Real-time Traffic Sign Detection with Vehicle Camera Images

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ABSTRACT

This paper presents a real-time traffic sign detection method using color properties and shape-based features for real-world environment applications. The proposed method has two main steps: color-based region segmentation and shape-based verification of the segmented area. In the first step, region-of-interest (ROI) is roughly segmented by a simple color-based thresholding method and each segment is corrected by a guided filter. Next, each ROI is verified through a shape analysis to decide whether the ROI is a circle or a triangle. For detecting circles, we compare three different methods: RSD, BCT, and STVUE. For triangles, RPD, VBT and STVUT were applied. We evaluated these alternatives with 232 experimental images containing 142 circular signs and 82 triangular signs. We found that RSD in the circle detection and STVUT in the triangle detection provide the best detection rates of 93% and 90% respectively. The main contribution of this paper is to present a novel approach for extracting boundary of traffic sign.

Categories and Subject Descriptors
I.4.9 **[Image Processing and Computer Vision]**: Application;
I.5.4 **[Pattern Recognition]**: Application – Computer Vision;

General Terms
Algorithms, Performance, Experimentation

Keywords
Traffic Sign Detection, Color Segmentation, Guided Filter

1. INTRODUCTION
Advanced Driver Assistance Systems (ADAS) are systems that provide assistance in driving process, and becoming more common in modern vehicles. The Traffic Sign Recognition (TSR) system as an ADAS requires a high accuracy and real time processing capabilities. Various methods have been proposed for TSR [1, 2, 3]. In the competition of German traffic sign recognition benchmark [4], the committee of CNN/MLP method of Ciresan [5] achieved a highest recognition rate of 99.15%. However, the competition covered only a multi-category classification and did not include traffic sign detection in the image. Even though the traffic sign recognition results are excellent, the traffic sign detection was not fully ready to be used in many real-time applications.

Figure 1 shows four types of the traffic signs used in Korea, warning, prohibition, mandatory and supplementary instructions. This paper focuses on the detection of the warning and prohibition

Figure 1. Traffic sign examples used in Korea

signs, since detection of these signs is critical when the driver misses them. Each has a red border that attracts the driver's attention. Most prohibition signs have circular shapes except the ones

Figure 2. The five exceptions in prohibition signs which are not circular shapes: (a) Yield, (b) No crossing, (c) Stop, (d) Slow, (e) No walking for Pedestrians

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

Figure 3. The overview of the proposed approach: (a) Input image, (b) Estimated boundary of a traffic sign, (c) Corrected boundary of a traffic sign (d) Vote map for a shape-based verification, (e) Detection result

shown in Figure 2. The warning signs have triangular shapes. In this paper, we focus on the prohibition signs with circular shapes and warning signs with triangular shapes.

Shape-based traffic sign detection has been studied a lot [11, 12, 13, 14, 15] and some achieved high performances. But the performances largely depend on the preprocessing performed for the images. Figure 3 shows an overview of the proposed approach.

In this paper, section 2 presents a method of boundary segmentation that makes use of color features, and section 3 compares three different shape-based verification methods. Section 4 shows the experimental results. Finally our conclusion is presented in section 5.

2. ROI SEGMENTATION

The traffic sign detection methods using color features are studied in [6, 7, 8], but these methods are sensitive to the illumination changes in the image. Although our approach also uses the color feature of the red border for the segmentation, the shape of the segmented area is first improved by a guided image filtering, and the shape-based verification is added to improve the overall boundary detection accuracy.

Color segmentation requires a real time processing and must be robust against the illumination changes. Thresholding in YUV and HSV color spaces was used for the boundary segmentation of traffic signs in [6, 7]. Kiran [8] proposed an enhanced hue and saturation method using a lookup table, and this method provided very good results in the good quality images. However, the approach is not suitable for poor quality or the complicated images.

Our approach corrects the estimated segments by adopting an image matting technique. Since most image matting methods are computationally expensive to be used in real-time applications, we adopt a guided image filtering that was proposed by He et al., [9].

