INTELLIGENT MACHINE VISION SYSTEM FOR ROAD TRAFFIC SIGN RECOGNITION

by Aryuanto Soetedjo1

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Aryuanto[1], Koichi Yamada[2] , F. Yudi Limpraptono[3]
Jurusan Teknik Elektro, Fakultas Teknologi Industri, Institut Teknologi Nasional Malang, Indonesia [1,3]
Jl. Karanglo Km 2 Malang
Dept. of Management and Information System Sciences, Nagaoka University of Technology, Nagaoka, Japan [2]
E-mail : aryuanto@fti.itn.ac.id[1]

Abstract

We proposed an intelligent machine vision system to recognize traffic signs captured from a video camera installed in a vehicle. By recognizing the traffic signs automatically, it helps the driver to recognize the signs properly when drivig, to avoid accidents caused by mis-recognized the traffic signs.The system is divided into two stages : detection stage to localize signs from a whole image, and classification stage that classifies the detected sign into one of the reference signs. A geometric fragmentation technique, a method somewhat similar to Genetic Algorithm (GA) is employed to detect circular sign. Then a ring partitioned method that divides an image into several ring-shaped areas is used to classify the signs. From the experimental results, the proposed techniques are able to recognize traffic sign images under the problems of illumination changes, rotation, and occlusion efficiently.

Keywords : Machine vision, traffic sign recognition, geometric fragmentation, ring partitioned matching.

INTRODUCTION

Road traffic signs are installed to regulate traffic, provide traffic designations and other useful information. They are installed at specific locations and appeared with colors (red, green, yellow, blue) in contrast againt road environment. Those arrangements are intended to make the drivers see the signs easily. However due to certain factors such as poor visibility, fatigue, lack of consentration, sometimes the drivers miss the signs, which could lead to the accident. In order to minimize such problem, an intelligent vision system to recognize traffic signs called Traffic Sign Recognition (TSR) is introduced.

TSR helps the driver to recognize traffic signs properly. It consists of a video camera installed in a vehicle to capture the signs and a processor to recognize the signs. Usually TSR is a part of Driver Assistance System (DAS) that assists the driver controlling the car (L. Fletcher, et. al., 2005, L. Peterson, et. al., 2006).

In (L. Fletcher, et. al., 2005), TSR and driver monitoring were combined to correlate eye gaze with the sign detection. When a traffic sign (speed sign) is detected by TSR, the system checks whether the driver has seen the signs or not (by the driver monitoring system). The system also checks whether the vehicle's speed conforms or not with the detected speed sign. If the driver has not seen the sign and the vehicle's speed does not conform to the speed limit, then a high priority alarm is generated to warn the driver the sign detection.

Many researchers have proposed algorithms for sign recognition. However it still becomes a challengeing topics, due to the facts that even though traffic signs are designed in color, shape and positioned in specific location according government's rules, they could be deformed, rotated, occluded by other objects, color painting become dirty or degraded. Furthermore, illumination and lighting changes make sign recognition a difficult task. Another important issue is fast computation. Since the recognition result should be provided in real time, it requires that the algorithm should be fast enough.

General approach for TSR is by dividing the task into two stages: detection stage and classification (or recognition) stage (A. de la Escalera, et. al., 2003, H. M. Yang, et.al., 2003, L. J. Hum and J. K. Hyum, 2003). In the detection stage, color is commonly used as a clue, since color contains many information about traffic signs and also reflects messages of the signs. When using color to detect the signs, the most common problem is when the illumination changes.

Another approach is using shape detection technique from gray scale images. The difficulties of this approach as described in (M. Lalonde and Y. Ling, 1995) are: the signs appear in cluttered scenes, which increases the number of candidates since many objects typical of urban environments can be confounded with road signs from a "shape" point of view (building windows, commercial signs, cars, etc); the signs do not always have a perfect shape; the signs taken by different view angles results in different shape; the variance in scale, signs get bigger as a vehicle moves toward them.

After sign candidates are detected from the detection stage, then classification stage is performed to classify them into one of reference signs. Mainly, the classification approaches could be divided into three categories: Template Matching method (M. Shneier, 2005), Statistical Pattern Recognition (C. Bahlmann, et. al., 2005), and Artificial Neural Networks (ANNs) (H. M. Yang, et. al., 2003). The problems confronted at this stage are the same as the detection stage, i.e. detected signs might be deformed, rotated, varying scaled, and illumination changes.

In this paper, an efficient algorithm for TSR is proposed. In the detection stage, it provides robust detection under the problems of illumination changes, rotation, varying scale, deformation, and occlusion. Meanwhile, the algorithm is fast in computation. Moreover, an approach for sign classification is proposed to overcome the drawbacks mentioned before.

