

Traffic sign detection based on AdaBoost color segmentation and SVM classification

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Abstract- This paper aims to present a new approach to detect traffic signs which is based on color segmentation using AdaBoost binary classifier and circular Hough Transform.

The Adaboost classifier was trained to segment traffic signs images according to the desired color. A voting mechanism was invoked to establish a property curve for each of the candidates. SVM classifier was trained to classify the property curves of each object into their corresponding classes.

Experiments conducted on Adaboost color segmentation under different light conditions such as sunny, cloudy, fog and snow fall have showed a performance of 95%. The proposed system was tested on two different groups of traffic signs; the warning and the prohibitory signs. In the case of warning signs, a recognition rate of 98.4% was achieved while it was 97% for prohibitory traffic signs. This test was carried out under a wide range of environmental conditions.

Keywords: Traffic signs, AdaBoost, Color Segmentation, Hough Transform, Classification.

I. INTRODUCTION

Driver Support Systems (DSS) can detect and recognize traffic signs in real time. This helps to improve the traffic flow and safety [1; 2] and avoids hazardous driving conditions such as collisions.

Traffic sign recognition is one of the less studied subjects in the field of Driver Support Systems. Research groups have focused on other aspects, related more with the development of an automatic pilot to detect road borders or obstacles in the vehicle's path such as other vehicles or pedestrians. Accidents can occur, for example, because drivers do not notice a sign in time or by lack of attention at a critical moment. In bad weather conditions such as heavy rain showers, fog, or snow fall, drivers pay less attention to traffic signs and concentrate on driving. In night driving, visibility is affected by the headlights of traffic oncoming and drivers could easily be blinded.

In order to prevent this kind of accidents, a group of traffic signs called warning signs are employed to warn road users of such kinds of danger in the coming parts of the road. Since human visual perception abilities depend on the individual's physical and mental conditions, these abilities can be affected by many factors such as tiredness, and driving tension. Hence, it is very important to have an automatic system which can recognize these kinds of traffic signs. Giving this information to drivers in good time can prevent accidents, save lives, and increase driving performance [3; 4].

Therefore, traffic sign recognition is an important field in Intelligent Transport Systems (ITS). This is because of the importance of traffic sign in daily life. They define a visual language which can be interpreted by drivers. They represent the current traffic situation on the road, show dangers and difficulties around the drivers, give warnings, and help them with their navigation by providing useful information which makes driving safe and comfortable [5].

This paper aims to present a new approach to detect two of the most import groups of traffic signs which are the warning and prohibitory traffic signs. The system is based on using an Adaboost binary classifier for color segmentation and circular Hough Transform to detect the presence of a traffic sign.

The structure of the paper is as follows. In Section II, the work related to the current approach is presented. Section III illustrates an overview of the suggested system. Section IV presents the Adaboost color segmentation approach and the traffic sign recognition using the circular Hough Transform is described in Section V. In Section VI, the results achieved by the proposed approach are presented and finally, the conclusions are given in Section VII.

II. RELEVANT WORK

In recent years, research in traffic sign recognition has grown rapidly because of the real need for such systems in future vehicles. Performance indexes headed by these systems include high recognition rates, real-time implementation, many traffic sign categories as recognition objects, robustness for variant environments, and feasibility under poor visibility conditions.

Sermanet and LeCun [6] employed Convolutional Networks (ConNets) to classify traffic signs. It is a biologically inspired multi-stage architecture which automatically learns invariant features. The authors used two-stage architecture in which features from the first stage is fed to the second one. The system yielded an accuracy of 98.97% during the first phase and 99.17 when the network capacity was increased.

Chen et al. [7] proposed a computer vision based system for real-time robust traffic sign detection and recognition. Color segmentation was achieved by color-based method to scan the scene for region of interests. Sign candidates were detected by a set of Haar wavelet features obtained from AdaBoost training. The Speeded Up Robust Features (SURF) were applied for the sign recognition. The proposed system achieved 90% accuracy in real-time.

Jiang et al. [8] presented an approach to detect and recognize traffic signs which was composed of three steps which are color segmentation, shape detection and pictogram recognition. Recognition was achieved by a novel feature extraction involves OTSU method which is robust against illumination variations and distortions. Performance achieved by the proposed method was around 98%.

