Real-time detection of speed-limit traffic signs on the real road using Haar-like features and boosted cascade

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7 authors, including:

Taewoo Lee
Sejong University

Yeong-Woo Choi
Sookmyung Women's University

Kwangyong Lim
Yonsei University

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Won J. Jeon
Samsung R&D Center,
300 Orchard Parkway,
San Jose, CA 95134, USA
+1-408-318-0428
wjjeon@gmail.com

Taewoo Lee
Computer Science, Yonsei University
134 Shinchon-Dong,
Seodaemun-Gu, Seoul, Korea
+82-2-2123-3876
gunmong@yonsei.ac.kr

Byeongdae Woo, Kwangyong Lim
Computer Science, Yonsei University
134 Shinchon-Dong,
Seodaemun-Gu, Seoul, Korea
+82-2-2123-3876
{bdwoo, kylim}@yonsei.ac.kr

Gustavo Adrian Ruiz Sanchez
Computer Science, Yonsei University
134 Shinchon-Dong,
Seodaemun-Gu, Seoul, Korea
+82-2-2123-3876
gars@yonsei.ac.kr

Yeongwoo Choi
Computer Science
Sookmyung Women's University
Chungpa, Yongsan-Gu, Seoul, Korea
+82-2-710-9763
ywchoi@sookmyung.ac.kr

Hyeran Byun
Computer Science, Yonsei University
134 Shinchon-Dong,
Seodaemun-Gu, Seoul, Korea
+82-2123-2719
hrbyun@yonsei.ac.kr

ABSTRACT
Along with the development of the intelligent vehicle, the Advanced Driver Assistance System(ADAS) has recently become an important issue. Traffic signs on the road provide crucial information to the driver. Recognizing all the traffic signs on the side of the road can be a difficult task for a driver who should watch the road ahead. To solve this problem, this paper proposes real-time detection methods using Haar-like features in a real road driving environment. We implement a reliable reduction method of the search area to improve the detection speed, masking methods and histogram equalization to improve the detection rate. The proposed method has shown higher detection rate and two times faster performance time than previous works.

Categories and Subject Descriptors
I.4.9 [**Image Processing and Computer Vision**]: Application; I.5.1[**Pattern Recognition**] Models – Neural nets; I.5.4 **[Pattern Recognition**]: Application – Computer Vision;

General Terms
Algorithms, Measurement, Verification, Experimentation

Keywords
Speed-Limit Traffic Sign, Haar-like Feature, Searching Area Reduction, Color Segmentation, Real Road Driving Environment, Real-time Detection.

1. INTRODUCTION
Recently, the Advanced Driver Assistance System (ADAS) has become one of the key technics studied in the field of intelligent vehicles. ADAS, as an intelligent vehicle technology based on computer vision, it requires high performance, convenience and safety, given that the system provides visual data from the front of the vehicle which is critical for driving safety. Traffic sign detection and recognition technology of vision-based ADAS prevents accidents by giving notice of traffic prohibitions. EURO NCAP[1], the European New Car Assessment Program, decided to grade the Safety Assistance. A Speed Assistance System which informs to the driver the speed limit is included and becomes essential for vehicle safety.

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Many approaches have been studied to detect traffic signs. Most studies use specific data of constrained environments or focus only on detection accuracy. One of these approaches was the German Traffic Sign Detection Benchmark(GTSDB)[2], which was held in Germany. Most of the high ranked teams in the competition showed a high detection rate. It is hard for these techniques to be applied in a real driving environment because the competition only considered detection rate, not speed. Furthermore, the data provided was recorded only during the daytime with clear sky conditions.

There are two ways to detect traffic signs; using color[3,4,5] and using shape[6,7]. These methods do not consider the illumination variations. In this paper, to solve this problem our system detects the traffic signs using a reliable area reduction with color and Haar-like features.