The paper is organized as follows. In section 2, the proposed system for traffic detection and classification is described. In section 3, the experimental results are presented. Finally conclusion is described in section 4.

PROPOSED SYSTEM

Our proposed system is depicted in figure 1. It is divided into detection stage and classification stage. At first, an image acquisition process is used to capture traffic sign images from the real scene. In the detection stage, sign candidates is localized from an image. By localizing signs, further step to classify signs is concentrated only in a small region of interest. Thus, signs classification could be processed efficiently and it saves the computation time.

To detect signs, we employ color analysis followed by shape analysis. We adopt the normalized RGB color system to overcome the illumination problem, while no additional hardware required for color conversion, since most of digital video camera system use RGB color system.

In this research we deal with red circular signs only, therefore in the shape analysis, we employ an ellipse detection technique (A. Soetedjo and K. Yamada, 2006) to detect those circular signs. An ellipse is general representation of a circle. The circular sign appears as an ellipse when it is taken with a camera from oblique direction.

In the classification stage, we employ a ring partitioned matching method (A. Soetedjo and K. Yamada, 2005) which classifies the signs into one of the reference signs without introducing training process. Hence we do not need to prepare a huge sample images for training process.

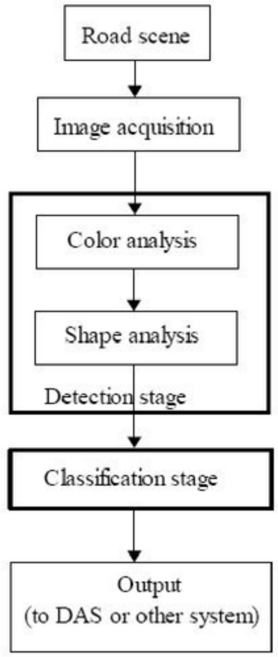

Figure 1 Traffic sign recognition system.

Detection

First step in the detection is color thresholding. Since only circular signs with red color border are considered, red color thresholding is employed. The algorithm could be expanded easily for handle the signs with the border's colors are other than red, eg. yellow, blue, etc. The red color thresholding extracts red objects from a whole image.

Points (x,y) in an image are classified into *red* if $R(x,y)/(R(x,y)+G(x,y)+B(x,y)) > TR$, where $R(x,y)$, $G(x,y)$, and $B(x,y)$ are the values of red, green and blue of point (x,y) in RGB color space. TR is a red threshold. After red color thresholding, a " blob" image is obtained. It contains all objects with red colors. Therefore an ellipse detection is applied to the blob image to detect the circular sign objects.

To detect an ellipse, at first edge point is extracted from the blob image. Edge points are commonly extracted using Canny, Sobel or Laplacian of Gaussian (LoG) edge detectors, which extract edge points of all objects. Since we need only extract the edge points of elliptical objects, the classification of boundary points (H. Chun-Ta and C. Ling-Hwei, 1996) is adopted. This method extract edge point effectively, since the noisy points or points that do not lie on the edges of ellipses are discarded or reduced.

After edge points are extracted, a geometric fragmentation technique (A. Soetedjo and K. Yamada, 2006) is employed to extract or detect the ellipses. This

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technique detects ellipses by finding and combining the left and right fragments of elliptical objects. The search for fragments resembles a genetic algorithm (GA) in the sense that it uses the terms of individual, population, crossover, and objective function, but it conducts a concurrent random search in a small two dimensional space devised heuristically. Thus it reduces computation time.

Figure 2 illustrates the fragments for ellipse extraction.

An ellipse is found by combining the left fragment and right fragment. To find fragments, a method somewhat similar GA, using tools such as individual, population, and crossover, but using only the framework of the concurrent search (not the evolution), is employed.

An individual of the left (right) fragment is represented by a six points. The searching process is done as follows:

Step 1. Generate the initial population.

Step 2. Evaluate objective values of individuals in the initial population. If the values exceed a threshold, add them to the candidate list.

Step 3. Randomly select pairs of individuals not in the candidate list.

Step 4. Mate two individuals using a single point crossover with a fixed position.

Step 5. Evaluate objective values of the new individuals. If these values exceed a threshold, add them to the candidate list. If two members in the candidate list are too close, retain the better one.

Step 6. Go to step 3 until N-iteration.

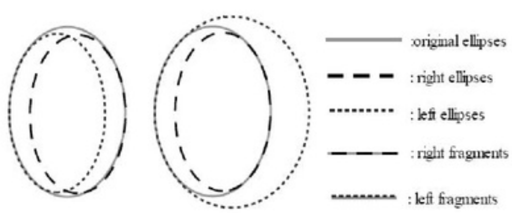

Figure 2. Illustration of the fragments.

After searching for fragments, we have two candidate lists: one of left fragments and the other of right fragments. The original ellipse is found by combining the two fragments. Since a fragment is represented by a set of six points, twelve points are obtained after the combination.