The guided filter is an edge-preserving smoothing operator like a bilateral filter, and it uses a guidance image to calculate filter weights. For a thresholded image I^t and a guidance image I which is an input color image, the output image I' is acquired by

$$I'(p) = \sum_q W_{p,q}(I) I^t(q) \tag{1}$$

where $I'(p)$ is a value of pixel p in I', $I^t(q)$ is a value of pixel q in I^t, and $W_{p,q}$ is a filter weight depending on the guide image I. For the guide image, the filter weight $W_{p,q}$ is deinfed as

$$W_{i,j} = \frac{1}{|w_k|^2} \sum_{k:(i,j)\in w_k} \left(1 + \frac{(I(i)-\mu_k)(I(j)-\mu_k)}{\sigma_k^2 + \epsilon}\right) \tag{2}$$

where $|w_k|$ is a number of pixels in the filter window w_k, and μ_k , σ_k are mean and variance of I in w_k. The guided filter calculates a local optimization in each window. However, the closed-form solution to matting [10] seeks a global optimum $E(\alpha)$ as

$$E(\alpha) = (\alpha - \beta)^T \Lambda (\alpha - \beta) + \alpha^T L \alpha \tag{3}$$

where α is an alpha matte, and β is a trimap. In our case, α is an optimized boundary image I' and β is an estimated boundary of the traffic sign I^t. L is a matting Laplacian matrix and is defined as

$$L_{i,j} = \sum_{k:(i,j)\in w_k} \left(\delta_{i,j} - \frac{1}{|\omega|}\left(1 + \frac{(I(i)-\mu_k)(I(j)-\mu_k)}{\sigma_k^2 + \epsilon}\right)\right) \tag{4}$$

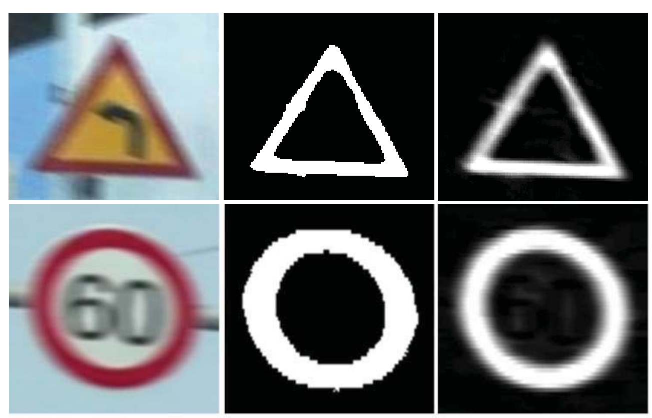
where δ is the Kronecker delta. Then the Laplacian matrix can be expressed using the filter weight $W_{i,j}$ in (2) as:

$$L_{i,j} = |\omega|(\delta_{i,j} - W_{i,j}) \tag{5}$$

If the roughly estimated boundary image I^t is defined well, we can obtain an optimized boundary image I'. This method can handle the motion blurred images such as the ones in Figure 4 that are introduced frequently in the real driving conditions.

3. SHAPE-BASED VERIFICATION

We introduce three different circle detection and three different triangle detection methods. Each method uses a gradient orientation for detecting the boundary shape and is relatively fast.



(a) Input image (b) Thresholding (c) Optimized result

Figure 4. Examples of boundary segmentation even in motion blurred images

3.1 Circle detection

We introduce three different circles detection methods and compare each method in the shape verification. All the methods treat each pixel as an element of the circle, and each pixel estimates the center of the circle with its gradient orientation. There are two alternative methods: single pixel voting and pair-wise pixel voting. In the single pixel voting, each pixel votes for the center of the circle. In the pair-wise pixel voting, the pair-wise pixels are considered as elements of a circle and vote for the center of the circle.

3.1.1 Radial Symmetry Detector

Radial Symmetry Detector (RSD) [11] is a single pixel voting method to detect a circle. It estimates center of the circle which has distance r from each pixel in gradient orientation. Each pixel

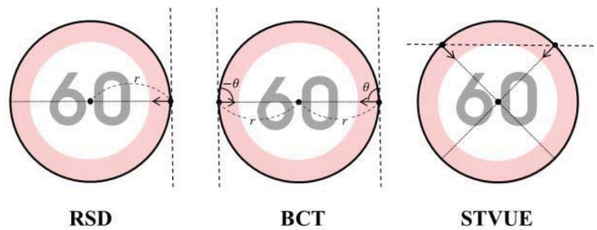


Figure 5. Circle detection methods

votes for the estimated center of a circle, and this step is run repeatedly in all the possible radii.

3.1.2 Bilateral Chinese Transform

Belaroussi [12] proposes a Bilateral Chinese Transform (BCT) for the road sign detection that includes speed signs. BCT is a pair-wise pixel voting scheme, and it can detect circle, square, and rectangle. If a pair-wise pixel has parallel or converse orientation within a distance in a specific range, a pair-wise pixel votes for their middle point.