A high performance of recognition relies on a high performance of detection. In this paper, we focus on speed and accuracy of detection. In chapter 2, we propose a reliable candidate area reduction method for real-time detection. In chapter 3, we explain the Haar-like features and Boosted Cascade algorithm for speed-limit traffic signs. In chapter 4, we explain two methods to enhance accuracy rate, mask training and histogram equalization. The remaining chapter of this paper consists of the experimental results.

2. Reducing Searching Areas
In this section, we propose searching area reduction methods to detect traffic signs quickly on high quality images taken by a camera installed on a vehicle. To reduce the candidate area, we use a combination of 4 methods: 1) Reduction of the lower area in an image, 2) Color segmentation, 3) Local variance, 4) Morphology. As result, the candidate areas are reduced to an average of 6%

on day-1 dataset (see Table 2), 8% on day-2 dataset, 15% on day-3 dataset and 3% on night dataset.

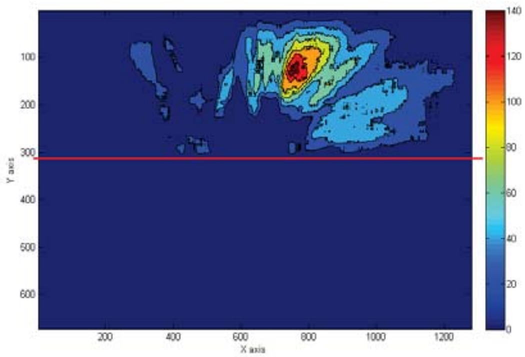


Figure 1. The sum of the pixel intensities of 3,380 images including traffic signs. Red color indicates a higher appearance density.

2.1 Exclusion of the Lower Area

In general, traffic signs are placed in front and on the top of vehicle. Figure 1 shows the appearance density of the traffic signs in 3,380 images. Most traffic signs appear on the upper right side of the front view and occasionally at the upper left side due to signs on the centerline. Eventually, we can ignore the candidate area under the red line.

2.2 Color Segmentation

According to the Vienna Convention on Road Signs which most countries follow, speed-limit signs have a circular shape with a red border and white ground. The color, especially red, is an important factor to detect traffic signs. The color segmentation algorithm works on the HSV space which define color relationships the same way the human eye does. The HSV space is nonlinear related to the RGB space.

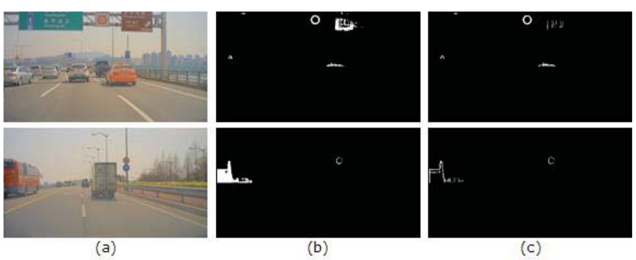


Figure 2. (a) Input image, (b) color segmentation, (c) local variance after color segmentation.

We use a single threshold for color segmentation. The range of threshold is determined by the color distribution of the traffic signs from 2,203 images which excludes 1% of the total intensities, 0.5% being the higher intensities and 0.5% the lower intensities. The binary map of the color segmentation is made out using this threshold.

2.3 Local Variance

The color segmentation method has a problem of illumination changes. If the range of the threshold increases in order to solve the illumination changes problem, the noise also increases. We use the local variance to change this problem. The local variance is the variation between the intensity of a center pixel and the average intensity of its neighbors in the mask.

$$v_i = x_i - \frac{1}{S}\sum_{m \in M_i} m \qquad (1)$$

where v_i is the variance in the rectangle local area of the i_{th}pixel and M_i is a set form by the i_{th}pixel and its neighbors. S is a normalizing factor (the size of the mask). The bigger the mask size is, the more the computation amount increases and the more the noise decreases. In this paper, a 7x7 mask is used. The results are shown in Figure 2.

2.4 Morphology

We use morphology operations in order to remove small noise. At first, an erosion operation removes the noise with a 2x2 size kernel with its center point on the upper left side. Second, using an 18x18 size kernel with the center point at (5, 5), we perform dilation to make the candidate area bigger and, therefore, easier to search for.