Then the original ellipse is extracted using these twelve points. We combine the two fragments as follows: a left fragment is combined with a right fragment if they are close together and the left one is on the left side of the right one, and vice versa. When multiple ellipses exist in an image, several combinations are obtained. To determine the appropriate combination, the combined individual is evaluated by counting the number of points along the circumference of the combined ellipse.

Classification

After traffic sign is detected from an image, then it is classified into one of the reference signs. The ring partitioned method (A. Soetedjo and K. Yamada, 2005) is employed for the classification. It consists of pre-processing step and matching step.

In the pre-processing step, a method to convert RGB image into grayscale image, which is invariant to illumination changes and shadows as depicted in figure 3.

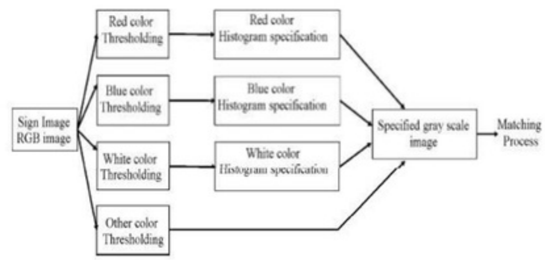

Figure 3. Pre-processing.

Traffic signs treated in this research are limited to circular signs with red color border (include "no entry sign"). Using this limitation, there are three kinds of colors in the signs: red, blue and white. Color thresholding is then applied to RGB images to extract the red, blue, white and the other colors of images. Pixels (x,y) are classified into *red* if $R(x,y)/(R(x,y)+G(x,y)+B(x,y))>TR$, *blue* if $B(x,y)/(R(x,y)+G(x,y)+B(x,y))>TB$, *white* if $R(x,y)>TW$ and $G(x,y)>TW$ and $B(x,y)>TW$, and the others otherwise. Colors in the others are treated as black. $R(x,y)$, $G(x,y)$ and $B(x,y)$ are the red, green and blue values of the pixels (x,y), respectively. TR, TB and TW are the red, blue and white thresholds, respectively.

After color thresholding, a grayscale image for each color can be obtained. Since original image is segmented by four colors thresholding, there are four grayscale images corresponding to each color. Using the histogram specification technique (R.C. Gonzalez and P. Wintz, 1987), a technique to convert an image into one with a particular histogram specified in advance, we could convert images into ones with prespecified histograms. By selecting different grayscale range in each image, finally we can combine four images into an image where grayscale range for red, blue, white, and the other color (black color) are definitely separated.

In the matching step, the resulted grayscale image is partitoned into several ring-shaped areas as shown in figure 4. By dividing the image into several areas, (A. Soetedjo and K. Yamada, 2005) proved that the performance of classification is better compared to the one without partition. Furthermore, since the image is partitioned into ring areas, even if the image is rotated, the histograms of the sub-images do not change. Thus, the ring partitioned is invariant to the rotation

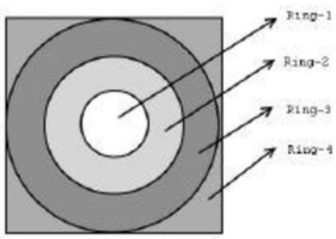

Figure 4. Ring partition.

To match between the target and reference images, two strategies are employed. In the first one, the distance between the target and reference image is calculated as

$$d^{TR} = \sqrt{\sum_i w_i \left(\sum_j (TH_i(j) - RH_i(j))^2 \right)}, \quad (1)$$

where $THi(j)$ is the normalized histogram of the target image of ring-i; $RHi(j)$ is the normalized histogram of the reference image of ring-i; i is a ring number; j is a grayscale level; w_i is the weighting factor of ring-i (between 0 and 1 and denotes the occlusion degree in every ring, 1 for no occlusion and 0 for occlusion at all).

In the second one, the distance between the target and reference image is calculated as

$$d^{TR} = \sqrt{\sum_i \left(\sum_j (THD_i(j) - RHD_i(j))^2 \right)}, \quad (2)$$

where THDi(j) is the normalized histogram of the target image of ring-i after discarding the occluded part; RHDi(j) is the normalized histogram of the reference image of ring-i after discarding the occluded part.

EXPERIMENTAL RESULTS

We implemented our algorithm using MATLAB and tested it on a Pentium-4, 2.6 GHz PC. In the detection stage, we used 100 real scene images taken by a digital camera in the daytime during sunny and cloudy weather. Of these, 25 contain signs partially occluded by utility poles or trees. Circular red signs in an image vary in number from one to three.

The detection result is shown in Tabel 1. Detection is defined as the ratio of correctly detected ellipses (outer ellipses of circular signs) to the total number of circular signs in images. A false alarm is defined as the ratio of detected ellipses that do not represent outer or inner ellipses of circular signs to the total number of circular signs in images.

