shape localization and classification.* For each pixel  $x$  in the voting map, both the voting accumulation and direction are checked. If there are enough votes coming from direction  $\theta$  at  $x$ , which is formulized as  $S_r^\theta(x)/l_r > Tr$  ( $0 < Tr < 1$  be a given threshold),  $\theta$  is then defined as a primary direction of  $x$ . Here,  $S_r^\theta(x)/l_r$  is a normalized accumulation and measures a relative contribution from the corresponding  $\theta$ -degree edge points to a shape centered at  $x$ . Moreover, if all the primary directions of  $x$  meet a template distribution, such as  $\{30^\circ, 150^\circ, 270^\circ\}$  for a down-triangle,  $\{0^\circ, 90^\circ, 180^\circ, 270^\circ\}$  for a square, etc., a target shape, with its center at  $x$  and radius of  $r$ , will be detected and its type can be classified based on the matched template. In our implementation, the distributions of voting directions are represented as 0-1 bit strings. For example, a pixel with the primary directions of  $\{30^\circ, 150^\circ, 270^\circ\}$  is represented as,

330<sup>0</sup> 300<sup>0</sup> 270<sup>0</sup> 240<sup>0</sup> 210<sup>0</sup> 180<sup>0</sup> 150<sup>0</sup> 120<sup>0</sup> 90<sup>0</sup> 60<sup>0</sup> 30<sup>0</sup> 0<sup>0</sup>  
0 0 1 0 0 0 1 0 0 0 1 0

Thus shape classification is conducted by comparing the Hamming distances between the string being examined and those of all templates.

## 2.2. Non-regular shape detection

Different from regular polygons, a non-regular polygon may not have a single inscribed circle whose center is equidistant to all its sides. However, the circles always exist that are tangential to at least three sides of the polygon. Through the approach presented above, the centers of these partial inscribed circles (namely the partial radial symmetry centers) can be located, which shows evidence that parts of the polygon may exist. Then according to some geometrical relationship among the partial radial symmetry centers, the presence of the whole polygon would be finally identified. Using the Japanese cross-walking sign and road board detection as examples, we illustrate our method as follows.



**Figure 4. Non-regular polygon detection, (left) Cross-walking sign detection; (right) Road board detection**

*Example 1.* A Japanese cross-walking sign is shaped as a pentagon composed of a regular triangle above and a rectangle below (Fig. 4-left). The width-height ratio of the rectangle is 3:1, and the radii of the two partial inscribed circles (called the left circle and the right circle) are both 0.79 times as long as the height of the rectangle. The distance between the circle centers is 1.42 times of it. Similar to regular shape detection, the partial radial symmetry centers are located by analyzing the voting accumulations and directions. When the primary directions of a pixel  $x$  are distributed as  $\{0^\circ, 90^\circ, 330^\circ\}$ ,  $x$  would be the center of a left circle; while distributed as  $\{90^\circ, 180^\circ, 210^\circ\}$ ,  $x$  be the center of a right circle. After detecting a pair of the left and the right circles, a target pentagon can be identified if the circles pair subjects to the following shape rules.

$$\begin{aligned} r_{right} = r_{left} = r, \quad y_{right} - y_{left} = 0, \\ \frac{x_{right} - x_{left}}{r} = \frac{1.42}{0.79} = 1.8 \end{aligned} \quad (1)$$

Here  $r_i$ ,  $x_i$ ,  $y_i$  ( $i$ =right, left) represents the radius and the center coordinates of the circle respectively. However, it would be time-consuming if we check the rules (1) for every pairs of the left and the right circles. Here we use a faster approach based on hypothesis test. When a left circle is detected, a hypothesis would be made that it is inscribed in a target pentagon, and the center of the corresponding right circle is estimated according to (1). Then the test whether the right circle actually exists can be determined by checking the voting map at the center position of the

estimated right circle. As a result, the computation burden is reduced since not all the pairs of the circles need be checked.

*Example 2.* A road board is usually designed as rectangular shape but with an uncertain width-height ratio (Fig. 4-right,  $1 < ratio_{min} \leq a/b \leq ratio_{max}$ ). Two partial inscribed circles are shown in Fig. 4-right, where the left one corresponds to the direction template  $\{0^\circ, 90^\circ, 270^\circ\}$ , and the right one to  $\{90^\circ, 180^\circ, 270^\circ\}$ . With these two kinds of circles, target rectangles can be detected in a similar way as the above Example 1, except that the shape rules different from (1) are used.

$$\begin{aligned} r_{right} - r_{left} = 0, \quad y_{right} - y_{left} = 0, \\ ratio_{min} \leq \frac{x_{right} - x_{left} + 2r}{2r} \leq ratio_{max} \end{aligned} \quad (2)$$

The inequality in (2) results from the uncertainty of the target shape.

Besides these two examples, our method is applicable to the detection of other specified polygons simply by changing the direction templates and the shape rules. Also, it can detect regular and non-regular shapes at the same time since it performs voting under a uniform scheme. In addition, with the angle between any two primary directions being considered (which is a rotation-invariant measure) the method can also deal with shape rotation.