3. Speed-Limit Traffic Sign Detection using Haar-like Features

In this section, we briefly explain the Viola-Jones[8] algorithm and how to apply this algorithm to detect traffic signs. The Viola-Jones algorithm is very useful to detect objects fast and accurately. This algorithm has 3 key factors: 1) Haar-like features, 2) Adaboost algorithm, and 3) Cascade algorithm.

3.1 Haar-like features

It is hard to discriminate whether the object is the target object or not. Paul viola and Michael Jones proposed the Haar-like features based on the Haar wavelet to solve this hard problem. As can be seen in Figure 3.(a), a Haar-like feature is defined by the value of the difference between the white area and the black area. Various Haar-like features have been studied, and Lienhart et al.[9] used 45 degree tilted features(see Figure 3.(b)) and Li et al.[10] proposed disjoint Haar-like features consisting of nonadjacent rectangles.

In this paper, we use 5 Haar-like features proposed by Viola-Jones. In general, the speed-limit traffic signs are formed as a simple geometrical shape and positioned vertical against the ground. Accordingly, we don't need to use tilted or complex Haar-like features.

3.2 Adaboost Algorithm

There are about 18,000 Haar-like features within a 24x24 sliding window. Most features are meaningful, but the importance of the features differ according to the training samples. The Adaboost algorithm is used to select the important features among a tremendous amount of features.

The Adaboost Algorithm trains iteratively a strong classifier which is the sum of several weak classifiers. A weak classifier that has the minimum error rate is selected and added to the strong classifier with a weight regarding the error rate at each iteration. Until the strong classifier satisfies the end criteria, the algorithm keep training.

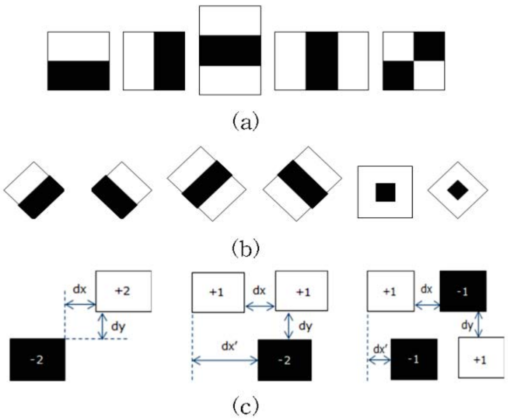


Figure 3. (a) Viola-Jones's features, (b) Lienhart's features, (c) Li's features.

In this paper, we train a classifier using the Gentle Adaboost algorithm. In contrast to the Real Adaboost that could predict reliability, the Gentle Adaboost shows good performance at classifying the target object and background since the Gentle Adaboost reduces and fixes the weight of the wrong classified samples.

3.3 Cascade

The target object occupies a very small area in the image. It is inefficient for the sliding window to check all the weak classifiers at each pixel. The Cascade method solves this computational problem of Adaboost. the Cascade method rejects the background image at earlier stages. If the image of the sliding window passes all the stages, that image is classified as a target object.

To train the cascade structure, there are several problems like, how many stages are needed, how many weak classifiers are needed at each stage, and in which stage to assign a weak classifier. We are not able to optimize the cascade structure, but to make it efficient.

Using a maximum false rate, a minimum correct rate and a total correct rate, we train the cascade classifier iteratively. In this paper, we set the maximum false rate as 0.5, the minimum correct rate as 0.999 and the total correct rate as 0.0005. Eventually, the number of stages is 11.

4. Methods to Improve Detection Rate.

In this section, we propose two methods to improve the detection rate on the images captured under a bad environment. First**,** we apply a mask kernel on the training samples**.** Second, histogram equalization complements the limitation of the local normalization.

4.1 Masking

The Haar-like features are basically rectangles. The speed-limit traffic signs, however, are circles. Therefore, the background part outside of the circle in the sliding window is unpredictable. Generally, when the weak classifiers are selected at the Adaboost algorithm step, the weak classifiers that have less importance are ignored. However, if the background part is extraordinary such as in Figure 4, it is hard to expect a good result. To solve this problem, we ignore completely the outside of the circle using a mask kernel in the training step.