Table 1 Detection results

Average detection	Average false alarms	Average detection time
0.845	0.10	2.44 second

Figure 5. No occluded signs.

Figure 6. Occluded signs.

Figures 5 and 6 show the typical detection results, where the detection result is represented by the blue ellipse drawn in the image. Figure 5 shows the detection result when the traffic signs are not occluded. Both two signs are detected properly. In figure 6, two signs are occluded by a pole. Those two signs are also detected properly as shown by the blue ellipses drawn in the figure.

In the classification stage, we classify the signs into one of the nine reference images as shown in figure 7.

Figure 7. Red circular images as the reference.

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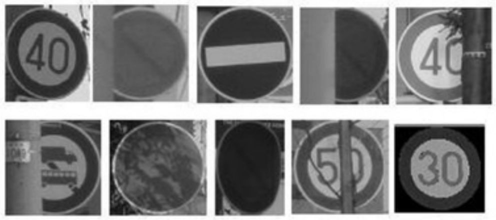

Figure 8. Some of the tested signs.

The signs obtained from the detection stage are cropped into rectangular image. Some of them are shown in figure 8. The number of images we tested in the classification stage are 180 images. The classification results are shown in Table 2. This results show the effectiveness of ring-partitioned matching for classifying images compared to the non ring-partitioned matching (conventional histogram matching).

Table 2 Classification results

Method	Matching rate
No ring-partitioned	66.96%
Artificial neural network (BPN)	89.29%
Ring-partitioned without weighting factors	88.39%
Ring-partitioned with weighting factors	95.53%
Ring-partitioned by discarding occluded part	94.64%

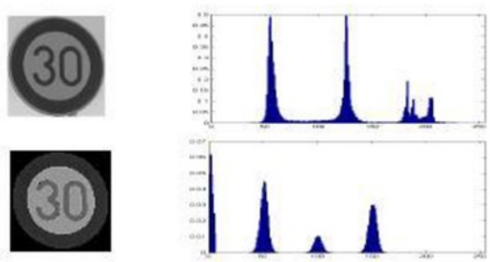

Figure 9. High brightness image

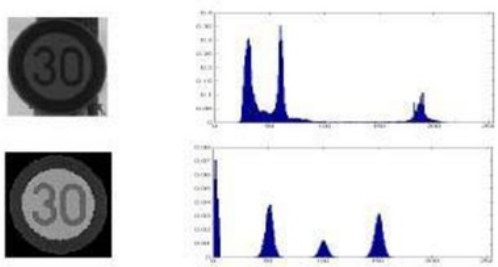

Figure 10. Low brightness image.

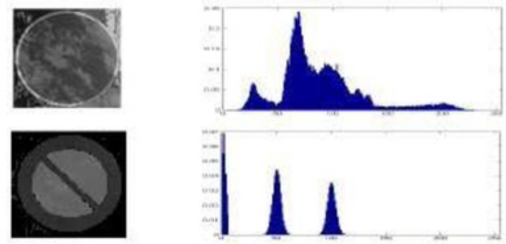

Figure 11. Shadowed image.

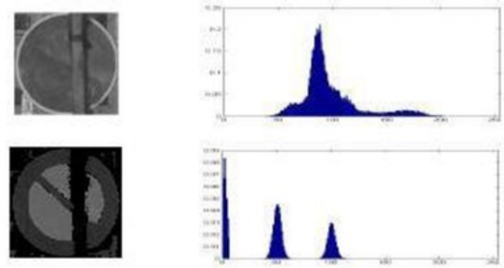

Figure 12. Occluded image.

Figures 9-12 show some of the specified grayscale images obtained using the method discussed in section 2.2 from the target images. In every figure, the upper side shows the usual grayscale image and its histogram, the lower side shows the specified grayscale image and its histogram.

In figures 9 and 10, two traffic sign images (the same sign) with different illumination are shown. The histograms of the usual grayscale images show the differences for both images, even they are the same limit speed sign. Meanwhile, the proposed specified grayscale images have the similar histograms.

In figure 11, there are leaf shadows in traffic sign image. The proposed method reconstructs the image properly. Figure 12 shows the occluded image. The occluding object (tree) can be detected and shown as black object.

CONCLUSION

In this paper, a method for traffic sign recognition is proposed. It consists of detection stage followed by classification stage. In the detection stage, a fast and robust ellipse detection using geometric fragmentation is employed. In the classification stage, a ring-partitioned matching is employed. It classifies red circular signs effectively, even under the problems of illumination changes, rotation, and occlusion.

For further research, we will extend the proposed system to recognize all the traffic signs other than red circular signs, and also implement the system into real hardware. Futhermore integrating the system with the Driver Assistance System (DAS) will be developed.

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