Yanlei et al. [9] developed a dual-focal active camera system to obtain a high resolution image of traffic sign. The system consisted of an active telephoto camera which worked as an assistant of a wide angle camera. High resolution images of traffic sign were captured and the shape, color features and the relationship between continuous frames were exploited together in the traffic sign detection. The proposed system achieved 96% for shape detection and 94% for color and shape detection.

III. SYSTEM OVERVIEW

The block diagram of the proposed approach is illustrated in Figure 1. The image under consideration is first color segmented by the Adaboost classifier and filtered from noise and other undesired small blobs based on the size of these blobs. Canny edge detector is then applied to extract the edges of all candidate objects in the image under consideration. These candidates are labeled and a voting scheme based on circular Hough Transform is applied to build the property curve of each objects. A Support Vector Machine (SVM) classifier which is trained to classify the property curves is exploited to classify the objects in the image into their traffic sign categories. The SVM classifier is trained with curves which are smoothed with LOWESS regression [10]. Therefore, all property curves produced by the voting mechanism are also smoothed in the same manner. This process continues until the list of all labeled objects is exhausted.

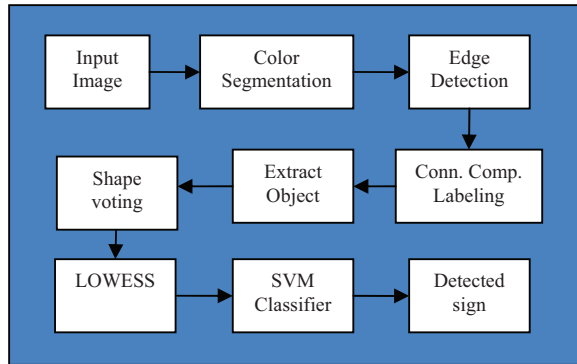


Fig. 1. Block diagram of the proposed system.

IV COLOR SEGMENTATION with ADABOOST

AdaBoost [11] is a very popular boosting algorithm. It is a machine learning meta-algorithm to perform supervised learning which combines several weak learners to create a strong learner. A weak learner is a classifier which can classify samples with success rates a slightly more than randomly guessing the sample's class. A strong learner is a classifier that can classify data with rather high rates which means much better rates than what can be achieved by weak learners. A weak learner finds a separation boundary between negative and positive classes based on finding the location of the boundary th in the suitable dimension D and the location

of the positive class with respect to the negative one $lp \in \{-1, +1\}$. Since this weak learner fails in most cases to separate the two classes, AdaBoost combines a number of weak learners to form a strong learner in order to achieve better separation between classes.

To achieve color segmentation, Adaboost was trained with a number of traffic sign images. The training images were collected from traffic scenes where the traffic signs exist. The parts of the images containing the traffic signs were separated manually from the images and exploited as positive samples for the training. The other parts of the image were employed as the negative samples. Figure 2 depicts a set of images used as positive and negative samples.



Fig. 2. Adaboost is trained with positive (color to be segmented) and negative (other colors) classes.

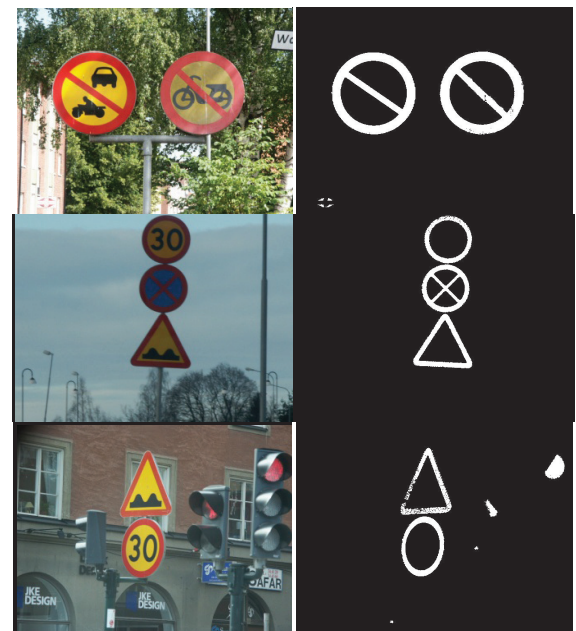


Fig. 3. Results of color segmentation.

All pixels in the training images were converted from RGB into HSV color space. Then they were merged together with the corresponding target color to form a matrix in which each

row consists of the pixel's Hue, Saturation, and the corresponding color code.

