# Traffic Sign Detection for Vision-based Driver's Assistance in Land-based Vehicles

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***Abstract*—In this paper, an algorithm for traffic sign detection based on color and shape detection is developed. The algorithm uses images taken by a low resolution camera mounted in front of a moving car. Two types of traffic signs, yellow warning signs and red stop signs, are tested and detection results are summarized. The conclusion is that color-based detection is sensitive to illumination condition and shape detection is sensitive to the complexity of the background.**

## I. Introduction

Autonomous vehicle has been an active area of research for a few decades. Intensive research has been done on using a front viewing camera for vehicle localization and navigation, environment mapping, and obstacle avoidance.

There are four main goals that every traffic sign detection algorithm is aiming to achieve. The first goal is that the algorithm must be accurate. Accuracy is the most basic requirement and evaluation metric for the algorithm. For application of driver's assistance, high accuracy under nominal condition may be enough. But in other applications, for example, in the context of fully autonomous cars, accuracy in worse case scenario must be considered and properly monitored.

Being able to achieve high accuracy in different environmental conditions immediately leads to the second evaluation metric for the detection algorithm - robustness. Since it is hard to predict what kinds of condition the vehicle will encounter, to achieve high accuracy, the algorithm must be able to achieve the desirable result even under adverse conditions. The integrity and consistency of the algorithm must be evaluated in addition to the accuracy under nominal condition.

The third metric for evaluation is that the detection algorithm has to be fast. The ultimate goal for the detection algorithm is to be implemented in real time. Again, in the application of autonomous vehicles, first of all, the computational power is limited. Secondly, detection of traffic sign is only a small task in an autonomous system network. And thirdly, autonomous vehicles are moving at a relatively fast speed and usually require a reaction towards a traffic sign within a few seconds.

Finally, the last evaluation metric for the detection algorithm is the cost. In order to achieve autonomous driving, the vehicle already requires various sensors including GPS, inertial sensors, radar, and even Lidar. Although camera is not the most expensive sensor on board, being able to achieve a relative high detection rate using low-cost camera is still in the industry's best interest.

## II. Related Work

There are three major types of traffic sign detection methods that have been intensively studied in the literature. These three types of methods are: color-based methods, shape-based methods, and learning based methods.

### A. Color-based Detection Methods

In [1], Varun introduced a threshold method to detect the color red in the RGB color space. In [2], Kuo and Lin presented a method also to detect red color and the method operates in the HSI color space. HSI stands for hue, saturation, and intensity. It is a common cylindrical-coordinate transformation from an RGB color model. Another commonly used cylindrical representation of colors is hue, saturation, and value, or HSV color space. In order to detect more colors, Paclik in [3] used the HSV color space representation and were able to obtain any target color by thresholding the Hue value.

### B. Shape-based Detection Methods

Another category of detection methods is based on shape recognition. In [4], [5] the authors look at the Hough tranform of the edge image and detect the shape in the image solely based on the angle separations. In [6], a Gradient-based centroid voting scheme was developed to find the centroid of close shapes in a gradient image.

### C. Learning-based Detection Methods

Traditional traffic sign detection methods usually require some apriori knowledge of the color and shape of the traffic sign. In recent years, machine-learning techniques have been studied and implemented as detection algorithms. In [7], Viola and Jones developed a detector based on machine-learning using an attentional cascade of boosted Haar-like classifiers.

## III. Algorithm

The algorithm implemented in this paper is based on color detection followed by shape detection using Hough transform. The algorithm takes an input image and pre-process the image through color enhancement. Then the algorithm perform color segmentation according to a target color. The output


Fig. 1. Image taken from a front-viewing camera mounted on a moving car.


Fig. 2. Image after color enhancement.

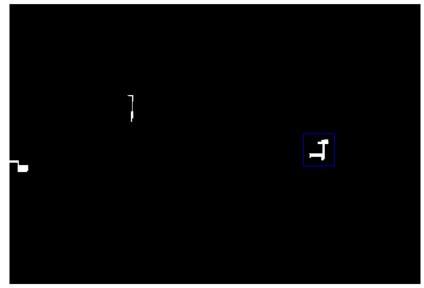

Fig. 3. Binary image after red color segmentation.

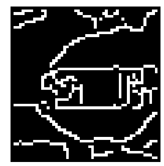

Fig. 4. Edge image of one of the extracted region of interest.

after this step is a binary image with regions containing the target color labeled. Then an edge detector is applied to each region. Hough transform is then performed on the edge image. Detection result is determined by looking at the distribution of peaks in Hough transform.

Figure 1 shows a typical input image to the algorithm. For this image, the stop sign is the desirable output from the detection algorithm.

### A. *Color Enhancement*

The very first step in this detection algorithm is enhancement of colors. The purpose of this step is to make the colors in the image more distinguishable and to prepare for color space transformation. The color enhancement part contains the following steps:

- Transform the image from RGB space to L*a*b space
- Apply adapted histogram equalization on the luminosity layer
- Transform the processed image back to RGB space

Figure 2 shows the input image after applying color enhancement.