## 3. EXPERIMENTAL RESULTS

We apply our method to traffic sign detection and test its performance on both static images and on-board videos. Table 1 summarizes the results on about 50 static images, where some pictures are taken by us and others downloaded from a website (<http://roadanalysis.uah.es/>). Different signs with four types of regular shapes in Japan, China and Europe are included in this test set. Table 2 lists the results on several video clips. The data are captured by a Panasonic on-board camera mounted behind the rear view mirror of a car in daytime and nighttime respectively. The resolution is 640 by 480. Traffic signs (Japanese stop sign and cross-walking sign) appear in these video clips with the size of from 20 to 50 pixels wide, which corresponds to the capture distance from 50 to 15 meters away. For multi-shape detection, our algorithm is able to run at a speed of 150-200 ms/frame on a popular PC without code optimization. When running on 320\*240 images, the speed can achieve 30-40 ms/frame. Some detection results are shown in Fig. 5.

The results indicate that both the regular and non-regular shapes are correctly detected at a rate of >90% for the daytime data, and >85% for the nighttime data. The rate of false detection (false positives) is about 15% on average. Compared with the results reported in [4] (with correction detection of 95% and false detection of 75%), our method achieves a similar rate of correct detection, but greatly reduces the false detection. The missing detections mainly happen when targets are very small or edges are very weak.

The false detections are mainly caused by small clutters, such as leaves, branches, etc. However, the road board detection suffers a higher rate of false detection, because in a traffic scene there are many horizontal and vertical edges coming from buildings, over-bridges, poles, trees, fences, etc. The edges from different objects are likely to form a virtual rectangular shape (Fig. 5-h). In our future work, adding the intensity information (gray values or colors) to the voting scheme and then checking their consistency in the edge points which contribute to a voting peak may be helpful to solve the kind of problems.

#### 4. CONCLUSIONS

We propose a novel method for shape detection based on the radial symmetry nature and direction-discriminated voting. Multiple shapes including circles, regular and non-regular polygons can be simultaneously detected under a general framework. This method is applied to traffic sign detection, and the experimental results demonstrate satisfied robustness and efficiency performance.

#### 5. REFERENCES

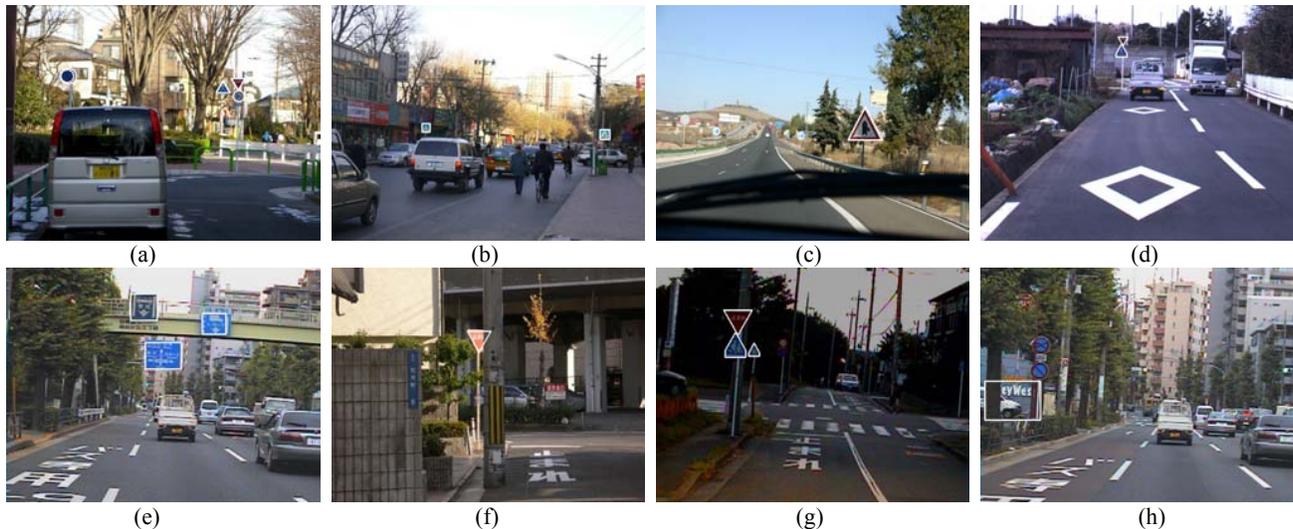
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**Table1. Performance on static images**

Shape	Number of targets	Correct detection	False detection
Up-triangle	13	100%	1
Down-triangle	32	94%	2
Square	14	93%	6
Circle	50	90%	8

**Table2. Performance on video clips**

Shape	Number of targets	Correct detection	False detection
Down-triangle (stop sign in daytime)	109	98%	13
Down-triangle (stop sign in nighttime)	59	86%	10
Pentagon (cross-walking sign)	267	97%	26
Rectangle (road board)	41	91%	29



**Figure5. Multi-shape detection (image resolution: 640\*480,  $r \in \{6,8,10,12,14,16,18,20\}$ ,  $l_r=1.4*2r$ ,  $Tr=0.25$ ), (a) Japanese sign detection; (b) Chinese sign detection; (c) European sign detection; (d) Japanese cross-walking sign detection; (e) Road board detection; (f) Detection with a partial occlusion; (g) Detection in nighttime; (h) False detection due to trees and fences**