Segmentation was achieved by exposing the image to be segmented to the Adaboost classifier pixel by pixel. Each pixel was first converted from RGB into HSV, and the H and S values were employed in the segmentation. The output of the Adaboost classifier is a binary image in which the color to be segmented is represented by 1 and the other colors by 0. Figure 3 shows the results of segmentation using this algorithm.

V. TRFFIC SIGN DETECTION

The Hough Transform is a feature extraction technique which transforms an image from its Cartesian coordinates to its Polar form.

Consider a line segment $y = mx + b$ in the image space. For a vertical line represented by its parameters slope m and intercept b , the value of m becomes infinity. To avoid this problem, the line segment can be considered by $\rho = x \cos \theta + y \sin \theta$ where $\rho \in \mathbb{R}$ is a vector representing the shortest distance of the line from the origin and $\theta \in [0, \pi[$ is the angle of this vector from the x -axis, as shown in Figure 4. Any point in the image space will be represented by a sinusoidal curve in the Hough space. Moreover, two points on a line segment generate two curves which are superimposed at a location which corresponds to a line in the image space.

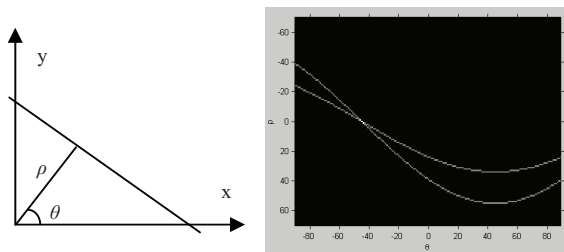


Fig. 4. Left: line segment representation Right: Hough Transform of two points on the line.

The Hough Transform in this form is not suitable to detect complex objects such as triangles, circles, and rectangles due to noise and shape imperfection. Circular Hough Transform can instead be invoked to detect these objects. It can be described as a transformation of center point of the object in x - y plane to the parameter space. The equation of a circle in x - y plane is given by:

$$(x - h)^2 + (y - k)^2 = r^2 \dots \dots \dots (1)$$

where h and k represent the x and y coordinates of the center of the circle and r is its radius. The parametric representation of the circle is given by:

$$x = h + r \cos(\theta) \dots \dots \dots (2)$$

$$y = k + r \sin(\theta) \dots \dots \dots (3)$$

To determine the presence of any object in the image, it is necessary to accumulate votes in the three-dimensional parameter space i.e. h , k , and r . A voting mechanism which aims to find the distribution of the votes in the Hough space is illustrated in Figure 5.

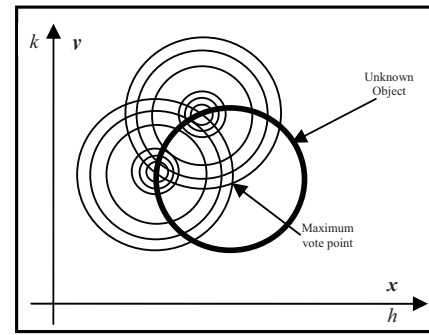


Fig 5. Voting mechanism based on Hough Transform.

This voting mechanism specifies the number of votes given to any object in the image, and the location of the object. In this mechanism, each white pixel of the object is considered as the center of a set of concentric circles with different radii. For each radius of the set of circles, a vote is given to each intersection of the circles, and the maximum number of votes is computed. This means that for each radius of the concentric circles there is one point in the Hough space (h , k) which represents the maximum voting.

A circle is detected by its peak generated by the voting mechanism while a triangle is characterized by a smooth curve and the absence of the peak in the voting curve, as depicted in Figure 6.

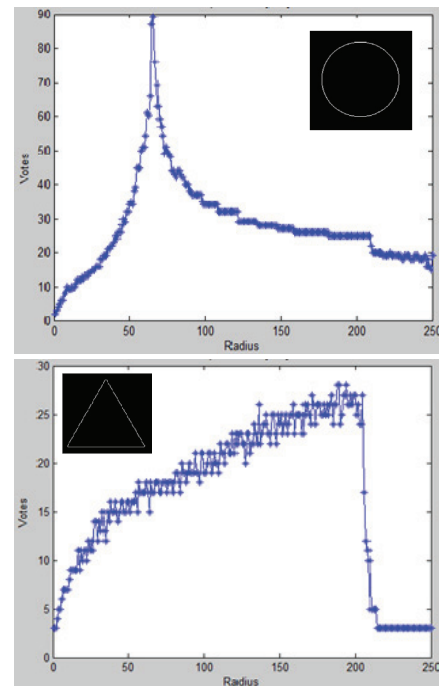


Fig. 6. Voting mechanism of a circle (top) and a triangle (bottom).