### B. *Color Segmentation*

Color segmentation contains the following general steps:

- transform the image into desired color space
- Extract the target color by thresholding the proper value
- Return a binary mask of the desired color regions

The color space transformation and thresholds are different for different target colors. The algorithm presented in this paper only looks at detection of two colors, red and yellow,

*1) Red Color Detection:* A combination of two threshold method was used for red color detection. The first threshold method was described in [2] and is in the HSI color space with $H \geqslant 0$ and $H < 0.111\pi$ or $H \geqslant 1.8\pi$ and $H < 2\pi$, $0.1 < S \leqslant 1$,$0.12 < I < 0.8$. The second method, as described in [3], is in the HSV space and the threshold is $160/179 < H < 1$. Finally, regions detected positive by both methods are labeled as red color regions.

*2) Yellow Color Detection:* The color space used here is HSV as in [3] but with a different threshold value of $24/179 < H < 28/179$.

After apply color segmentation with the target color, it can be seen in Figure 3 that three regions were detected to contain the color red.

### C. *Edge Detection*

After color segmentation step, a binary image of the target color was generated. For each of the regions with positive color detection result,

- Perform region counting and labeling on the binary image
- Extract a rectangular region for each of the labeled region
- Apply canny edge detector on each of the extracted grayscale image region

Figure 4 is the edge image of one of the region of interest in the original image.

### D. *Hough Transform*

The final part of the algorithm is Hough transform. Again, for each of the detected regions,

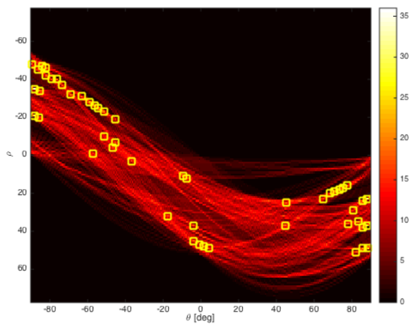


Fig. 5. Hough transform with peaks for one of the extracted region of interest.

Fig. 6. Region containing the stop sign as the final detection result.

- Apply Hough transform on the edge image
- Compute a distance score between the distribution of peaks and a target shape distribution to determine if there is a desired shape present

In this paper, the algorithm only looks at two types of shape, a diamond and an octagon. An upright diamond shape traffic sign will have two distinctive peaks at $\pm 45$ degrees. But for most traffic signs, the content inside the diamond will also result in three additional peaks at 0 degree and $\pm 90$ degrees. The peak distribution for an octagon is the same as a diamond sign. So the peak distribution for both shapes should be centered around $-90$ degrees, $-45$ degrees, 0 degree, 45 degrees, and 90 degrees.

In the Hough transform heat map in Figure 5, it can be seen that most peaks are concentrated at $\pm 90$ degrees and 0 degree. And there are some weaker peaks centering around $\pm 45$ degrees as well. This indicates that a diamond or octagon shape is likely to be present in this region of interest.

After comparing the distribution of Hough transform peaks in each of the region of interest, the algorithm successfully detects the stop sign and the final detection result is shown in Figure 6. It is interesting to note that even though the image contains a lot of noise and was motion blurred by the movement of the car, the detection algorithm is still able to extract the proper edges and the peak pattern in the Hough transform is still preserved.

TABLE I
SUMMARY OF DETECTION RESULTS

| Test Set | Correct detection | Incorrect detection |
|---|---|---|
| yellow warning signs | 6/10 | 4/10 |
| red stop signs | 8/10 | 2/10 |

## IV. Experimental Results

The implemented algorithm was tested on two sets of traffic signs. The first set is the diamond-shaped yellow warning signs and the second set is the red stop signs. Each set contains 10 different images. The first set contains 10 images with distinctive warning signs. The second set contains only stop signs. Both sets of images are of various quality and under different illumination condition. The location and size of the signs also vary from image to image. Table I shows a summary of detection results on each of the test sets. The second set achieves a higher accuracy. This is because compared to the color red, yellow is more commonly found in natural scenery and therefore results in difficulty in effective color segmentation. In addition, the assumption of vertical and horizontal edges in the warning signs is not always valid. For example, the pedestrian warning sign does not have distinctive horizontal and vertical edges.

## V. Conclusion

Several conclusions can be drawn by looking at the experimental results. First of all, illumination condition can vary from image to image and can greatly affect the results from both the color segmentation step and the edge extraction step. Low resolution image is another big challenge for effective edge extraction. And the complexity of background can result in great amount of outliers in Hough transform and therefore create huge error in shape detection.

Furthermore, currently the algorithm requires apriori knowledge of the color and shape of the traffic sign being detected. The algorithm will not be able to tell if the given information is incorrect.

Clearly, certain limitation presents in the current detection algorithm and detection results are highly dependent on the quality of the images. Machine-learning techniques can potentially improve the detection result and should be looked into for the improvement of detection accuracy.

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