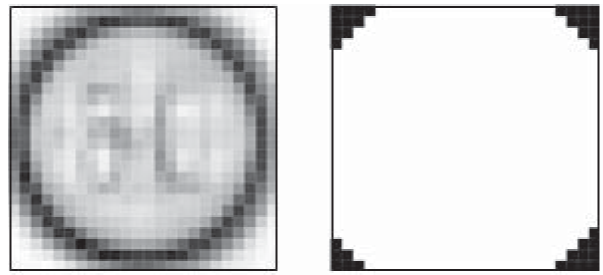


Figure 4. (a) Standard variation sum of the prohibitory traffic sign images, (b) the masking area using (a) image

Additionally, the number of features in the sliding window gets reduced given that the mask kernel reduces the area that has to be trained with the Haar-like features. Moreover, the background part rarely influences the detection rate since it is not an important part for traffic sign detection.

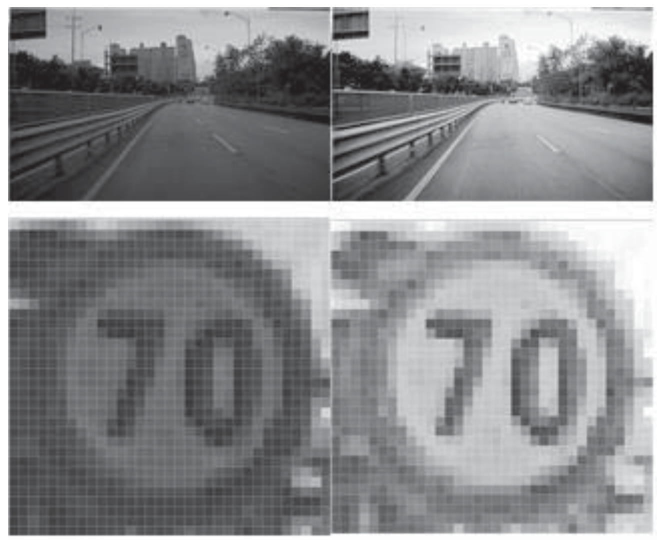


Figure 5. (a) Image taken in a cloudy weather, (b) image after histogram equalization

4.2 Histogram Equalization

The change in illumination is one of the factors that make the detection of traffic signs hard. Especially, Haar-like features are easily influenced by illumination changes since the feature uses the image intensity. Viola-Jones suggested that the Haar-like features had to be normalized by standard variation and used square integral image for a fast calculation.

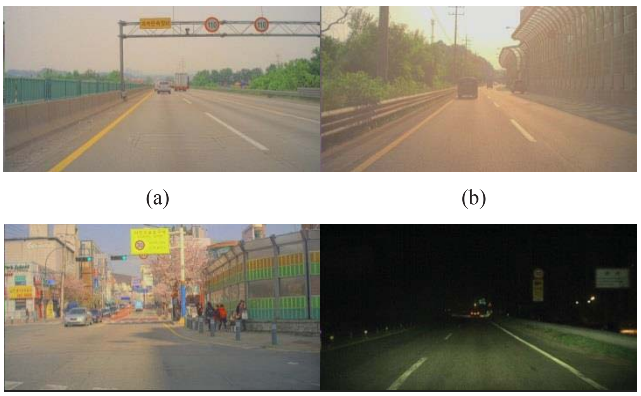
The Haar-like features tends to increase the intensity difference between the white and black area when the standard variation of the window increases. However, if the standard variation of the window decreases, the absolute difference value of the Haar-like features increases. In that case, the miss and false detection rates increase on the images of the sky, the asphalt road, and the walls of big building which suffers from illumination changes.

The histogram equalization complements the limitation of the local normalization. If the standard variation normalizes in a local area, the histogram equalization normalizes in a global area. For example, the difference of intensity decreases in parts, such as the sky or the road surface, where the difference of intensity is small. Otherwise, the difference of intensity increases in parts, such as where the traffic signs are blurred by backlight and illumination.