Property curves generated by the voting mechanism were smoothed by LOWESS regression and normalized in both axes to $[0,1]$ as depicted in Figure 7. A training set of 150 curves were collected and an SVM classifier was trained with these curves.

As depicted in Figure 8, once the image under consideration is segmented, Canny edge detection is then applied to produce the edges of each of the candidate objects. These objects were sequentially separated from the image and a voting curve was

created, smoothed and send to the SVM classifier for classification. Usually, Canny edge detector generates two edges which represent the outer and inner edges of the object under consideration. However, in many cases, one of the two circles may be unhealthy because of imperfection, noise, and the presence of other objects with the same color as the traffic sign.

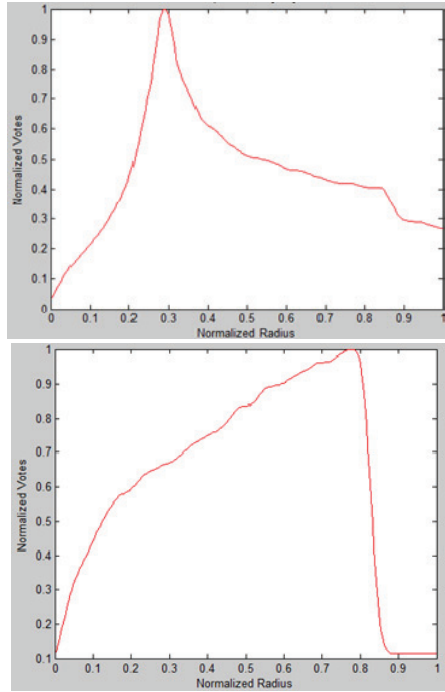


Fig. 7. Normalized property curves of a circle (top) and a triangle (bottom).

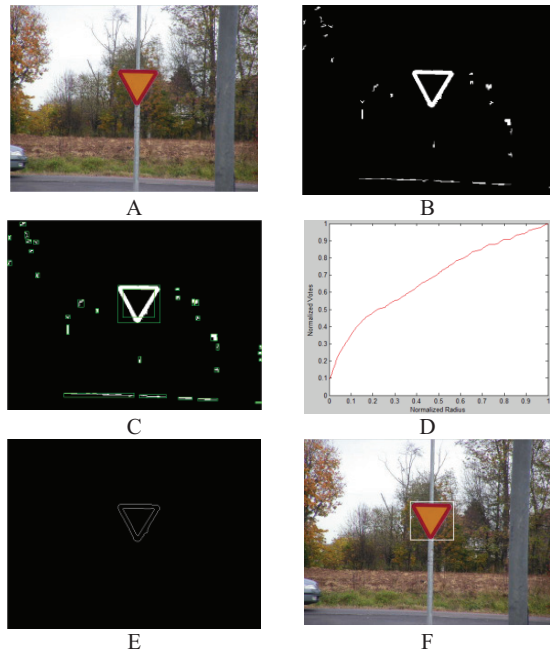


Fig. 8. The steps to detect the traffic signs. A: original image, B: Segmented image, C: Treating candidates, D: Generating property curve, E: Finding suitable candidate, F: Mark traffic sign.

To solve this problem, the following set of rules were applied:

- If two circles, which are concentrated in each other, are detected: this means that the two edges of the traffic sign are healthy and one traffic sign is detected. The location is bounded by a bounding box.
- If one circle, which is located inside another object, is detected: this means that the outer edge of the traffic sign is destroyed while the inner edge is healthy. A bounding box based on the detection of the inner edge of the sign is drawn.
- If one circle, which is not located inside another object, is detected: this means that the inner edge of the circle is destroyed while the outer edge is healthy. A bounding box based on the detection of the outer edge of the sign is drawn.

VI. RESULTS and ANALYSIS

To analyze the performance of the proposed approach, the following experiments were conducted.