3.1.3 Single Target Vote for Upright Ellipses

Single Target Vote for Upright Ellipses (STVUE) [13] is similar to BCT and it is also a pair-wise pixel voting method. The main idea is that a pair-wise pixel votes for the intersection point of two straight lines passing each other. Considered pair is same x-coordinate for more performance.

3.2 Triangle detection

We introduce and compare three different triangle detection methods. Each method treats each pixel is as an element of the triangle. These methods can detect triangle and other polygons.

3.2.1 Regular Polygon Detector

Radial Symmetry Detector (RPD) [14] is a regular polygon detector. The main idea is that every pixel votes for the lines which are orthogonal to the pixel's orientation. One of these lines passes

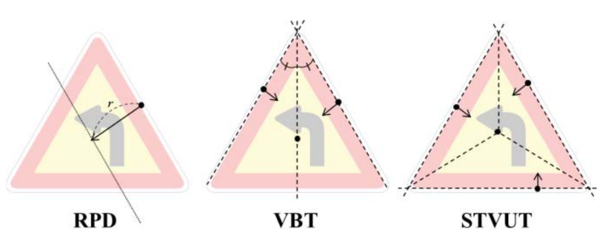


Figure 6. Triangle detection methods

through the center of the triangle. As a result, the center of the triangle is on the intersection of many lines.

3.2.2 Vertex Bisector Transform

Vertex Bisector Transform (VBT) [15] is a pair-wise pixel voting scheme. This method is pair-wise pixel voting type. VBT votes for a bisector of orthogonal line of each pixel's orientation

3.2.3 Single Target Vote for Upright Triangles

Single Target Vote for Upright Triangles (STVUT) [13] is three pixels voting method. If three pixels are not positioned on a line, three pixel's position and orientation can determine a triangle. STVUT votes for a center of triangle which is determined by three pixels.

4. EXPERIMENTS

In the experiment, we use the image data that are obtained from both the vehicle's black box and the installed mobile phone camera in the car. Our data also include dark and noisy images as shown in Figure 7. The 232 images are used in the experiment and 142 circular signs and 82 triangular signs are included in the data.

First, we compare circular and triangular sign detecting methods as explained in Section 3. The detection rates according to the number of vote maxima were measured for the extensive perfor-

Figure 7. Some examples of experimental data

mance comparisons. When the detection rate is high and the number of vote maxima is small, the false positive rate is low and the true positive rate is high. Thus a stable method should have a high detection rate with a small number of considered vote maxima.

Table 1. The detection rates of circular signs (warning signs) according to the number of vote maxima

Number of vote maxima	RSD (%)	BCT (%)	STVUE (%)
5	90.1	77.5	85.9
10	93.0	77.5	88.7
15	93.0	88.7	90.1
20	93.0	88.7	90.1

In Table 1, the RSD has the highest detection rate with a small number of vote maxima.

Table 2. The detection rates of triangular signs (prohibit signs) according to the number of vote maxima

Number of vote maxima	RPD (%)	VBT (%)	STVUT (%)
5	73.2	75.6	87.8
10	82.9	80.5	89.0
15	86.6	85.4	90.2
20	86.6	85.4	90.2

Table 2 shows that STVUT has the highest detection rate with a small number of vote maxima. We confirm that the detection rate is not affected even when the number of vote maxima exceeds 15.

Next, we compare the warning and prohibition sign detection rates according to the segmentation method mentioned section 2. In this experiment, the number of vote maxima was set to 15.

Table 3. The circular sign (warning sign) detection rates according to method of segmentation

Method	Enhanced H & S [8] (%)	Thresholded V in YUV (%)	Our method (%)
RSD	85.9	88.7	93.0
BCT	74.6	77.5	88.7
STVUE	88.7	85.9	90.1

Table 3 shows that our method provides the highest detection rate. Even though the detection rate of BCT is the lowest in every case, its detection rate is also improved with our segmentation method.

Table 4. The triangular sign (prohibit sign) detection rates according to method of segmentation

Method	Enhanced H & S [8] (%)	Thresholded V in YUV (%)	Our method (%)
RPD	72.0	73.2	86.6
VBT	73.2	73.2	85.4
STVUT	85.4	85.4	90.2

Table 4 shows that our method has the highest detection rate. The detection rate of RPD and VBT are the lower than STVUT, but the results are better with our segmentation method

5. CONCLUSION

We propose a real-time traffic sign detection method using color properties and shape-based features for real environment applications. And the method improves the detection rate of the signs with reduced speed.

Our future work is to improve the detection rates with the images captured at night or in bad weather conditions. We plan to evaluate our approach with other types of traffic signs.

6. ACKNOWLEDGMENTS

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