However, in the night images, the histogram equalization distorts the intensity of the traffic signs because the small area lit by the car headlights is too bright and the rest of the area is dark. We can control when to apply the histogram equalization using the CAN communication system of the vehicle.

5. Experiments and Results

The detection algorithm was evaluated in the system shown in Table 1. We performed the experiments on the dataset offered by Hyundai Mobis. The dataset was captured on the roads of South Korea under various conditions, such as daytime, nighttime, backlight, rain, fog and cloudy weather. We split the dataset into four subsets (see Table 2).



(a) (b)

(c) (d)

Figure 6. (a) Day-1 dataset, (b) Day-2 dataset, (c) Day-3 dataset, (d) Night dataset

Table 1. Experimental environment

CPU	Intel(R) Core(TM) i5-3570 @3.4GHz
Memory	8.00 GB
O. S.	Windows 7 Enterprise Service Pack 1
Tool	Microsoft Visual Studio 2010

We determine the result as correct if the searched area overlaps more than 45% of the ground truth, and the distance between the center of the searched area and the ground truth is less than 10% of the ground truth's width or height[11,12]. The evaluation items are true positives, false negatives, false positives, recall, and detection time

Table 2. Dataset type

Day-1	810 traffic signs under the clear sky
Day-2	163 traffic signs in a bad illumination environment
Day-3	284 traffic signs with an extraordinary background
Night	492 traffic signs in the night time

5.1 Detection Results

First, we reduce the candidate area and perform the histogram equalization on the test images. Second, we detect the traffic signs in day-1, day-2 and day-3 datasets using the classifier trained with the masking method. In the night dataset, we exclude the histogram equalization. As can be seen in Table 3 and Table 4, the detection rate of the proposed methods is greater than or equal to the basic viola-jones methods. The detection time becomes almost two times faster.

(a) (b)

Figure 7. Result images in (a)Day-2 and (b)Night dataset.

Table 3. Detection rate results (%)

	Day-1	Day-2	Day-3	Night	Avg
Viola-Jones	97.9	74.2	90.8	96.1	94.1
Proposed	98.0	92.0	96.8	96.1	96.7

Table 4. Detection time results (ms)

	Day-1	Day-2	Day-3	Night	Avg
Viola-Jones	164	246	136	123	155
Proposed	67	71	80	67	70

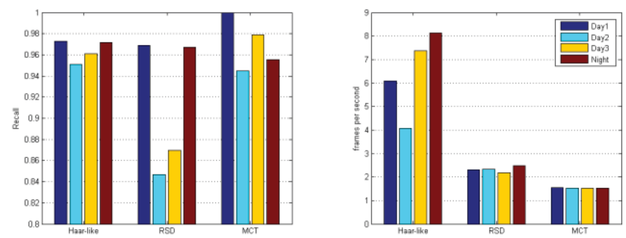


Figure 8. Comparison with other methods. (a) detection rate, (b) detection speed

5.2 Comparison with other methods

We compare with other two methods. One of them is the Radial Symmetry Detection(RSD)[6]. The RSD method detects circles fast. However, if there are too many circles and the illumination changes in the image, the detection rate decreases substantially. The other method is the Modified Census Transform(MCT)[13]. The MCT method detects traffic signs well in a bad environment using local features. However, the method's computational cost is high due to the transformation of an image into a MCT map. Figure 8 shows the comparison results.

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6. Conclusion

In this paper, we discussed the real-time detection of a speed-limit traffic sign on the real road. It is hard to expect good result using only one method since a real-time detection on real road needs simultaneously high accuracy and high performance. We, therefore, approached the problem in many ways, through the reduction of the candidate area for a high performance, masking methods, and histogram equalization for a high detection rate using

Haar-like features. As a result, the proposed method shows better performance in terms of speed and accuracy compared to previous works.

7. ACKNOWLEDGEMENTS

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