A. Adaboost color segmentation

This color segmentation was tested using a large number of traffic sign images which were collected under wide range of environmental conditions. The method was tested on more than 200 images under different light conditions (sunny, cloudy, foggy, and snow conditions) and different backgrounds, as shown in Table 1. They established very good robustness. Segmentation is successfully achieved in more than 95% of the cases under investigation.

TABLE I
RESULTS of ADABOOST BASED COLOR SEGMENTATION

Condition	No. of images	Success %
Bad Lighting	47	96.7
Blurred	34	97.0
Fog	14	85.7
Highlight	20	95
Snow Fall	18	94.4
Dusk/Down	27	96.2
Sunny	40	97.5

Segmentation time required by the proposed approach is measured for 50 randomly selected images. By using Matlab and a Dell Latitude E6400 computer, the average time needed for color segmentation was 0.25 sec. Figure 9 depicts that segmentation time which is almost constant regardless of the contents of the image or the size of the traffic sign in the image.

B. Detection of Traffic Signs

The proposed approach was tested on two different sets of images which comprise 111 and 103 images, respectively. The first set is the Warning signs and the second one is the Prohibitory signs.

Table 2 depicts the detection results of the warning sign group which was achieved under different light conditions. There were 125 traffic signs and the proposed system could detect 123 of these signs. The average detection rate was 98.4%. The proposed system was also tested against the non-traffic signs objects. It rejected 117 out of 121 objects in this group.

The same test was employed for the Prohibitory signs. Table 3 presents the detection results of this set. There were

130 traffic signs and the proposed system could detect 126 of these signs. The detection rate achieved for this set of signs was 97.0%. The proposed system rejected 148 not-traffic sign objects out of 154 used in this test. Figure 10 shows a number of signs detected by this approach.

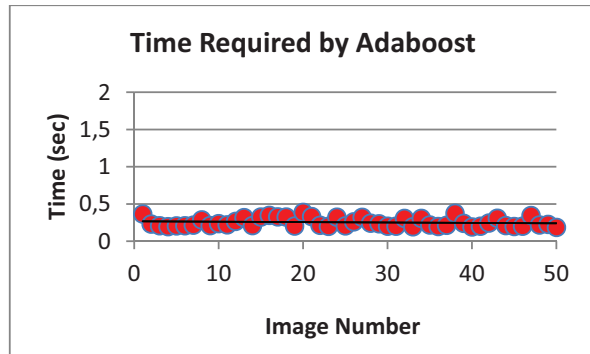


Fig. 9: Time required by the Adaboost color segmentation.

VII. CONCLUSION

In this paper, a new method to detect traffic signs was proposed. It utilized Adaboost for color segmentation and circular Hough transform together with SVM for classification. Experiments conducted to evaluate the performance of the proposed approach showed that this approach has high performance in the context of color segmentation and the ability to detect the traffic sign groups involved in the test.

The system was tested on two different dataset of traffic signs which represent the warning and the prohibitory. In both cases results were very promising.

The proposed system will be expanded with more training to include other types of traffic signs and other colors such as the circular mandatory traffic signs with blue color and the informative signs.



Fig. 10: Results of traffic sign detection of warning and prohibitory signs.

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TABLE II
DETECTION of WARNING SIGNS.

Condition	No. Of Images	Positive Objects	TP	FN	Negative Objects	TN	FP
Sunny	19	21	20	1	13	13	0
Highlight	11	11	8	0	10	10	0
Blurred	15	17	17	0	10	9	1
Bad Lighting	23	27	27	0	33	32	1
Noisy	19	22	21	1	42	40	2
Snow Fall	6	7	7	0	2	2	0
Fog	7	8	8	0	3	3	0
Dawn/Dusk	11	12	12	0	8	8	0
Total	111	125	123	2	121	117	4

TABLE III
DETECTION of PROHIBITORY SIGNS.

Condition	No. Of Images	Positive Objects	TP	FN	Negative Objects	TN	FP
Sunny	15	21	21	0	26	25	1
High Light	14	15	15	0	18	18	0
Blurred	18	20	20	0	21	20	1
Bad Lighting	20	31	29	2	33	32	1
Noisy	7	9	9	0	15	13	2
Snow Fall	11	13	12	1	20	20	0
Fog	5	6	5	1	2	2	0
Dawn/Dusk	13	15	15	0	19	18	1
Total	103	130	126	4	154	148	6